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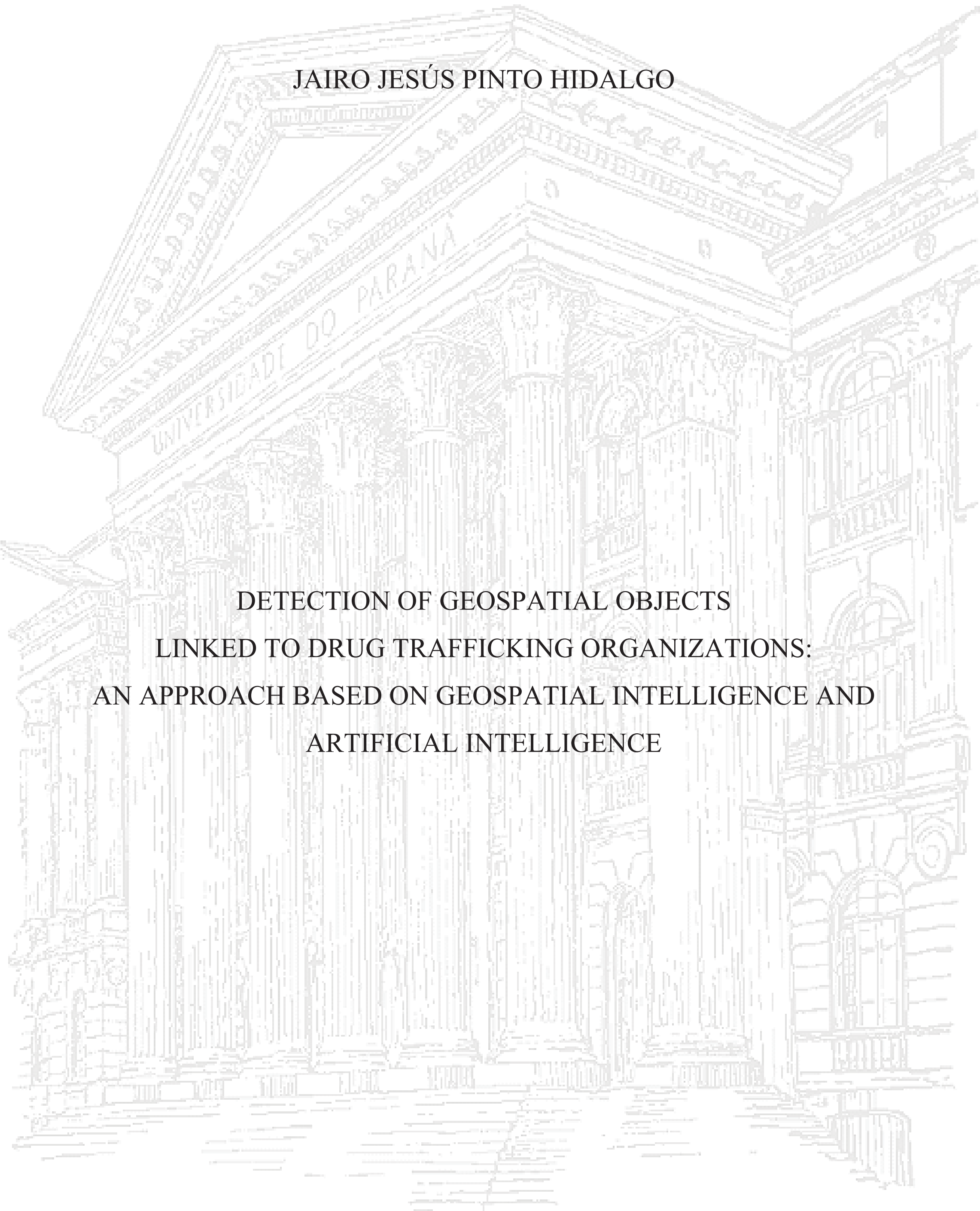

DETECTION OF GEOSPATIAL OBJECTS LINKED TO DRUG TRAFFICKING ORGANIZATIONS: AN APPROACH BASED ON GEOSPATIAL INTELLIGENCE AND ARTIFICIAL INTELLIGENCE

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DETECTION OF GEOSPATIAL OBJECTS LINKED TO DRUG TRAFFICKING ORGANIZATIONS: AN APPROACH BASED ON GEOSPATIAL INTELLIGENCE AND ARTIFICIAL INTELLIGENCE

Tese apresentada ao Programa de Pós-Graduação em Ciências Geodésicas, Setor de Ciências da Terra da Universidade Federal do Paraná, como requisito parcial à obtenção do título de Doutor em Ciências Geodésicas.

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A outorga do título de doutor está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

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Cuando comencé este camino del doctorado, nunca pensé, que el día al que más temor le tenía llegaría…

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"Un soldado de la justicia y de la ley es más grande que el conquistador del universo…".

Simón Bolívar

"If you know the enemy and know yourself, you need not fear the result of a hundred battles. If you know yourself but not the enemy, for every victory gained you will also suffer a defeat. If you know neither the enemy nor yourself, you will succumb in every battle."

Sun Tzu, The Art of War

"When you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind."

William Thomson

RESUMO

As Organizações de Tráfico de Drogas (OTDs) não reconhecem fronteiras administrativas ou políticas. A resiliência, evolução e convergência com outras atividades do crime organizado, como os crimes ambientais transnacionais, são as principais características dessas organizações. Aproveitam os espaços geográficos que estão fora do controle efetivo do Estado, onde encontram oportunidades geoestratégicas específicas para cometer o crime. Suas atividades são diversas, utilizam as infraestruturas de transporte terrestre, aéreo, marítimo e fluvial para estabelecer rotas desde as áreas de produção até os mercados consumidores, empregando múltiplos *modus operandi* e meios de transporte. Nos últimos 10 anos, ecossistemas importantes, como a Amazônia, foram afetados pela degradação ambiental acelerada e pelo estabelecimento de atividades vinculadas às OTDs. Consequentemente, essas organizações criminosas converteram a região sul-americana no epicentro global do tráfico de drogas e do comércio transnacional ilegal de recursos naturais, representando uma séria ameaça ao Estado de Direito e ao desenvolvimento sustentável dos países afetados. A partir do uso de técnicas de inteligência geoespacial e métodos de inteligência artificial, esta tese propõe uma metodologia baseada no ciclo de inteligência para detectar objetos geoespaciais vinculados a organizações de tráfico de drogas, utilizando imagens de satélite multiespectral, dados da verdade do terreno e informação de fontes abertas. Neste contexto, através da criação dos conjuntos de dados de imagens de satélite para aplicações de inteligência artificial, *CocaPaste-PI-DETECTION* e *AmazonCRIME*, são treinados modelos de aprendizagem profunda especializados em tarefas de classificação de imagens e de detecção de objetos. Os resultados obtidos geram previsões cujas métricas de avaliação são superiores a 90%. As capacidades de generalização dos modelos foram analisadas e diferentes experimentos foram realizados. Um conjunto de dados também foi gerado usando técnicas de processamento de linguagem natural, o que permite escanear o entorno e identificar tendências e possíveis rotas de tráfico de cocaína. Os conjuntos de dados foram colocados à disposição da comunidade científica e acadêmica para fins de pesquisa. A partir de experiências operacionais em interdição de drogas e da literatura acadêmica, foi descrita uma base conceitual para a compreensão da dinâmica das OTDs, processos de produção de cloridrato de cocaína, inteligência geoespacial a partir de uma perspectiva de aplicação da lei e inteligência artificial aplicada ao sensoriamento remoto. Os resultados obtidos nesta tese mostram coerência com a literatura existente sobre crime organizado e tráfico de drogas, permitindo a geração de uma imagem de inteligência atualizada e demonstrando como a aplicação da metodologia proposta poderia fortalecer a tomada de decisões destinadas à formulação de estratégias de intervenção e prevenção contra as organizações do tráfico de drogas.

Palavras-chave: inteligência geoespacial; sensoriamento remoto; ciclo de inteligência; inteligência artificial; aprendizagem profunda; processamento de linguagem natural; informação de fontes abertas; rotas do tráfico de cocaína; organizações do tráfico de drogas; crimes ambientais transnacionais; objetos geoespaciais; cocaína.

RESUMEN

Las Organizaciones del Tráfico de Drogas (OTDs) no reconocen fronteras administrativas o políticas. La resiliencia, evolución y convergencia con otras actividades del crimen organizado como los crímenes ambientales transnacionales, son las principales características de estas organizaciones. Aprovechan espacios geográficos que están fuera del control efectivo del Estado, donde encuentran oportunidades geoestratégicas específicas para la comisión del delito. Sus actividades son diversas, utilizan las infraestructuras de transporte terrestre, aéreo, marítimo y fluvial, para establecer rutas desde las áreas de producción hacia los mercados de consumo, empleando múltiples *modus operandi* y medios de transporte. En los últimos 10 años, importantes ecosistemas como el Amazonas se han visto afectados por una acelerada degradación ambiental y el establecimiento de actividades vinculadas a las OTDs. Por consiguiente, estas organizaciones criminales han convertido a la región sudamericana en el epicentro mundial del tráfico de drogas y del comercio transnacional ilegal de recursos naturales, representando una grave amenaza para el Estado de Derecho y el desarrollo sostenible de los países afectados. En esta tesis se propone una metodología basada en el ciclo de inteligencia para detectar objetos geoespaciales vinculados a las organizaciones del tráfico de drogas a partir de imágenes satelitales multiespectrales, datos de la verdad en el terreno e información de fuentes abiertas, utilizando técnicas de inteligencia geoespacial y métodos de inteligencia artificial. En este contexto, mediante la creación de los conjuntos de datos de imágenes satelitales para aplicaciones de inteligencia artificial, *CocaPaste-PI-DETECTION* y *AmazonCRIME*, se entrenan modelos de aprendizaje profundo especializados en tareas de clasificación de imágenes, y tareas de detección de objetos. Los resultados obtenidos generan predicciones cuyas métricas de evaluación son superiores al 90%. Se analizan las capacidades de generalización de los modelos, y se realizan diferentes experimentos. También se genera un conjunto de datos mediante técnicas de procesamiento de lenguaje natural, que permite escanear el entorno e identificar tendencias y posibles rutas del tráfico de cocaína. Los conjuntos de datos se ponen a disposición de la comunidad científica y académica con fines de investigación. A partir de experiencias operativas en la interdicción de drogas y de la literatura académica, se describe una base conceptual que permite comprender la dinámica de las OTDs, los procesos de producción de clorhidrato de cocaína, la inteligencia geoespacial desde la perspectiva de la aplicación de la ley y la inteligencia artificial aplicada en percepción remota. Los resultados obtenidos en esta tesis muestran consistencia con la literatura existente sobre el crimen organizado y tráfico de drogas, permitiendo generar una imagen de inteligencia actualizada, y demostrando cómo la aplicación de la metodología propuesta podría fortalecer la toma de decisiones destinadas a la formulación de estrategias de intervención y prevención contra las organizaciones del tráfico de drogas.

Palabras claves: inteligencia geoespacial; percepción remota; ciclo de inteligencia; inteligencia artificial; aprendizaje profundo; procesamiento de lenguaje natural; información de fuentes abiertas; rutas del tráfico de cocaína; organizaciones del tráfico de drogas; crímenes ambientales transnacionales; objetos geoespaciales; cocaína.

ABSTRACT

Drug Trafficking Organizations (DTOs) do not recognize administrative or political boundaries. Resilience, evolution, and convergence with other organized crime activities, such as transnational environmental crimes, are the main characteristics of these organizations. They take advantage of geographic spaces that are outside the effective control of the State, where they find specific geostrategic opportunities for the commission of the crime. Their activities are diverse, using land, air, sea, and river transport infrastructures to establish routes from production areas to consumer markets, employing multiple *modus operandi* and means of transport. In the last 10 years, important ecosystems such as the Amazon have been affected by accelerated environmental degradation and the establishment of activities linked to DTOs. Consequently, these criminal organizations have turned the South American region into the global epicenter of drug trafficking and illegal transnational trade in natural resources, posing a serious threat to the rule of law and sustainable development in the affected countries. This thesis proposes a methodology based on the intelligence cycle to detect geospatial objects linked to drug trafficking organizations from multispectral satellite imagery, ground truth data, and open-source information, using geospatial intelligence techniques and artificial intelligence methods. In this context, deep learning models specialized in image classification and object detection tasks are trained by creating satellite imagery datasets for artificial intelligence applications, CocaPaste-PI-DETECTION and AmazonCRIME. The results obtained generate predictions whose evaluation metrics are higher than 90%. The generalization capabilities of the models are analyzed, and different experiments are carried out. A dataset is also generated using natural language processing techniques, which allows environment scanning and identifying trends and possible cocaine trafficking routes. The datasets are made available to the scientific and academic community for research purposes. Based on operational experiences in drug interdiction and academic literature, a conceptual basis is described to understand the dynamics of DTOs, cocaine hydrochloride production processes, geospatial intelligence from a law enforcement perspective, and artificial intelligence applied in remote sensing. The results obtained in this thesis show consistency with the existing literature on organized crime and drug trafficking, allowing the generation of an updated intelligence picture, and demonstrating how the application of the proposed methodology could strengthen decision-making to formulate intervention and prevention strategies against drug trafficking organizations.

Keywords: geospatial intelligence; remote sensing; intelligence cycle; artificial intelligence; deep learning; natural language processing; open-source information; cocaine trafficking routes; drug trafficking organizations; transnational environmental crimes; geospatial objects; cocaine.

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ABREVIATION LIST

AI	Artificial Intelligence
AMERIPOL	Comunidad de Policías de América
ANAC	Agência Nacional de Aviação Civil
ANNs	Artificial Neural Networks
ANTIDROGAS-GNB	Comando Nacional Antidrogas de la Guardia Nacional Bolivariana
BC	Base de Cocaína
CC	Clorhidrato de Cocaína
CEOFANB	Comando Estratégico Operacional de la Fuerza Armada Nacional Bolivariana
CIENA	Centro Internacional de Estudios Estratégicos Contra el Narcotráfico
CITES	Convention on International Trade in Endangered Species of Wild Fauna and Flora
CNNs	Convolutional Neural Networks
CoE-Brazil	Center of Excellence for Illicit Drug Supply Reduction (Brazil - UNODC)
CoE-Mexico	Center of Excellence for Illicit Drug Supply Reduction (Mexico – UNODC)
CPCC	Complejo de Producción de Clorhidrato de Cocaína
CV	Comando Vermelho
DEA	Drug Enforcement Administration
DL	Deep Learning
DMP	Drugs Monitoring Platform
DNNs	Deep Neural Networks
DOS	United States Department of State
DTOs	Drug Trafficking Organizations
ELN	Ejército de Liberación Nacional
EMCDDA	European Monitoring Centre for Drugs and Drug Addiction
EPL	Ejército Popular de Liberación
ES	Environmental Scanning
ESA	European Space Agency

EUROPOL	European Union's law enforcement agency
FARC-EP	Fuerzas Armadas Revolucionarias de Colombia - Ejército del Pueblo
FDN	Famila do Norte
FNN	Feedforward Neural Network
FSPB	Forças de Segurança Pública no Brasil
GDELT	Global Database of Events, Language, and Ton
GEE	Google Earth Engine
GEFRON	Grupo Especial de Segurança de Fronteira
GeoAI	Geospatial Artificial Intelligence
GEOINT	Geospatial Intelligence
GEOSDB	GEOINT seizure database
GIScience	Geographic Information Science
HRW	Human Rights Watch
IACA	International Association of Crime Analysts
IBGE	Instituto Brasileiro de Geografia e Estatística
ICMP	Illicit Crop Monitoring Program
ICP	Information Collection Plan
ICS	Individual Cocaine Seizures
IDS	Individual Drug Seizures
IFP-BC	Infraestructuras de Producción Primaria para Producir Base de Cocaína
IFP-PBC	Infraestructuras de Producción Primaria para Producir Pasta Base de Cocaína
IGAC	Instituto Geográfico Agustín Codazzi
IGVSB	Instituto Geográfico de Venezuela Simón Bolívar
INCB	International Narcotics Control Board
INE	Instituto Nacional de Estadística
INPE	Instituto Nacional de Pesquisas Espaciais
INTERPOL	International Criminal Police Organization
KDE	Kernel Density Estimation
LAC	Latin America and the Caribbean
mAP	mean Average Precision

ML	Machine Learning
NATO	International Criminal Police Organization
NGA	National Geospatial-Intelligence Agency
NIIRS	National Imagery Interpretability Rating Scale
NLP	Natural Language Processing
NPS	New Psychoactive Substance
OAS	Organization of American States
OCG	Organized Crime Group
OECD	Organisation for Economic Co-operation and Development
OpenAIP	Open Aeronautical Information Publication
OSCE	Organization for Security and Co-operation in Europe
OSINT	Open-source intelligence
PBC	Pasta Básica de Cocaína
PCC	Primeiro Comando da Capital
PF	Polícia Federal
PONAL	Policia Nacional de Colombia
PRF	Polícia Rodoviária Federal
RAISG	Red Amazónica de Información Socioambiental Georreferenciada
ReLU	Rectified Linear Unit
RF	Receita Federal
RPN	Regional Proposal Network
RS	Remote Sensing
SENAD	Secretaria Nacional de Políticas sobre Drogas e Gestão de Ativos
SIMCI	Sistema Integrado de Monitoreo de Cultivos Ilícitos
SOUTHCOM	U.S. Southern Command
SUNAD	Superintendencia Nacional Antidrogas
TEC	Transnational Environmental Crimes
UF	Unidade Federativa
UNDP	United Nations Development Programme
UNDPKO	United Nations Department of Peacekeeping Operations
UNEP	United Nations Environment Programme
UN-GGIM	United Nations Committee of Experts on Global Geospatial Information Management

UNHRC	United Nations Human Rights Council
UNICRI	United Nations Interregional Crime and Justice Research Institute
UNODC	United Nations Office on Drugs and Crime
UNSC	United Nations Security Council
UPAC	Agricultural Production Units with Coca
WDPA	World Database on Protected Areas

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1 INTRODUCTION

Drug trafficking organizations (DTOs) do not recognize borders, they operate at local, national, regional, and trans-regional levels (EUROPEAN UNION, 2020). They are organized and characterized by planning, preparation, and continuity over time (Antonopoulos & Papanicolaou, 2018). Their activities become increasingly efficient as they are dynamic, constantly evolving, and adapting (UNODC, 2021a, 2021c), taking advantage of spaces that are beyond the effective control of the State (Brown et al., 2020), where they find specific geostrategic opportunities for crime (Pinto, 2017; Taylor et al., 2013).

They are complex organizations with highly defined command and control structures that produce, transport, and distribute large quantities of illicit drugs (IACA, 2017; U.S. DEPARTMENT OF JUSTICE, 2010) for financial gain. But their activities are not limited to drug trafficking, they are linked to various illicit activities, like illegal mining (INTERPOL, 2022a; UNODC, 2022b), among other transnational environmental crimes (TEC), and related crimes (extortion, kidnapping, human trafficking, money laundering, homicides, rape, corruption, and bribery of public officials, gasoline smuggling, commercialization of chemical substances). They use the available transportation infrastructure: land (roads and railways), air, maritime, and river, to establish routes (national or international) for illegal markets, using multiple camouflage and concealment techniques (Bergman, 2018; PONAL, 2020).

Drug trafficking has become one of the most serious problems facing Latin America and the Caribbean (LAC) (Bergman, 2018; UNODC, 2012b). This is the archetypal criminal activity of organized crime (Antonopoulos & Papanicolaou, 2018). It constitutes a serious threat to society, the stability of institutions, public health, and human welfare (INTERPOL, 2022b). It violates respect for human rights and manifests itself in different intensities, depending on the specific realities of each country (OAS, 2013), with LAC standing out as the region most affected by cocaine production, distribution, trade, and consumption worldwide (UNODC, 2021c).

The World Drug Report 2022 estimates that cocaine manufacture increased by 11% from 2019 to 2020, reaching a record level of 1,982 tons, while Colombia, Peru, and Bolivia, continue to be the main source of illicit coca cultivation and cocaine production globally (UNODC, 2022b). North America and Europe stand out as the main consumer and destination markets for this substance (DOS, 2022; EMCDDA, 2022b; UNODC, 2022b). Cocaine is generally transported from South American producer countries to North America, Europe, and Africa using various routes, methods, and means of transport (EMCDDA, 2022a; UNODC, 2022c). In this sense, the dynamics between production areas and consumption markets lead to trafficking modalities and routes from a circumscribed origin to specific destinations, making cocaine trafficking a clear threat to society (UNODC, 2021a).

There is a strong relation between armed conflicts, production infrastructures, and the expansion of illicit coca cultivation with the destruction of important environmental assets (CIENA, 2014; Negret et al., 2019; Wrathall et al., 2020), such as the Amazon and border regions. Coca crops, for example, play a considerable role in deforestation (UNODC, 2022b). They are often connected and overlap with gold-producing areas, becoming a strategy by DTOs to diversify their sources of income while remaining active in the drug trade (UNODC, 2022a; Zabyelina & van Uhm, 2020). In addition, there are indications that coca and cocaine production processes could extend to transit and consumption countries (UNODC, 2022c).

Transnational environmental crime has become one of the main financial drivers of organized crime, directly affecting natural resources and generating serious consequences and threats to the maintenance of peace, security, human health, economy, and sustainable development of civil society and governments (EUROPOL, 2022; INTERPOL, 2018a). They refer to any activity or omission against the law, cross borders, are based on the illegal use of natural resources, originating direct impacts on the environment, irreversible and far-reaching. Their transnational character links them to other organized crime activities (White, 2018). They use sophisticated techniques, modern technologies, and connection networks like drug trafficking (UNEP, 2012) (clandestine airstrips, roads, clandestine ports, and river networks), which allow them to operate and connect between countries and continents.

In the last 10 years, important ecosystems such as the Amazon region, which extends across several countries (Bolivia, Brazil, Colombia, Ecuador, Guyana, French Guiana, Peru, Suriname, and Venezuela), have become an important air, land, and river corridor for new routes and activities linked to DTOs. Highlighting illegal gold mining, deforestation, drug trafficking, illicit coca crop production, clandestine airstrips, and cocaine production infrastructures as the main criminal activities affecting the region (EL PACCTO, 2019; EXÉRCITO BRASILEIRO, 2018; INSIGHT CRIME, 2020a; Pinto & Jordán, 2013; UNODC, 2012a, 2022b).

Venezuela has been denounced for its participation and complicity with armed drug trafficking groups, illegal mining, and crimes against humanity (DOS, 2022; UNHRC, 2020; UNHRC, 2022) and is characterized as an important transit country, departure point, and route for establishing illegal aircraft and airstrips that transport cocaine to international markets (DEA, 2021; INSIGHT CRIME, 2020a; Pinto, 2017). Brazil is considered an important transit and destination country for cocaine produced in South America (DOS, 2022; UNODC, 2022). Some studies suggest that it is the largest cocaine market in South America (UNODC, 2021c) and probably the second largest cocaine consumer globally (DOS, 2022). Several investigations have identified and confirmed the existence of more than 2,576 areas related to illegal gold, diamond, and coltan mining, distributed throughout the Brazilian Amazon region (RAISG, 2020a). In 2020, it registered a 34% increase in deforestation (INPE, 2020).

Consequently, DTOs represent a serious threat to the rule of law[1] and sustainable development of the affected countries, turning the South American region into the global epicenter of drug trafficking and illegal transnational trade in natural resources (GLOBAL INITIATIVE, 2016; UNODC, 2019a).

There is a global effort to identify and monitor activities linked to DTOs, like the Integrated System for Monitoring Illicit Crops (SIMCI) of the United Nations Office on Drugs and Crime in Colombia, which in collaboration with the Colombian government, implements methodologies based on remote sensing and field verifications to monitor illicit coca crops, illegal mining and the characterize various activities related to drug supply (Rincón-Ruiz et al., 2016; UNODC, 2022a, 2022e).

Another initiative is Brazil's Center of Excellence for Illicit Drug Supply Reduction (CoE-Brazil), which is the result of a partnership between the National Secretariat for Drug Policy and Asset Management (SENAD) of the Ministry of Justice and Public Security, UNODC, and UNDP, which researches and analyses the dynamics of drug trafficking and organized crime based on scientific evidence (CoE-Brazil, 2022a; UNODC, 2022c).

These institutions and several researchers have shown that geospatial data on interdiction activities, such as individual drug seizures (IDS), eradication of illicit crops, dismantling of production infrastructures; origin-destination routes, and the dynamics of illicit

[1] Principle of governance in which all persons, institutions, and entities, public and private, including the State itself, are subject to laws that are publicly promulgated, equally enforced, and independently applied, and are consistent with international human rights norms and principles. It also requires that measures be taken to ensure respect for the principles of the rule of law, equality before the law, separation of powers, participation in decision-making, legality, non-arbitrariness, and procedural and legal transparency (United Nations, 2022d).

drug and illegal mining markets, are relevant for the analysis and formulation of intervention strategies (CoE-Brazil, 2021, 2022b; EMCDDA, 2016, 2022c; Magliocca et al., 2019; Pennsylvania State University, 2020a; Pinto, 2017; Pinto & Jordán, 2013; PONAL, 2020; Santos, 2022; UNODC, 2017a, 2019a, 2022b). Therefore, the detection of geospatial objects linked to the activities of DTOs allows contributing to the strategic analysis aimed at understanding the patterns, trends, and dynamics of these criminal organizations.

However, criminal activity is not public and open; it is difficult to measure organized crime and collect reliable information (Blanco & Cohen, 2017; Dugato & Aziani, 2020; Reichel & Albanese, 2013). Not all countries collect extensive and high-quality data that is publicly available and useful for strategic analysis (CoE-Mexico, 2014). Nor are they found with geospatial attributes that allow linking organized crime events to a location on the Earth's surface. The illicit nature of DTOs makes it very difficult to collect data on these illicit activities. For example, in border regions, like the border between Venezuela and Colombia, the infrastructures where the different cocaine production processes are carried out are in places with geographic characteristics that guarantee clandestinity, being their detection the main challenge to face this threat. In most cases, identification is done by obtaining information from human sources or through reconnaissance and exploration during illicit crop eradication activities, border patrols, and drug interdiction operations.

In Brazil, there are difficulties in creating a national database that consolidates and compiles, in a unified manner, data on the dynamics of drug trafficking, which is articulated by different Brazilian public security forces or *forças de segurança pública no Brasil* in Portuguese (FSPB) which have an institutional scope of action in the federative republic (states, Federal District and municipalities) (CoE-Brazil, 2022b). In other words, each police institution has its own data system, and they are not shared. So, the absence of a solid integration, which could promote the cooperation of intelligence activities, constitutes one of the main challenges for combating organized crime in a national context (Gonçalves, 2004). The lack of coordination and cooperation between police agencies is a factor that influences the detection of organized crime at national and international levels (Reichel & Albanese, 2013). In addition, the capacity to collect, process, and disseminate information in LAC countries, including methodologies and conceptual bases, is disproportionate (OAS, 2013).

This dynamism and the described drawbacks become complex challenges for investigation and law enforcement. They restrict the opportunity for strategic analysis of organized crime, which enables a timely and more complete criminal intelligence. Due to the inherent geospatial nature of activities linked to DTOs and the rapid evolution and adaptation of criminals, methods are required to facilitate the intelligent collection of evidence sources that provide an environmental scanning[2] (ES) to support policy and operational decision making for the prevention and interdiction of DTOs.

Geospatial Intelligence (GEOINT) and Artificial Intelligence (AI) become important tools to discover geospatial links and patterns of georeferenced features and activities on Earth associated with organized crime (Pinto & Centeno, 2022b). They are appropriate technologies for the prevention and confrontation of DTOs since law enforcement relies on collecting and analyzing large amounts of data from various intelligence sources related to human behavior (UNICRI, 2019).

With the advent of Geospatial Big Data (Kussul et al., 2017; S. Li et al., 2016), and the availability of large amounts of geospatial data, it was established the basis for the use of artificial intelligence methods and especially Deep Learning in many of the GEOINT community's tasks dedicated to combating drug trafficking and organized crime (Biltgen & Ryan, 2016; Clark, 2014, 2020; Lowenthal, 2019; Pinto & Centeno, 2022a,b; SOUTHCOM, 2017). When applied to image analysis, Deep Learning algorithms, such as Convolutional Neural Networks – CNN) use multiple neuronal layers to automatically extract and learn high-level abstract features from the original pixel values of images (Cheng & Han, 2016; L. Zhang, Xia, et al., 2016; Zhang, Zhang, et al., 2016). They have been used to build tools that can detect, predict, and communicate the dynamics of organized crime, challenging traditional methods and promising greater efficiency aimed at its prevention and confrontation (UNICRI, 2020a).

Some applications are based on satellite image classification and geospatial object detection (Ma et al., 2019; Janowicz et al., 2020; Camps-Valls et al., 2021; del Rosso et al., 2021) to detect clandestine airstrips, illegal mining, coca cultivation, deforestation (Pinto & Centeno, 2022b), marijuana cultivation (Ferreira et al., 2019), or poppy crop (Liu et al., 2018; Wang et al., 2021). Other approaches use natural language processing (NLP) techniques for

[2] Environmental scanning is understood as the process of continuously gathering information for tactical and strategic purposes, about events occurring in the external environment, to identify and interpret potential trends and key factors, which impact law enforcement. This process involves obtaining both objective and subjective information (EUROPOL, 2021; Ingle & Staniforth, 2017; UNODC, 2010b), to produce knowledge about what is happening and to better understand how to respond to new scenarios (Kruse & Svendsen, 2017).

mining unstructured qualitative and quantitative data, such as police reports and digital news articles (Chen et al., 2004; Y. Hu, 2018) to look for information.

Measuring and identifying DTOs is not easy and is expensive. It requires many human, financial and logistical resources (EUROPOL, 2011). In addition, the scenarios that characterize organized crime cause a series of physical and psychological risks, which can even lead to human losses.

This thesis aims to contribute with some solutions to counteract these challenges, as well as to the academic literature and the field of policy making in the context of organized crime; developing a methodology based on the intelligence cycle that combines geospatial intelligence techniques and artificial intelligence methods, to detect geospatial objects linked to drug trafficking organizations, based on multispectral images from Sentinel-2 and PlanetScope satellites, ground truth data, geospatial information and open-source information.

Three specific aspects of using artificial intelligence within the field of geographic information science (GIScience) to produce geospatial intelligence are treated. The first is developing a system for detecting potential primary production infrastructures to produce coca paste (IFP-PBC) in satellite images. The second is a system that classifies and identifies areas of illegal mining, airstrips, illicit coca cultivation, and deforestation in satellite images. Both approaches use deep learning techniques. The third is related to the use of open-source information and natural language processing methods (web scraping and regular expressions) to create a database from available reports of news websites related to individual cocaine seizures (ICS) and detect potential cocaine trafficking routes and trends using geospatial analysis methods and cartographic techniques. Current drug trafficking literature documented by recognized national and international sources corroborates the results and illustrates the practical potential for generating knowledge about the dynamics of this illicit market.

Considering the previous discussion, the following hypothesis is proposed:

1.1 HYPOTHESIS

Geospatial intelligence and artificial intelligence methods have the potential to detect geospatial objects linked to drug trafficking organizations in multispectral satellite imagery and open-source data with sufficient accuracy and precision to extract features and collect information to identify them.

The constant evolution and adaptation of drug trafficking and organized crime dynamics over time constitute one of the main challenges for law enforcement and investigation. Therefore, the design of deep learning models and natural language processing algorithms, using scientific, transparent, reliable, and reproducible methods, would effectively counter the threat posed by drug trafficking organizations to society.

1.2 AIMS

The general aim is to develop an intelligence cycle-based methodology to detect geospatial objects linked to drug trafficking organizations from multispectral satellite imagery, ground truth data, geospatial information, and open-source information, using geospatial intelligence techniques and artificial intelligence methods.

To achieve this general objective, the following specific objectives were established:

- Create reference datasets based on multispectral imagery from Sentinel-2 and PlanetScope satellites, ground truth data, geospatial information, and open-source information to train deep learning models and develop natural language processing algorithms specialized in geospatial object detection, image classification, and information extraction, linked to DTOs.
- To evaluate available information considering the source’s reliability and the information validity.
- To evaluate the viability of including specialized deep learning models in the collation/processing stage of the intelligence cycle process, to detect and classify geospatial objects linked to DTOs in multispectral remote sensing imagery.
- To evaluate the viability of including natural language processing methods in the collation/processing stage of the intelligence cycle process, aiming at extracting relevant data related to DTOs, from open-source information.

- Demonstrate the potential of adapting the intelligence cycle-based methodology to environmental scanning with a strategic approach and provide insights into the dynamics of DTOs, considering the geospatial context.
- Publicly share reference datasets with the scientific and academic community to foster research on geospatial intelligence and artificial intelligence to support policy and operational decision-making aimed at preventing and interdiction DTOs.

1.3 THESIS OUTLINE

Given the contributions described above, this thesis is organized as follows:

- Chapter 2 presents the main lines of literature and documents some operational experiences related to the dynamics of drug trafficking organizations and organized crime, which serve as a base for this study. A contextualization of geospatial intelligence and artificial intelligence is presented, focusing mainly on the methods applied in this research.
- Chapter 3 systematically describes the proposed methodology for detecting geospatial objects linked to DTOs based on the intelligence cycle.
- Chapter 4 uses the proposed methodology to guide and develop the research experiments.
- Chapter 5 discusses the results obtained.
- Finally, Chapter 6 presents the main conclusions, contributions of the thesis, and recommendations for future research.

2 LITERATURE REVIEW

2.1 ORGANIZED CRIME

Organized crime focuses exclusively on rationally planned acts that reflect the efforts of a group of individuals (UNODC, 2020a) to obtain economic benefits through illicit activities. Planning, preparation, complexity, and continuity over time distinguish organized crime from spontaneous transgressions (Antonopoulos & Papanicolaou, 2018).

An organized crime group (OCG) is defined by the United Nations Convention against Transnational Organized Crime (UNODC, 2004) under four general characteristics:

1. A structured group of three or more people.
2. The group exists for a period.
3. Acts in concert with the aim of committing one or more serious crimes.
4. Aims at obtaining, directly or indirectly, financial, or other material benefits.

So, for this research, organized crime is defined as: "*an ongoing criminal enterprise that works rationally to profit from illicit activities that are often in high public demand. Its continued existence is maintained through the corruption of public officials and the use of intimidation, threats, and force to protect its illicit activities*" (UNODC, 2020a).

The illicit activities of organized crime can be systematically exploited to secure an ongoing criminal enterprise. Conceptually, illicit markets exploited by organized crime are reflected in three main categories (Albanese, 2020): a) Provision of illicit services, b) provision of illicit goods, and c) infiltration of legitimate business or government. (Table 1).

The **provision of illicit goods** offers specific products that a segment of the public desires but cannot obtain through legal means. For example, illicit drugs such as cocaine generate a demand whose manufacture, distribution, and trade are illicit and subject to drug prohibition laws. The illicit trade in natural resources such as gold is another example of this category. **The provision of illicit services** represents an attempt to satisfy public demand for services that legitimate society does not provide. For example, money, prostitution, or gambling. **Infiltration of legitimate business or government**, generally non-consensual activities, can generate violence, threats, extortion, and economic damage in general. In this case, bribery is another action of organized crime to protect its illicit activities, paying or offering illicit favors to corrupt public officials.

TABLE 1 - EXAMPLES OF SOME CRIMINAL MARKETS EXPLOITED BY ORGANIZED CRIME

Provision of illicit goods	Provision of illicit services	Infiltration of legitimate business or government
– Drug trafficking – Natural resource trafficking – Firearms trafficking – Wildlife Trafficking – Forest crimes – Stolen and banned property – Counterfeiting	– Human trafficking – Fraud and cybercrime – Commercial vices (prostitution, illegal gambling, loansharking, among others)	– Extortion – Money laundering – Corruption – Racketeering – Bribery – Coercive use of legal businesses or government agencies (from the inside or the outside)

Source: (Albanese, 2015, 2020).

2.2 DRUG TRAFFICKING

Drug trafficking is probably one of the most emblematic activities of organized crime and evidence indicates that the illegal economy of this market is based on corruption (OAS, 2013). It is a global illicit trade involving the cultivation, manufacture, distribution, and sale of substances (narcotic or psychotropic) subject to drug prohibition law (UNODC, 2022f). It is estimated that almost half a million people died from drug use in 2019 (UNODC, 2021b). In 2020, globally, 1 in 18 people aged 15-64 years (284 million people, 5.6% of the population) used at least one illegal drug (UNODC, 2022b).

The international legal framework for drug control consists of three main international conventions: 1) the Single Convention on Narcotic Drugs of 1961 (as amended in 1972); 2) the Convention on Psychotropic Substances of 1971; and 3) the United Nations Convention against Illicit Traffic in Narcotic Drugs and Psychotropic Substances of 1988, and the Ministerial Declaration of 2019 (UNODC, 2019b, 2022g).

The Single Convention on Narcotic Drugs of 1961 merged all multilateral treaties existing up to the date of its publication, created the International Narcotics Control Board, and extended drug control to the cultivation of plants used as the primary input for the production of narcotic drugs (opium poppy, coca bush, cannabis plant), including the consumption of opium, coca leaf chewing, consumption of cannabis resin and non-medical use of cannabis (United Nations, 2022a). It presents the list of narcotic drugs under international control, known as the Yellow List, divided into four parts. It controls about 163 narcotic drugs and their preparations (INCB, 2021a), including Cocaine, Heroin, Cannabis, Fentanyl, among others. It classifies substances according to their therapeutic value and potential risk of abuse. It prohibits the production, manufacture, export and import, trade, possession, or consumption of such substances, establishing limits for medical and scientific purposes.

The Convention on Psychotropic Substances of 1971 expanded international drug control to include the control of various synthetic drugs according to their dependence-forming potential and therapeutic value (United Nations, 2022b). These substances included amphetamine-type stimulants, hallucinogens (e.g., LSD, ecstasy, or MDMA), sedatives, anxiolytics, analgesics, and antidepressants (United Nations, 2022b). The substances are organized in the Green List of psychotropic substances and control about 166 psychotropic substances (INCB, 2021b).

The Convention against Illicit Traffic in Narcotic Drugs and Psychotropic Substances of 1988 aims to control precursor chemicals in manufacturing illicit drugs and the growing problem of international trafficking. It includes money laundering and illicit trafficking in precursor chemicals as drug trafficking activities, provides special law enforcement measures, and strengthens the obligation of countries to impose criminal penalties to combat illicit drug production, possession, and trafficking (United Nations, 2022c). It introduces the substances included in the Red List, which specifies precursors, reagents, and solvents frequently used in the illicit manufacture of narcotic drugs or psychotropic substances (INCB, 2022). It currently controls 30 precursor chemicals (INCB, 2022), including hydrochloric acid, sulfuric acid, and potassium permanganate. International cooperation is promoted through mechanisms for the extradition of major drug traffickers and mutual legal assistance between countries in drug-related investigations and prosecutions (United Nations, 2022c).

The Ministerial Declaration of 2019 is a document unanimously approved by the member countries, aimed at strengthening national, regional, and international actions to accelerate the implementation of the joint commitments to address and counteract the global drug problem (UNODC, 2019b). Among the commitments made, the importance of law enforcement agencies, civil society, and the scientific and academic community in drug policies is highlighted, the use of evidence-based practices is recommended, and the determination to prevent, significantly reduce, and seek to eliminate the illicit cultivation and production, manufacture, trafficking and abuse of narcotic drugs and psychotropic substances, including synthetic drugs and new psychoactive substances, among others, is reiterated (UNODC, 2019b).

As with other markets, drug trafficking is driven by the value of illicit drugs to consumers. There are various types of drugs; however, the main groups of illicit drugs of global concern are described in Table 2.

Drugs can be controlled on the supply side (providers, production, transit, commercialization) or the demand side (consumption). Supply-side control means restricting or regulating people's access to drugs. This has been the dominant strategy, with prohibition being the most prominent. Demand-based control policies focus on preventing drug use and addressing the consequences of drug use. This public health strategy seeks to limit its effects and reduce its use (Bergman, 2018).

TABLE 2 - ILLICIT DRUG GROUPS

Drug Group	Drug Subgroup
Amphetamine-type stimulants (ATS)	Amphetamine, Methamphetamine, prescription stimulants
Cannabis-type drugs	Cannabis herbs (marijuana), Cannabis oil, Cannabis plants, Cannabis resin, Cannabis seed, and other types of cannabis
Cocaine-type	Cocaine hydrochloride, Coca paste, Coca leaf, and other Cocaine-type drugs
Ecstasy-type substances	Ecstasy-type substances
Hallucinogens	LSD, other hallucinogens
New psychoactive substance (NPS)	Aminoindanes, GBL/GHB, Ketamine and phencyclidine-type substance, Phenethylamines, Piperazines, Plant-based NPS, Synthetic cannabinoids, Synthetic cathinone, Tryptamines
Opioids	Heroin, Illicit morphine, Opium, Other illicit opiates, Other illicit opioids, Pharmaceutical opioids, Poppy plants, Poppy straw (seed heads, pods, or capsules)
Precursors	Precursors
Sedatives and tranquilizers	Barbiturates, Benzodiazepines, GBL/GHB, Other sedatives and tranquillizers
Solvents and Inhalants	Solvents and inhalants

Source: (UNODC, 2022h).

In addition to obeying the concepts of supply, demand, and supply chain of narcotics and NPS, drug trafficking can be described as a systematic network model (criminal business) where each actor has an important role among the elements that compose it, where processes are optimized until reaching the end user (consumer). These actors operate in different geographical scenarios, ranging from local, national, and international contexts and even between continents.

Consequently, a series of variables framed in a logical structure is established to conceptualize and characterize the threat that drug trafficking represents for States. Generally, this process is described as a production chain composed of 1) dynamizing actors; 2) production; 3) trafficking; 4) distribution and commercialization; and 5) related crimes. Each link has defined components and role specialization, in which the driving forces participate in one or more stages through different direct or indirect interrelationships (PONAL, 2020). They are briefly described below (PONAL, 2020):

Dynamizing Actors. These actors can promote, articulate, and operate directly or indirectly in the stages and components of drug trafficking. They have buying-selling and supplier-client relationships. Components: organized crime organizations (DTOs, organized armed groups, organized criminal groups, organized common crime groups); occasional crime and instrumentalized population (growers, peasants, consumers, people used for drug trafficking by coercion, error, without malice or guilt, actions of unimputable persons). Role specialization: those in charge of the security of illicit crops or production infrastructures, accountants, packers, logistical operators, criminal outsourcing, among others.

Production. This is the point of origin of the drug supply. It guarantees the availability of drugs and feeds other stages and components. Components: illicit crops, NPS, infrastructure to produce alkaloids or chemical substances, chemical inputs and precursors, purity, and cutting (drug adulteration). Role specialization: growers of illicit plants, collectors, input providers, "chemist," owner of the production infrastructure (laboratory), cook, and other service personnel.

Trafficking. It is related to sustaining supply and connects or complements the production stage with the distribution and commercialization stages. Its activities include negotiating and transporting illicit drugs to the national and international collection centers or distribution or transit platforms, using innumerable modus operandi. Components: national and international land, air, maritime, and river routes, collection centers, concealment and camouflage methods, and gray zones. Role specialization: vehicle drivers (transporter), pilots, route controllers, muleteers, intern, apostille clerk, alliance manager, liaison for offering bribes to public officials, among others.

Distribution and Commercialization. This refers to the dynamics of transporting illicit drugs in small quantities from collection centers to different national and international markets for sale and the destination, the consumer. Components: supply, micro-trafficking, drug dealing, and consumption. Role specialization: owners of the outlets, jibaro, consumer recruiter, consumers, among others.

Related Crimes. These are a set of associated or complementary crimes arising from the activities of the four stages described above. For example, crimes against the environment, natural resources, public health, public administration, economic and social order; crimes such as money laundering, cybercrime, extortion, human trafficking, kidnapping, financing of terrorism, among others that arise for the operation of drug trafficking. Role specialization: front men, people who launder assets, hired assassins, kidnappers, terrorists, dredging rafts bosses (illegal mining), among others, depending on the criminal activity.

Drug traffickers are criminals. They generate death, violence, corrupt society, destroy the economy, families, patrimony, and instrumentalize vulnerable populations to maintain their illicit operations (illicit crops, production, trafficking, distribution, commercialization of drugs). Their routes are constantly adapted to the circumstances to maintain a regular product supply. This dynamism is mainly due to the pressures and actions of public security forces. Therefore, they are cyclical, as are their modus operandi.

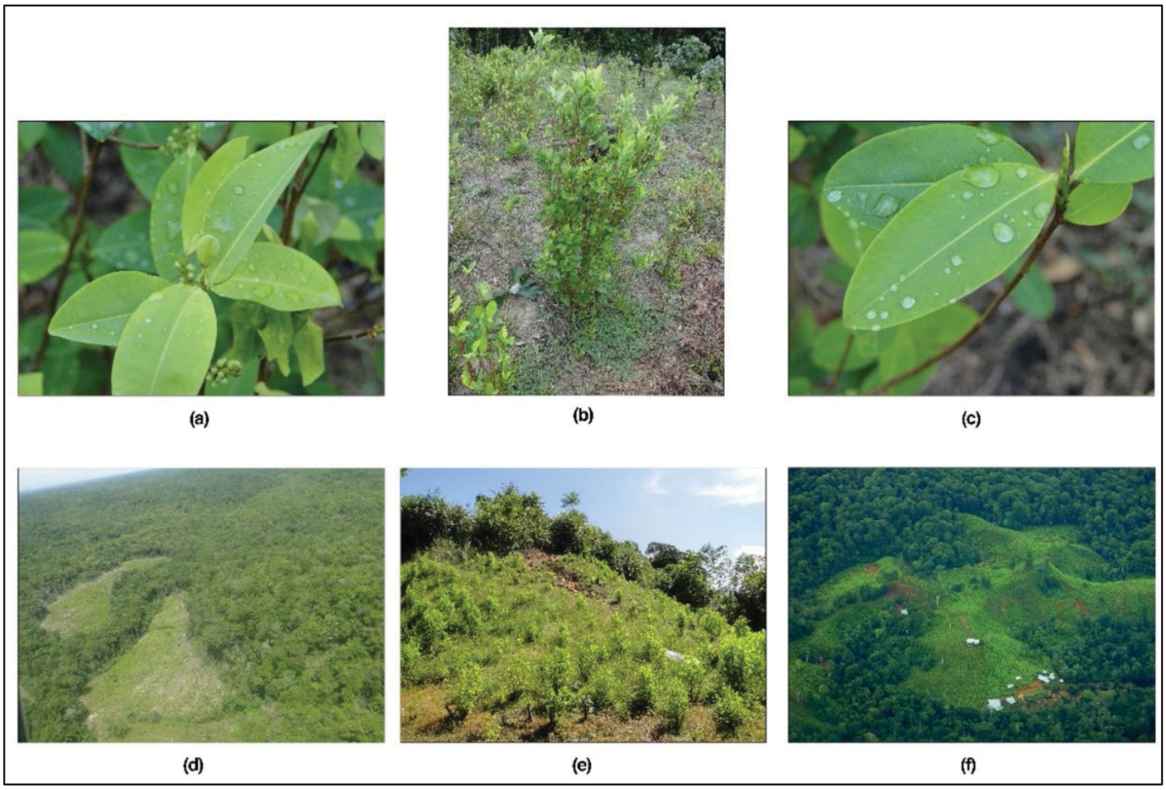
2.2.1 Cocaine hydrochloride production process

Cocaine hydrochloride, the most common salt employed in cocaine consumption products, is presented in powder form and contains a variable number of other substances that can be classified as impurities (alkaloids, solvents, and cocaine base) or as cutting agents (diluents and adulterants) (UNODC, 2021c). Its production is concentrated in four distinct stages from the following products: 1) coca leaf; 2) coca paste or *pasta básica de cocaína* in Spanish (PBC); 3) cocaine base or *base de cocaína* (BC); and 4) cocaine hydrochloride or *clorhidrato de cocaína* (CC) (UNODC, 2021c).

Cocaine, the main alkaloid obtained from coca leaves (UNODC, 2018a), is under international control by the Single Convention on Narcotic Drugs of 1961 (United Nations, 2022a). Coca leaves are obtained through illicit crop production. There are more than 250 species, but in practice, cocaine is extracted from the leaves of the species *Erythroxylum coca* and *Erythroxylum novogranatense* (UNODC, 2021c). Globally, these crops are concentrated in the Andean region, mainly in Colombia (66%), Peru (23%), and Bolivia (11%) (UNODC, 2021b). However, any territory in the tropics above 1,800 m above sea level is favorable for coca cultivation (UNODC, 2022i). There is evidence that coca cultivation also occurs in other countries in the region, such as Honduras (INSIGHT CRIME, 2022), Guatemala, Panama (CIENA, 2020), and Ecuador (UNODC, 2010a). To a lesser extent, Venezuela's border region with Colombia is also affected by coca cultivation (ANTIDROGAS-GNB, 2016; Pinto, 2017; UNODC, 2018b), probably due to the “balloon effect” (ANTIDROGAS-GNB, 2016) an analogy used to describe the movement of coca crops and production from one region or country, typically to evade interdiction efforts (Bagley, 2012) (Figure 1).

PBC is the first product obtained in the initial phase of the extraction of alkaloids from the coca leaf, from fuels (mainly gasoline), and sulfuric acid. This substance has a high percentage of organic residues, sugars, tannins, and other substances present in the coca leaf (SIMCI, 2018). BC is the second intermediate product between coca leaf and CC, obtained from the refining (oxidation) of PBC, using oxidizing substances, preferably potassium permanganate. This process removes impurities to leave as much cocaine as possible and reach high purity levels, normally between 80% and 95% (SIMCI, 2018; UNODC, 2021c). Subsequently, re-oxidation takes place; this is an intermediate process undertaken to homogenize PBC and BC before the conversion process to CC (CIENA, 2020). Finally, CC is the product obtained from PBC/BC through a series of reactions that include pH changes and precipitation processes to end with the addition of hydrochloric acid or hydrogen chloride to form the salt (SIMCI, 2018).

FIGURE 1 - COCA PLANTS AND TERRITORIES AFFECTED BY ILLICIT COCA CULTIVATION



(a), (b), (c), (d), (e) Border region of the Jesús María Semprún municipality, Zulia state -Venezuela (Author, 2016, 2017); (f) Colombia (SIMCI, 2021).

Cocaine is found in various consumer products, generally occurring in two chemical forms: salt (cocaine hydrochloride) and base (Wexler, 2014). Depending on the main component and method of manufacture, as described in Table 3, it is possible to distinguish three major groups of products derived from the base and salt forms.

TABLE 3 - COCAINE CONSUMPTION PRODUCTS

Group	Main Component	Common names and packaging of some by-products	Form of consumption
Manufacturing process consumer products (MCPs)	Derivatives of coca paste and cocaine base	Brazil: *pedras/crack* (manufactured from PBC or BC, different from the crack in North American and European markets), *oxi, merla, tijolo/tablete/barra de PBC.* Other South American countries: *PBC, paco, basuco* (garbage-dirt-cocaine or *basura-sucia-de-cocaína* in Spanish), *pitillo, mono, baserolo, pay, chespy*, among others.	Smokable substance
Freebase consumer products (FCPs)	Derivatives of the conversion of cocaine salt to its base form	Commonly known as a crack in European and North American markets. Freebase (made by the consumer himself).	Smokable or injected substance
Consumer products based on cocaine hydrochloride	Cocaine hydrochloride (usually in powder form)	Brazil: *tijolo/tablete/barra de cocaína, pacote, papelote, porções, trouxinha, pino, escama de peixe*. Other countries in South America: Colombia, Venezuela: *paquete/ bloque/ panelas de cocaína, blanca, coca, nieve, perico, cocaína, mandanga,* among others.	Nasal insufflation

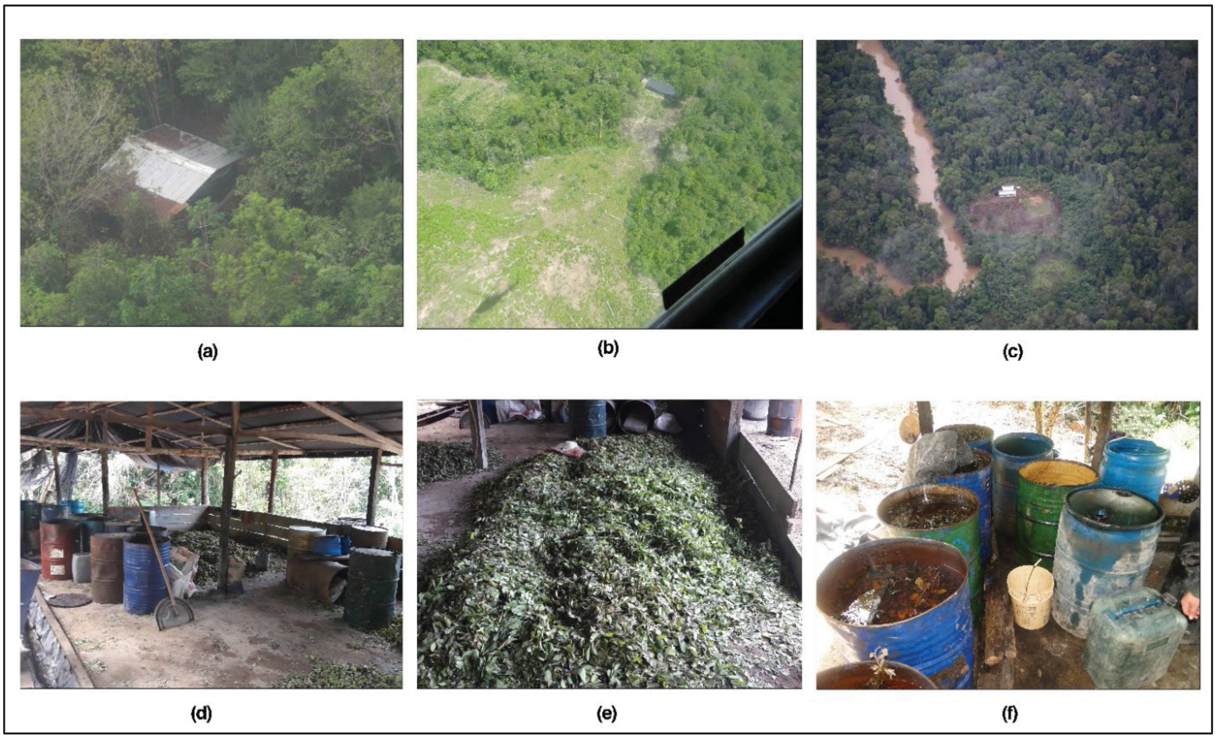
Source: (Author. 2022; EMCDDA, 2022a; UNODC, 2021c).

2.2.2 Infrastructures associated with cocaine hydrochloride production processes

Cocaine hydrochloride production is carried out through infrastructures with basic elements and rudimentary adaptations to develop coca leaf transformation processes. It requires a series of steps where indispensable chemicals are used to extract the alkaloid and for refinement (CIENA, 2018). There are different types of infrastructures whose characteristics, geographic location, elements, and structures will vary according to the processes carried out. They are classified into 1) Primary Production Infrastructures to produce Coca Paste (IFP-PBC); 2) Primary Production Infrastructures to produce Cocaine Base (IFP-BC); and 3) Cocaine Hydrochloride Production Complexes (CPCC) (CIENA, 2018; SIMCI, 2018).

The Primary Production Infrastructures to produce Coca Paste (IFP-PBC), or extraction infrastructures, are where the alkaloid extraction process starts. They are known in criminal parlance as *cocinas, chagras, chongos* (CIENA, 2018) or *picaderos* in Spanish. They are generally located close to coca cultivation areas, at distances not exceeding 100 meters, some near river networks. On some occasions, they have been found constructed as houses, their structure made of wood (CIENA, 2018), and they may have the roof covered with black plastic, dry vegetation (straw), or zinc sheets (Figure 2). There, the processes of chopping coca leaves, maceration, extraction of alkaloids, and production of PBC or directly BC are carried out. Elements, such as plastic and metal containers, scythes, gasoline, sulfuric acid, cement (CIENA, 2018), lime, caustic soda, urea, agricultural tools, licit crops in the surroundings, mechanical scales, among others, are commonly found there.

FIGURE 4 - PRIMARY PRODUCTION INFRASTRUCTURES TO PRODUCE COCA PASTE



(a), (b), (d), (e), (f) Border region of Jesús María Semprún municipality, Zulia state -Venezuela (Author, 2016, 2017); (c), Colombia (CIENA, 2018).

In the Primary Production Infrastructures to produce Cocaine Base (IFP-BC) or oxidation infrastructures, coca alkaloid refining processes are carried out, and are intended to produce BC through PBC oxidation, using potassium permanganate (SIMCI, 2018). They are located as components of large CPCC; in some areas, the existence of re-oxidation infrastructures has been identified as an intermediate process for the chemical homogenization of the alkaloid before entering the process of conversion into CC, aimed at obtaining the maximum percentage of purity (CIENA, 2018, 2020). Elements such as washing machines, rustic filtering machines, bain-marie heating equipment known as *gusanos* in Spanish and other elements can be found there.

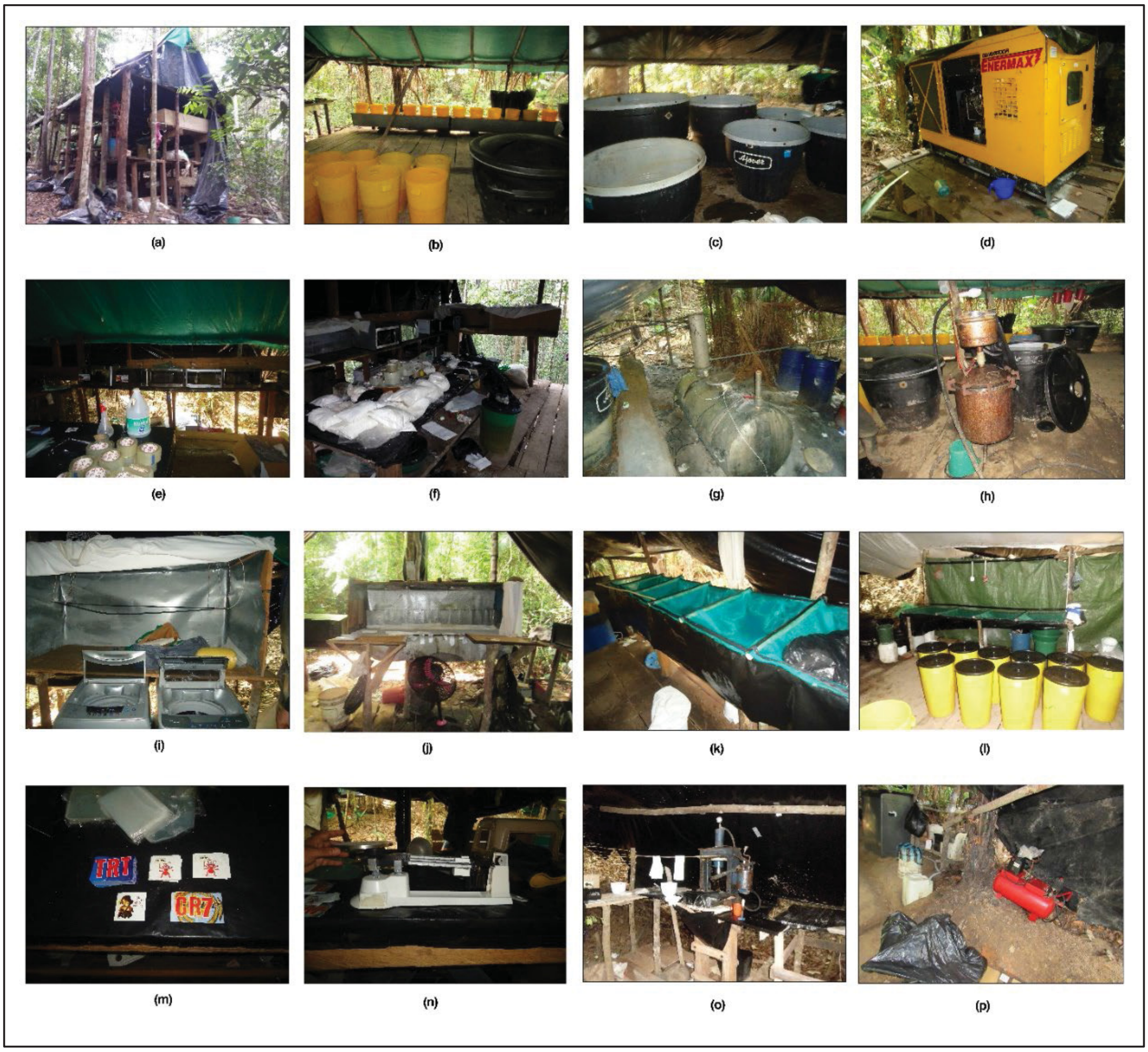
The Cocaine Hydrochloride Production Complexes (CPCC) are interconnected infrastructures functioning as a structural whole for the illicit production of CC. The dynamics go beyond the conversion infrastructures known as *cristalizaderos*[3] in Spanish, as they connect different infrastructures with specific functions, e.g., the storage of chemicals, oxidation, recycling, heating systems, packaging areas, solvent recovery areas, dormitories, kitchen, among others, all within a synergy that results in the production of large quantities of CC from PBC or BC (CIENA, 2018; SIMCI, 2019).

These can be found with rustic filtering machines, *gusanos*, microwave ovens, labels to identify cocaine blocks (*logos* or *marquillas* in Spanish), drying racks with large lamps (CIENA, 2018) (i.e., wooden boxes with lamps, and on the front they are covered by a thick white cloth), chemicals, vacuum packers, metal molds, handmade distillers known as *marcianos* in Spanish, tables with thick cloth (*escurrideros* or *hamacas* in Spanish), electric plants, hydraulic press, washing machines, air compressor, scales, communication equipment, solar panels, water pumps, among other elements (Figure 3).

CPCC is built in remote places, in areas of difficult access such as mountains or dense forest, generally near water sources and far from coca cultivation areas. They can also be found just a few meters from the borders; some of them share their location in the territory of both countries. Another characteristic is that they are guarded by armed groups that exercise strong territorial control, so there is a high probability of ambushes when interdiction and dismantling activities are carried out. These geographical and tactical characteristics give them the advantage to guarantee clandestine conditions and avoid detection from aerial platforms such as helicopters, drones, or satellites. CPCC are also found in several South American countries, mainly in coca producers (INCB, 2020). However, they have been detected also at the border region of Brazil and Bolivia (O GLOBO, 2022), and even Europe (EMCDDA, 2022a), posing a serious global threat in terms of the spread of DTOs.

[3] They are complex infrastructures, requiring a greater number of chemicals (CIENA, 2018), such as acids (sulfuric acid, hydrochloric acid); bases (ammonia, sodium hydroxide); salts (calcium chloride, potassium permanganate, sodium metabisulfite); and solvents (ethyl acetate, isopropyl alcohol, methyl - ethyl - ketone, mixtures and recycles) (OAS, 2018). They are considered the central structure where the activities aimed at CC manufacturing are carried out (SIMCI, 2017).

FIGURE 7 - COCAINE HYDROCHLORIDE PRODUCTION COMPLEXES



The border region of Jesús María Semprún municipality, Zulia state -Venezuela (Author, 2017).
(a) *cristalizadero* (external façade); (b) *gusano;* (c) plastic containers with liquid inputs; (d) electric plant; (e) microwave ovens and packaging materials; (f) drying and packaging area (microwave ovens, dryers with lamps, packaging materials, chemicals); (g) *marciano;* (h) rustic filtering machine; (i) washing machines, dryers with lamps; (j) drying area (dryer with lamps); (k) *escurrideros* or *hamacas;* (l) plastic containers with liquid supplies; (m) *logos* or *marquillas*; (n) weighing scales; (o) hydraulic press; (p) air compressor.

2.2.3 Drug trafficking routes

Another characteristic of the DTOs is that they use the transportation infrastructure available in the countries to establish routes (national, international, or transnational) to illegal markets, using multiple camouflage techniques, concealment, and means of transportation (Bergman, 2018; PONAL, 2020), They are characterized by their points of origin, which are generally producer countries, using transit or resupply points, and destination, which are generally collection centers, from where final distribution takes place (AMERIPOL, 2012).

The **national routes** are generally used to illicitly transport chemical inputs (liquids and solids), fuels, logistical resources, coca paste to cocaine hydrochloride production complexes, or the final product (illicit drugs) for internal consumption in population centers or to ports, airports, and border areas, to be used as platforms for international destinations.. The **regional routes** use countless border crossings to reduce interdiction controls and place illicit drugs in neighboring countries, generally in ports or storage centers. These routes connect with national routes. **Transnational routes** use the transportation infrastructure of various countries for the supply and transit of illicit drugs to their destination points (countries of consumption or transit). Routes can be by **land, air, maritime,** or **river**. Depending on the mode of concealment and means of transport used, they can be used together for the transit of drugs to their final destination. (Table 4).

TABLE 4 - TYPES OF DRUG TRAFFICKING ROUTES

Route type	Channels	Means of transport	Main modalities
Land	– Highways – Main or secondary access roads – Roads – Trails – Railway networks – Subway networks	– All kinds of vehicles – Freight transportation – Freight trains – Public passenger transportation – Cargo animals (mules, horses, donkeys) – People (human mules)	– Contaminated loads of products from the primary and secondary sector – Hidden in vehicle compartments (internal, fuel tanks, spare tire, among others) – Double bottom in vehicles – Double bottom in platforms of heavy load vehicles – Shipments through national and international postal packages (couriers) – Hidden in baggage, personal items, among others – Adhered to the body – The fly or *la Mosca* in Spanish. It consists of sending a person in a drug-free vehicle to warn the drug-carrying vehicle of the presence of interdiction checkpoints on highways or roads. It generally maintains a minimum distance of 1km.
Air	– National and international air corridors – Public and private airstrips – Clandestine airstrips – Heliports – Farms – Open fields	– Airports – Airlines – Commercial aircraft – Private aircraft – Illegal fixed-wing aircraft (generally Cessna Conquest, Beechcraft King Air, Beechcraft Duke, others) with internal adaptations to transport drugs and fuel – Helicopters – Drones	– Hidden in aircraft compartments – Baggage, packages, cargo, postal bags, equipment, or merchandise. – Adhered to the body – Impregnated in clothing – Ingested or introduced into the organism "human mules," "human couriers" (generally in the stomach, introduced in the intimate parts, implants in breasts, buttocks, or thigh)

Maritime	– Public and private maritime ports – Port installations in general	– Cargo export vessels (merchant ships) – Small vessels – Submersibles – Semi-submersibles – Fishing vessels – Go-fast boats, sailboats, yachts – Buoys with GPS systems	– Contamination of export cargoes (containers) – Contamination of transport and foreign trade vessels – Tanker vessels – Double bottom in vessels – Blind hook method (rip-off) – Hidden in subway compartments (*caletas*) near coasts – Sea scales – Adaptation of devices on the hull of the vessel
River	– Ports – Clandestine ports – River networks	– Small boats – Rudimentary boats (bongos, canoes, rafts) – Gabarre (flat-bottomed boat or barge) – Passenger boats	– Hidden in sacks, tanks, or rural infrastructures on the riverside – Adhered to the body – Hidden in merchandise – Hidden in subway compartments (*caletas*) near riverside

Source: (Author, 2022).

Drug trafficking routes can be scenarios of violence caused by the struggle between different actors, such as conflicts between criminal organizations and conflicts between these criminal groups and state authorities (Bergman, 2018), who seek to control the circulation of drugs (OAS, 2013). So, the selection of routes is not random; it is a rational choice with a high level of planning, looking for opportunities to reduce risks in the face of possible seizures and guarantee the highest economic returns (Sampó & Troncoso, 2022).

These routes become geostrategic objects, as they are generated from knowledge of natural obstacles (mountains, rivers, jungles), political obstacles (borders), the combination of various elements and circumstances (hostile populations, conflicts, under police or customs control) (Labrousse, 2011) and the geographical context in general. They can also be used to transport other illicit goods (INTERPOL, 2022b). For example, include natural resources such as gold, wild animals, chemicals, contraband, arms, human trafficking, money, among others.

2.2.4 Clandestine airstrips

The use of clandestine airstrips is one of the main modalities of DTOs for drug trafficking, mainly for cocaine trafficking from countries of the Southern Cone, Central America, and the Caribbean, using illicit aircraft (Pinto, 2017; PONAL, 2020; UNODC, 2022j). They are also used for the trafficking of natural resources such as gold (IGARAPÉ-INTERPOL, 2021), coltan, human trafficking, animals, arms, illicit merchandise, and the movement of people involved in organized crime.

These airstrips are not registered by the competent aeronautical authorities and are usually made of dirt or grass, although they have also been found to be paved (El DEBER, 2022; REDRADIOVE, 2020). They are built in remote areas or border regions, whose geographic characteristics is flat relief, with little unevenness and low vegetation in the surroundings, allowing them to guarantee landing and take-off operations of illicit aircraft. For example, in Venezuela, they are generally established in agricultural farms and remote regions, located mainly in the states bordering Colombia, with the states of Zulia and Apure being the most affected by the presence of clandestine airstrips involved in DTOs (CEOFANB, 2022a, 2022b; SUNAD, 2021b; INSIGHT CRIME, 2020a; Pinto, 2017). (Figure 4). They are also usually built-in jungle ecosystems such as the Amazon, characterized by a strong intervention of vegetation for risky landing and take-off maneuvers (24 Horas, 2022; Aresinfoservice, 2020; NewsAvia, 2017). Generally, they are built at night so as not to generate suspicion or be detected in the event of a probable aerial patrol by law enforcement agencies.

FIGURE 10 - CLANDESTINE AIRSTRIPS IN VENEZUELAN TERRITORY

(a) Zulia state (Author, 2016); (b) Apure state (Author, 2015).

Airstrip may have varying size. Pinto (2017) identified airstrips ranging from 2,471 m to 623 m using remote sensing satellite images. However, the length depends on the aircraft's landing and take-off capabilities (distance). For example, there is evidence that DTOs prefer Cessna Conquest and Beechcraft Duke aircraft for cocaine trafficking in South America (UNODC, 2012a). However, smaller ultralight, rustic and simplified aircraft have also been detected (PONAL, 2020). The Cessna Conquest requires approximately 544 m for take-off and

333 m for landing (PLANEPHD, 2022a), and the Beechcraft Duke 632 m for take-off and 401 m for landing (PLANEPHD, 2022b). So, it can be inferred that airstrips are adapted to the type of available aircraft. Another characteristic of illicit airstrips is that they can be reached by trails, roads, forests, rural infrastructure, or river networks, which allow connecting drug transit with various combinations of routes and means of transport.

Because aircraft violate air traffic security and countries' sovereignty, the *modus operandi* for drug trafficking through clandestine airstrips is a fast and extremely planned action, which does not exceed 3 minutes. They use various technological equipment, such as high-frequency radios, satellite phones, and GPS devices. For drug trafficking through this modality, there are generally groups of people with a specific role: a) to fuel the aircraft; b) to load or unload the drugs from the aircraft; c) personnel deployed around the airstrip to carry out vigilance functions; d) drivers and escorts for the vehicle transporting the drugs; e) to supply food and drinks to the pilots; f) in charge of money transactions; g) airplane mechanics; among other functions. In cases where the airstrips are used at night to orient the pilot, they usually illuminate the airstrip with the lights of rustic vehicles located at the ends of the airstrip or place improvised torches in aluminum cans or *mechurrios* in Spanish along the airstrips.

When aircraft are intercepted in flagrante, it can be observed that they commonly have internal adaptations, such as removing the seats so that they can transport the largest amount of drugs, approximately 500 kg per trip (UNODC, 2022j). Similarly, other elements are identified, such as satellite telephones and notebooks with geographic coordinates of other clandestine airstrips and supply points.

The DTOs often use local people, who have a quick reaction and capacity to rehabilitate the airstrips or build another parallel airstrip when they are destroyed by the security agencies, leaving them operational in a very short time without major difficulties. They also use airstrips registered by the aeronautical authorities located on private aerodromes or farms and, through threats or coercion, force the owners to allow this type of illicit operation.

2.2.5 Individual drug seizure

Despite the fluid nature and continuous adaptability of drug trafficking routes, individual drug seizure (IDS) data become important indicators to identify them (EMCDDA, 2016, 2022b; PONAL, 2020). An IDS is the result of police operations that ends in a singular interception or apprehension of drugs and/or New Psychoactive Substances (NPS), considering the specific place and time of occurrence may refer to one or more drugs seized per individual case (UNODC, 2022k). They should be interpreted as interdiction activities influenced by the strategies, resources, and priorities of law enforcement authorities (EMCDDA, 2022b; UNODC, 2015).

IDS data have been a key element of most countries' illicit drug market monitoring systems (Singleton et al., 2018). They have various analytical, operational, and political applications (EMCDDA, 2019). They help determine the size of these markets, and the availability of substances, identify trends and threats and assess the impact of policies and programs (Singleton et al., 2018; UNODC, 2019a). They make it possible to identify routes, mainly those that are not commonly visible, main destinations, modus operandi, trafficking articulation nodes, and favor the recognition of new destinations and strategic areas that facilitate the establishment of focal points for attention and control. Therefore, any analysis from a supply reduction perspective will involve evaluating the proportion of illicit drugs seized (Reuter & Greenfield, 2001).

They gain special value when they have geographic attributes (UNODC, 2015), georeferenced, case by case, since every challenge facing the planet, whether global, regional, or local, inherently has a geospatial component (Chainey, 2021; Clark, 2020); in turn, they also help produce intelligence for drug interdiction (EUROPEAN UNION, 2020), evaluate the police activity in a spatiotemporal context, and generate relevant information to improve situational awareness and decision making.

However, a review of some official websites of public security forces and statistical institutions indicates that, in most LAC countries, the availability of official quantitative, qualitative, and geo-referenced data related to the IDS, is not publicly available and is invariably incomplete, or are offered in the form of results counted by periods (generally annual and biannual). Therefore, knowledge of routes, *modus operandi*, criminal actors, among other variables, is limited to general reports or specific operations (ANTIDROGAS-GNB, 2016; CIENA, 2021; DEA, 2021; GEFRON, 2022), strategic studies (CoE-Brazil, 2021; INSIGHT CRIME, 2021a), or global and regional reports (EMCDDA, 2022c; UNODC, 2022b). These limitations suggest that the data are sensitive, classified, and probably have some inconsistency in the collection methods.

The criminal activity is not public and open. It is difficult to measure organized crime and collect reliable information (Blanco & Cohen, 2017; Dugato & Aziani, 2020; Reichel & Albanese, 2013). In LAC, not all countries collect extensive and high-quality data that is publicly available and useful for measuring organized crime (CoE-Mexico, 2014). In Brazil, for example, no unified national statistics on drug seizures exist, and the existing administrative records make it difficult to understand how criminal organizations operate and the state's response to this phenomenon (Baptista & Nascimento, 2022). Nor are they found with geospatial attributes that would allow the association of organized crime events with a location on the Earth's surface. The illicit nature of DTOs makes it very difficult to collect data on these illicit activities. Consequently, there is no public and unrestricted access database to analyze the routes, trends, and geographic patterns of activities related to DTOs.

Evidence has shown that it is possible to identify which routes are important for DTOs in a given period through the number of individual drug seizures as a direct indicator. However, due to the pressures exerted by interdiction activities, other routes become important, or new trafficking routes are established (PONAL, 2020). In other words, they are constantly adapting to the extent that the circumstances of time, mode, and place allow them to achieve their objective, including the difficulties that geographical conditions, distances, means of transport, and destination may offer.

2.3 TRANSNATIONAL ENVIRONMENTAL CRIME

Transnational Environmental Crimes (TEC) have become one of the main financial drivers of organized crime, directly affecting natural resources and generating serious consequences and threats to the maintenance of peace, security, human health, economy, and sustainable development of civil society and governments (INTERPOL, 2018a). Crimes against the environment threaten the survival of all living species on the planet (EUROPOL, 2022).

The definition of “environmental crime” refers to any activity that contravenes an environmental legal norm, whether national or international, intended to ensure the conservation of the environment. The term is commonly used to describe illegal activities that damage the environment and are intended to benefit individuals, groups, or companies from the exploitation, damage, trade, or theft of natural resources (UNEP, 2014). In this sense, the transnational notion makes it possible to define TEC as illegal activities that violate legally constituted environmental norms, cross borders, involve illegal actors, products, and assets that belong to different countries, can be committed in one state, and have substantial effects in others (Elliott & Schaedla, 2016).

Their transnational nature links them to other criminal activities, such as drug trafficking, money laundering, terrorism, organized crime, corruption, and human trafficking, which vary between countries and geographic regions (White, 2018). In general, they lead to transformations in biological diversity that intensify climate change (EUROPOL, 2022; GLOBAL INITIATIVE, 2021; INTERPOL, 2018a; Zabyelina & van Uhm, 2020). In some cases, they are heavily structured by organized crime groups, large corporations, complicit governments, corrupt public officials, and highly specialized professionals (Gore et al., 2019). They use sophisticated techniques, modern technologies, and connection networks similar to drug trafficking (UNEP, 2012), for example, clandestine airstrips that allow them to operate and connect between countries and continents.

Therefore, the high level of organization of these criminal groups substantially affects public policies aimed at safeguarding environmental assets, requiring the use and dedication of many human, financial and economic resources (EUROPOL, 2011). In this sense, as these crimes persist, grow, and destroy important terrestrial ecosystems, such as the Amazon and border regions, the environmental impacts are direct and visible mainly in legally protected areas, turning them into air, river, and land corridors for new routes and activities linked to organized crime.

The different conceptions of harm give rise to diverse interpretations of the nature and dynamics of transnational environmental crimes. Among the main types of associated activities are (EUROPOL, 2022; IGARAPÉ-INTERPOL, 2021; INTERPOL, 2022a; UNEP, 2012, 2014; UNODC, 2022a, 2022b; White, 2018):

- Illegal exploitation of natural resources
- Illegal cross-border trade of fauna and flora species
- Illegal logging and its trade
- Illegal mining
- Deforestation
- Illicit crops (coca, marijuana, opium poppy)
- Illicit drug production
- Pollution of legally protected areas
- Illegal transportation and dumping of toxic wastes

- Transportation of hazardous materials, such as ozone-depleting substances
- Trafficking of precursor chemicals destined for cocaine production
- Trafficking of radioactive or nuclear substances
- Illegal, unreported, unregulated fishing
- Carbon trading and water management
- among others

Illegal mining, for example, encompasses the illegal extraction and trade of minerals, including the illegal use of toxic chemicals (such as cyanide and mercury) in mining activities. It has serious consequences for the economic development of governments, peace, and stability, as terrorist organizations, armed groups, and DTOs use this activity as a source of financing and a facilitator for money laundering. In addition to violating human rights in vulnerable communities (human trafficking, forced labor, sexual abuse, exploitation of women and children, and health problems) (EL PACCTO, 2019; IGARAPÉ-INTERPOL, 2021; INTERPOL, 2022a). In general, it causes serious impacts on the environment that contribute to deforestation, water, and soil contamination, loss of biodiversity and habitats, erosion, emission of atmospheric carbon (INTERPOL, 2022a; Pinto & Jordán, 2013), and the destruction of important environmental assets such as the national parks found in the Amazon. An example of the effect of this activity on the environment is displayed on Figure 5.

FIGURE 13 - ILLEGAL MINING IMPACTS

Parque Nacional Yapacana, Amazonas state, Venezuela (Author, 2005).

Gold mining in the Amazon region is carried out in three main forms: a) Alluvial: mining through digging open pits, generally along riverbanks; b) Boat: mining by dredging riverbeds; c) Pit: mining through underground tunnels. The most common type in the Amazon is alluvial (IGARAPÉ-INTERPOL, 2021).

The environmental impacts are direct, vary from country to country and region to region, affect livelihoods, and generate serious ecological problems. The consequences are irreversible in most cases; the economic, environmental, and health impacts can be significant enough to destabilize entire economies and ecosystems, reducing the use of natural resources for future generations (OECD, 2012), undermining the effectiveness of globally established environmental standards as well as multilateral environmental agreements and institutions (Elliott & Schaedla, 2016). It is, therefore, a challenge for governments to find the balance between appropriate regulatory and operational measures through prevention, detection, and enforcement, as most countries have borders with other countries. For example, the Amazon region is the largest tropical rainforest in the world. It is an area that encompasses nine different countries, but they have environmental crimes in common.

Within this perspective, according to the report "Transnational Crime and the Developing World 2017" (GFI, 2017), there are figures that indicate the enormous economic benefits obtained from illegal activities, which become sources of financing for violence, corruption, and organized crime. According to this study, the revenues generated by eleven main transnational crimes range between 1.6 and 2.2 trillion dollars annually, with illegal wildlife trade, fishing, logging, and illegal mining occupying the 7th, 8th, 9th, and 10th, respectively. (Table 5). The magnitude of these crimes weakens local and national economies, destroys the environment, and threatens the health and well-being of the population.

TABLE 5 - ESTIMATED TRANSNATIONAL CRIME VALUES

	Transnational Crime	**Annual Value Estimates (US$)**
1º	Drug trafficking	$426 to $652 billion
2º	Trafficking in small arms and light weapons	$1.7 to $3.5 billion
3º	Human trafficking	$150.2 billion
4º	Trafficking in organs	$840 to $1.7 billion
5º	Trafficking in cultural goods	$1.2 to $1.6 billion
6º	Counterfeiting	$923 to $1.13 billion
7º	Illegal wildlife trade	$5 to $23 billion
8º	Illegal fishing	$15.5 to $36.4 billion
9º	Illegal logging	$52 to $157 billion
10º	Illegal mining	$12 to $48 billion
11º	Crude oil theft	$5.2 to $11.9 billion
	Total	**$1.6 to $2.2 trillion**

Source: (GFI, 2017).

Environmental crime is not the only criminal activity that has an impact on the physical environment. There are other crimes in which organized crime generates serious consequences for biodiversity and poses risks to society. For example, in addition to the economic and public health effects of drug trafficking, illicit drug production has a considerable environmental impact (EUROPOL, 2022; UNODC, 2022b). Studies have been published suggesting that drug supply chains leave a carbon footprint depending on the quantity produced. For example, the carbon footprint of indoor cannabis is, on average, 16 to 100 times more than that of outdoor cannabis, and the footprint of 1 kilogram of cocaine is 30 times greater than that of 1 kg of cocoa beans (UNODC, 2022b).

Generally, the cultivation of plants used to produce illicit drugs takes place in fragile ecosystems, protected areas such as national parks and forest reserves, or areas under some type of special regimes such as border regions and can therefore have an impact on deforestation and soil erosion (EUROPOL, 2022; UNODC, 2022b). The production of synthetic drugs such as amphetamines, MDMA and the use of synthetic drug precursors are among the main sources of environmental damage related to organized crime since significant amounts of waste are generated during production processes (reagent, explosive, flammable, corrosive, and/or toxic residues, among others), which in most cases exceed 5 to 30 times the volume of the final product (EUROPOL, 2022; UNODC, 2022b).

As established in various decisions of international bodies such as INTERPOL, EUROPOL, UNODC, the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), the United Nations Security Council (UNSC), and others, environmental crime is recognized as a major global threat and needs to be urgently addressed. Identifying the organized crime groups behind environmental crimes is one of the main challenges for law enforcement (EUROPOL, 2022). However, the measures taken have been too moderate and inadequate in the face of the rapid growth of transnational environmental crimes (UNEP, 2014).

2.4 GEOSPATIAL INTELLIGENCE

National governments, military forces, law enforcement agencies, and businesses, including DTOs, conduct intelligence activities. The understanding of GEOINT is founded on a basic understanding of the intelligence field (Clark, 2020). In this sense, intelligence is the process by which value-added information that provides background, context, warning, and an assessment of risks, benefits, and likely outcomes is collected, analyzed, and provided to policymakers to support decision-making (Lowenthal, 2019; UNODC, 2011).

For the understanding of intelligence processes, it is important to describe the terminology commonly accepted by institutions such as UNODC, UNDPKO, INTERPOL, and the European Union: "data" are raw observations and measurements and interpreted; "information" is data put in context and given meaning; "knowledge" is information interpreted and understood; and in its simplest form "intelligence" could be described as processed information assessed, analyzed and presented in a decisional format (OSCE, 2017; UNODC, 2011).

Intelligence reduces uncertainty in conflicts; this can be competitive or opposing action resulting from the divergence of ideas or interests of two or more parties (Clark, 2019). Reducing uncertainty requires obtaining information the adversary prefers to keep hidden (Clark, 2020). For example, obtaining the location of infrastructures linked to cocaine production would allow information that the DTOs (adversary) try to hide and, in turn, obtain advantages for decision-making. Targets of intelligence-interest frequently have geospatial and temporal attributes, exist somewhere, and move or change over time. Locating the target and tracking its movements are essential intelligence elements (Clark, 2019). However, it requires the analysis of information from various sources. Sources can be open, closed, and/or classified (UNODC, 2011).

GEOINT it is characterized by its ability to create geospatial knowledge through critical thinking, geospatial reasoning, and analytical techniques (Bacastow & Bellafiore, 2009). Data can be structured (geographic coordinates, satellite imagery) or unstructured (text with geographic information about an activity, such as a street address or mention of a municipality or state) (Pennsylvania State University, 2020b). It differs from other intelligence disciplines because data are collected from multiple information sources (Clark, 2020). These can be closed source (government or private data that is not available to the public) and open source (any type of geospatial information collected from publicly available sources) (Pennsylvania State University, 2020b).

Geospatial intelligence is the analysis and exploitation of imagery and geospatial information to describe, evaluate and visually represent physical features and georeferenced activities on Earth. Consists of imagery, imagery intelligence, and geospatial information.

Imagery. A georeferenced visual record of any natural or anthropogenic features, objects, or related activities. A system of sensors and platforms collects this type of data. Platforms can be a satellite, airborne (aircraft, drones, aerostats, balloons, and dirigibles), ground-based and sea-based. Airborne, ground-based, and sea-based platforms may be manned or unmanned/unattended. Sensors fall into two primary categories, electro-optical (passive) and radio detecting and ranging - radar (active). Both have several types or variants, known as phenomenologies. Each phenomenology achieves different results with the data. Table 6 describes the characteristics and phenomenologies of sensors (NGA, 2018).

TABLE 6 - CHARACTERISTICS AND PHENOMENOLOGIES OF SENSORS

Sensor/Phenomenology	Acronym	Characteristics	Used for (examples)
Electro-Optical Sensor	**EO**	**Typically, a passive sensor, uses natural energy sources, ultraviolet through infrared portions of electromagnetic spectrum.**	**For detailed, literal, photo-like picture of a scene and the objects within it.**
Panchromatic	PAN	Uses the visible section of the spectrum to create black and white (grayscale) images.	Provides a literal picture of a scene, area, and/ or objects. Used in daytime, good weather conditions.
Infrared	IR	Uses the infrared portion of the spectrum to detect heat/ radiance.	Detects presence of living entities and active vehicles and equipment in day or night. May be limited by bad weather/light conditions, smoke.
Thermal Infrared	TIR	Uses infrared portions of the spectrum to indicate temperature level of heat/radiance.	Determines the operational status of equipment and factories. Penetrates smoke, tracks activities at airfields and ports, and allows applications for vegetation monitoring, climate change, land use changes, crop detection, and risk management, among others.
Multispectral Imaging	MSI	Uses tens of visible and infrared bands to provide a color image with more detail.	Sees beneath the water; detects camouflage, vegetation density, cover type, mineral, soils, and material analysis; illuminates shadowed materials; detects

			clandestine airstrips; identifies crops, illegal mining areas, and deforestation; detects infrastructure, among others.
Hyperspectral Imaging	HSI	Uses hundreds of visible and infrared bands to provide a greater detail and additional characteristics.	Same as multispectral but with greater levels of detail.
Light Detection & Ranging	LIDAR	Uses laser pulses in the visible and infrared sections of spectrum.	See objects beneath vegetation canopy, battlefield visualization or areas of strategic interest.
Overhead Persistent Infrared	OPIR	Uses visible and near infrared bands. Characterizes energy as an event, processes as a scene.	Provides persistent coverage. Detects missile launches, wildfires, hostilities, volcanos, and identifies weapons.
Radar Sensor	**Radar**	**Active sensor, emits manmade energy sources, uses microwave and radio wave portions of EM Spectrum.**	**Unlike EO, can be used in most weather, day or night.**
Synthetic Aperture Radar	SAR	Illuminates objects with microwave energy pulses. Applies signal processing to a series of pulses to produce a single image.	Penetrates foliage, material, and ground (with limitations), detects barriers and overhead power lines. Used in most weather, light conditions. Creates a black & white (grayscale) image.
Interferometric SAR	IFSAR	Uses SAR sensor to observe from two separate positions to generate elevation data of the Earth’s surface.	Identifies elevation data.

Source: (NGA, 2018).

Imagery Intelligence. The technical, geographic, and intelligence information derived through the interpretation or analysis of imagery and collateral materials. The data may be derived from analytic expertise, classified data, unclassified information, ground truth data, analysis techniques, or any combination of those sources. For example, an analyst may determine that an object in an image is an infrastructure linked to cocaine production based on expert knowledge of these infrastructures in coca cultivation areas. **Geospatial information** is derived from data collected through many different sources including, information related to the Earth's surface, which identifies the geographic location, geometry, statistical data, open-source information, humans, information derived from remote sensing, cartography, and surveying technologies, and charting, geodetic data, and related products (NGA, 2018). As previously described by NGA (2018), the geospatial information is summarized in Table 7:

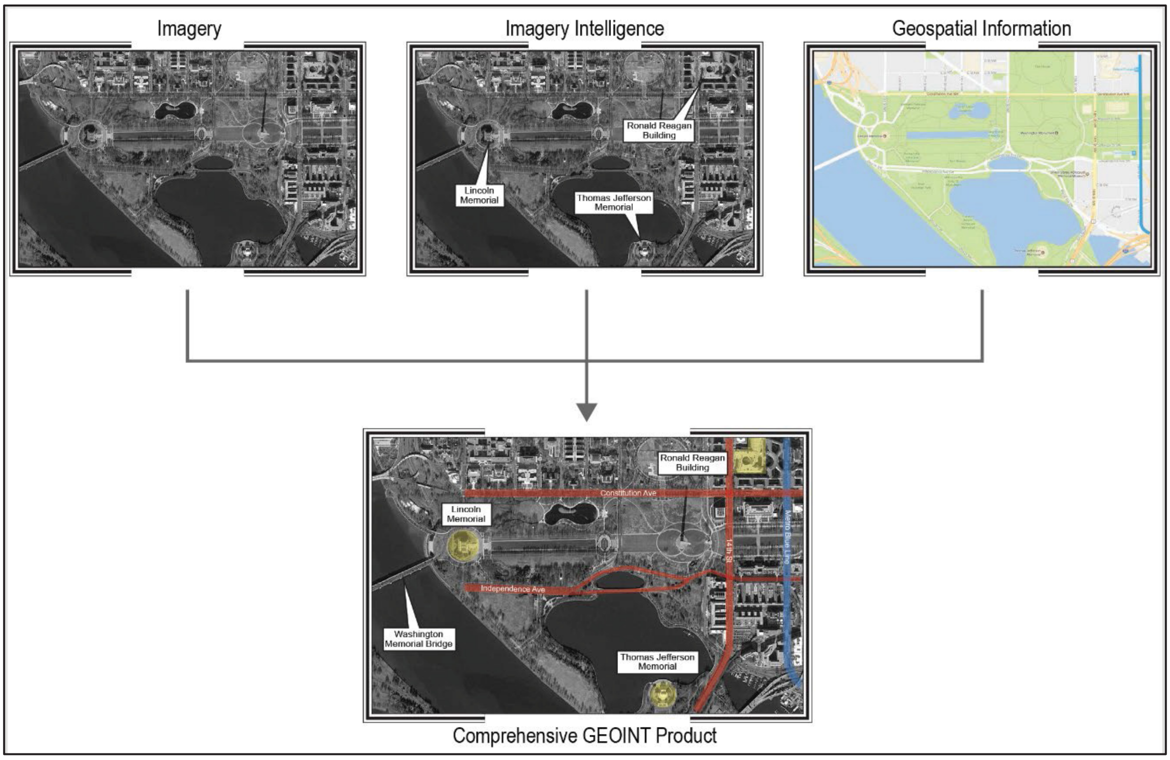
TABLE 7 - GEOSPATIAL INFORMATION CATEGORIES

Categories	Description
Aeronautical	Safety of navigation information such as vertical obstructions, no-fly zones, flight routes, approach procedures, airfield infrastructure and layout, and aeronautical charts.
Maritime	Safety of navigation information such as shipping routes, underwater obstructions, sailing restrictions, port infrastructure and layout, approach procedures, and nautical charts.
Topographic	Safety of navigation information such as trafficability and obstacles to movement, and other ground/surface feature-related information including infrastructure (roads, power grids), man-made features, population data, vegetation, and hydrography. Topography may also include connectivity of network elements within a geospatial database that allow for ground- based routing, navigation, and hydrology flow.
Elevation	Information about the height of objects on or in relation to the Earth. Elevation data includes heights of objects above the surface of the Earth (spaceborne and airborne), on the surface of the Earth (buildings and physical relief), and below the surface (bathymetry and underground facilities).
Human Geography	A social science discipline based on analyzing the interconnections between people and places, including patterns of human activities, in the context of their environment. It also seeks to explain how actions taken in one place/ population can impact another place/population. Human Geography includes sub-disciplines such as: population geography, political geography, cultural geography, and religious/ethnic geography. It may include both classified and unclassified information.
Geographic Names and Boundaries	Names and boundaries of cities, municipalities, towns, provinces, regions, states, and countries. Identification of major landmarks, facilities, and buildings.
Geodetic	Magnetic and gravimetric data (which have an impact on geo-positional systems), navigation tools, surveying, and systems of map grids and coordinate systems.
Geospatial information is usually requested from the following data sources: **Panchromatic, Multispectral, Infrared, SAR, LIDAR, SONAR, OPIR, Open-Source information.**	

Source: (NGA, 2018).

The combination of these three components generates a geospatial intelligence product, which is a more informative and useful way to satisfy specific requirements/Essential Elements of Information (EEI)/Requests for Information (RFI) better than any of the individual components can when used separately (NGA, 2018). (Figure 6).

FIGURE 16 - ELEMENTS OF GEOSPATIAL INTELLIGENCE



Source: (NGA, 2018).

In this sense, geospatial intelligence can identify, collect, and manipulate data related to organized crime (Biltgen & Ryan, 2016; Clark, 2020; Lowenthal, 2019; Pinto & Centeno, 2022a, b; SOUTHCOM, 2017). Currently, GEOINT combines technologies such as Remote Sensing (RS), Geographic Information Science (GIScience), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), human expertise, and Big Data processing to obtain intelligence information to reduce uncertainty (Clark, 2020; Coorey, 2018). They are particularly appropriate technologies for the prevention and confrontation of DTOs since law enforcement relies on collecting and analyzing large amounts of data from various intelligence sources related to human behavior (UNICRI, 2019). Remote sensing is highlighted as the most important tool to support GEOINT (Clark, 2020).

Remote Sensing is the art, science, and technology of obtaining reliable information about physical objects and the environment through processes of recording, measuring, and interpreting images and digital representations of energy patterns derived from sensor systems (e.g., Earth observation satellites) without having direct physical contact with the object (Chuvieco, 2020; Clark, 2020; Jensen, 2009). It is one of the most powerful tools for acquiring accurate and up-to-date information on the numerous processes occurring on the Earth's surface (Chuvieco, 2020). Remote sensing platforms are usually used in intelligence for surveillance or reconnaissance. Surveillance is defined as continuous permanence, while reconnaissance is permanence for a relatively short time. It focuses on mapping, characterizing, locating objects found on Earth, and tracking artificial objects (Clark, 2014).

2.4.1 Open-source information

Open-source information is related to the discipline of open-source intelligence (OSINT). This refers to publicly available information through lawful means, requires no restrictions on access, and is acquired, evaluated, and analyzed to meet specific intelligence or information requirements (Lowenthal & Clark, 2015). It is obtained from various sources (e.g., print news articles, news websites and newspapers, academic research, books, radio, television, internet, government reports, and databases, among others) (Johnson, 2010). It is considered the source of the first resource (Lowenthal & Clark, 2015) because it is usually the first step in the information-gathering process. Its reliance on sources, and legal and open methods establishes the basis for constituting up to 90% of the material used for effective intelligence gathering and analysis (Lim, 2016; Loch, 2017; INTERPOL, 2018b).

Data for examining organized crime and drug trafficking using OSINT, and especially articles from news websites, can be valuable due to the clandestine nature of this type of criminal activity (Pastor & Larsen, 2017; Chainey & Alonso, 2021). Investigative journalism and news articles in the media are one of the only data sources that document illicit activities on a spatial and temporal scale beyond official statistics (Tellman et al., 2020; Hudson, 2014) and probably provide consistent information on drug trafficking trends.

OSINT has become an integral part of the prevention, investigation, and detection of organized crime, being widely used by international organizations, law enforcement agencies, intelligence agencies, and military forces (Reichel & Albanese, 2013; IACA, 2017; Ingle & Staniforth, 2017), have demonstrated the potential to detect organized crime threats (Aliprandi et al., 2014; Akhgar et al., 2017; INTERPOL, 2022c; IACA, 2017; Pastor & Larsen, 2017; Brown et al., 2020; EUROPOL, 2021), provide contextual knowledge (Hobbs et al., 2014), offer additional geographic information to support intelligence analysis (Stefanidis et al., 2014), contribute to the United Nations Sustainable Development Goals (SDGs) (United Nations, 2022a), and complement official data on drug seizures made in various countries around the world (EMCDDA, 2019; UNODC, 2022d). However, like other intelligence disciplines such as Human Intelligence (HUMINT) (information from human sources), data obtained through OSINT, must be evaluated, as, being publicly available, the information is not collected firsthand (Clark, 2014) and may be incorrect, biased, or uninformative (Hulnick, 2002; United Nations, 2022e).

GEOINT, contributes to solving a wide variety of problems due to its ability to extract relevant information from different data (Baber, 2018; Clark, 2020). Recently, with the era of big data and the increasing generation of geospatial data, including structured and unstructured open-source data (UN-GGIM, 2020; Li et al., 2016; Karimi & Karimi, 2017), has enabled the use of these methods for analysis, decision-making, and problem-solving in many of the GEOINT community's tasks dedicated to public safety (UN-GGIM 2020; Dold & Groopman, 2017).

The use of open-source data frequently arises in research to detect organized crime threats (Akhgar et al., 2017; EUROPOL, 2021; INTERPOL, 2022c; Larsen et al., 2017; UNICRI, 2021). They have facilitated the development of technological tools that can collect, process, and describe past and current events and help anticipate future events (Pennsylvania State University, 2020b). In addition, they contain massive amounts of geographic information in the communication nodes and possible geographic references in the content, making them open source GEOINT data. They provide geospatial and temporal information, making it possible to complement official statistics, detect trends, identify locations associated with reported events, produce maps, analyze data, and add depth and detail to information about human behaviors and experiences (Pennsylvania State University, 2020b; Tomes et al., 2014; United Nations, 2022e, 2022f; Yuan, 2021). As a result, some approaches have turned to mine unstructured qualitative and quantitative data, such as police reports and digital news articles (Chen et al., 2004; Hu, 2018; Stock et al., 2022). Others have used open source GEOINT data to label samples and train deep learning algorithms capable of detecting geospatial objects in satellite imagery linked to organized crime (Pinto & Centeno, 2022a, b), generating innovative applications that challenge traditional methods and promise greater efficiency for crime prevention and confrontation (UNICRI, 2020b).

For example, the UNODC Drugs Monitoring Platform and the European drug monitoring system, through the use of GIScience and NLP methods, use open source GEOINT data and government sources to provide information with geographical attributes on drug trafficking trends, delivering data using interactive visualizations adapted to user-specific needs and improving early warning drug threat identification for law enforcement and analysts (UNODC, 2022k; EMCDDA, 2019). Similarly, EUROPOL's SOCTA (Serious and Organised Crime Threat Assessment) report and the US government's Consolidated Counterdrug Drug Database (CCDB) use multiple sources of information, including open-source data, to extract, record, and analyze events on the threat posed by DTOs to society (EUROPOL, 2021; McSweeney, 2020). In combination with different technological resources, these organizations evaluate the data and generate national, regional, and international intelligence images of drug trafficking dynamics in a geospatial context.

Some researchers have employed open-source data to identify the spatial expansion of organized crime groups (Stahlberg, 2022), elaborate criminal scripts of criminal activities (Chainey & Alonso, 2021), detect illicit drug market trends (Maybir & Chapman, 2021), detect NPS (Evans-Brown & Sedefov, 2018), development of geographic models of cocaine trafficking (Allen, 2013), and generate open-source intelligence and analysis of the global scope, related to security and defense, terrorism, organized crime among other domains (JANES, 2022; Larsen et al., 2017). Others have also implemented open-source data oriented to preventing organized crime and developing strategic early warning systems for environmental scanning and detection of organized crime threats (Casanovas et al., 2014; Brewster et al., 2014; Adderley et al., 2014). These studies have focused on using NLP techniques in combination with GIScience and other technological resources to collect and process information with geographical attributes related to organized crime manifestations, mainly extracted from news websites, newspapers, and government sources. Some particularities are highlighted in Table 8.

TABLE 8 - RELATED WORKS WITH OPEN-SOURCE INFORMATION

Title	Source	Methods	Objective/Scope
Drugs Monitoring Platform - United Nations Office on Drugs and Crime (DMP-UNODC) (UNODC, 2022l).	– Open Source GEOINT data – Government sources – News websites and newspapers – UNODC mandated data collection mechanisms	– GIScience – Web scraping – Technology resources	– Individual drug seizure – Drug trafficking routes and trends – International image of drug trafficking
Using open-source information to improve the European drug monitoring system (EMCDDA, 2019).	– Open Source GEOINT data – Open-Source data – News websites and newspapers – Government sources	– GIScience – Web scraping – Data mining – Technology resources	– Individual drug seizure – Illicit drug Monitoring – European Monitoring Centre for Drugs and Drug Addiction (EMCDDA)
Reliable drug war data: The Consolidated Counterdrug Database and cocaine interdiction in the “Transit Zone” (McSweeney, 2020).	– Open Source GEOINT data – News websites and newspapers – Government sources – Closed Source data – Multiple Intelligence	– Machine Learning – Data mining – GIScience – Technology resources	– Individual drug seizure – Drug trafficking events in the United States, Central America, Caribbean, Eastern Pacific, and Mexico – Consolidated

			Counterdrug Drug Database (CCDB)
European Union Serious and Organised Crime Threat Assessment, (SOCTA). A corrupting influence: the infiltration and undermining of Europe's economy and society by organized crime (EUROPOL, 2021).	– Open Source GEOINT data – Open-Source data – News websites and newspapers – Government sources – Primary data – Closed Source data – Multiple Intelligence	– Intelligence cycle – GIScience – Technology resources	– Organized Crime – SOCTA Methodology – European Union
Semantic Mining and Analysis of Heterogeneous Data for Novel Intelligence Insights (Adderley et al., 2014).	– Open Source GEOINT data – News websites and newspapers – Government sources – Closed Source data – Multiple Intelligence	– GIScience – Environmental scanning – Technology resources	– Organized Crime – Miscellaneous crimes – European Union – MOSAIC Platform
A structured methodical process for populating a crime script of organized crime activity using OSINT (Chainey & Alonso, 2021).	– Open Source GEOINT data – Open-Source data – News websites and newspapers	– Technology resources	– Organized Crime – Mexico
Fighting Organized Crime Through Open-Source Intelligence: Regulatory Strategies of the CAPER Project (Casanovas et al., 2014).	– Open-Source data – News websites and newspapers	– GIScience – Environmental scanning – Technology resources	– Organized Crime – Miscellaneous crimes – European Union – CAPER project
Environmental scanning and knowledge representation for the detection of organized crime threats (Brewster et al., 2014).	– Open Source GEOINT data – Open-Source data – News websites and newspapers	– Environmental scanning – Machine Learning – Data mining – GIScience – Technology resources	– Organized Crime – European Union – ePOOLICE project
Responding to New Psychoactive Substances in the European Union: Early Warning, Risk Assessment, and Control Measures (Evans-Brown & Sedefov, 2018).	– Open Source GEOINT data – Open-Source data – News websites and newspapers – Government sources	– GIScience – Web scraping – Data mining – Technology resources	– NPS – EMCDDA
From prison gangs to transnational mafia: the expansion of organized crime in Brazil (Stahlberg, 2022).	– Open-Source data – Primary data (expert interviews)	– Google Trends – GIScience – Technology resources	– Organized Crime – Brazil

Janes (JANES, 2022).	– Open Source GEOINT data – Open-Source data – News websites and newspapers	– Intelligence cycle – GIScience – Technology resources	– Security and Defense – Organized Crime – Terrorism – Individual drug seizure – Market analysis – Other domains – Global scope
Web scraping of ecstasy user reports as a novel tool for detecting drug market trends (Maybir & Chapman, 2021).	– Open Source GEOINT data – Open-Source data	– Web scraping – Data mining – Technology resources	– Illicit ecstasy market – Australia

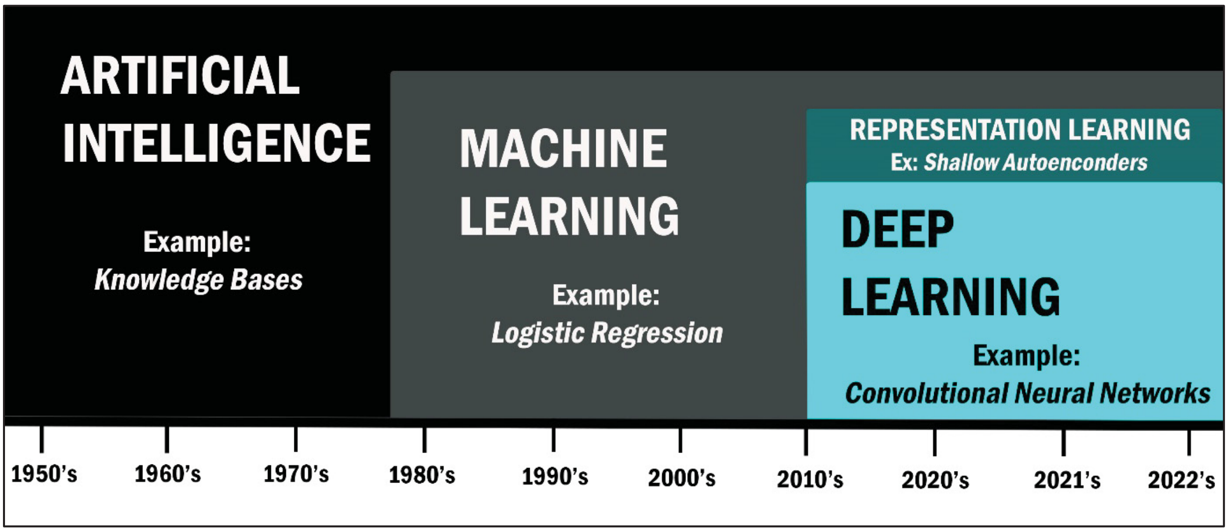
In general, the related works described demonstrate the practical potential of open-source data, highlighting geospatial information as the common element in identifying drug trafficking routes, trends, and threats. However, the main challenge exposed by the authors focuses on the verification and validity of the information; since being secondary and open access information, there is a risk of being incorrect or biased (United Nations, 2022e; Hulnick, 2002; Prunckun, 2019). In this sense, they point out the need to validate the information through processes of triangulation of information with other sources and methods, to facilitate efficient and evidence-based decision making. In addition, it is often commented that the illicit nature of data on the dynamics of DTOs makes their access extremely restricted, being one of the main limitations for researchers and law enforcement agencies.

2.5 ARTIFICIAL INTELLIGENCE

Artificial Intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs (McCarthy, 2007). It is a general field that encompasses machine learning and deep learning, as illustrated in Figure 7. It can be described as the effort to emulate intellectual tasks normally performed by humans (Chollet, 2021). Recently the Organization for Economic Co-operation and Development (OECD) has defined artificial intelligence as: "*a machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations, or decisions) for a given set of objectives*". It uses machine and/or human-based data and inputs to (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g., with machine learning) or manually; and (iii) use model inference to formulate options for outcomes. Artificial intelligence systems are designed to operate with varying levels of autonomy" (OECD, 2022).

Machine learning is one of the most popular fields of artificial intelligence. It allows the construction of algorithms with the ability to learn and improve automatically from large databases without being explicitly programmed (Goodfellow et al., 2016). Machine learning aims at enabling systems to use sample data and past experience to perform tasks without human intervention in unknown situations. It can also be defined as the process of solving a practical problem by: a) collecting a set of data and b) algorithmically building a statistical model based on that data set to solve the problem. There are several types of machine learning: a) supervised; b) unsupervised; c) semi-supervised; and d) reinforcement (Burkov, 2019).

FIGURE 19 - GENERAL FIELD OF ARTIFICIAL INTELLIGENCE



Source: Prepared by the author. Based on data from (Goodfellow et al., 2016; NVIDIA, 2022) (2022).

Supervised learning is task-based. Algorithms use previously labeled data sets to produce a model that takes a feature vector "x" as input data and generates output information that allows inferring the label of the feature vector. Human intervention is required to provide feedback. **Unsupervised learning** is data-driven. The algorithms do not use pre-labeled data; the goal is to create a model that transforms an input feature vector into another representation that may resume or enhance important characteristics. There is very little human intervention as the algorithms generate results independently. In **semi-supervised learning**, the dataset has both labeled and unlabeled samples. Generally, the number of unlabeled samples is greater than the number of labeled samples. It has the same objective as supervised learning. In **reinforcement learning**, algorithms learn from experience. The agent lives in an environment and can perceive the states of that environment as a feature vector. It executes actions through different rewards, sequential decision-making, and long-term goals (Burkov, 2019).

Deep learning is based on the use of structures called “Deep Neural Networks” (DNNs) (Goodfellow et al., 2016; LeCun et al., 2015). Deep learning has revolutionized the analytics landscape and become artificial intelligence's cornerstone. It is used to solve complex problems that typically involve large amounts of data, some of them difficult for traditional machine learning methods (Chollet, 2021), which require manually coded rules or human domain knowledge to identify features in the data (e.g., shape, pixel values, orientation, frequencies, etc.). Deep learning models learn directly from data and can increase their predictive accuracy when fed with new data.

Recent advances in artificial intelligence, the availability of large amounts of data, and the progress of computational power allow applying deep learning methods in a broad domain of applications ranging from image recognition, natural language processing, autonomous vehicles, medical assistance, and financial services (Haenlein & Kaplan, 2019).

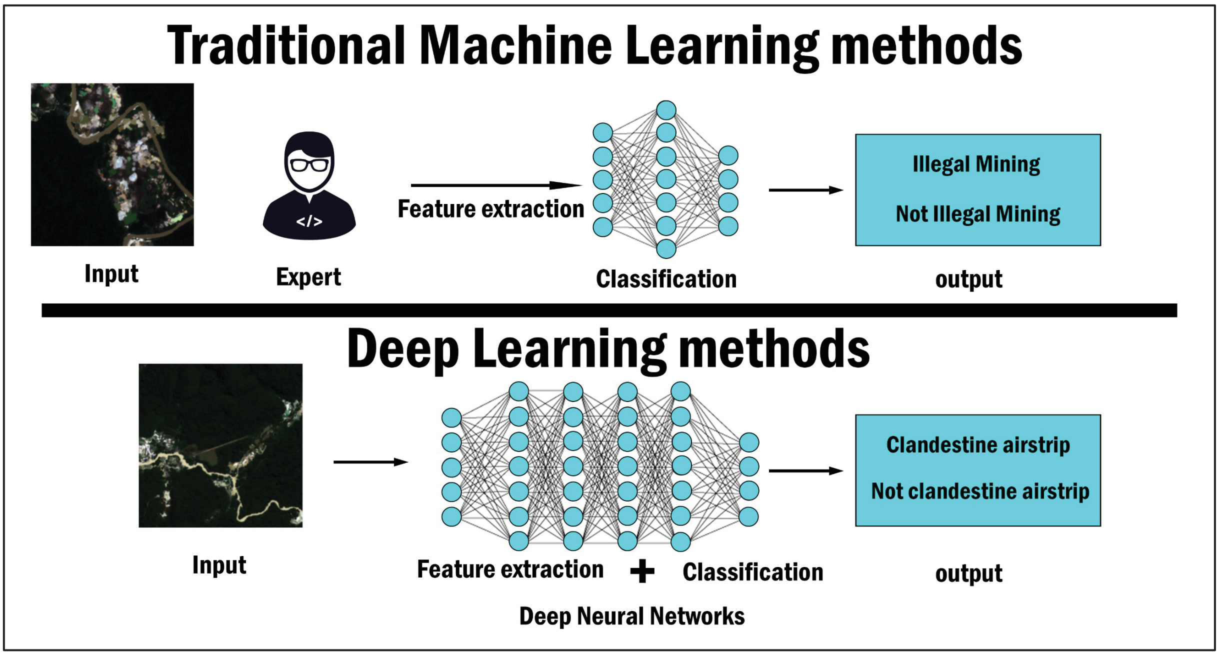
The application of artificial intelligence in the geospatial domain gave rise to a sub-discipline called Geospatial Artificial Intelligence (GeoAI) (UN-GGIM, 2020). GeoAI uses machine learning, geographic information science (especially remote sensing), data mining, and high-performance computing to extract and analyze information from large geospatial datasets (UN-GGIM, 2020; VoPham et al., 2018). Due to its ability to learn representative and discriminative features from data (LeCun et al., 2015), it has demonstrated significant success in object detection, and scene understanding tasks (Zhang et al., 2016) applied to remote sensing imagery (Camps-Valls et al., 2021; del Rosso et al., 2021), natural language processing applications for extracting data from geospatial information (Hu, 2018), allowing us to solve large-scale real-world problems (VoPham et al., 2018; Zhu et al., 2017).

2.5.1 Deep learning

Deep learning methods are characterized as "*learning-representation*" methods with multiple layers of representation, obtained by composing simple but nonlinear modules that transform the representation at one level (starting from the raw input) into a representation at a higher and slightly more abstract level. The key aspect of deep learning is that human engineers do not design these layers: they are learned from the data using a general-purpose learning procedure (LeCun et al., 2015).

One of the key features of deep learning methods is the impact of data representation on feature extraction during the learning process. Figure 8 illustrates the differentiation between traditional machine learning methods and deep learning methods. In traditional machine learning methods, the system operator performs feature extraction from the input data (variables in the dataset). Then the model transforms the features into meaningful outputs through exposure to known examples of inputs and outputs. In deep learning, the extraction of features (attributes, features) from the input data is performed by multi-layer structured Artificial Neural Networks (ANNs), which perform this input mapping in an automated fashion through a deep sequence of simple data transformations (layers), which learn through exposure to examples (Chollet, 2021; Goodfellow et al., 2016; LeCun et al., 2015). That is, most of the model parameters are learned from the results of previous layers. These methods stand out because they focus on pattern recognition and data learning.

FIGURE 22 - DIFFERENCES BETWEEN TRADITIONAL MACHINE LEARNING METHODS AND DEEP LEARNING METHODS



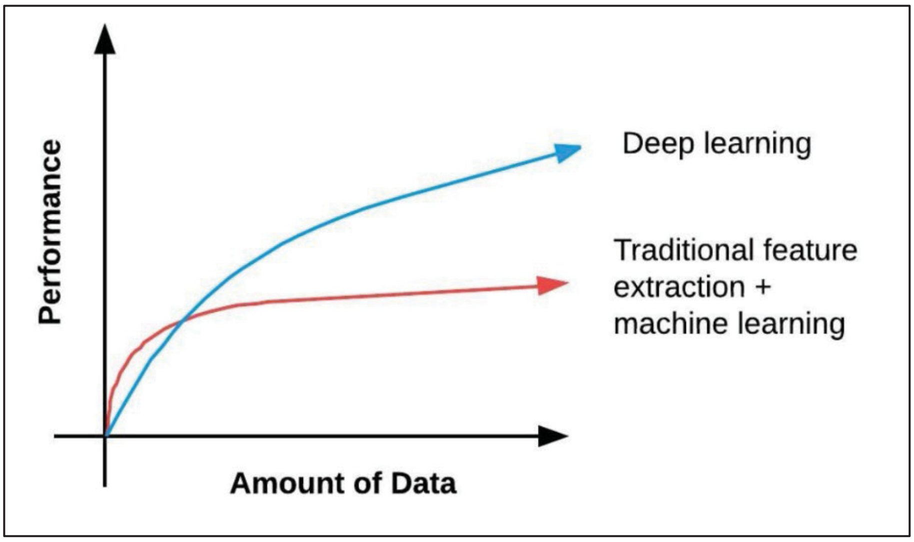
Source: Prepared by the author. Based on data from (Chollet, 2021; Goodfellow et al., 2016; LeCun et al., 2015). (2022).

Deep learning algorithms are composed of a series of neural networks arranged in multiple layers, from which the term Deep Neural Networks (DNNs) is derived (LeCun et al., 2015). Each layer is a relatively simple algorithm, linked to some type of activation function, that detects patterns. As the layers are stacked, complex features can be computed from the previous ones. In combination with the backpropagation algorithm. The net can efficiently be trained to learn from their mistakes without the need for manual engineering resources to extract features from the data during the training and learning process (LeCun & Bottou, 2012; Rumelhart et al., 1986). Deep learning architectures fall into three main categories:

Convolutional Neural Networks (CNNs), Pre-trained Unsupervised Networks (PUNs), and Recursive Neural Networks (RNNs) (Pedrycz & Chen, 2020).

The success of deep learning algorithms relies on the availability of a large set of samples to derive enough information to solve the problem. To train a deep net and obtain results with high accuracy it is necessary to have as many labeled samples as possible available for training, much more than traditional methods, as shown in Figure 9. Today, the availability of large data sets and graphics processing units (GPU) enabled building very accurate and deep neural networks, substantially outperforming the approaches of other traditional machine learning methods (Ng, 2015; Rosebrock, 2019).

FIGURE 25 - RELATIONSHIP BETWEEN DATA INCREMENT AND ACCURACY



Source: (Ng, 2015).

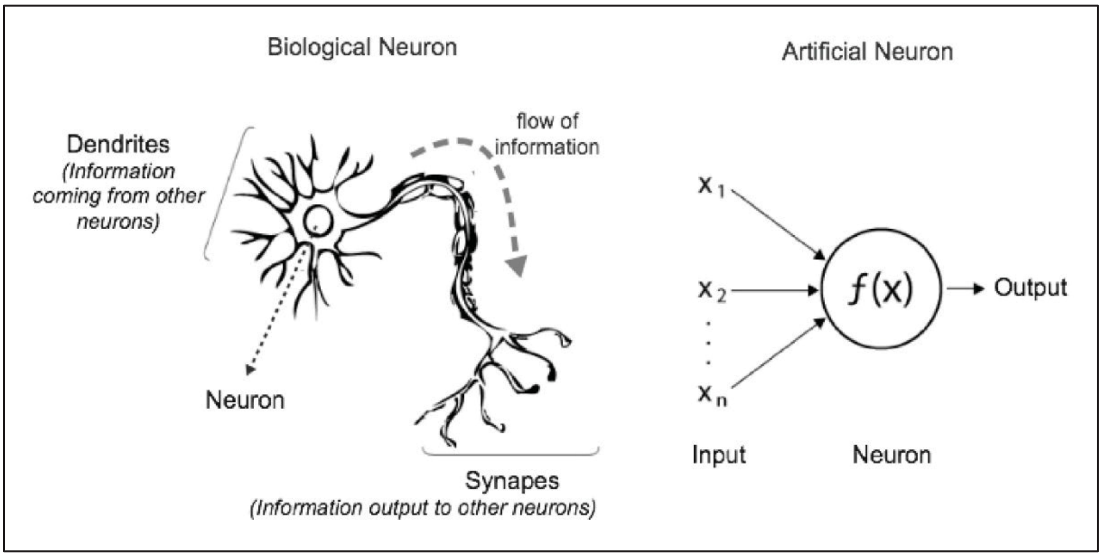
In the research, deep nets, convolutional nets, were used. As they are based on the principles of neural nets, the basic concepts of neural networks are introduced in the next section.

2.5.2 Artificial neural networks

Artificial Neural Networks were created inspired by the human brain's structure, function, and interaction of biological neurons. They are algorithms that use layers of mathematical neurons to process data. Information passes through and is modified by each layer; the previous layer's output provides input to the next layer. The first layer is called the “input layer,” the last layer is the “output layer,” and all layers in between are called “hidden layers” (Rosebrock, 2019).

Artificial Neural Networks (ANNs) were introduced in 1943 by neurophysiologist Warren McCulloch and mathematician Walter Pitts in their paper “*A Logical Calculus of Ideas Immanent in Nervous Activity*” (McCulloch & Pitts, 1943). Later, in 1957, psychologist Frank Rosenblatt further developed these studies and the artificial neuron to endow it with learning capabilities. He created the perceptron model (Rosenblatt, 1957), which receives several inputs and produces a single binary output, successfully recognizing simple shapes. The perceptron model, as shown in Figure 10, conceptually functions similarly to biological neurons. These receive electrical signals from their dendrites, modulate them, and trigger an output signal across their synapses. Finally, when the total strength of the input signals exceeds a certain threshold, the output feeds another neuron, and so on.

FIGURE 28 - BIOLOGICAL NEURON AND ARTIFICIAL NEURON



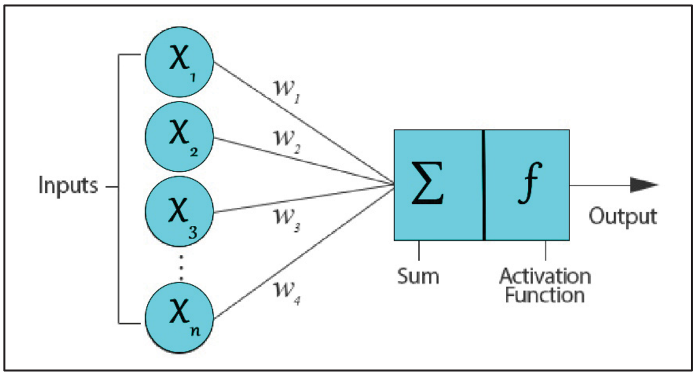
Source: (Elgendy, 2020).

In the artificial neuron, two consecutive functions are performed: 1) compute the weighted sum of the inputs to represent the total strength of the input signals, and 2) apply a transform to the result and verify if this result exceeds a threshold, when an output is produced. As not all input features are equally useful for the solution, each input is assigned a weight. These are called "connection weights."

Figure 11 illustrates the basic operation performed by an ANNs, which is composed of (Elgendy, 2020; Rosebrock, 2019):

- The **input vector** that feeds the neuron. In image processing, the input vector may include different features, like color or spatial features, that are supposed to be used in the solution of the problem, for example, classification. They are usually indicated by the capital letter *"X,"* representing a vector of inputs (*X1, X2, X3... Xn*).
- The **weight vector**: Each input is connected to a neuron via a weight *"W"*, which means that for each input *"X_i,"* there is an associated weight *"W_i."*
- The **weighted sum:** also known as a linear combination, is the sum of all inputs multiplied by their weights and then added to an additional term, the "bias." The idea is to weigh the inputs to produce the desired outputs.
- **The activation function**: it takes the input of the weighted sum and transforms it to the output domain, generally 0 to 1 or -1 to 1. After the transform, it is verified if the result is above a given threshold, to activate (trigger) the neuron output. There are different activation functions; the most common of which include: Identity, Step Function, Sigmoid, Softmax, Hyperbolic Tangen, Rectified Linear Unit (ReLU), and Leaky ReLU. For example, in the step function, the output is either 0 or 1. Other activation functions produce an output of probability or floating-point numbers.
- The **output** is passed to another neuron or used as output of the system.

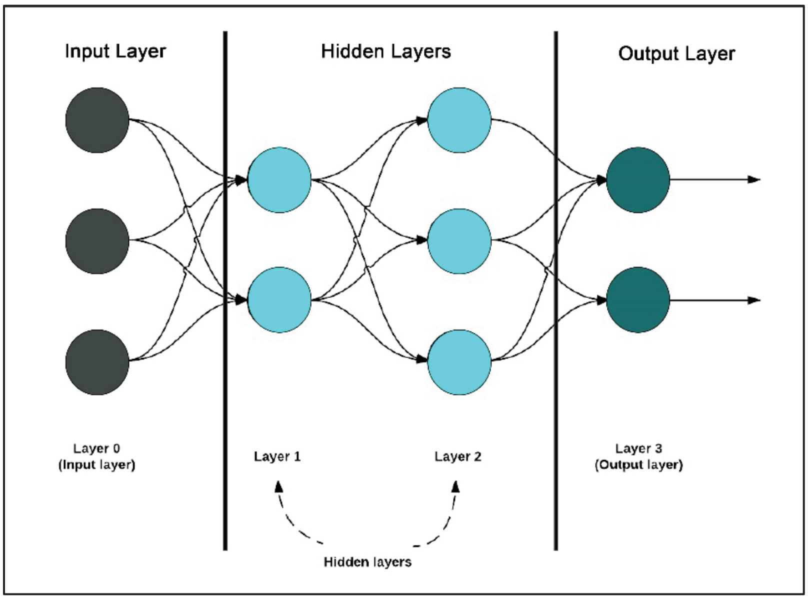
FIGURE 31 - BASIC OPERATION PERFORMED BY AN ANN



Source: Prepared by the author. Based on data from (Elgendy, 2020) (2022).

An artificial neural net (ANN) is composed by several layers of neurons. There are different types of ANNs architectures, the most common being the Feedforward Neural Network (FNN), displayed in Figure 12. In this type of architecture, only one connection is allowed between the nodes of layer *i* and those of layer *i+1*. No backward or interlayer connections are allowed; this type of architecture is considered the cornerstone of modern deep learning applied to computer vision. For example, CNNs are a special case of feedforward neural networks (Rosebrock, 2019).

FIGURE 34 - FEEDFORWARD NEURAL NETWORK



Source: Prepared by the author. Based on data from (Rosebrock, 2019) (2022).

The first layer is known as the input layer and is responsible for receiving the input data. The Last layer is where the result is presented. Between these two layers several other layers perform multiple computations from the original inputs, passing their results to the next layer. They are called “hidden layers”. In Figure 12, the network contains two hidden layers with 2 and 3 neurons, respectively; the number of neurons in each layer varies according to the complexity of the problem.

When dealing with a classification problem, the output layer has as many neurons as class labels, one node for each potential output. For example, if an ANN was ere constructed to classify the classes: airstrips, deforestation, forest, illegal mining, illicit crops, and water from a dataset constructed with satellite imagery, the output layer would be composed of six neurons corresponding to each class.

Solving a problem with an ANN, no matter how simple or complex its architecture may be, involves adjusting irs parameters according to the desired output. This phase is known as the training step. Each problem to be solved should be submitted to several “trial and error” training attempts, which are the ones that will allow finding the parameters and hyperparameters that best fit the model until favorable results are obtained based on the operator's criteria (Chollet, 2021; Elgendy, 2020; Howard & Gugger, 2020; Kelleher, 2019; Rosebrock, 2019; Trask, 2019).

The **parameters** are variables that the network updates during the training process, such as weights and biases. The model automatically adjusts these during training. The **hyperparameters** are variables external to the model that the operator adjusts before training the model. For example, number of hidden layers, activation functions, loss function, optimizer, batch size, number of epochs, learning rate, evaluation metrics, filters, stride, kernel size, and padding. They have a great impact on the accuracy of a neural network; there can be different optimal values for different hyperparameters; discovering these values is not straightforward and becomes one of the main challenges for training deep learning models (Elgendy, 2020; Goodfellow et al., 2016; Howard & Gugger, 2020; Ng, 2015; Rosebrock, 2019; STANFORD UNIVERSITY, 2022; Torres, 2020). Some complementary definitions for understanding and training ANN are described in Table 9.

The most popular solution for the training step is the feed-forward method. Here, the input data is used to produce an output. At the beginning, as the parameters are unknown, random values are used for the weights and bias, and the results are poor. These results are compared to the desired results in the output layer, and an error is computed. This is known as the feed-forward step. Knowing the error for a given input allows for adjusting the weights. This is done by propagating the error along the net from the output towards the input, the backpropagation phase. This process is repeated for each sample until the error rate at the output achieves an acceptable value.

TABLE 9 - COMPLEMENTARY DEFINITIONS FOR UNDERSTANDING AND TRAINING OF ARTIFICIAL NEURAL NETWORKS

Definitions	
Generalization	It refers to the model's ability to adapt and make predictions in a way that is appropriate to new data never seen before.
Regularization	It is a set of techniques that can prevent overfitting in neural networks and thus improve the accuracy of a deep learning model when faced with completely new data. Example: L1, L2, Dropout.
Underfitting	It occurs when the model cannot obtain a sufficiently low loss in the training set. In this case, the model does not learn the underlying patterns in the training data. It leads to a high error in both training and test data.
Overfitting	It occurs when the network models the training data very well but does not generalize the validation data well. In this case, the model is only adequate for the training data. It is as if the model has only memorized the training data and cannot generalize to other data it has never seen before.
Input shape	This is the hyperparameter that indicates how the input data is; it is the initial tensor in the first layer. This tensor must have the same shape as the training data. For example: if the images are 256 x 256 pixels in RGB (3 channels), the shape of the input data would be (256 x 256 x 3).
Label	Refers to what a model is intended to predict.
Training	This is the phase in which the model learns from the exposure of the input samples that have been labeled. In this way, the model iteratively learns the relationships between the features and the labels of the samples.
Data augmentation	These techniques increase the amount of data by adding slightly modified copies of existing data or newly created synthetic data from existing data. It acts as a regularization technique and helps to reduce overfitting when training a deep learning model.
Inference	It makes predictions by applying the already trained model to unlabeled samples you want to predict.
Number of hidden layers	A net can have as many layers as desired, each with as many neurons as you wish to place. The general idea is that the more neurons a net has, the more it will learn from training data. However, if there are too many neurons, this can lead to a phenomenon called overfitting. This means that the net has learned too much from the training data, memorizing it rather than learning its characteristics. Therefore, its ability to generalize is weak. To get the proper number of layers, one should start with a small net and observe the net's performance. Then one can add layers until satisfactory results are obtained.
Activation functions	The activation function introduces nonlinearity into the network's modeling capabilities. The main activation functions are: *Identity Function, Step Function, Sigmoid, Softmax, Tanh, ReLU,* and *Leaky ReLU.*
Loss function	Measures how far the net's prediction is from the true label. Evaluate the error difference between the calculated and desired outputs from the training data. For example, Mean Square Error (MSE) is common for regression problems, and *Cross Entropy* is common for classification problems.

Optimizer	Optimization algorithms find the optimal weight values that minimize the error. There are several types of optimizers to choose from. Among the most common: *Stochastic Gradient Descent (SGD), Batch Gradient Descent, Mini-batch SGD, momentum, Nesterov acceleration, RMSprop, AdaGrad, Adadelta, Adam, Adamax, Nadam*, others.
Batch size	For passing the training data through a network, it is necessary to divide it into smaller batches. The batch size is the argument that indicates the size of the mini-batch (number of subsamples) given to the network, after which the parameter is updated. Larger batches learn faster but require more space in computer memory. A good default value for the batch size might be 32. Sizes are also used: 32, 64, 128, 256, and others.
Number of epochs	Indicates the number of times the training data has passed through the neural net in the training process. A high number of epochs causes the model to fit the data too well and can have generalization problems in the testing and validation data set. It can also cause problems with vanishing gradients and exploding gradients. A less than optimal number of epochs can limit the model's potential because the model does not get enough training. After all, it has not seen enough data, so good predictions are not obtained.
Learning rate	This hyperparameter controls the extent to which the model should change in response to the estimated error each time the model weight is updated. Choosing the learning rate is a challenge since too small a value can result in a long training process that may get stuck, while too large a value may result in learning a suboptimal set of weights too quickly or an unstable training process. The value of the learning rate depends on the optimizer used; it corresponds to a value between 0 and 1. For example, for the SGD optimizer, a value of 0.1 works well, but for the Adam optimizer, it is recommended to use between 0.001 and 0.01
Evaluation metrics	Evaluation metrics: refers to how the output produced by the network is evaluated against the reference data. Evaluation metrics explain the performance of a model. An important aspect of evaluation metrics is their ability to discriminate between model results. *(Accuracy, Precision, Recall, Confusion Matrix, mean Average Precision*, among others).
Filters	Used in CNN. This is the number of kernel filters in each convolution layer (the depth of the hidden layer).
Stride	Used in CNNs. This is the number of steps by which the filter slides over the image. A step of 1 or 2 is recommended as a good starting point.
Kernel size	Used in CNNs, indicates the size of the convolution filter or kernel. Usually 2, or 3, or 5.
Padding	Adding columns and rows of zero values around the image border to reserve the image size in the next layer.

Source: (Baydin et al., 2018; Elgendy, 2020; Goodfellow et al., 2016; Howard & Gugger, 2020; Ng, 2015; Rosebrock, 2019; STANFORD UNIVERSITY, 2022; Torres, 2020).

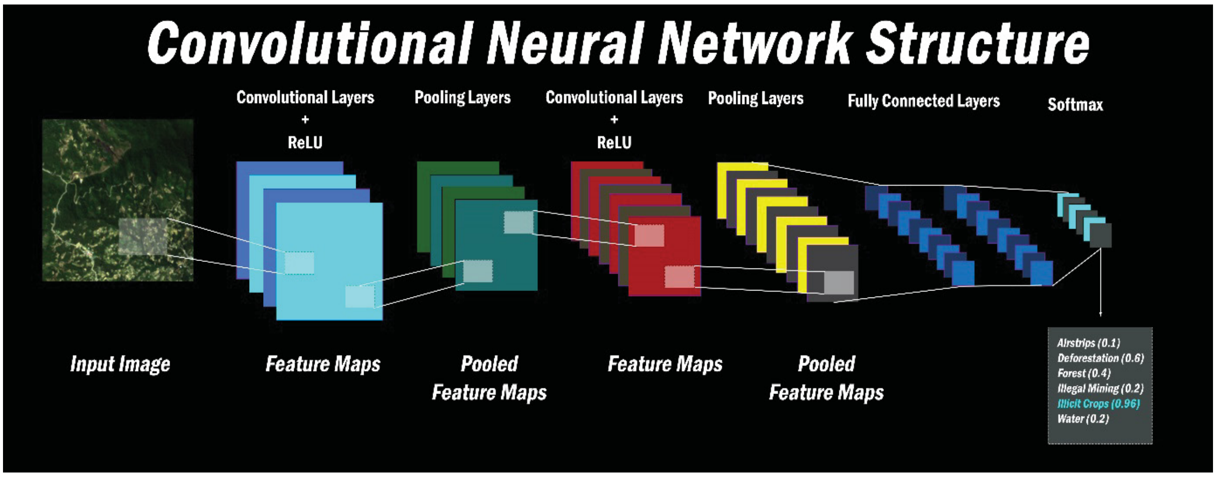
2.5.3 Convolutional neural networks

Convolutional neural networks (CNN) are a special case of feedforward neural networks (Rosebrock, 2019). They use a special architecture adapted to take advantage of the images' spatial structure, which is ideal for analyzing images faster (Nielsen, 2015). Their layers of neurons are used to learn and extract features from an image by applying a series of convolution filters. As several layers are stacked, deeper layers can compute more complex features. Convolutional layers are inspired by the structure of the human visual cortex (Bengio, 2009; Hubel & Wiesel, 1962), where a series of layers process an input image and identify progressively more complex features. They are widely used in computer vision and have become instrumental in achieving impressive results in image recognition.

A CNN is a sequence of layers. Each layer transforms one volume of activations into another through a differentiable function (LeCun et al., 2015). These allow the model to learn abstract features (Maretto, 2020). Three main layers are used to build a CNN architecture: **Convolutional layer**, **Pooling Layer,** and **Fully-Connected Layer**. These layers are stacked and form a complete CNN architecture. For example, as illustrated in Figure 13, a CNN for image classification could have the architecture [INPUT - CONV - RELU - POOL - FC] (Rosebrock, 2019; STANFORD UNIVERSITY, 2022):

- INPUT [256x256x3] will hold the raw pixel values of the image, in this case, an image of width 256, height 256, and with three color channels R, G, B.
- The CONV layer will compute the output of neurons connected to local regions in the input, each computing a dot product between their weights and a small region connected to the input volume. This might result in volume such as [256x256x12] if we decided to use 12 filters.
- RELU layer will apply an elementwise activation function, such as the max (0, x) thresholding at zero. This leaves the size of the volume unchanged ([256x256x12]).
- POOL layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as [128x128x12].
- FC (i.e., fully-connected) layer will compute the class scores, resulting in a volume of size [1x1x6], where each of the 6 numbers corresponds to a class score, such as among the 6 categories of AmazonCRIME dataset, built for the development of one of the experiments of this thesis. As with ordinary ANN and, as the name implies, each neuron in this layer will be connected to all the numbers in the previous volume.

FIGURE 37 - STRUCTURE OF A CONVOLUTIONAL NEURAL NETWORK



Source: Prepared by the author. Based on data from (STANFORD UNIVERSITY, 2022) (2022).

In this way, CNN transforms the original image, layer by layer, from the original pixel values to the final class scores. Some layers contain parameters, and some do not. The CONV/FC layers perform transformations that are a function not only of the activations in the input volume but also of the parameters (the weights and biases of the neurons). The RELU/POOL layers will implement a fixed function. The parameters of the CONV/FC layers will be trained with gradient descent so that the class scores that the CNN computes are consistent with the labels in training set for each image (STANFORD UNIVERSITY, 2022).

Convolutional layers are the most important component of a CNN. They act as a feature search window that slides over the image pixel by pixel to extract meaningful features. This is done by applying convolution to the image (I) with a two-dimensional kernel (K).

$$S(i,j) = (I \star K)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n) \tag{1}$$

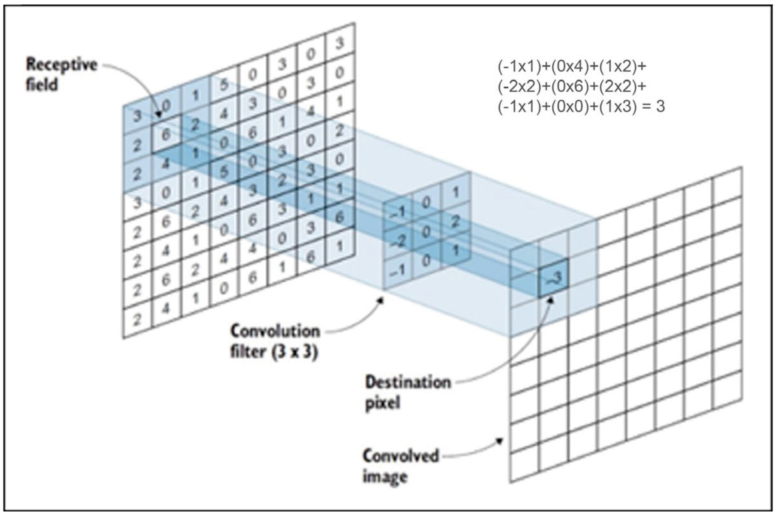
$\star$ = convolution

I = two-dimensional input image

K= filters or convolution kernels

The result of the convolution is a modified image. As illustrated in Figure 14, a small 3 x 3 kernel, the filter, is sliding over the input image, and the result is stored in a new image, preserving the position of the original region. This produces a so called "feature map" or "activation map" (Elgendy, 2020; S. Khan et al., 2018), where the result of each feature detector is stored.

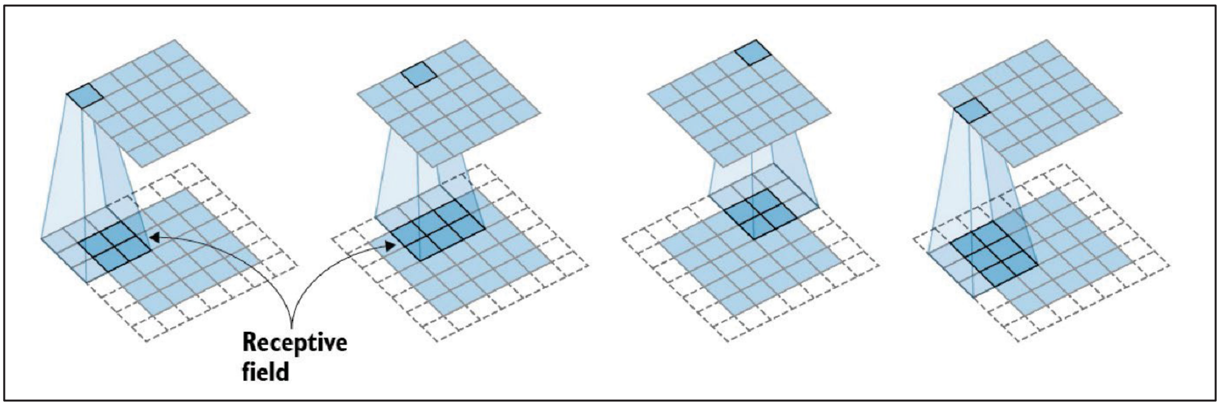
FIGURE 40 - IMAGE CONVOLUTION



Source: (Elgendy, 2020).

As each filter has a width and a height, the area of the image that the filter convolves is called the local receptive field (Brownlee, 2016; Elgendy, 2020; Rosebrock, 2019). Each neuron of the first hidden layer will be connected to a small region of the input neurons (Nielsen, 2015), as displayed in Figure 15.

FIGURE 43 - LOCAL RECEPTIVE FIELD



Source: (Elgendy, 2020).

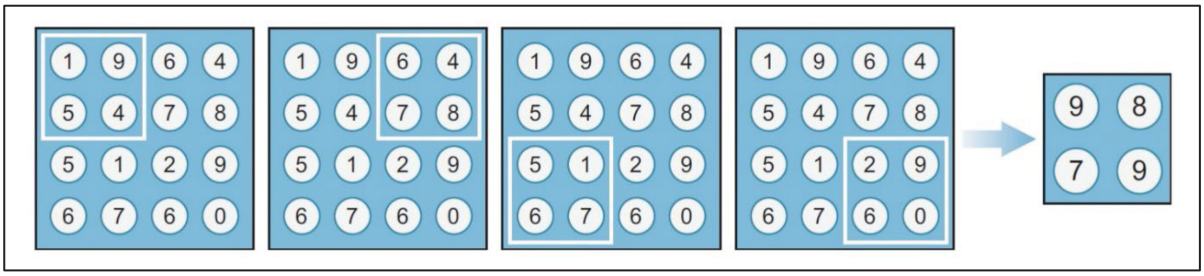
Filter/kernel size is one of the hyperparameters to consider when creating a convolution layer. It refers to the dimensions of the convolutional kernel (width x height); like most neural network hyperparameters, there is no specific value that fits all problems (Davies, 2017). Smaller filters capture very fine details of the image, and very large filters leave out minute details of the image; they are usually square and range in size from 2 x 2 (small) to 5 x 5 (large).

Each hidden neuron has a bias and weights connected to its local receptive field, these sets of weights will be used (shared) for all neurons in the hidden layers. So, each layer will learn a set of position-independent latent features derived from the image, considerably reducing the number of parameters involved in the network. A nonlinear activation function is applied to each component of the feature map, the most common being the Rectified Linear Unit (ReLU) (LeCun et al., 2015), to improve the generalization of the convolutional layer. This allows CNNs to be shift invariant.

The **pooling layers**, located after a convolutional layer, are intended to progressively reduce the spatial dimensions of the feature map to reduce the number of parameters and computations in the network that occur when multiple convolution layers are added, as well as controlling overfitting (Goodfellow et al., 2016; F. Hu et al., 2015) and, therefore, reducing computational complexity. Typically, layer pooling is performed with a statistical function such as the max-pooling function, which takes the maximum input value to create its feature map (Rosebrock, 2019) and reduces the total number of parameters passed to the next layer. Other statistical functions can be applied, such as average-pooling, weighted average-pooling, global-pooling, and L2-norm pooling (Goodfellow et al., 2016; STANFORD UNIVERSITY, 2022).

Like convolution kernels, pooling kernels are windows of a certain size that slide over the image with a stride value. The difference is that they have no weights or values; they just slide over the feature map to select a representative value to be used by the following layers, and ignore the remaining values. Figure 16 illustrates an example of the max-pooling function, where a clustering filter is created with a size of 2 x 2 and a stride value = 2. The clustering layer reduced the size of the feature map from 4 x 4 to 2 x 2.

FIGURE 46 - MAX-POOLING FUNCTION OPERATION

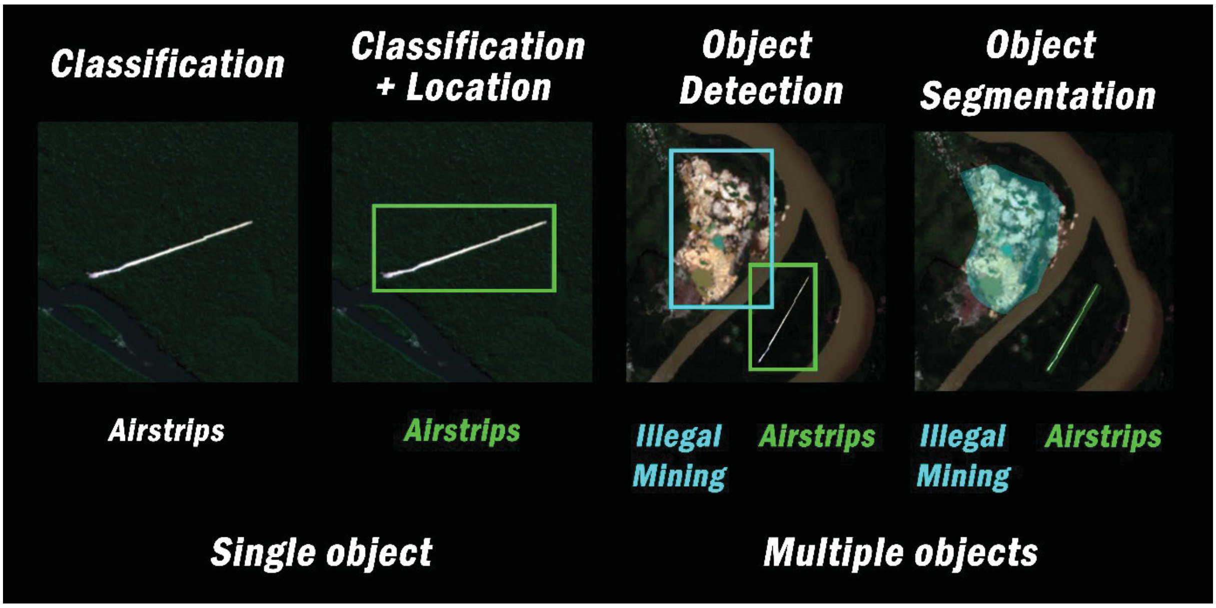


Source: (Elgendy, 2020).

Finally, after the features are extracted and consolidated by the convolution and pooling layers, **fully-connected Layer** (FC) are used to classify the image. Typically, one or two fully connected layers are aggregated and characterized by a nonlinear activation function or SoftMax activation function, which allows outputting prediction probabilities for each defined class (Goodfellow et al., 2016; STANFORD UNIVERSITY, 2022). Each layer of a CNN applies a different set of filters (hundreds or thousands), which combine the results, feeding the output to the next layer of the network, allowing the CNN to automatically learn the values of these filters during training.

In the context of image classification, a CNN can learn, for example, to detect edges in the raw pixels in the first layer, use these edges to detect shapes, and subsequently, use these shapes to detect high-level features in the higher layers of the network (STANFORD UNIVERSITY, 2022), allowing predictions to be made about the image content. So, CNN have been widely used in computer vision tasks, like classification, classification with localization, object detection, and object segmentation (semantics and instances) (Davies, 2017; STANFORD UNIVERSITY, 2022), in addition to other applications such as style transfer, coloring, reconstruction, resolution enhancement, image synthesis, image captioning (Hassaballah & Awad, 2020), among others. Some examples are shown in Figure 17.

FIGURE 49 - MAIN COMPUTER VISION TASKS



Source: Prepared by the author. Based on data from (Davies, 2017; STANFORD UNIVERSITY, 2022) (2022).

In **image classification**, an entire image is given a label from a predefined set of categories. The model must predict the correct label for an image based on its contextual information extracted from the pixel values. Typically, an image belongs to only one class.

Classification with location consists of assigning a class label to an image and displaying the object's location in the image using a bounding box. The model needs to identify the position of an object on the screen.

Object detection is a more challenging task than the previous two. It involves image classification with localization, considering the multiple objects in the scene; these are also localized and classified with a bounding box.

Object segmentation is the task of dividing parts of an image with pixel precision and thus predicting the segment that corresponds to each pixel. The network predicts a class value for each input pixel. A line is drawn around each detected object in the image that identifies the specific pixels of each object. There are two conceptual approaches to segmentation: semantic segmentation (all pixels matching a class are segmented) and instance segmentation (pixels of each instance of a class must be segmented).

2.5.4 Convolutional neural networks for classification and object detection tasks

Deep learning has proven to be an alternative to extract features from large image datasets automatically. Various architectures have been applied and have generally outperformed traditional methods. In the field of remote sensing, particularly CNN have become a powerful tool that has achieved great success in the processing, analysis, and visual recognition of large-scale remote sensing images, excelling in image classification, object detection, scene understanding, image fusion and registration, image segmentation (Caisse, 2020; Camps-Valls et al., 2021; del Rosso et al., 2021; Ma et al., 2019; UN-GGIM, 2020; Zhang, et al., 2016), among other applications.

The satisfactory results of using CNN for **image classification** tasks in the field of computer vision have motivated its application in numerous applied studies in Earth observation (Camps-Valls et al., 2021; Cheng et al., 2017; del Rosso et al., 2021; Ma et al., 2019; Zhang, et al., 2016; Zhu et al., 2017). Satellite image classification based on deep learning methods has played an important role that has received special attention from the remote sensing community.

Significant efforts have been made, from the generation of new CNN architectures focused on the classification of remote sensing images to the construction of datasets for scene classification (Cheng et al., 2017; del Rosso et al., 2021). However, these remain one of the main limitations and topics of interest for developing new applications based on deep learning (Camps-Valls et al., 2021; del Rosso et al., 2021; UN-GGIM, 2020). In this sense, a brief review of some related works based on deep learning methods for remote sensing image classification tasks is described in Table 10.

TABLE 10 - RELATED WORKS ON THE USE OF DEEP LEARNING METHODS FOR REMOTE SENSING IMAGE CLASSIFICATION TASKS

Title	Review
Deep learning in remote sensing scene classification: a data augmentation enhanced convolutional neural network framework (Yu et al., 2017).	The potential of learning methods for characterizing complex patterns in remotely sensed imagery is discussed. The authors highlight the need for large datasets to train complex architectures. They also expound on the limited number of reference datasets for remote sensing applications, which restricts application in different fields. They present a "data augmentation" methodology validated on three datasets, which allows for improving the training data volume for training CNNs and improving scene classification performance.
Multi-label Classification of Satellite Images with Deep Learning (Gardner & Nichols, 2017).	In this study, the authors use data enhancement and data assembly techniques. They trained three CNN architectures (Basic CNN, VGG-16, and ResNet-50) to perform a multi-label classification of satellite images of the Amazon. The application of the models allowed them to easily identify climatic conditions and natural terrain features in the images, as well as structures and human activities (roads, agriculture, deforestation, and illegal mining areas). The results conclude that using CNN models becomes a favorable tool for the scientific community and governments to support decision-making to protect the Amazon rainforest.
Satellite Image Classification with Deep Learning (Pritt & Chern, 2017).	The authors highlight the importance of remote sensing imagery for many applications, such as disaster response, law enforcement, and environmental monitoring. However, as these applications require manual identification of objects located over large geographical areas, they propose using deep learning methods, such as CNNs, to automate the processes. They train and describe a learning system that combines CNNs with image metadata. The results allowed classifying objects and facilities in high-resolution multispectral satellite images with an accuracy of 95%.
Deep Learning - A New Approach for Multi-Label Scene Classification in PlanetScope and Sentinel-2 Imagery (Shendryk et al., 2018).	The authors developed deep learning models capable of classifying atmospheric conditions, dominant land cover, and land use classes from the “Understanding the Amazon from Space” dataset. This dataset is composed of PlanetScope images of the Amazon rainforest. They trained a CNN to perform scene classification, obtaining an F β performance of 0.91. Subsequently, they evaluated the transferability of the models trained with PlanetScope imagery to Sentinel-2 imagery about the Australian humid tropics. The results concluded that the models were suitable for classifying satellite imagery of similar resolution, such as Sentinel-2.
A Survey on Deep Learning-Driven Remote Sensing Image Scene Understanding: Scene Classification, Scene Retrieval and Scene-Guided Object Detection (Gu et al., 2019).	A review is conducted on deep learning-based remote sensing methods and their impact on scene classification, image retrieval, and object detection applications in remote sensing images. They highlight the need for large datasets for specific tasks. Future and potential applications such as model transfer, remote sensing image captioning, image labeling, and scene interpretation across multiple sources are discussed.

Siamese Convolutional Neural Networks for Remote Sensing Scene Classification (Liu et al., 2019).	The authors consider the lack of labeled, small-scale datasets and the lack of image diversity to be a major concern for the remote sensing community. In this regard, to mitigate that impact for scene classification tasks, they propose the application of a Siamese CNN with the ResNet-50 architecture, which combines the identification and verification models of CNN. A metric learning regularization term is explicitly imposed, which forces Siamese CNNs to be more robust. The results showed that the proposed method outperformed existing methods.
Eyes in the Skies: A Data-Driven Fusion Approach to Identifying Drug Crops from Remote Sensing Images (Ferreira et al., 2019).	The authors propose a deep learning method using an image classification approach with different CNN architectures. They combine data sources obtained by law enforcement authorities to detect marijuana cultivation areas from remotely sensed images. To validate the proposed approach, they generate a dataset of remotely sensed images containing Cannabis Sativa (marijuana) cultivation scenes detected by police operations in a Brazilian region called " *Polígono da Maconha*." The results showed a promising use that can help police institutions formulate drug interdiction strategies.
Remote Sensing Image Scene Classification Using CNN-CapsNet (Zhang et al., 2019).	The authors propose a remote sensing image classification architecture called CNN-CapsNet. This architecture leverages the capabilities of deep CNN models and the CapsNet architecture. It uses a cluster of neurons as a capsule to replace the traditional neural network. It encodes the properties of spatial information to achieve the equivalence of a fully connected layer. The proposed architecture is evaluated on three public remote sensing image datasets (UC Merced with 21 categories, AID with 30 categories, and NWPU-RESISC45 with 45 categories). The results showed that the proposed method could lead to competitive classification performance compared to other state-of-the-art methods.
Hydra: An Ensemble of Convolutional Neural Networks for Geospatial Land Classification (Minetto et al., 2019).	A CNN model for remote sensing image classification called Hydra is described. They use two CNN architectures, ResNet and DenseNet. They demonstrate the application of the Hydra framework to two remotely sensed image datasets for classification tasks, FMOW, and NWPU-RESISC45. The contributions of the results allow the trained models to be made publicly available to the scientific and academic community.
A full convolutional network based on DenseNet for remote sensing scene classification (Zhang et al., 2019).	CNN applied to remote sensing image classification has two common issues: (1) a large number of parameters in the models, which easily leads to over-fitting, and (2) some models are not deep enough, so they cannot extract more abstract semantic information. They propose the application of a CNN based on DenseNet with 100 layers deep for the classification of remotely sensed images. They incorporate an adaptive clustering operation into the network, allowing it to accept input images of different sizes. They achieve significantly better results than the original architecture.
Remote Sensing Image Scene Classification Meets Deep Learning: Challenges, Methods, Benchmarks, and Opportunities (Cheng et al., 2020).	The authors provide a systematic survey of deep learning methods for remote sensing image classification by reviewing more than 160 papers. They conclude that using CNNs for remote sensing image classification tasks has experienced significant advances, enabling broad applications in diverse fields. They evaluate the performance of more than 24 representative algorithms on three commonly used benchmark datasets and review some remote sensing image scene classification methods based on the Generative Adversarial Network - GAN. Finally, they discuss opportunities for future research.

Object detection methods based on CNN are one of the main activities in computer vision and one of the most challenging (STANFORD UNIVERSITY, 2022). Their application involves locating natural or cultural features of interest and identifying their category on the ground through bounding boxes (Camps-Valls et al., 2021; Hassaballah & Awad, 2020) which is a particularly useful task in remote sensing by identifying geospatial objects in satellite images. Deep learning methods designed for this type of task are classified into: 1) regression-based methods and 2) region proposal-based methods (Rosebrock, 2019).

Regression-based methods use single-stage object detectors for object class prediction and integrate the detection process into a single deep neural network (Zhao et al., 2019). Among the most popular architectures are You Only Look Once (YOLO) (Redmon et al., 2016), Single Shot Multibox Detector (SSD) (Liu Wei & Anguelov, 2016), and RetinaNet (Lin et al., 2017). The advantage of regression-based algorithms is that they are much simpler and faster, as they do not need to produce candidate region proposals followed by feature resampling steps (Wu et al., 2020).

The **region proposal-based methods** divide the object detection structure into two stages: the first stage concentrates on generating proposals of candidate regions containing objects. The second stage classifies the proposals defined in the first stage into object classes to improve the coordinates of the bounding boxes that detect the object (Li et al., 2020). Among the main region, proposal-based architectures are R-CNN (Girshick et al., 2014), SPPnet (He et al., 2015), Fast R-CNN (Girshick, 2015), Faster R-CNN (Ren et al., 2015), Mask R-CNN (He et al., 2017), PANet (Liu et al., 2018). These methods have been shown to have higher accuracy than regression-based methods (Wu et al., 2020).

Like deep learning methods for image classification tasks, deep learning methods designed for object detection tasks have been employed by the remote sensing community to generate numerous applications. A review of some representative works that have implemented these methods to detect different classes of geospatial objects in satellite imagery is given in Table 11.

TABLE 11 - RELATED WORKS ON THE USE OF DEEP LEARNING METHODS FOR REMOTE SENSING IMAGES OBJECT DETECTION TASKS

Title	Review
Toward Fast and Accurate Vehicle Detection in Aerial Images Using Coupled Region-Based Convolutional Neural Networks (Deng et al., 2017).	Aerial imagery is used for vehicle detection. A vehicle detection framework is proposed that combines hierarchical feature maps with R-CNN to extract the location and attributes of "vehicle" objects simultaneously. This approach overcame the limitations related to localization performance and manual engineering to extract features.

Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network (Guo et al., 2018).	The daily acquisition of large amounts of aerial and satellite imagery has facilitated deep learning methods for object detection tasks. The authors propose using a multi-scale unified convolutional neural network to detect geospatial objects in high-resolution imagery. The results yield an average accuracy of 89.6%, demonstrating the effectiveness of the presented method applied to remote sensing images.
Deep convolutional neural networks for airport detection in remote sensing images (Budak et al., 2018).	This study applies methods based on region proposals to detect airports in remote sensing images. The CNN model is structured by five convolutions and three fully connected layers. They used normalization layers, dropout techniques, and data augmentation to build and train the model. They conducted several experiments to evaluate the performance giving an accuracy of 95.21%.
Opium Poppy Detection Using Deep Learning (X. Liu et al., 2018).	This study proposes a method for object detection in remotely sensed images based on regression (Single Shot multibox Detector - SSD). The objective is to identify the location of poppy (opium) plots and map their spatial distribution. This type of crop is the main input for different types of narcotic substances, such as heroin, which causes great damage to physical and mental health and threatens the economy of governments. The results showed an accuracy of 95%, providing an alternative way to obtain the geographical coordinates of the areas affected by poppy crops.
Illegal Buildings Detection from Satellite Images using GoogLeNet and Cadastral Map (Ostankovich & Afanasyev, 2018).	Considering the automatic detection of illegal buildings in remote sensing images as an important problem for the scientific community and government agencies, the authors propose a methodology incorporating remote sensing techniques with deep learning methods for detecting illegal buildings. They integrate several techniques to generate regional proposals with the CNN GoogLeNet architecture. The proposed approach generates acceptable results in both building detection and legality assessment.
A Deep Learning Framework for Automatic Airplane Detection in Remote Sensing Satellite Images (Hassan et al., 2019).	The limited number of labeled satellite images is one of the main drawbacks of training, so they adopt the training of a Faster R-CNN model for automatic aircraft detection by transfer learning. The results show that the proposed approach obtains a high accuracy for object detection in satellite images.
Large-Scale Oil Palm Tree Detection from High-Resolution Remote Sensing Images Using Faster R-CNN (Zheng et al., 2019).	Faster R-CNN is a widely used object detection algorithm for detecting tree crowns from remote sensing images. However, it has not been proven to have efficient results in detecting palm trees due to two arguments: 1) the size of each palm tree is too small (17×17 px in 0.6 m QuickBird images); 2) other similar types of trees around. The authors apply an adaptation to the network to solve this problem, filtering the detected trees as false positives. This approach allows them to improve detection, achieving an average F1 of 94.99%.
Airport Detection Based on Improved Faster R-CNN in Large Scale Remote Sensing Images (Yin et al., 2020).	An object detection method using a Faster R-CNN architecture is proposed for airport detection in large-scale remote sensing images. A multi-scale training is applied to the model to improve the robustness in detecting airports of different sizes, adopt a modified multi-task loss function to improve the accuracy, introduce data mining strategies, and use non-maximal suppression methods to remove redundant bounding boxes during training. The results can accurately detect different types of airports with a high detection rate.
An Improved Faster R-CNN Algorithm for Object Detection in Remote Sensing Images (R. Liu et al., 2020).	Remote sensing images have characteristics compared to conventional images. For example, the angle of view, the direction of the object, and the scale are different. These factors make it difficult to detect objects in satellite images. To solve these limitations, the authors propose an improved method of the Faster R-CNN algorithm. They combine the pyramidal feature

	structure, Soft-NMS, and RoI-Align technology. The results improved the speed accuracy compared to the original Faster R-CNN algorithm.
Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends (Hoeser & Kuenzer, 2020).	The authors provide an overview of deep learning methods for image segmentation and object detection tasks in remotely sensed imagery. They analyze the main architectures from 2012 to 2019, highlighting the Faster R-CNN architecture for its research impact on the remote sensing community. They review the leading deep learning frameworks, the most popular being TensorFlow, Pytorch, and Raster Vision, for applications on datasets composed of remotely sensed imagery. The research bridges the gap between theoretical concepts in computer vision and practical applications in remote sensing.
Pedestrian detection and monitoring with high spatial resolution images using convolutional neural networks and image processing (Caisse, 2020).	This research combines deep learning-based methods and image processing techniques to detect and track pedestrians from high-resolution images obtained in an external environment. Pedestrians are detected in the images using Faster R-CNN Inception v2 and SSD MobileNet v2 architectures. The bounding boxes of the detected pedestrians are segmented to extract features and compute histograms. Subsequently, the spatial correspondence between the elements of the different images is analyzed based on the classification of consecutive elements according to the histograms of the detected objects. The results generated accuracies higher than 80% being the model able to handle problems of appearance changes and partial occlusions.

Due to its capabilities to improve accuracy, the CNN architecture **DenseNet-201** (Huang et al., 2017) was selected in this thesis for image classification tasks. Several works (Abdani et al., 2019; Koh et al., 2021; Khan et al., 2021) have shown that CNN can be essentially deeper, more accurate, and more efficient to train if they contain shorter connections between layers near the input and those near the output, this is the principle of DenseNet-201, connecting each layer to all others in the form of feedback. Among its main advantages, this type of network reduces the problem of vanishing gradients, strengthens feature propagation, promotes feature reuse, and significantly reduces the number of training parameters (Huang et al., 2017).

For the object detection tasks, the **Faster R-CNN** architecture (Ren et al., 2015) was selected because this type of architecture has been shown to have higher accuracy than regression-based methods (Wu et al., 2020) and promising results in detecting geospatial objects in remote sensing imagery (Deng et al.,2017; Guo et al., 2018; Li et al., 2020; Yao et al., 2017).

The objective of Faster R-CNN is to adopt a short module to generate regional proposals instead of the selective search algorithm. The workflow is composed of two main modules: the first module is the Regional Proposal Network (RPN), a fully convolutional network used to generate regional proposals to simultaneously predict object boundaries and scores at each image position. The second module is the Fast R-CNN object detector, used to classify the proposals generated in the first module (Ren et al., 2015).

The central idea is to build a single model that shares the same convolutional feature layers for the RPN detector and the Fast R-CNN, down to its own fully connected layers. In this way, the image must pass through the CNN only once to generate the proposed regions and their respective features. Because the convolutional layers are shared, it is possible to use the CNN model to generate region proposals more efficiently and accurately than traditional region proposal methods (Ren et al., 2015).

General training aspects of these architectures are described in the experiments chapter.

2.5.5 Satellite imagery datasets for artificial intelligence applications

The central and most important component of deep learning is the dataset. It contains the input data that will enable training supervised artificial intelligence models and will strongly determine the performance of any data-driven learning process. Furthermore, obtaining satisfactory results will depend heavily on the quality and quantity of training samples. This is considered the bottleneck of artificial intelligence since data sets, especially remote sensing applications, are scarce, and their preparation generates a lot of time and effort (del Rosso et al., 2021; Pinto & Silva, 2022a, b).

A satellite image dataset for artificial intelligence applications includes pairs of satellite images and labels (del Rosso et al., 2021). For image classification tasks, each image must be correctly labeled. For object detection tasks, each bounding box must accurately delimit the geospatial object in which one is interested in locating and classifying. The dataset should be representative, i.e., encompassing as many features as possible that one wishes to classify or detect. For example, suppose the objective is to classify scenes or detect objects linked to drug trafficking organizations (such as clandestine airstrips, illicit coca crops, coca paste production infrastructures, illegal mining, among others). In that case, the training dataset should include several examples for each class.

As a rule of thumb, it is recommended to have between 1000 - 5000 or more sample images per class. The number of images per class should be approximately uniform since class imbalance creates a bias in the representation of categories during training. Although there are several techniques to correct this problem, the best option is to balance the classes in the dataset (Goodfellow et al., 2016; Rosebrock, 2019).

During the construction of a dataset with remote sensing images, it is important to keep in mind the major differences from conventional imagery (Hoeser & Kuenzer, 2020):

- The position of the sensor in remote sensing data has an aerial perspective relative to the scene. In contrast, a conventional image is captured from a side perspective, so the same types of objects appear differently.
- Data used in the computer vision field are usually three-channel RGB images. In contrast, remote sensing data usually contain multispectral images, so they must be considered when transferring computer vision models to remote sensing applications.
- Input data for computer vision models usually come from the same sensor and platform, whereas in remote sensing applications, images can come from different sensors.
- Objects appearing in remote sensing images do not have a general orientation. This means that objects of the same class can appear with a 360° rotation, which must be considered when building the dataset and selecting the deep learning model.
- In conventional imagery, objects of interest tend to be in the center of the image and at high resolution. In contrast, objects in remote sensing data may be outside the nadir, at the edges, and have different spatial resolutions.
- In remote sensing data, objects or classes tend to be denser and more heterogeneous than in conventional imagery.

Some of the tools to create and label a satellite image dataset for artificial intelligence applications are mentioned: ArcGIS Pro (ESRI, 2022), Deep learning framework Orfeo ToolBox (Cresson, 2018), Google Earth Engine (Gorelick et al., 2017), Labelbox (Labelbox, 2022), LabelImg (Tzutalin, 2015), Makesense.ai (Skalski, 2019), Raster Vision (AZAVEA, 2021), among others.

In this regard, image classification, image segmentation, and object detection tasks can be considered more difficult and complex due to the characteristics of remote sensing data. To overcome this problem, several special datasets built with remote sensing images have been created. These have contributed to the development of specific applications of artificial intelligence applied to satellite remote sensing data for Earth observation. Table 12 presents some of the satellite imagery datasets for artificial intelligence applications.

TABLE 12 - SATELLITE IMAGERY DATASETS FOR ARTIFICIAL INTELLIGENCE APPLICATIONS

Dataset	Source	Image size	Number of images	Task / Computer Vision	General information
UC Merced Land Use Dataset (Yang & Newsam, 2010).	Color aerial images	256 x 256	2,100	Classification	21 land cover classes
SAT-4 (Basu et al., 2015).	Color aerial images	28 x 28	500,000	Classification	4 land cover classes
SAT-6 (Basu et al., 2015).	Color aerial images	28 x 28	405,000	Classification	6 land cover classes
Brazilian Coffee Scenes Dataset (Penatti et al., 2015).	SPOT	64 x 64	51,004	Classification	2 classes
Brazilian Cerrado-Savanna (Nogueira et al., 2016).	RapidEye	64 x 64	1,311	Classification	4 classes
Planet: Understanding the Amazon from Space (PLANET, 2017).	Planet's Flock 2	256 x 256	150,000	Classification	13 land cover categories / Amazonian rainforest
RESISC45 (Cheng et al., 2017).	Color aerial images	256 x 256	31,500	Classification	45 classes
So2Sat LCZ42 (Xiang Zhu et al., 2019).	Sentinel-1 Sentinel -2	32 x 32	400,000	Classification	17 classes
EuroSAT (Helber et al., 2019).	Sentinel-2	64 x 64	27,000	Classification	10 land cover classes
DeepGlobe – Building Detection (Demir et al., 2018).	WorldView-3	650 x 650	24,586	Semantic segmentation	1 class
DOTA (Xia et al., 2018).	Color aerial images	800 x 800 to 4000 x 4000	2,806	Object Detection	15 classes 188.000 instances
SEN12MS (Schmitt et al., 2019).	Sentinel-1, Sentinel-2, MODIS Land Cover	256 x 256	541,986	Classification	MODIS Land Cover maps can either be used as labels or auxiliary data
BigEarthNet (Sumbul et al., 2019).	Sentinel-2	120 x 120 60 x 60 20 x 20	590,326	Classification	43 Corine Land Cover classes
Cactus Aerial Photos (López-Jiménez et al., 2019).	Color aerial images	32 x 32	17,000	Classification	2 classes

LandCover.ai (Boguszewski et al., 2021).	Color aerial images	9000 x 9000	41 orthophotos	Semantic segmentation	3 land cover classes
OpenSARUrban (Zhao et al., 2020).	Sentinel -1	100 x 100	33,358	Classification	10 classes Urban Interpretation
Agriculture-Vision (Chiu et al., 2020).	Color aerial images	512 x 512	21,061	Instance segmentation	6 types of annotations

It is noted that there is a variety of special datasets publicly available to encourage research related to artificial intelligence applications using remotely sensed imagery. Sentinel data are frequently used to compose this type of dataset because they are free (easily accessible) and offer a relatively good spatial resolution. Another factor to consider is the size of the study area. In the case of large extensions, satellite images offer advantages over aerial photographs.

For object detection and semantic segmentation applications, datasets mainly consist of color aerial photographs or satellite images of very high spatial resolution (around 50 cm). On the contrary, when images of lower spatial resolution are available, the datasets are used for classification tasks, as delineating small objects becomes difficult.

However, the availability of reference datasets for applications in the domain of interest of this research is scarce. Publicly available satellite imagery datasets are mainly targeted for agricultural applications, land use and land cover, and detection of common natural and cultural features. In addition, the geographic representation of most of these datasets is biased towards other regions of the world, considerably limiting their application in the South American region.

2.5.6 Natural language processing

Natural Language Processing (NLP) is a field of artificial intelligence that allows computers to use natural language (text and speech) to communicate with humans and learn from what they have written (Russell & Norvig, 2020). NLP comprises primarily three steps: lexical analysis, syntax analysis, and semantic analysis (Graham & Marguerat, 2019). Combined with machine learning algorithms and geospatial analysis techniques, it can detect signals and identify trends and threats by processing and evaluating news websites and other online platforms (Hu, 2018; INTERPOL, 2022c).

In the law enforcement context, it has proven helpful in several crime prevention applications (Srinivasa & Thilagam, 2019; Das et al., 2020; UNICRI, 2020b; Shah et al., 2022), offering considerable potential for data collection and processing and information extraction (contextual and geographical) from textual data (INTERPOL, 2022a; UNICRI 2020c; Carnaz et al., 2021; Janowicz et al., 2020; Hu, 2018), such as articles from news websites.

Information extraction refers to the automatic extraction of contents, such as: a) entities (keywords or phrases); b) relationships between entities; c) attributes that describe entities, and c) higher-order structures such as lists or tables. Extraction methods are classified into rule-based and learning-based methods – statistical (Sarawagi, 2008). Rule-based methods require human experts to encode the rules or regular expressions for information extraction; they are considered efficient because they employ domain-specific features to identify and classify the entities of interest (Sharma et al., 2022). Their main limitation is that they demand human expertise considering domain knowledge and language (Sarawagi, 2008) are quite specific and cannot be transferred to other domains (Goyal et al., 2018).

Statistical learning-based approaches rely on algorithms and weighted sums that, through automated processes, extract knowledge or identify patterns in the data (Kelleher et al., 2020). These approaches require many labeled examples to train machine learning models that generate good accuracy, are expensive, and time-consuming (Kelleher et al., 2020; Sarawagi, 2008; Sharma et al., 2022; Srinivasa & Thilagam, 2019). Additionally, they require specialists with domain knowledge in the labeling process.

In this thesis, an approach that resembles the one applied by the European drug monitoring system (EMCDDA, 2019) was adopted for the use of NLP techniques. It is based on extracting information through web scraping techniques and using regular expression rules to extract information related to individual drug seizures. Web scraping techniques automatically extract information from web pages using software (For example, the development of scripts using a programming language such as Python) (Mitchell, 2018). Regular expressions (regex) are a sequence of characters (letters, numbers, and special characters) that form a pattern that can be searched for in every text (Deitel & Deitel, 2020; Hunt, 2019). For example, a pattern can be defined as a list of words, numbers, codes, among others, and used to search for the referred pattern in a text, i.e., the method can go through the entire list of defined words and find matches in a text. Generally, if the text is structured as a table, regular expressions can be used to extract information and analyze it (Russell & Norvig, 2020). This approach has shown consistent and favorable results in recognition of entities related to geographic locations (toponyms) on news websites (Lieberman, 2011), which is fundamental to the objectives of this research.

3 MATERIALS AND METHODS

The GEOINT analytical method is based on the intelligence cycle (Pennsylvania State University 2020c; NGA, 2018; US ARMED FORCES, 2017). This methodology was adopted in this research for detecting geospatial objects linked to drug trafficking organizations. It has been recognized by several organizations and researchers for its ability to analyze and identify security-related activities geographically referenced on Earth based on transparent, reliable, and reproducible scientific methods (Meillón, 2008; UNODC, 2011; IACA, 2017; INTERPOL 2014a; NGA, 2018; US ARMED FORCES, 2017; Clark, 2019; Perazzoni, 2021; EUROPOL, 2021; Pinto & Centeno, 2022a, b; Pennsylvania State University, 2020c). The intelligence cycle is not unique to intelligence research but has parallels with research processes in other academic disciplines. For example, the research process that is used in social sciences research shares the same cyclical pattern (Prunckun, 2019). It is an easy-to-understand systematic process for transforming data into value-added intelligence. It is composed of six stages 1) Direction/task; 2) Collection; 3) Evaluation; 4) Collation/Processing; 5) Analysis (GEOINT Analysis); 6) Dissemination (UNODC, 2011; INTERPOL, 2014a; US ARMED FORCES, 2017). (Figure 18).

FIGURE 52 – THE INTELLIGENCE CYCLE

Source: Prepared by the author. Based on data from (INTERPOL, 2014a; UNODC, 2011; US ARMED FORCES, 2017) (2022).

It starts with a decision or a task assignment, followed by a planning phase where data and information are collected and evaluated according to a recognized evaluation system. The information is organized for further processing and exploitation in the following stages. The information is then analyzed, and the result is a product that satisfies the interested party's specific intelligence requirements. When applied in public security, its actions aim to prevent, neutralize, and repress criminal acts that threaten public order and the safety of people and property (ABIN, 2020).

3.1 DIRECTION/TASKING

This stage is the most important; it is the starting point of the intelligence cycle. It starts with identifying the problem or research objective, defining tasks, planning, priorities, and identifying resources (satellite images, maps, ground truth data, open-source information, geospatial information, documents, software, and hardware, among others). The analytical effort is directed through tasking and proper planning, which will be necessary to create knowledge, information, and GEOINT products, which can contribute to the solution of the stated problem (UNODC, 2011; US ARMED FORCES, 2017).

Planning allows for efficient use of resources, reduces the risk that the collection, storage, and processing of data and information are not in line with the national and international legal framework, and consequently compromises the success of the research results (UNODC, 2011; OSCE, 2017). In this section, the task definition, resources, and study area should be described.

3.2 COLLECTION

The intelligence process is based on the ability to obtain and use data. This stage includes activities related to acquiring GEOINT data and information necessary to satisfy assigned objectives (US ARMED FORCES, 2017). It identifies the information needed and establishes the means to obtain it (INTERPOL, 2014a). However, the collection and storage of data are one of the main problems to overcome in the intelligence process since, in order to generate strategic analytical products, data are generally obtained in different formats (structured, unstructured, digital, physical, geo-referenced, or non-georeferenced, among others) (UNODC, 2011; Clark, 2014).

Data overload and the collection of unnecessary or inadequate information should be avoided. To this end, a structured and accurate collection approach should allow for all means to be explored to ensure orderly and accurate information collection. The information collection plan (ICP) should include the information categories important for analysis, specific data elements, and possible sources of information (UNODC, 2011). The ICP should be flexible to allow for adjustment as research objectives change. It can take, for example, the form of a data collection table, with a structure that allows a picture of the data and what is needed to be developed (Prunckun, 2019).

3.3 EVALUATION

The evaluation step analyzes the source's reliability (the information provider) and the validity of the information (UNODC, 2010b). This is a key element of the intelligence cycle that should be conducted simultaneously or immediately after collecting information. The source and the information require independent assessments and must be evaluated following a recognized assessment system (UNODC, 2011). There are different methods for assessing the information, but the most widely applied and understood is the 4 x 4 system, which is accepted as common practice by law enforcement agencies (Carter, 2021; INTERPOL, 2014a; NATO, 2016; OSCE, 2017; UNODC, 2010b, 2011). Table 13 describes this practice.

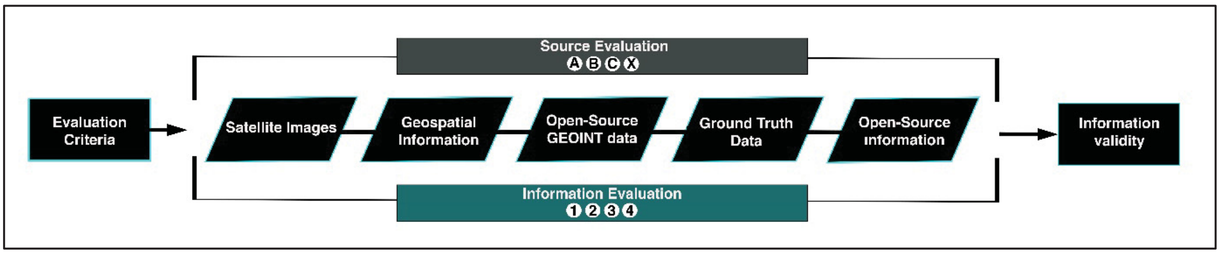
TABLE 13 - METHOD OF EVALUATION OF SOURCES AND INFORMATION WITH THE 4 X 4 SYSTEM

Source Evaluation		Information Evaluation	
A	Where there is no doubt of the authenticity, trustworthiness, and competence of the source, or if the information is supplied by a source which, in the past, has proved to be reliable in all instances.	**1**	This is information where the accuracy is not in doubt.
B	Sources from whom information received has in most instances proved to be reliable.	**2**	This information is known personally to the source but not known personally by the official passing it on.
C	Sources from whom information received has in most instances proved to be unreliable.	**3**	This information is not known personally to the source but corroborated by other recorded information.
X	The reliability of the source cannot be assessed.	**4**	This information is not known personally to the source and cannot be corroborated.

Source: (UNODC, 2010b, 2011).

This process consists of ranking the data according to the confidence level. For this purpose, each piece of information is labeled using a code composed by a letter (source evaluation) and a number (information evaluation), according to Table 13. These codes describe the degree of confidence in the data. For example, A1 is the best assessment (the reliability, competence, and information of the source are not in doubt), and X4 is the poorest assessment (the source's reliability cannot be assessed, and the information cannot be corroborated). The workflow applied to evaluate the sources and information used in this thesis is shown in Figure 19.

FIGURE 55 - WORKFLOW FOR EVALUATING SOURCES AND INFORMATION



Source: (Author, 2022).

3.3.1 Evaluation criteria

The evaluation of sources and information should be conducted separately according to the following criteria: reliability of the source, frequency of information from a given source, and validity of the information itself (Lowenthal & Clark, 2015). During the evaluation process, the following questions should be attempted to be answered:

- How reliable is the source of information?
- Has the source provided information before?
- What is the source's information history?
- Is the source's primary purpose to provide information on our topic of interest?
- Does the source generate information on our topic of interest frequently?
- Is the information recent?
- Can the information be confirmed by other independent sources that are reliable?
- Is the information from the source consistent?
- Does the information make logical sense?
- Is the information from the source based on scientific evidence?

Subsequently, the corresponding evaluation must be assigned to each element of the ICP based on these criteria. There is a general convention that any information assessed as A1, B1, A2 or B2 is considered "true and accurate" (UNODC, 2010b), i.e., it does not have to be corroborated again. Their application is shown in the experiments.

Evaluation is not an exact science and must be based on professional notions and criteria. It is an integral stage of analysis that should not be influenced by personal interests, as the evaluator's judgment plays a relevant role when assigning a score to sources and information. However, among the advantages of this method is the ability it gives the analyst to visualize, in context, the need for further data collection. These are discrete techniques that, in addition to saving resources for information validation, do not expose investigators and law enforcement agencies to environments that in some cases could be dangerous or unsafe, such as the study area that is the subject of this research. These are methods that can be replicated and allow confirmation of the reliability and accuracy of the intelligence generated.

3.3.2 National imagery interpretability rating scale

Additionally, in remote sensing image analysis, the intelligence community generally uses the National Imagery Interpretability Rating Scale (NIIRS) to rate images based on interpretability flaws. This system uses numerical ratings from 0 to 9, with criteria indicating the amount of information that can be extracted and interpreted from an image (FAS, 1998). Table 14 describes the use of the scale with some examples. The higher number represents better interpretability of the image.

TABLE 14 - NIIRS RATING SCALE

NIIRS	Description	Resolution Spatial (m)
0	Cannot be interpreted	
1	Distinguish between major land use classes Detect a port or airstrip	> 9
2	Detect large buildings Detect forest clearings in suspected coca-growing areas	4.5 – 9.0
3	Detect individual houses Detect fixed-wing aircraft on a dirt or grass airstrip Distinguish between cropland and pastureland	2.5 – 4.5
4	Detect marijuana harvest based on the absence of vegetation in known marijuana fields Identify farm buildings as barns, silos, or residences	1.2 – 2.5
5	Identify Christmas tree plantations Identify individual lines painted on paved roads, aprons, parking lots	0.75 – 1.2
6	Detect mixed cropping in small farm plots Detect coca harvest based on the absence of leaves on coca bushes in known coca fields	0.40 – 0.75
7	Identify a manhole cover Identify farm or construction tools by general shape	0.20 – 0.40

8	Identify grill detailing and/or the license plate on a passenger/truck type vehicle Detect scoring of poppy bulbs	0.10 – 0.20
9	Identify individual grain heads on small grain Identify individual barbs on a barbed wire fence	< 0.10

Source: (FAS, 1998).

3.4 COLLATION/PROCESSING

At this stage, the collected information is organized and converted into a structured format, which allows the information to be processed for further analysis (UNODC, 2011; US ARMED FORCES, 2017). Processing can include automated, semi-automated, and manual procedures (US ARMED FORCES, 2017), such as data analysis, artificial intelligence, machine learning, deep learning, computer vision, natural language processing, remote sensing techniques, GIScience methods, among others (NGA, 2018).

It serves to eliminate irrelevant or incorrect information (data cleaning) (UNODC, 2011; Prunckun, 2019) and allows for verifying the relevance and usefulness of the information (Carter, 2021). Information collation/processing can be so closely related to the analysis phase that it is sometimes difficult to distinguish between the two processes (OSCE, 2017).

As described in the literature review, this thesis used deep learning models (convolutional neural networks) and natural language processing techniques in the collation/processing stage, in addition to using different cartographic and visualization techniques, which allowed continuity with the intelligence cycle methodology for the extraction of information and generation of knowledge.

3.5 GEOSPATIAL INTELLIGENCE ANALYSIS

This stage is key in the intelligence process; it can be described as a careful examination of information that extracts meaning and essential characteristics to produce intelligence (UNODC, 2011) and visually represent the information in GEOINT products (US ARMED FORCES, 2017). The analytical process can be operational (or tactical) and strategic (INTERPOL, 2014b; UNODC, 2011).

Operational analysis assists in the management and execution of short-term tasks (IACA, 2017; UNODC, 2011) and aims to achieve a specific result (e.g., arrests, drug seizures) (INTERPOL, 2014b). The strategic analysis focuses on long-term objectives and examines trends, crime patterns, and changes in the crime environment (IACA, 2017). It identifies threats to public safety, opportunities to control action, the development of possible avenues for change in policies, programs, and legislation, and assists decision-makers in establishing the priorities needed to address them (INTERPOL, 2014b; UNODC, 2011).

In the analytical process, information that has been evaluated and processed is combined (data integration) to test the research hypothesis using statistical tests or specialized analytical techniques, depending on the data type (Prunckun, 2019). This allows the data to be interpreted, patterns and trends to be identified, additional data collection to be guided, and more accurate inferences, conclusions, predictions, and estimates to be made (UNODC, 2011; OSCE, 2017).

In this sense, geospatial intelligence is geospatial analysis; in essence, it is geography (Pennsylvania State University, 2020c). It makes conscious use of geographic concepts, critical thinking, spatial thinking, geospatial reasoning, analytical methods, and geospatial analysis methods to reveal, analyze, investigate, and explain, in a geographic context, spatially referenced observations of phenomena manifest on Earth (Pennsylvania State University 2020c; Grekousis, 2020; Kresse, 2022; NGA, 2018).

In law enforcement analysis in areas such as drug trafficking investigations and environmental crimes, GIScience and GEOINT contribute significantly (Pennsylvania State University 2020a; Clark, 2020). When combined with multiple sources of information, such as multispectral imagery, geospatial information, ground truth data, and open-source information, GEOINT analysis can identify trends, criminal patterns, modus operandi, and threats and provide long-term strategic assessments of organized crime (IACA, 2017; INTERPOL, 2014a; UNODC 2022n; Clark, 2014; Pinto, 2017). It facilitates the creation of new GEOINT products, such as maps, dashboards, and analytical reports, among others (NGA, 2018), which provide strategic knowledge and a handy form of power to strengthen decision-making against the adversary (Lacoste, 2014). In this sense, the strategic nature of geographic reasoning offers significant inputs to support interdiction and prevention strategies aimed at generating impacts on drug trafficking activities.

This thesis focuses on strategic analysis. Deep learning models are explored through inference processes to identify the detection and classification capabilities of geospatial objects linked to DTOs in satellite imagery. NLP algorithms are implemented for environmental scanning and information extraction to identify patterns, trends, and possible cocaine trafficking routes. Geospatial analysis methods and cartographic techniques are applied to analyze the data and produce geospatial intelligence.

3.5.1 Geospatial analysis methods and cartographic techniques

Kernel Density Estimation (KDE) – is one of the most used cartographic techniques for visualizing and analyzing spatial patterns of crime-related points (Chainey, 2021; Ratcliffe, 2010). It was selected on the basis that research has shown it to be an effective technique for identifying areas with a high level of crime (hot spots), allows estimation of the density of events in geographic space, and can detect and visualize patterns at different spatial scales, captures patterns that obey Tobler's (1970) first law of geography[4], and offers an aesthetic appearance of the map compared to other techniques (Chainey & Uhlig, 2008; Chainey, 2021; Grekousis, 2020; Pinto & Centeno, 2022a; Santos, 2022; Cai et al., 2013; Zhang, 2022; Eck et al., 2005). The density at each location indicates the concentration of points within the neighboring area (high concentrations as peaks, low concentrations as valleys).

Summarize individual cocaine seizure counts – this technique is commonly used in operational and strategic crime analysis. It allows calculating the number of events in a polygon or line vector (e.g., a state or road segment) and displaying the information on a thematic map (ESRI, 2021a; Piza & Baughman, 2021). It has been used in strategic studies and demonstrated consistency in drug trafficking trend analysis (CoE-Brazil, 2021; UNODC, 2022d).

Hierarchical density-based spatial clustering of applications with noise (HDBSCAN) – are machine learning methods that have been effective in spatial data mining and geography of crime to detect patterns based on geographic location and distance to a specific number of neighbors (Grekousis, 2020; ESRI, 2021a; Piza & Baughman, 2021). Among the existing clustering methods, the HDBSCAN algorithm stands out due to: (a) its stable performance in handling different densities in the data; (b) its well-coded program; (c) its effectiveness in excluding noise and outliers from the data; and (d) intuitive and robust way of setting the parameters to obtain meaningful clusters automatically, compared to other methods (Campello et al., 2015; Zhao et al., 2005; Chen, 2019; Cui et al., 2021; Grekousis, 2020; Butt, 2021). It is a hierarchical clustering algorithm that applies incremental geographic distances based on the data (Campello et al., 2015). In recent studies, HDBSCAN has also been applied in the strategic analysis of DTOs (CoE-Brazil, 2021). Therefore, it is important to explore the feasibility of HDBSCAN for clustering points linked to DTOs (e.g., individual drug seizures) and mapping patterns, trends, and potential threats that can be uncovered.

[4] “All places are related to each other, but places closer in space have a greater relationship than distant ones” (Tobler, 1970).

Proportional symbol maps – this technique is one of the best practices for the cartographic representation of quantitative information associated with point locations (Robinson et al., 2017; Slocum et al., 2022). It is widely used to analyze global and regional drug trafficking trends (UNODC, 2022b) since geo-referenced records of individual drug seizures with quantitative attributes of the quantities seized make it possible to visualize locations with significant seizures, make visual numerical comparisons between symbols (United Nations, 2021; Field, 2018) and identify possible patterns and trends.

Intelligence layers – this technique overlaps different types of geospatial information, or a combination of information derived from various sources, providing more detail and context to interpret the overall picture (NGA, 2018; United Nations, 2021). It is notable for its ability to generate a new layer of information that allows patterns and analytical conclusions to be revealed better than any of the individual components when used separately (NGA, 2018; Slocum et al., 2022).

3.6 DISSEMINATION

It is the timely transmission of GEOINT products in an appropriate format that can be printed or electronic (US ARMED FORCES, 2017). They are generally disseminated in structured analytical reports, formal oral presentations, newsletters (UNODC, 2011), maps, dynamic and interactive geospatial products, visual representations of patterns and trends, graphics that provide quick target reference, and 3D visualizations (US ARMED FORCES, 2017), among others. This stage completes the initial process of the intelligence cycle, where the GEOINT product is delivered to the decision-maker (UNODC, 2011; Prunckun, 2019).

3.7 GEOINT products

GEOINT products allow the visualization and geo-location of intelligence gathered from intelligence collection disciplines, known as INTs. (Table 15). As well as information from non-intelligence sources. The products range from simple to advanced, depending on the type and amount of information used, the level of analytic complexity, and the use of different processing and geospatial analysis techniques (Clark, 2020; NGA, 2018).

TABLE 15 - INTELLIGENCE DISCIPLINES

Intelligence Disciplines (INTs)	Description
Human Intelligence (HUMINT)	Intelligence obtained through clandestine or overt HUMINT activities or operations and activities utilizing human sources or other human assets.
Imagery Intelligence (IMINT)	The technical, geographic, and intelligence information derived through the interpretation or analysis of imagery and collateral materials.
Signals Intelligence (SIGINT)	A form of technical intelligence derived from the exploitation of foreign electronic emissions. SIGINT can be in the form of the actual information content of a signal or in the form of its temporal and spectral characteristics, called signal operating parameters. SIGINT includes both the raw data and the analysis product of that data. This intelligence category includes all Communications Intelligence, Electronic Intelligence, and Foreign Instrumentation Signals Intelligence.
Measurement and Signature Intelligence (MASINT)	Scientific and technical intelligence information obtained by quantitative and qualitative analysis of data. MASINT, which is derived from specific technical sensors, identifies distinctive features associated with the source, emitter, or sender. It can measure physical characteristics of targets and events of interest to determine composition, location, and/or performance.
Open-Source Intelligence (OSINT)	Intelligence is produced from publicly available information that is collected, exploited, and disseminated in a timely manner to an appropriate audience to address a specific intelligence requirement.
Geospatial Intelligence (GEOINT)	The exploitation and analysis of imagery and geospatial information to describe, assess, and visually depict physical features and geographically referenced activities on the earth. Geospatial intelligence consists of imagery, imagery intelligence, and geospatial information.
Conflation or adding one or more of these layers to a GEOINT product is considered multi-INT, which means that input from at least one additional INT was used to provide as much context as possible to a GEOINT product depicting a specific object, area, or activity.	

Source: (Clark, 2020; NGA, 2018).

Although data is used to create GEOINT products, in some cases, data itself is the product. The basis of a product may consist of one or a combination of several GEOINT components. This base may be a map or an image of a specific location showing the terrain, objects, and other visible features. Different types of information can be superimposed on the base to provide more detail and context. This information must be georeferenced, and the precise location within the geographic coordinates in the reference system must be available. As described in Table 16, various information can be integrated to generate GEOINT products for specific purposes (NGA, 2018).

TABLE 16 - GEOINT INFORMATION TYPES TO GENERATE GEOINT PRODUCTS

Information	Description
Geospatial Layers	Comprise geospatial information including boundaries, infrastructure (such as highways, ports, airports, power grids), elevation data, geodetic data, human geography data (population, cultural, political/religious geography), safety of navigation data, and identification of key facilities and natural or manmade features.
Mission Layers	Provide general information relevant to the purpose and area for which the product is being used. The information may include Weather conditions and climate, logistics data, locations of friendly forces, routes and alternatives, local terrain characteristics, population and government information, and other data obtained through commonly used unclassified sources.
Intelligence Layers	Information derived from various intelligence sources, or a combination of those sources. For example, the location of eradicated illicit crop areas, cocaine production infrastructures, clandestine airstrips, individual drug seizures, illegal mining areas, drug trafficking routes, among other potential targets. GEOINT serves as a base for depicting data from other intelligence disciplines (INTs).
Elevation	The majority of GEOINT products use one or more of the layers described above. However, a more sophisticated product can be developed by adding elevation to create a three-dimensional (3D) model or simulation that provides a more realistic representation of an environment or object.
Time	The element of time can be used to create temporal products. These products can simulate factors such as speed, tides, wind direction, and changing daylight to help the analyst determine how each factor will affect a mission or event.
Motion	Location, elevation, and time can be combined to create a virtual, interactive scene that allows users to familiarize or train in a simulated environment before operating in a real situation. Such simulations also allow analysts to experience different perspectives from which to analyze objects and scenarios.
Activity	Most GEOINT analysis and products focus on providing as much information as possible about a specific object or area. However, activity-based analysis examines human, vehicular, and other activity related to that object or area, which can lead to different areas and show correlations between areas, people, and objects. Three processes that contribute to activity-based analysis are listed below. **Object-Based Production (OBP):** OBP is the standardized intelligence community (IC) process in which sensor observations are captured, structured, stored, and shared. The process also brings together information related to an object from all available intelligence sources—and systems of different security levels. Examples of objects include natural features (illicit crops, illegal mining areas), people, vehicles, buildings (clandestine airstrips, cocaine production infrastructures), and events. **Structured Observation Management (SOM):** SOM is the method in which GEOINT observations from satellites and sensors, and other sources are captured, structured, stored, and shared in a standardized format compatible with the OBP format. This ensures that GEOINT information can be integrated into the IC's OBP process. **Activity-Based Intelligence (ABI):** ABI is a methodology that incorporates the OBP information into a process that

	can detect when the object changes or activities related to an object occur and then provide an electronic "alert" to analysts interested in that object. By examining this new information about the object, analysts can discover relationships with other objects or locations and detect patterns of activity and behavior.

Source: (NGA, 2018).

In this sense, using different data types, data processing, or analysis techniques, it is possible to create various GEOINT products. Most provide a common visualization of a scene or environment, with geospatial attributes supporting complex planning and decision making. In the field of geospatial intelligence, these products can be grouped into 3 categories: a) Mission/Event Preparation, b) Assessments, and c) Detection (NGA, 2018).

Mission/Event Preparation – the product is used to prepare a mission, operation, or major event. The products assist with activities such as route planning and security preparations (NGA, 2018) and focus on familiarizing the area, including identifying key landmarks, and existing or potential hazards. They are usually map or imagery products that easy navigation by identifying elements such as buildings, routes, water depth, terrain features, obstacles, and threats.

Assessment – products that provide analysis for what is shown in an image or on a map, and provide information on the "*who, what, when, where, how, and why,"* usually in the context of the purpose for which it has been developed. Such products may be a simple image of a facility and parking lot, with notations that indicate the type of facility, information on parked cars, and how many people may be in the facility and what types of activities they may be conducting. A more complex product may show a hazardous material leak, with notations on potential effects over time using variable factors such as wind speed and tides (NGA, 2018).

Detection – they are designed to find natural and manmade objects that are not visible or easily identifiable to the human eye. Various types of earth observation sensors, such as remote sensing satellite imagery (passive or active) and specialized data processing techniques (NGA, 2018), such as **geospatial analysis** techniques and **artificial intelligence** methods, are used to develop GEOINT detection products. These products can be used for many purposes, such as to "see" beneath foliage and camouflage, identify heat emissions, detecting geospatial objects linked to drug trafficking organizations, such as those of interest in this research (illicit crop cultivation areas, primary production infrastructures to produce coca paste, clandestine airstrips, individual cocaine seizures, illegal mining areas, deforestation, and drug trafficking routes) among others.

4 EXPERIMENTS

International evidence has successfully demonstrated that indicators related to the illicit drug market, especially administrative data such as **individual drug seizures**, **price**, **purity,** and other **crime-related DTOs** dynamics, when they have geospatial attributes, are of great value in detecting routes, identifying trends, adapting interdiction operations and supporting decision-makers in the formulation of public policies and priorities needed to address the threat posed by these criminal organizations (Benítez et al., 2019; CoE-Brazil, 2021; EMCDDA, 2019; PONAL, 2020; SIMCI, 2018; Singleton et al., 2018; UNODC, 2022b).

Consequently, as described in the previous chapters, the limited availability of geo-referenced data on activities related to DTOs considerably restricts the analytical capacity of the researchers and institutions responsible. In this sense, **three experiments** were carried out using geospatial intelligence techniques and artificial intelligence methods, which allowed the processing of the information and detection of the geospatial objects that are of interest in this thesis.

In general terms, the computational workflow of the experiments was developed in the Python programming language using the jupyter Notebook environment. This allowed running the codes to collect and process the data in an interactive and organized manner, facilitating the reproduction of the results in a readable and executable format (Kluyver et al., 2016). Visualization, geospatial analysis, and cartographic creations were performed using ArcGIS Pro and QGIS software. Experiments 1 and 2 focus on using convolutional neural networks to detect and classify geospatial objects linked to DTOs in PlanetScope and Sentinel-2 multispectral satellite imagery. Experiment 3 uses NLP methods to identify cocaine trafficking routes and trends considering the geospatial context (geographic location of occurrence).

For the maps of Brazil, the country's official geodetic reference system, SIRGAS2000, with a polyconic cartographic projection (IBGE, 2015, 2018), was used. For the maps of the Amazon Rainforest and the border region of Venezuela with Colombia, the WGS84 system was used. For the world map, the WGS84 system was also used with a compromise projection (Robinson), following the cartographic recommendations of the United Nations (2021) and the USGS (2019). Particular aspects are described in each section of the experiments.

4.1 EXPERIMENT 1. GEOSPATIAL INTELLIGENCE AND ARTIFICIAL INTELLIGENCE FOR DETECTING POTENTIAL COCA PASTE PRODUCTION INFRASTRUCTURE IN THE BORDER REGION OF VENEZUELA AND COLOMBIA[5] [6]

4.1.1 Direction/tasking

4.1.1.1 Task definition

This experiment aims to detect potential IFP-PBC in complex border areas on satellite images and identify the geographic location and possible trends in the dynamics of this type of infrastructure. Additionally, a dataset will be built to assess the potential of artificial intelligence to automate their detection in remote sensing imagery. It will not cover the dynamics and links with other forms of organized crime. It is expected that the final products will strengthen the capacities of security forces, organizations, and academic institutions to develop strategies for the fight against organized crime and the reduction of drug supply.

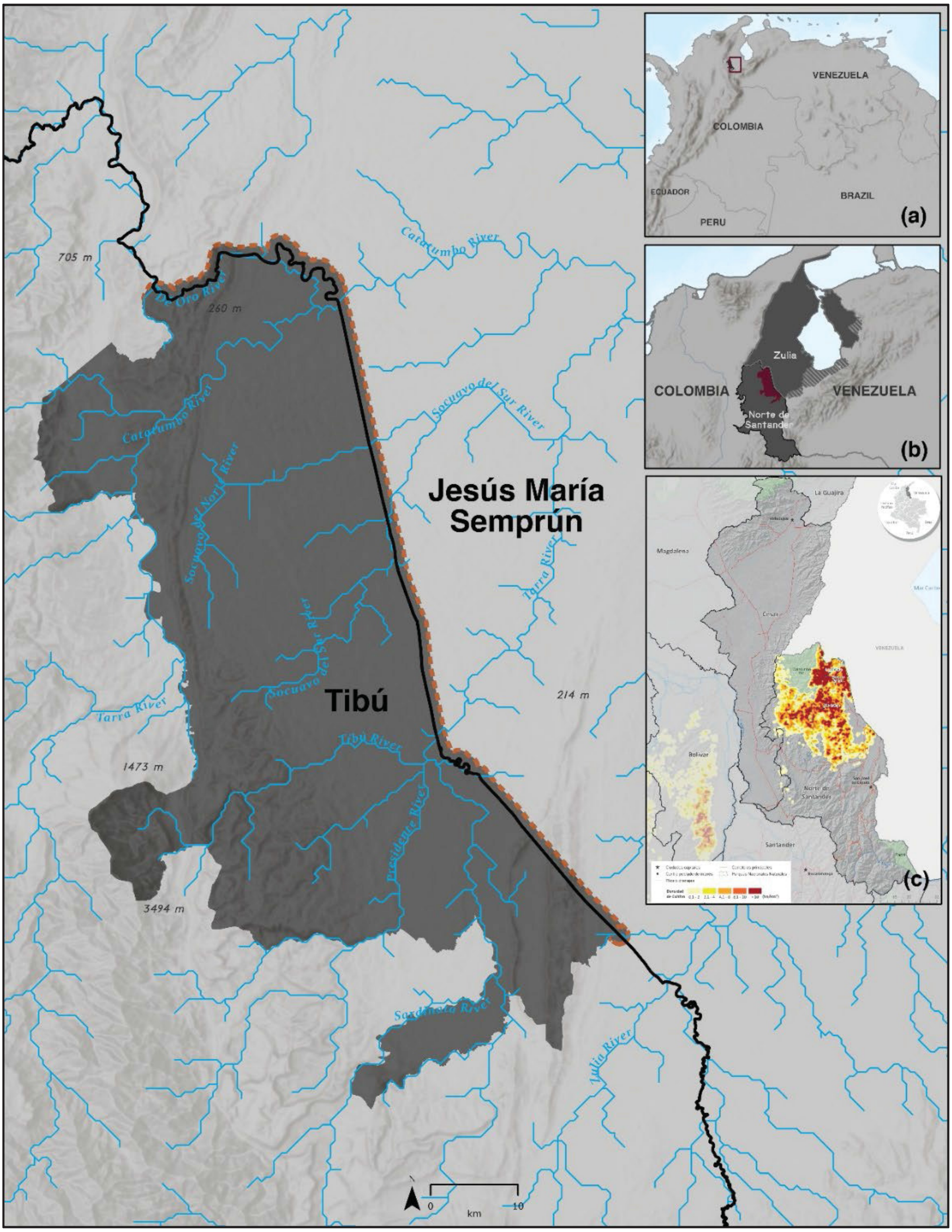
4.1.1.2 Study area (Venezuela-Colombia border region)

The study area lies in the border municipality of Tibú in the department of Norte de Santander (Colombia), with an area of influence of one kilometer toward the municipality of Jesús María Semprún in the state of Zulia (Venezuela). The area of influence is defined based on the maximum distance of coca cultivation movement, identified during eradication activities in Venezuelan territory (Figure 20). In both municipalities, the climate is warm, and the vegetation is characterized by high dense humid forests, with flat and mountainous areas (higher than 1000 meters above sea level). Due to their ecosystemic complexity, these have conditions of road isolation, but with an extensive hydrographic network that allows the interconnection between the territories, highlighting the Catatumbo river (INE, 2011; MJD-UNODC, 2016).

[5] This experiment is based on Pinto & Centeno (2022a). https://doi.org/10.1080/19361610.2022.2111184

[6] The research was recognized and published as one of the scientific discoveries made by Planet's science community: https://www.planet.com/pulse/publications/planet-images-and-artificial-intelligence-used-to-detect-coca-paste-production-supporting-surveillance-strategies-against-drug-trafficking/

FIGURE 58 - STUDY AREA – EXPERIMENT 1



The central polygon is the border municipality of Tibú in the department of Norte de Santander, with an area of influence of 1 km towards the municipality of Jesús María Semprún in the state of Zulia. The continuous line represents the border division between the two countries. The dashed line represents the boundary of the 1 km area of influence between the two countries. (a) Relative location in South America. (b) Relative location between the department of Norte de Santander and the state of Zulia. (c) Map of coca cultivation density in the Catatumbo region, 2020, Source: (SIMCI, 2021). The higher the intensity of the tones, the higher the density of illicit coca cultivation.

Tibú has an area of 2,737 km^2, bordered to the north and east by Venezuela, to the south by the municipalities of Cúcuta and Sardinata, and to the west by the municipalities of San Calixto, El Tarra, and Teorama (IGAC, 2016). It occupies the first place of the territories affected by coca cultivation in Colombia, with 19,334 ha, representing 13% of the national total (SIMCI, 2021). In 2020, an increase in the participation of agricultural producers with coca in the primary processing of coca leaf was identified, evidencing a significant increase in the production of PBC within the Agricultural Production Units with Coca (UPAC) (farms totally or partially dedicated to coca cultivation and other agricultural activities) (SIMCI, 2021).

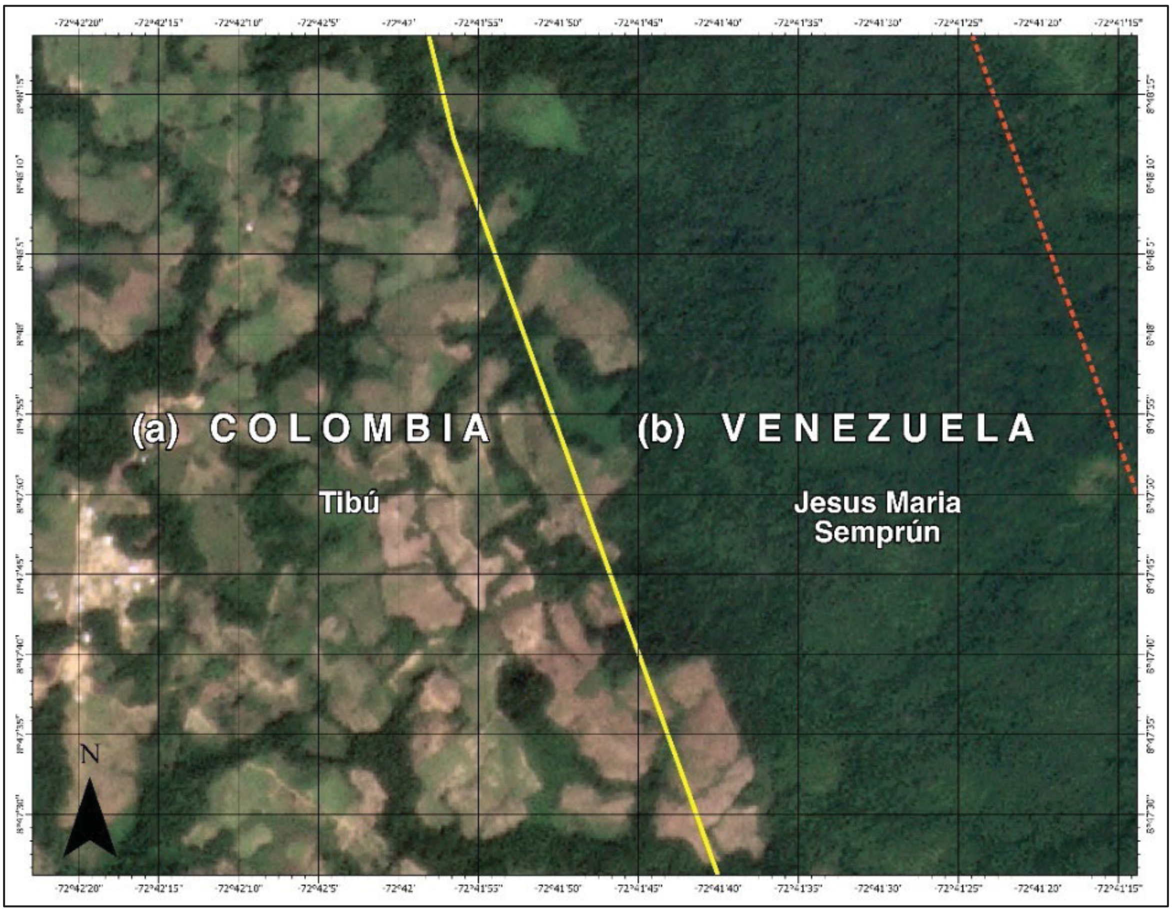
This border is the epicenter of trade with Venezuela, especially in the tertiary sector. The territory has been the scene of an intense internal conflict. Illegal economic activities have been established such as coca crop cultivation, infrastructures linked to cocaine production, and smuggling, which have served as an economic source for populations with a high degree of vulnerability whose benefits have been exploited by illegal armed groups operating along the borderline (MJD-UNODC, 2016), and consolidate transit channels, especially for cocaine trafficking and production (MJD-UNODC, 2016; SIMCI, 2020; UNDP, 2014).

Jesús María Semprún has an area of 6,003 km^2, bordered to the north by the municipality of Machiques de Perijá, to the east by the municipality of Catatumbo, and to the south and west by the department of Norte de Santander (INE, 2011). As shown in Figure 21, there is evidence of areas affected by coca crops moving from Tibú municipality into Venezuelan territory (ANTIDROGAS-GNB, 2016; Pinto, 2017; SUNAD, 2021a, 2022a; UNODC, 2018b).

Interdiction and dismantling of IFP-PBC and CPCC are frequent (ANTIDROGAS-GNB, 2016; CEOFANB, 2021; INCB, 2020; SUNAD, 2021a, 2021b, 2022a). IFP-PBC are generally located near areas affected by coca cultivation, and CPCC in remote, difficult to access locations, near water tributaries and clandestine routes.

The municipality is characterized by the presence of illegal armed groups, such as the National Liberation Army (ELN), the Popular Liberation Army (EPL), and dissidents of the former Revolutionary Armed Forces of Colombia (FARC-EP). They exercise strong territorial control over the border and drug trafficking routes to ensure a constant flow between the two countries (Colombia and Venezuela) (DOS, 2022; HRW, 2019) and use the territory for criminal activities, including kidnapping, extortion, drug trafficking, gasoline smuggling, recruitment of Venezuelan migrants, homicides, rape (HRW, 2019; INSIGHT CRIME, 2020b, 2021b), installation of IFP-PBC and CPCC (ANTIDROGAS-GNB, 2016; CEOFANB, 2021), commercialization of chemical substances, among other illicit activities. The corruption of high-level public servants linked to drug trafficking also takes place in the municipality (SUNAD, 2022b).

FIGURE 61 - TERRITORIES AFFECTED BY COCA CULTIVATION IN VENEZUELAN TERRITORY



PlanetScope Image, 3 m, 2022/01/01.
(a) Coca cultivation in Tibú municipality. (b) Coca cultivation moved to Jesús María Semprún municipality. The continuous line represents the border division between the two countries. The dashed line represents the boundary of the 1 km area of influence between the two countries. Source: (Author, 2022).

4.1.1.3 Resources

Table 17 describes the data, information, software, and hardware used to develop this experiment.

TABLE 17 - RESOURCES USED FOR DEVELOPING THE RESEARCH – EXPERIMENT 1

Software
– ArcGIS Pro Intelligence 2.9 / Environmental Systems Research Institute (ESRI) – Anaconda Distribution/Python 3.8 – ArcGIS API for Python 1.9.1 – Deep Learning Frameworks for the ArcGIS System – JupyterLab – Windows 10 Operating System – Microsoft 365 Apps
Hardware
– Processor: Intel® Core™ i7-8750H CPU @ 2.20GHz – GPU: NVIDIA GeForce GTX 1060 – RAM: 16 GB – SSD: 250 GB – HDD: 2TB – Google Cloud Platform (1 GPU NVIDIA Tesla K80 / 4vCPUs, 15GB RAM)
Satellite Images
– PlanetScope georeferenced images, 4 multispectral bands, 3 m, and 5 m spatial resolution
Geospatial Information
– Vectors of basic cartography of Venezuela and Colombia (boundaries of countries, states, departments, municipalities, hydrography, among others) – Density vectors of coca crops in Colombia
Ground Truth Data
– Geographical coordinates of the areas of coca crops eradicated in Venezuelan territory – Photographs by IFP-PBC – Photographs by CPCC – Photographs of plantations of illicit coca crops
Open-Source Information
– Monitoring reports of territories affected by illicit crops in Colombia – Public databases – Books and academic publications – Studies and research of governmental agencies, international law enforcement agencies – News websites and newspapers

4.1.2 Collection

Data were obtained as described in the Information Collection Plan (ICP). (Table 18).

TABLE 18 - INFORMATION COLLECTION PLAN - EXPERIMENT 1

Satellite Images

Information/Requirement	Description	Source of Information
PlanetScope images of the study area: 1. 20210219_152328_97_240c_3B 2. 20210219_152331_24_240c_3B 3. 20210801_151825_18_240a_3B 4. 20210817_143059_77_245d_3B 5. 20210817_143104_37_245d_3B 6. 20210807_142904_06_2465_3B 7. 20210817_143106_66_245d_3B 8. 20210817_143102_07_245d_3B 9. 20210823_142830_32_241d_3B 10. 20210926_142659_71_241f_3B 11. 20211003_151233_01_1063_3B 12. 20211231_143006_08_2458_3B 13. 20211003_151228_45_1063_3B 14. 20211003_151226_93_1063_3B 15. 20220125_151109_26_227b_3B 16. 20220110_142146_34_2463_3B 17. Monthly Mosaic – October 2020	Instrument: PSB. SD. Spatial Resolution: 3 m /5 m (mosaic) Temporary Resolution: Diary/nadir Spectral Resolution: 4 bands Blue: 465 - 515 nm Green: 513 - 549 nm Red: 650 - 680 nm NIR: 845 - 885 nm Radiometric Resolution: 8 bits Format: GeoTIFF Spatial Reference: WGS-84 Frame Size: 32.5 km x 19.6 km Level: 3B Cloud cover: < 5%	Education and Research Program (Planet Team, 2017).

Geospatial Information

Information/Requirement	Description	Source of Information
Basic vector maps of Colombia and Venezuela	Georeferenced vectors (WGS 1984) in shapefile format: border boundaries, departments, states, municipalities, and hydrography.	Geographic Institute Agustín Codazzi (IGAC, 2021). Venezuelan Geographic Institute Simón Bolívar (IGVSB, 2012).
Coca crop density vectors 2020 – Colombia	Georeferenced vectors (WGS 1984), reported for the 2020 census period.	Integrated Illicit Crop Monitoring System – UNODC (MJD, 2021).

Ground Truth Data

Information/Requirement	Description	Source of Information
Geographical coordinates of the areas of illicit coca crops eradicated in Venezuelan territory Photographs of plantations of illicit coca crops in Venezuelan territory Photographs of IFP-PBC and CPCC in Venezuelan territory	The detection of illicit coca cultivation areas was carried out using GEOINT techniques, using remote sensing images from the Miranda, Sentinel-2, and Landsat-8 satellites. Subsequently, during the operational participation in different land interdiction activities in the border region of Venezuela with Colombia, the geographical coordinates in sexagesimal degrees and photographs of the areas of eradicated coca crops, IFP-PBC and CPCC, dismantled in Venezuelan territory, were taken.	The data were collected in the field by the Author in the border anti-drug operations: (a) Sierra XXIV-2014 (TELESUR, 2014); (b) Raspaculo-2015; (c) Catatumbo South-2015; (d) Caño Motilon Sur-2016; (e) Rio Tarra-2016 (ANTIDROGAS-GNB, 2016); (f) Paso del Tornado-2017 (GNB, 2017); (g) Sierra-2017 (SUNAD, 2017).

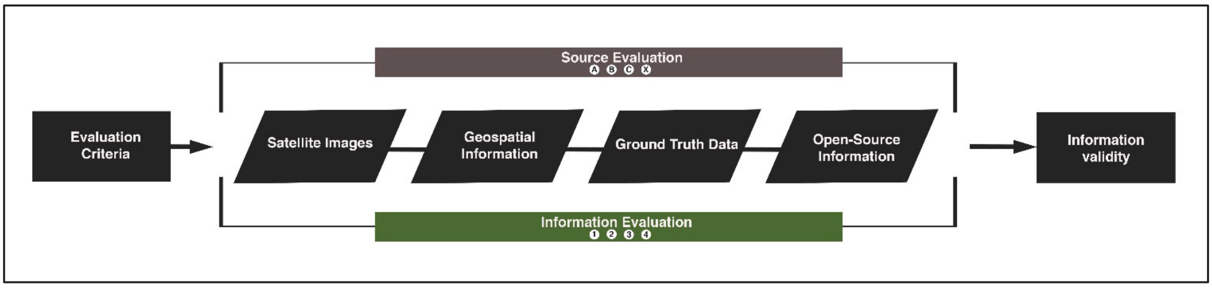
Open-Source Information		
Information/Requirement	**Description**	**Source of Information**
Monitoring reports of territories affected by illicit crops in Colombia. Years 2020 and 2021	The UNODC Illicit Crop Monitoring Program (ICMP) promotes the development of a global project that, through technical and objective evidence, supports the conduct of monitoring studies on coca in Bolivia, Colombia, and Peru, on the poppy in Afghanistan, Mexico, and Myanmar, and a study on cannabis in Nigeria (UNODC, 2022m). Annually they generate reports that, through remote sensing techniques, geographic information systems, and extensive field assessments, contemplate the results related to the location, extension, and evolution of illicit crop areas.	UNODC – Colombia (SIMCI, 2020, 2021).
Bulletins: Infrastructures for the Processing of Illicit Drugs and Artisanal Chemical Substances Cocaine Market Analysis 2020	Publications of the International Center for Strategic Studies against Drug Trafficking (CIENA) of the National Police of Colombia.	CIENA (CIENA, 2018, 2020).
Regional characterization of the problems associated with illicit drugs in the department of Norte de Santander	Publication of the Ministry of Justice and Law and UNODC. This document offers information on the drug problem in the department of Norte de Santander.	Colombian Drug Observatory, SIMCI-UNODC (MJD-UNODC, 2016).
Master's Thesis: Characterization of activities associated with illicit drug trafficking in Venezuela's border area with Colombia, using remote sensing techniques	The purpose of this investigation was the spectral and spatial characterization of activities associated with illicit drug trafficking on the border of Venezuela with Colombia. Images of Miranda and Landsat-8 satellites, GEOINT techniques, and field verifications supported by interdiction and eradication activities of coca crops were used. The results generated proposals adopted by the National Anti-Drug Command of the Bolivarian National Guard to create a Monitoring System for Illicit Crops and the Anti-Drug Monitoring and Spatial Analysis Division or *División de Monitoreo y Análisis Espacial Antidrogas* in Spanish (DIMAE) (ANTIDROGAS-GNB, 2016).	Central University of Venezuela (Pinto, 2017).
Magazine: National Anti-Drug Command Operational Vanguard 2016	It provides an operational and descriptive balance of the main anti-drug border operations in Venezuelan territory in 2015 and 2016.	Bolivarian National Armed Forces. National Anti-Drug Command (ANTIDROGAS-GNB, 2016).

News Operation *Ave Fenix IV-2021* Operation *Febrero Rebelde - 2022*	In these news reports, military and government authorities report on the results of interdiction operations carried out in the municipality of Jesús María Semprún, Zulia state, Venezuela. In the photographs, the maps generated by the DIMAE are visualized. They identify the geographical coordinates of the dismantled infrastructures and the areas of coca crops transferred to Venezuelan territory.	Ministry of People's Power for Internal Relations, Justice and National Peace Anti-Drug Superintendence (SUNAD, 2021a, 2022a).
Other publications and bibliographic references	153 bibliographic references were consulted in this experiment.	Consult the bibliographic references of the article.

4.1.3 Evaluation

The workflow applied to evaluate the sources and information used in this investigation is shown in Figure 22.

FIGURE 64 - WORKFLOW FOR ASSESSING SOURCES AND INFORMATION – EXPERIMENT 1



Source: (Author, 2022).

Based on the criteria described in section 3.3, the corresponding evaluation was assigned to each piece of the ICP.

4.1.3.1 Satellite images

- Source: Planet Labs. Education and Research Program. Information: PlanetScope Images. **Evaluation: A1**. The source is reliable in all cases, and the images were obtained through the Education and Research Program. These images are obtained directly from the remote sensing platforms managed by the source. These data are characterized by a daily observation frequency. They capture georeferenced images of what is on the Earth's surface. The images used in this experiment were graded at **NIIRS level 3** since the spatial resolution varies between 3 m and 5 m.

4.1.3.2 Geospatial information

- Source: IGAC. Information: Basic vector maps of Colombia. **Evaluation: A1**. The source and information are official. Approved by the National Government. They are publicly available on the source's website.
- Source: SIMCI - UNODC. Information: Coca Crop Density Vectors 2020 - Colombia. **Evaluation: A1**. The source has proven to be reliable in all cases. The information was obtained by the source through a methodology based on scientific evidence, approved in Colombia by the National Government, and internationally recognized by the United Nations and Boku University (Rincón-Ruiz et al., 2016). It has a reliability of more than 90% since 1999. The georeferenced vectors are publicly available on the source's website.
- Source: IGVSB. Information: Basic vector maps of Venezuela. **Evaluation: A1**. The source and information are official. Approved by the National Government. They are publicly available on the source's website.

4.1.3.3 Ground truth data

- Source: Data collected in the field in anti-drug border operations (*Sierra XXIV - 2014, Raspaculo - 2015, Catatumbo Sur - 2015, Caño Motilon Sur - 2016, Rio Tarra - 2016, Paso del Tornado - 2017, Sierra - 2017*). Information: a) geographic coordinates of the areas of coca crops eradicated in Venezuelan territory; b) photographs of plantations of illicit coca crops in Venezuelan territory; c) photographs of IFP-PBC in Venezuelan territory; and d) photographs of CPCC in Venezuelan territory. **Evaluation: A1**. There is no doubt about the authenticity of the source and the accuracy of the information. Data were collected by the Author directly during operational participation in interdiction activities.

4.1.3.4 Open-source information

- Source: SIMCI - UNODC. Information: Monitoring reports of territories affected by illicit crops in Colombia. **Evaluation: A1**. The source is an international organization of recognized trajectory, whose work is of worldwide reference and is based on the international drug control conventions described in the literature review, conventions against transnational organized crime and against corruption, and the international instruments against terrorism. It has proven to be reliable in all cases. The reports are generated through a methodology based on scientific evidence, approved in Colombia by the National Government, and internationally recognized by the United Nations and Boku University. (Rincón-Ruiz et al., 2016). They are publicly available on the source's website.

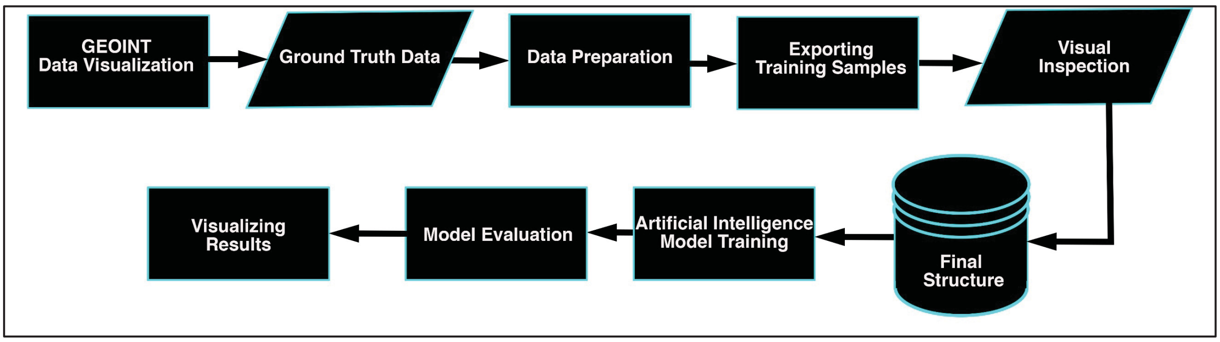
- Source: CIENA. Information: a) Bulletin: Infrastructures for the Processing of Illicit Drugs and Artisanal Chemicals; and b) Bulletin: Cocaine Market Analysis 2020. **Evaluation: A1**. The source and frequency of the information are reliable (law enforcement). The information in the bulletins was obtained by direct observation of the source. They are publicly available on the source's website.
- Source: Colombian Drug Observatory and SIMCI - UNODC. Information: Regional characterization of the problems associated with illicit drugs in the department of Norte de Santander. **Evaluation: A1**. The source and the information come from an official Colombian government agency and an international organization. Both have proven to be reliable, often generating information that has been produced directly by the source, intended for public policy formulation and decision making. The document is publicly available on the source's website.
- Source: Central University of Venezuela (UCV). Information: Master's Thesis - Characterization of activities associated with illicit drug trafficking in Venezuela's border area with Colombia, using remote sensing techniques (Pinto, 2017). **Evaluation: A1**. There is no doubt about the authenticity of the source and the accuracy of the information. The field data and research results are based on scientific evidence and were generated directly by the Author. The work is available on the website and in the UCV library.
- Source: Bolivarian National Armed Forces National Anti-Drug Command. Information: Magazine: National Anti-Drug Command Operational Vanguard 2016. **Evaluation: A1**. The source and frequency of the information are reliable (law enforcement). The information in the magazine has been obtained by direct observation by the source, where it documents the operational results of drug interdiction activities. It is a publication for internal distribution. The authors make it available to the scientific community through the link provided in the references of this research. (ANTIDROGAS-GNB, 2016).

- Source: Ministry of People's Power for Internal Relations, Justice and National Peace. Anti-Drug Superintendence. Information: News (Operation *Ave Fenix IV - 2021*, Operation *Febrero Rebelde - 2022*). **Evaluation: A1**. The source and information come from an official agency of the Venezuelan government. It has proven to be reliable, frequently publishing information on anti-drug interdiction operational results. The publications are publicly available on the source's website.
- Source: Bibliographic references of the article. Information: Other publications. **Evaluation: A1, A2 or B2**. The bibliographic references in this article are from reliable sources and from open sources that have proven to be reliable in most cases. The information may or may not be personally known to the source but is corroborated by other reliable sources of information. The information is coherent, makes logical sense and is based on scientific evidence in most cases. Access to this information can be consulted in the references of this research.

4.1.4 Collation/processing

Successful deep learning applications require large amounts of data to train the models. Data is the fuel that drives the machine learning engine (Scharre et al., 2018). For this reason, the most important component of deep learning models is the quality and quantity of the dataset used for training. However, due to the characteristics of remote sensing data, generating and labeling this type of dataset is a complex and challenging task, requiring the acquisition of numerous samples of satellite imagery, along with data associated with real terrain features (Hoeser & Kuenzer, 2020; UN-GGIM, 2020). The following workflow was constructed to detect potential coca paste production infrastructure (IFP-PBC) in remote sensing images, as shown in Figure 23. Each phase developed in this experiment is described below.

FIGURE 67 - WORKFLOW EXPERIMENT 1



Source: (Author, 2022).

4.1.4.1 GEOINT data visualization

Visualization organizes geospatial data and information to be analyzed and/or displayed in a visible medium (UNODC, 2011). It allows the examination and integration of information from multiple intelligence sources and facilitates linking satellite imagery with actual ground data.

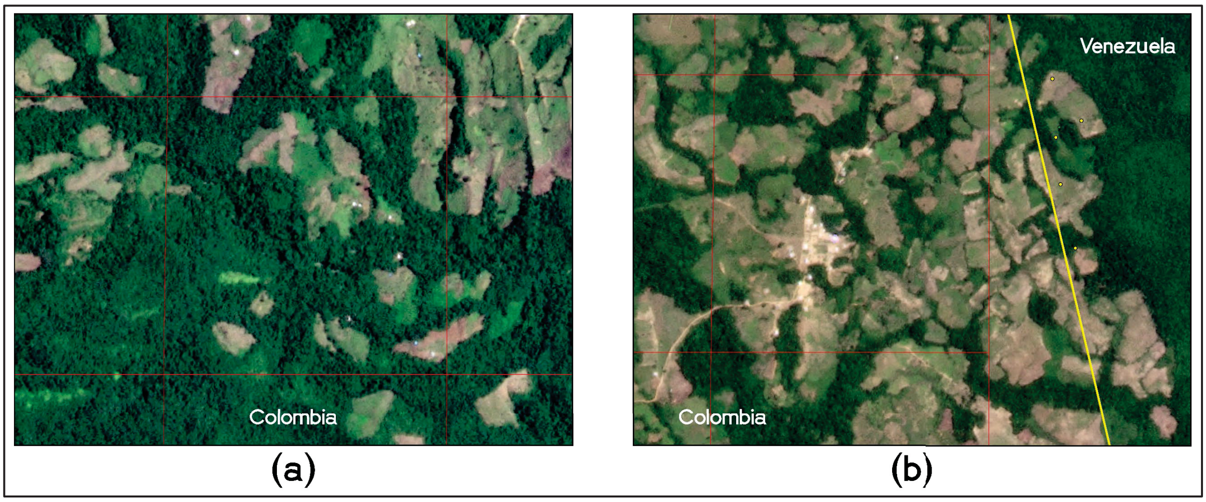
The Python 3.8 programming language, the open-source web application JupyterLab and the deep learning and geoprocessing modules of ArcGIS Pro Intelligence 2.9 were used as the main tools for visualization and processing. All images (17 in total) were visualized and processed in RGB color composites. No additional processing was performed. Subsequently, the boundary vectors of countries, states, departments, municipalities, hydrography, coca cultivation density of Colombia, and the geographic coordinates of coca cultivation areas eradicated in Venezuelan anti-drug border operations were integrated. These geographical coordinates were converted into point vectors.

4.1.4.2 Ground truth data

This phase relates the potential IFP-PBC identified in the satellite images based on characteristics and data obtained by direct observation and field measurements. In this sense, considering the characteristics of infrastructures dedicated to PBC production described in the literature review, specific activities and rural infrastructures located in the study area were defined as potential IFP-PBC for this experiment. For example, considering their appearance (geospatial objects whose spectral behavior, tone, shape, texture, and pattern are interpreted as infrastructure with a zinc roof), and the geographic context, including their proximity to coca fields, allows linking them to PBC production, i.e., (a) infrastructures involved in agricultural practices of coca cultivation, (b) infrastructures destined to the collection of coca leaves, and (c) infrastructures dedicated to the processes of extraction of coca alkaloids to produce PBC/BC.

Therefore, in the PlanetScope images of the year 2021 (1 to 14 of the ICP), we selected the objects with characteristics of being potential IFP-PBC from the overlapping vectors of coca cultivation density 2020 of Colombia and vectors of eradicated areas of Venezuela. Geospatial objects with similar characteristics in population concentrations were not selected for the training samples. Some examples are shown in Figure 24.

FIGURE 70 - GROUND TRUTH DATA IMAGES



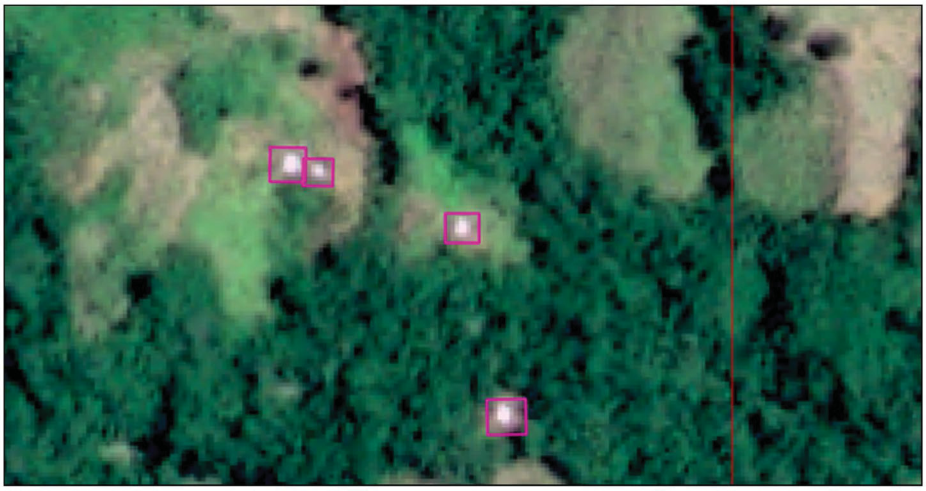
PlanetScope Images, 3 m, RGB, 2021. (a) Geospatial objects defined as potential IFP-PBC were selected as samples, specifically the zink roofs scattered in the coca cultivation areas. (b) Geospatial objects not selected. Samples of zink roofs present in urban agglomerations were not selected. The solid line represents the border division between the two countries. The grid represents Colombia's coca cultivation density vectors in 2020. The dots represent the vectors of eradicated coca cultivation areas in Venezuela. Source: (Author, 2022).

It is important to highlight that the PlanetScope images are from 2021. The vectors on the ground are from the years 2020 (Colombia), and 2014, 2015, 2016, 2017, 2021, 2022 (Venezuela); the study area corresponds to a territory permanently affected during the last 10 years by illicit coca cultivation (SIMCI, 2021; UNODC, 2022b).

4.1.4.3 Data preparation

In this phase, the samples were selected and labeled using the deep learning tools of ArcGIS Pro Intelligence 2.9. A classification scheme was created as IFP-PBC. As shown in Figure 25, a bounding box identified each object, which was labeled as a representative sample of the respective IFP-PBC class. A total of 16,829 training samples were selected and labeled from the study area. This phase was one of the most laborious and required considerable time and effort.

FIGURE 73 - SELECTION OF TRAINING SAMPLES



PlanetScope Images, 3 m, RGB, 2021.
The rectangular polygons indicate the selection of IFP-PBC potentials. Source: (Author, 2022).

4.1.4.4 Exporting training samples

Selected samples of the satellite images were exported for local storage in RGB band composites, 128 x 128 pixel size, GeoTIFF format.

4.1.4.5 Visual inspection

Next, a visual inspection was performed to rule out errors, difficult-to-interpret images, or distortions (e.g., geometric distortions, radiometric distortions, and cloud cover, among others). A total of 51 samples were discarded.

4.1.4.6 Final structure dataset

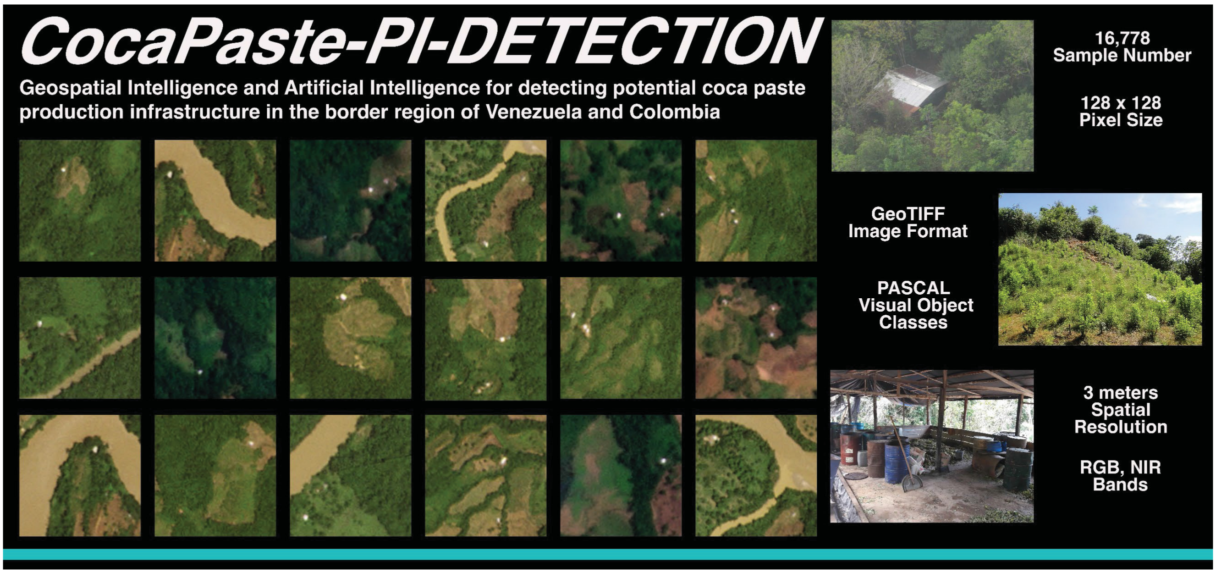
The resulting set of training samples was named *CocaPaste-PI-DETECTION* (Coca Paste Production Infrastructures Detection). This dataset comprises 16,778 images in GeoTIFF format, tagged in PASCAL Visual Object class format, for geospatial object detection tasks, specifically potential IFP-PBC. The tag files are XML files containing the image name, class value, and bounding boxes. The features are described in Table 19.

TABLE 19 - CHARACTERISTICS OF THE TRAINING SAMPLES OF THE COCAPASTE-PI-DETECTION DATASET

Image Format	GeoTIFF
Pixel Size	128 x 128
Sample Number	16,778
Images	PlanetScope
Meta Data Format	PASCAL Visual Object Classes
Bands	4 (RGB, NIR)
Visual Band Combination	RGB
Spatial Resolution	3 m
Spatial Reference	WGS-84
Level	3B

The *CocaPaste-PI-DETECTION* dataset is publicly available in the repository: (https://doi.org/10.17632/gmhsjwr24n.1) (Pinto, 2022). An overview and some examples are illustrated in Figure 26.

FIGURE 76 - SOME SAMPLE RGB IMAGE CLIPPINGS AND OVERVIEW OF THE *COCAPASTE-PI-DETECTION* DATASET



Source: (Author, 2022).

4.1.4.7 Artificial intelligence model training (Faster R-CNN architecture)

The Faster R-CNN architecture was selected to train the model to detect potential IFP-PBC due to the promising results in detecting geospatial objects in remote sensing images (Deng et al., 2017; Guo et al., 2018; K. Li et al., 2020; Yao et al., 2017). To train the model, the *CocaPaste-PI-DETECTION* data set was divided into two subsets: a) 80% for training data and b) 20% for validation data. The training data are used to train the model, and the validation data are used to evaluate the model that allows adjustment of the hyperparameters during training. Techniques were applied to increase the diversity of the training data set from the existing samples by applying random transformations such as rotating, scaling, and flipping the images (data augmentation).

The early stopping technique was also used to set the number of training epochs, one of the most widely used regularization practices in deep learning (Goodfellow et al., 2016). This technique identifies when model performance begins to degrade. It measures the error concerning the validation data, often showing a decrease at the beginning of training, followed by an increase as the network begins overfitting. Therefore, training stops at the minor error point concerning the validation data set (Bishop & Nasrabadi, 2006). The described techniques are used to avoid overfitting during training and improve the model's generalization performance. Table 20 specifies the hyperparameter settings and computational resources used.

TABLE 20 - HYPERPARAMETER CONFIGURATION AND COMPUTATIONAL RESOURCES FOR MODEL TRAINING WITH THE FASTER R-CNN ARCHITECTURE

Dataset	*CocaPaste-PI-DETECTION*
Splitting	Train: 80% Validation: 20%
Input shape	128 x 128 x 3
Batch size	32
Learning rate	3.019951720402016e-05
Training epoch	114 (early stopping)
Backbone	Resnet50
Hardware	Google Cloud Platform (1 GPU NVIDIA Tesla K80 / 4vCPUs, 15GB RAM)
Programming language	Python 3.8
Framework	Deep Learning Frameworks for the ArcGIS System

4.1.4.8 Model evaluation

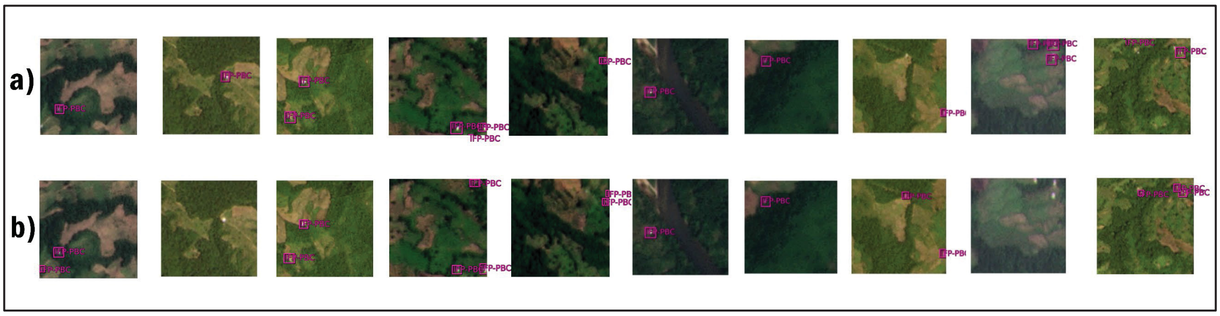
Once the training is completed, the output produced by the model is evaluated by comparing it to the reference data through evaluation metrics. These metrics explain the performance of a model and can discriminate between model results.

Object detection systems make predictions based on a bounding box and a class label. To evaluate the model's performance in recognizing IFP-PBC potentials, **mean Average Precision (mAP)** was used as the evaluation metric. This is the main metric for measuring the accuracy of object detection models in images (MICROSOFT, 2022). It compares the overlap between the prediction bounding box and the ground truth bounding box (the boundary of the actual object). The higher the score, the more accurate the model's detection. The mAP score of the model was 90.07%.

4.1.4.9 Visualizing results

Shown in Figure 27 are some results obtained by the model. The images in the top row represent the ground truth, and the images in the bottom row correspond to the model predictions. The ability of the model to detect the objects of interest in the satellite images can be appreciated; in some cases, it detects potential IFP-PBC that were not labeled in the ground truth data.

FIGURE 79 - RESULTS OBTAINED FROM THE MODEL



(a) Ground Truth Images, (b) Predictions. Source: (Author, 2022).

Similarly, some examples can be observed where the model failed, probably due to possible geometric and radiometric distortions caused by the relief of the study area or due to the spatial resolution image. Atmospheric effects may also be influencing the detection of objects. Likewise, it is important to consider that the sensor captures the data in the remote sensing images from an aerial perspective, so geospatial objects of the same type may have a different orientation or spectral reflectance, generating confusion in the model to detect potential IFP-PBC in the satellite images.

4.1.5 Geospatial intelligence analysis

In this experiment, the proposed model is explored by inference processes to identify the detection capabilities of potential IFP-PBC in satellite images. Subsequently, the geospatial analysis method Kernel Density Estimation (KDE) (hot spots) is applied as a technique to identify and analyze the concentrations and patterns detected by applying the model (inference).

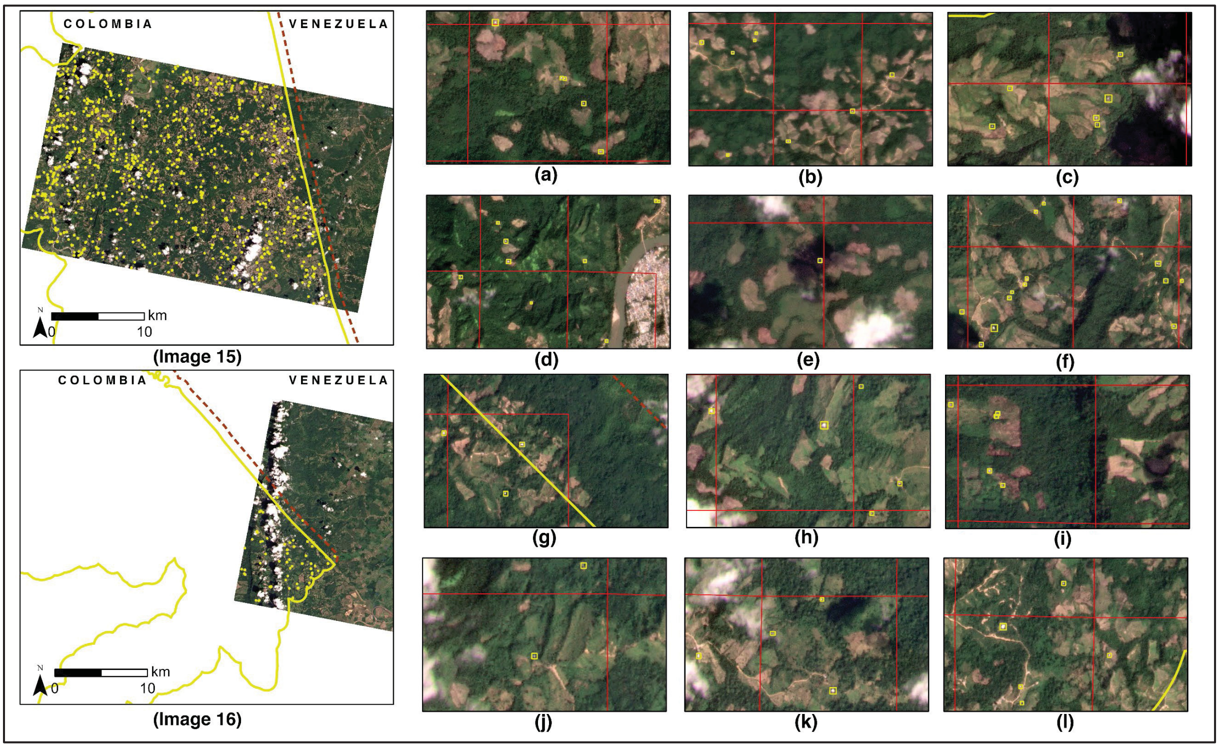
4.1.5.1 Inference

This phase makes predictions by applying the previously trained model to unlabeled samples. Considering that the *CocaPaste-PI-DETECTION* dataset was built with PlanetScope images of 3 m spatial resolution in 2021, two tests were conducted for the inference phase.

a) Application of the model on PlanetScope 3 m spatial resolution images year 2022

From ICP images 15 and 16 (the year 2022), two regions corresponding to the extent of the study area were selected. We applied the model, and as shown in Figure 28, it is possible to appreciate the capabilities to efficiently detect potential IFP-PBC in satellite images totally unknown by the network of different dates. The image (d) shows that it only detects zinc roofs found in coca cultivation areas and discriminates from those found in population concentrations. Another relevant example is shown in the image (e), where the model, despite the cloud shadow, detects the zinc roof in the satellite image. Results are in Table 21.

FIGURE 82 - SPATIAL DISTRIBUTION MAP OF THE IFP-PBC POTENTIALS DETECTED BY THE MODEL IN TEST (A)



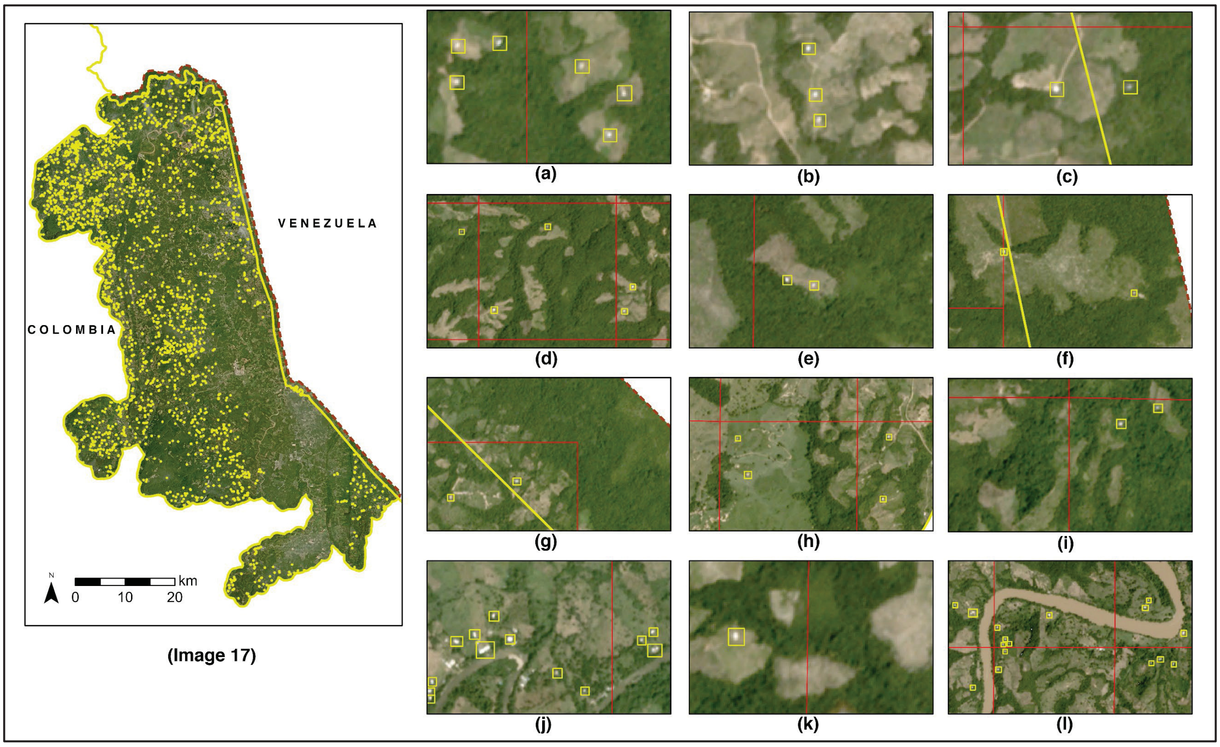
The rectangular polygons are the potential IFP-PBC predicted by the model. The grid represents the 2020 coca cultivation density vectors in Colombia. The solid line represents the border division between Colombia and Venezuela. The dashed line represents the boundary of the 1 km area of influence between the two countries. Source: (Author, 2022).

b) Application of the model on PlanetScope 5 m spatial resolution images year 2020

This test evaluated the model using PlanetScope - October 2020 mosaic images of 5 m spatial resolution (ICP image 17). A cutoff corresponding to the entire study area was generated. The model was applied only in the areas within Colombia's 2020 coca cultivation density vectors and the 1 km area of influence of Venezuela.

As shown in Figure 29, the results indicate that the model performs well in this type of imagery and can be used to monitor large regions such as the Tibú municipality and the border region of the Jesús María Semprún municipality. As in the previous test, the model demonstrated efficient predictions in different terrain conditions and was able to identify potential IFP-PBC in satellite images of different dates with a lower spatial resolution than the one used for training. This suggests that the model can also be employed in the monthly PlanetScope mosaics of 5 m spatial resolution. Results are in Table 21.

FIGURE 85 - SPATIAL DISTRIBUTION MAP OF THE IFP-PBC POTENTIALS DETECTED BY THE MODEL IN TEST (B)



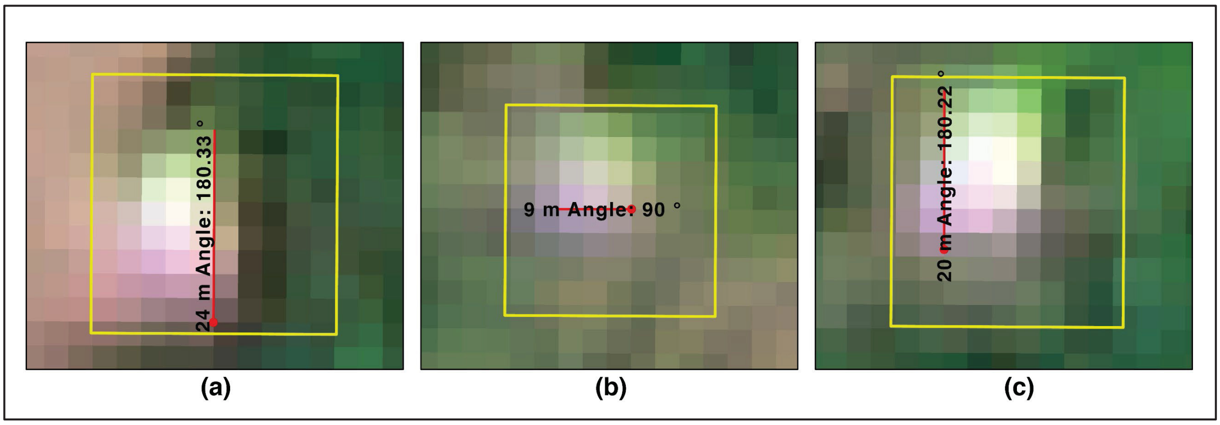
The rectangular polygons are the potential IFP-PBC predicted by the model. The grid represents the 2020 coca cultivation density vectors in Colombia. The solid line represents the border division between Colombia and Venezuela. The dashed line represents the boundary of the 1 km area of influence between the two countries. Source: (Author, 2022).

TABLE 21 - RESULTS OBTAINED IN THE INFERENCE PHASE OF TESTS (A) AND (B)

Test	Image	Area/km^2	Time (minutes)	Potential IFP-PBC detected		
				COL	VEN	Total
(a)	15	676.15	12	1,008	06	1,014
	16	80	3	63	04	67
(b)	17	3,077	44	2,754	24	2,778
Software	Windows 10; ArcGIS Pro Intelligence 2.9					
Hardware	Processor Core i7-8750H; GPU: NVIDIA GTX 1060; RAM: 16 GB					

The results showed that the model reached a mAP score of 90.07%, showing overfitting after 114 training epochs. This probably occurred due to the spatial resolution (3 m) of the satellite images used to build the training dataset; the model must learn numerous features, and there are various sizes of zinc roofs, so there may be an imbalance of training samples that generate confusion in the model (Figure 30). The results also show how, in short times, it is possible to identify these infrastructures automatically, saving considerable time and resources. In practice, it would be very difficult and time-consuming to identify these geospatial objects linked to DTOs manually and through visual interpretation. However, the results are favorable and can offer solutions and contributions.

FIGURE 88 - EXAMPLES OF SIZES OF THE ZINC ROOFS OF THE TRAINING SAMPLES



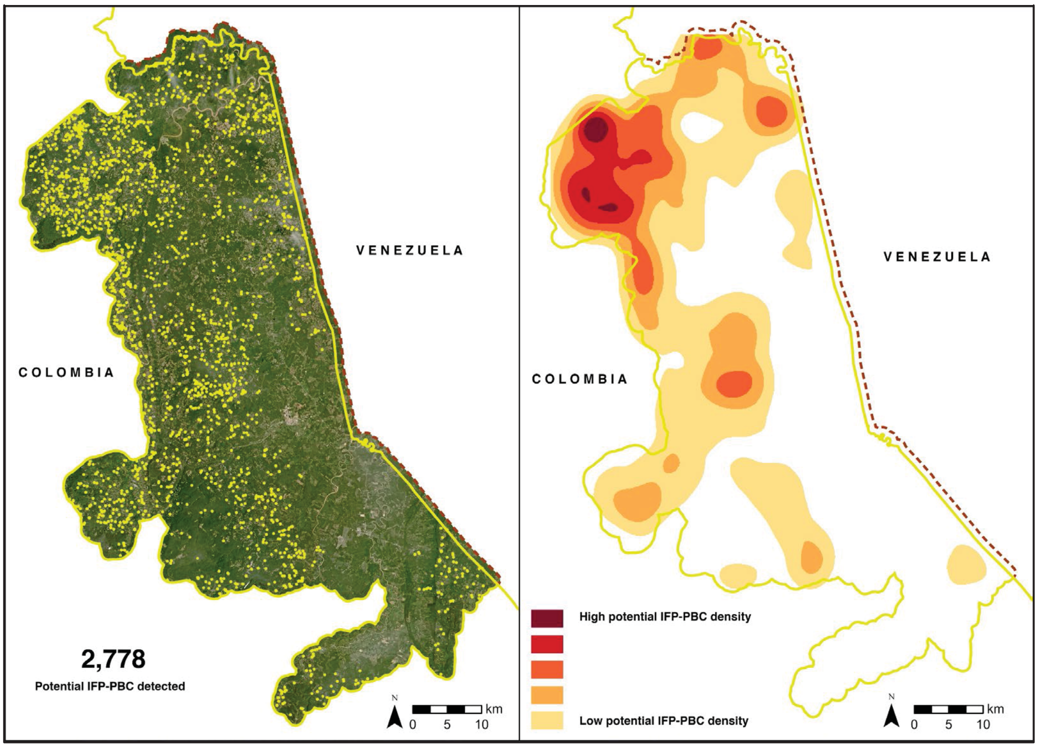
PlanetScope Images, 3 m, RGB, 2021.
The rectangular polygons are the results predicted by the model. (a) 24 meters. (b) 9 meters. (c) 20 meters
Source: (Author, 2022).

This experiment performed training with images in the RGB band combination. Some studies (Ferreira et al., 2019; Liu et al., 2018; Pinto & Centeno, 2022b) suggest that training GeoAI models with NIR (Near Infrared) band combinations allow a higher extraction of features during training, mainly if the presence of vegetation influences the geospatial objects of interest in the spatial context. It is necessary to perform experiments with this band combination and explore whether the model capabilities improve the accuracy in detecting potential IFP-PBC.

4.1.5.2 Kernel density estimation

From the polygons obtained from test (b) predictions, the georeferenced points corresponding to the central location of each polygon were generated. Subsequently, the technique was executed using the KDE tool of ArcGIS Pro. This implements the kernel function based on Silverman's rule-of-thumb algorithm to calculate a predetermined bandwidth based on the standard distance of points (ESRI, 2021b; Silverman, 1986). (Figure 31).

FIGURE 91 - KDE HOT SPOT MAP OF THE DISTRIBUTION OF POTENTIAL IFP-PBC



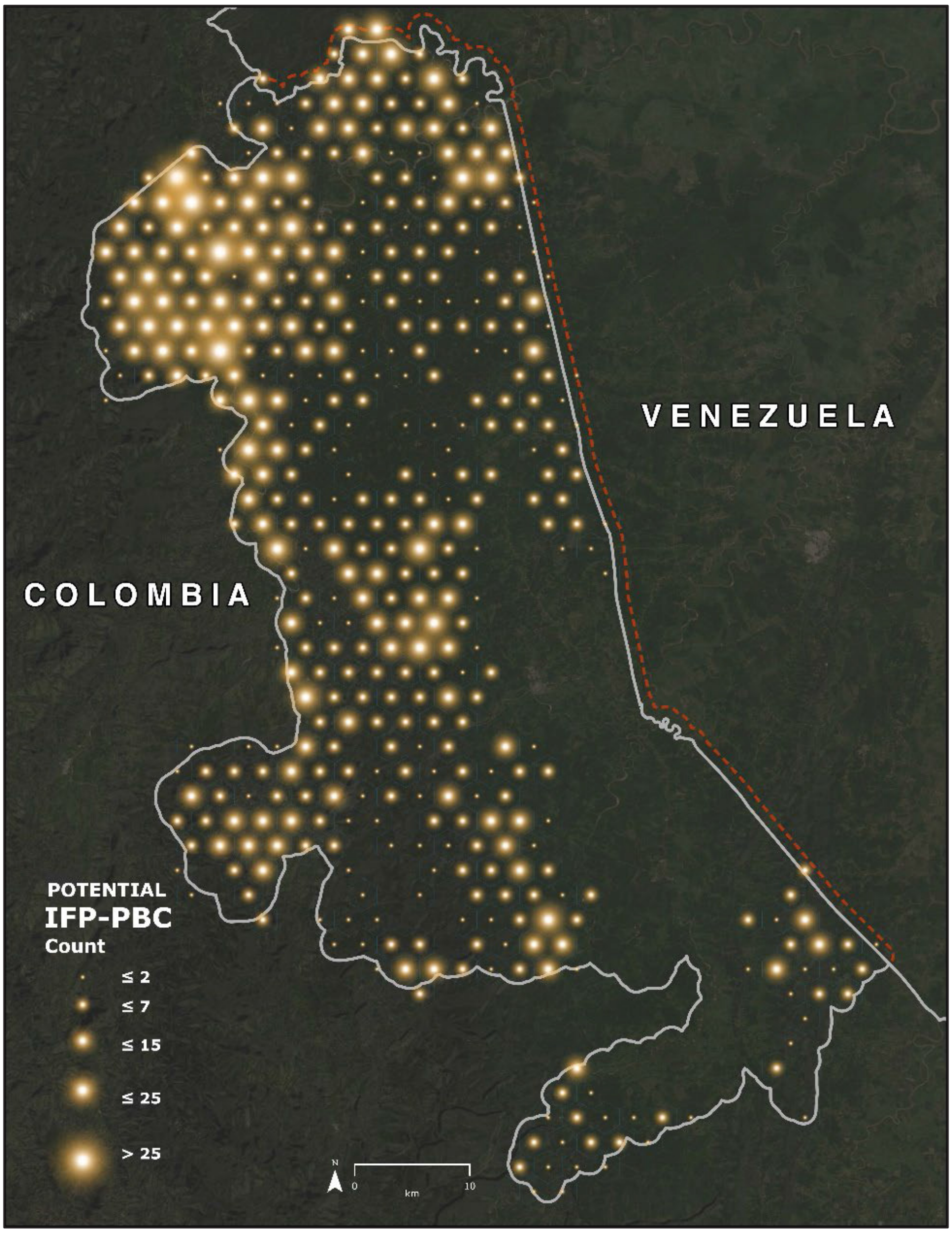
Source: (Author, 2022).

A higher density is observed in the northwest region and a relatively low density in the southern region. Similarly, some concentrations are evident in the central region, and spatial patterns are identified that suggest opportunities for installing this type of infrastructure in the proximity of the border region with Venezuela. These results demonstrate how integrating GEOINT, and artificial intelligence can contribute to strategic analysis and support the identification of trends and threats in complex territories strongly threatened by cocaine production and trafficking.

4.1.6 Dissemination

As described in the methods, this stage completes the initial process of the intelligence cycle. From the experiments performed, Figures 26, 28, 29, 31 and 32, are considered as the main dissemination products of this experiments. Figure 32 represents a GEOINT product that may be intended to provide an overview of high-risk areas affected by the presence of potential IFP-PBC. We suggest that a monthly update would allow us to explore trends, patterns, and changes in these infrastructures in the region.

FIGURE 94 - HIGH-RISK AREAS AFFECTED BY POTENTIAL IFP-PBC



Based on the results obtained from the model in the inference phase (test b), this map was created using a 5 square kilometer tessellation and then grouping and symbolizing the location of IFP-PBC in specific geographic areas. Source: (Author, 2022).

4.2 EXPERIMENT 2. AMAZONCRIME: A GEOSPATIAL ARTIFICIAL INTELLIGENCE DATASET AND BENCHMARK FOR THE CLASSIFICATION OF POTENTIAL AREAS LINKED TO TRANSNATIONAL ENVIRONMENTAL CRIMES IN THE AMAZON RAINFOREST[7] [8]

4.2.1 Direction/tasking

4.2.1.1 Task definition

This experiment focuses on detecting and classifying possible areas linked to transnational environmental crimes in satellite images of the Amazon rainforest. As in the previous experiment, the methodology for creating a training dataset for image classification tasks is described. It is demonstrated through the training of GeoAI models how the predictions identify and classify these illicit activities in natural protected areas of the Amazon region.

4.2.1.2 Study area (Amazon Rainforest)

The Amazon region extends across several countries (Bolivia, Brazil, Colombia, Ecuador, Guyana, French Guiana, Peru, Suriname, and Venezuela) and has an approximate area of 8,470,209 km^2, equivalent to 40% of the territory of South America (RAISG, 2020b), generates between 16% and 20% of fresh water and 10% of the world's biodiversity, produces more than 10% of the planet's oxygen and is considered the largest rainforest in the world (CAF, 2019). However, despite being an important strategic region due to the abundance of water, energy, and mineral resources it possesses, it is one of the scenarios where complex transnational environmental crimes are verified (EL PACCTO, 2019; INTERPOL, 2022a; Perazzoni, 2021; Pinto & Jordán, 2013; RAISG, 2020b; UNODC, 2018a, 2022b; Zabyelina & van Uhm, 2020).

This sub-region of South America has long been vulnerable to anthropological activities. In the last 10 years, illegal mining, illicit drug trafficking, illicit coca crop production, and the construction of clandestine airstrips have intensified (EL PACCTO, 2019; EXÉRCITO BRASILEIRO, 2018; IGARAPÉ-INTERPOL, 2021; INSIGHT CRIME, 2020c; UNODC, 2012b). Illicit coca cultivation, for example, is often connected to and overlaps with gold-

[7] This experiment is based on Pinto & Centeno (2022b). https://doi.org/10.4995/raet.2022.15710
[8] The figures in the article were selected to represent the cover of the volume in which it was published: https://polipapers.upv.es/index.php/raet/issue/view/1132

producing areas, becoming a strategy by organized crime to diversify their sources of income while remaining active in drug trafficking (UNODC, 2022a; Zabyelina & Van Uhm, 2020).

In this context, environmental crimes in the Amazon rainforest are complex. They contribute to the effects of climate change, air, soil, and water pollution; deforestation is the most frequent crime and the element in common with illegal gold mining, illicit coca cultivation, and various activities related to other transnational environmental crimes, such as the construction of clandestine airstrips (IGARAPÉ-INTERPOL, 2021; INSIGHT CRIME, 2020a; UNODC, 2012a). Table 22 lists in more detail the main activities are contributing to deforestation in the Amazon rainforest.

TABLE 22 - MAIN ACTIVITIES THAT CONTRIBUTE TO DEFORESTATION AND ENVIRONMENTAL DEGRADATION IN THE AMAZON RAINFOREST

Activities	Impacts / Consequences
– Illegal exploitation and trade of timber and other forest resources	– Massive destruction and uncontrolled loss of forests
– Agricultural and cattle-raising activities	– Destruction of underwater ecosystems
– Infrastructure construction	– Soil fragmentation
– Illegal mining (gold, coltan, copper, tin, tungsten, among others)	– River pollution and sedimentation
– Clandestine airstrips, clandestine ports	– Dead water phenomenon (scarcity of fauna, flora, and fish)
– Transportation of heavy machinery (dredges, backhoes)	– Modification of the chemical composition of water (with lead and salt)
– Illicit coca crops	– Health risks
– Drug Trafficking	– Impacts on Wildlife
– Establishing drug production infrastructures	– Direct and indirect contamination in indigenous communities
– Petroleum activity	– landslide risk
– High levels of chloride, chromium, and lead in water bodies	– Increased violence in the region
– Use of mercury and cyanide to separate gold from other minerals	– Water and soil contamination with mercury and cyanide
– Firearms Trafficking, ammunition, and explosives	– Invasion of indigenous territories
– Human Trafficking	– Transmission of deadly diseases, such as malaria
– Prostitution	– Precarious working conditions, labor exploitation
– Child sexual exploitation	– Obtaining falsified electronic licenses to exploit preserved areas
– Slave labor	– Weakening of environmental protection institutions in the region
– Extortion	– Impunity for crimes committed in the region. Habitat loss
– Coercion	– Soil erosion
– Money laundering	– Decreased farm incomes
– Illegal trade of oil and oil products, such as gasoline	– Spread of infectious diseases
– Illegal trade in endangered species of fauna and flora	– High poverty, unemployment, and social exclusion rates
– Homicides	– Climate change
– Displacement of peasant and mining communities from their places of origin	
– Presence of armed groups, guerrillas, paramilitaries	
– Corruption	

– Falsification of licenses for timber extraction – Murder of environmental activists – Torture and massacres – Air and river corridors for drug and illegal mining trafficking – False claims about the origin of minerals – Use of front companies to facilitate the extraction and transportation of illegal minerals, as well as to purchase mercury – Burying of machinery and logistical resources on the ground to avoid detection by law enforcement forces	

Source: (EL PACCTO, 2019; GLOBAL INITIATIVE, 2016; IGARAPÉ-INTERPOL, 2021; INTERPOL, 2022a; Pinto & Jordán, 2013; RAISG, 2020b; Ungar, 2018; UNODC, 2018b).

The region is currently characterized by the high percentage of gold extracted by illegal miners associated with armed groups and DTOs (INTERPOL, 2022a). Around 28% of the gold extracted in Peru, 30% in Bolivia, 77% in Ecuador, 80% in Colombia, and between 80% and 90% in Venezuela, is produced in flagrant violation of the law (EL PACCTO, 2019; GLOBAL INITIATIVE, 2021), operating in protected areas and breach of environmental, fiscal, and labor legislation.

Consequently, the presence of these organized crime groups in the Amazon rainforest has turned the South American region into the global epicenter of illegal transnational trade in natural resources and drug trafficking (EL PACCTO, 2019; GLOBAL INITIATIVE, 2021; UNODC, 2019a), generating a major threat to the ecological balance of biodiversity and ecosystems.

4.2.1.3 Resources

Table 23 describes the data, information, software, and hardware used to develop this experiment.

TABLE 23 - RESOURCES USED FOR DEVELOPING THE RESEARCH – EXPERIMENT 2

Software
– QGIS 3.12 – Anaconda Distribution/Python 3.8 – TensorFlow 2.2 – GDAL Python package – Google Earth Engine (GEE) – JupyterLab – Windows 10 Operating System – Microsoft 365 Apps
Hardware
– Processor: Intel® Core™ i7-8750H CPU @ 2.20GHz – GPU: NVIDIA GeForce GTX 1060 – RAM: 16 GB – SSD: 250 GB – HDD: 2TB – Google Cloud Platform (1 GPU NVIDIA Tesla K80 / 4vCPUs, 15GB RAM)
Satellite Images
– Sentinel-2 georeferenced images, 13 multispectral bands, 10 m spatial resolution
Geospatial Information
– Vectors of the Amazon rainforest (Amazon rainforest, illegal mining, deforestation, forests, hydrography, and protected areas)
Open Source GEOINT Data
– Airstrip geographic coordinates
Ground Truth Data
– Photographs of clandestine airstrips – Photographs of illegal mining in the Amazon rainforest
Open-Source Information
– Monitoring reports of territories affected by illicit crops in Colombia, Peru and Bolivia – Public databases – Books and academic publications – Studies and research of governmental agencies, international law enforcement agencies – News websites and newspapers

4.2.2 Collection

Data were obtained as described in the Information Collection Plan (ICP). (Table 24).

TABLE 24 - INFORMATION COLLECTION PLAN - EXPERIMENT 2

Satellite Images

Information/Requirement	Description	Source of Information
Sentinel-2 images of the study area: Image collections of the Amazon rainforest Years: 2016, 2017, 2018, 2019, 2020	Instrument: MSI Spatial Resolution: 10 m / 20 m / 60 m Temporary Resolution: 10 days / 5 days Spectral Resolution: 13 bands Coastal aerosol: 433 - 453 Blue: 458 - 523 nm Green: 543 - 578 nm Red: 650 - 680 nm Red edge 1: 698 - 713 nm Red edge 2: 733 - 748 nm Red edge 3: 773 - 793 nm NIR: 785 - 900 nm NIRn: 855 - 875 nm Water vapour: 935 - 955 nm Cirrus: 1360 - 1390 nm SWIR1: 1565 - 1655 nm SWIR2: 2100 - 2280 nm Radiometric Resolution:12 bits Format: GeoTIFF Spatial Reference: WGS-84 Frame Size: 290 km Level: 1C Cloud cover: < 5%	Google Earth Engine (GEE) (GEE, 2022; Gorelick et al., 2017). European Space Agency (ESA, 2015).

Geospatial Information

Information/Requirement	Description	Source of Information
Vectors of the Amazon rainforest	Georeferenced vectors (WGS 1984) in shapefile format: Amazon rainforest, illegal mining, deforestation, forests, hydrography, and protected areas.	Amazon Network of Georeferenced Socio-Environmental Information (RAISG, 2020a). Mapbiomas (MapBiomas, 2020). World Database on Protected Areas (WDPA) (UNEP-WCMC, 2020).

Open Source GEOINT Data

Information/Requirement	Description	Source of Information
Airstrip geographic coordinates	Geographical coordinates of legally registered aerodromes located in the Amazon rainforest territory. Obtained through the National Civil Aviation Agency (ANAC) and the Open	National Civil Aviation Agency (ANAC, 2020).

	Aeronautical Information Publication (OpenAIP) platform.	Open Aeronautical Information Publication (openAIP, 2020).

Ground Truth Data

Information/Requirement	Description	Source of Information
Photographs of illegal mining and clandestine airstrips in the Amazon rainforest Geographic coordinates of illegal mining areas	Photographs and geographic coordinates of areas affected by illegal mining and clandestine airstrips, obtained during participation in operational activities of interdiction and dismantling of illegal mining camps in the Venezuelan Amazon region.	Border Patrol. Venezuelan National Guard. *Parque Nacional Yapacana* (2005).

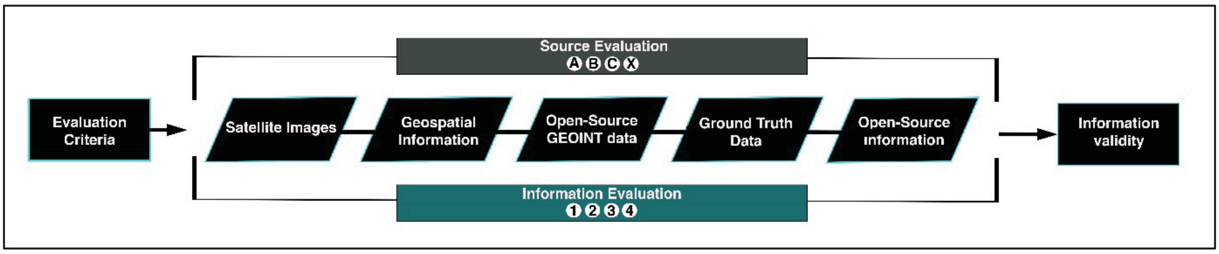
Open-Source Information

Information/Requirement	Description	Source of Information
Monitoring reports of territories affected by illicit crops Colombia: years 2018 and 2020 Peru: years 2016 and 2017 Bolivia: years 2016 and 2018	The UNODC Illicit Crop Monitoring Program (ICMP) promotes the development of a global project that, through technical and objective evidence, supports the conduct of monitoring studies on coca in Bolivia, Colombia, and Peru, on the poppy in Afghanistan, Mexico, and Myanmar, and a study on cannabis in Nigeria. Annually they generate reports that, through remote sensing techniques, geographic information systems, and extensive field assessments, contemplate the results related to the location, extension, and evolution of illicit crop areas.	UNODC – Colombia (SIMCI, 2019, 2020, 2021). UNODC – Peru (UNODC, 2017b, 2018c). UNODC – Bolivia (UNODC, 2017c, 2019c).

4.2.3 Evaluation

The workflow applied to evaluate the sources and information used in this investigation is shown in Figure 33.

FIGURE 97 - WORKFLOW FOR EVALUATING SOURCES AND INFORMATION – EXPERIMENT 2



Source: (Author, 2022).

Based on the criteria described in section 3.3, the corresponding evaluation was assigned to each piece of the ICP.

4.2.3.1 Satellite images

- Source: European Space Agency. Google Earth Engine. Information: Sentinel-2 Images. **Evaluation: A1**. The source is reliable in all cases, and the images were obtained through the GEE platform, which facilitates access to and processing of Sentinel-2 images from the European Space Agency. These data are characterized because they support land cover monitoring promptly. They capture georeferenced images of what is on the Earth's surface. The images used in this experiment were graded at **NIIRS level 1** since the spatial resolution is > 9 m.

4.2.3.2 Geospatial information

- Source: RAISG. Information: Vectors of the Amazon rainforest (Amazon rainforest, illegal mining, deforestation). **Evaluation: A2.** The source is a consortium of civil society organizations formed by six Amazonian countries (Bolivia, Brazil, Colombia, Ecuador, Peru, and Venezuela), with support from international cooperation (RAISG, 2020a). It has proven to be systematically reliable, generating frequent reports, statistical data, and social, environmental, and geospatial information on the Amazon rainforest. The data and publications are available on the source's website.
- Source: *Mapbiomas*. Information: Vectors of the Amazon rainforest (deforestation, forests). **Evaluation: A2.** The source is a multidisciplinary network of specialists that, using remote sensing, GIS, computer science, and cloud processing techniques, generates annual time series of land use and land cover mapping of the Amazon biome (Souza et al., 2020). It has proven to be systematically reliable. Data and publications are available on the source website.
- Source: WDPA Information: Vectors of the Amazon rainforest (protected areas). **Evaluation: A2.** The source is a joint project between the United Nations Environment Programme (UNEP) and the International Union for Conservation of Nature (IUCN), managed by the UNEP World Conservation Monitoring Centre (UNEP-WCMC) (Bingham et al., 2019). It has proven to be consistently reliable. It frequently generates information and geospatial data on global terrestrial and marine protected areas. Data and publications are available on the source website.

4.2.3.3 Open-source GEOINT data

- Source: ANAC. Information: Airstrip geographic coordinates. **Evaluation: A1.** The source and information are official. Approved by the National Government. They are publicly available on the source's website. The ANAC is a federal institution regulating and overseeing all civil aviation activities and aeronautical and airport infrastructure in Brazil (ANAC, 2020). It registers and supervises aerodromes in the national territory. They are publicly available on the source's website.
- Source: openAIP. Information: Airstrip geographic coordinates. **Evaluation: A2.** The source is a web platform that provides accurate and up-to-date aeronautical data and information. It is free to use, and any country's geographical coordinates of officially registered aerodromes can be obtained (openAIP, 2020). It has proven reliability and competence. It has proven to be consistently reliable in the generation of aeronautical data. They are publicly available on the source's website.

4.2.3.4 Ground truth data

- Source: Data collected in the field in anti-drug border operations and border patrol in the *Parque Nacional Yapacana – 2005*. Information in Venezuelan territory: a) photographs of clandestine airstrips; and b) photographs of illegal mining in the Amazon rainforest; c) geographic coordinates of illegal mining areas; d) geographic coordinates of clandestine airstrips. **Evaluation: A1**. There is no doubt about the source's authenticity and the information's accuracy. Data were collected by the Author directly during operational participation in interdiction activities.

4.2.3.5 Open-source information

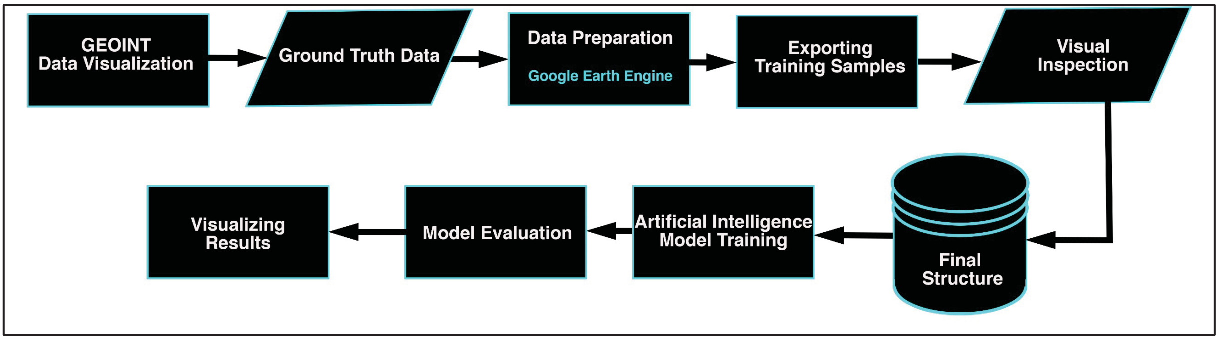
- Source: SIMCI - UNODC. Information: Monitoring reports of territories affected by illicit crops in Colombia. **Evaluation: A1.** The source is an international organization of recognized trajectory, whose work is of worldwide reference and is based on the international drug control conventions described in the literature review, conventions against transnational organized crime and against corruption, and the international instruments against terrorism. It has proven to be reliable in all cases. The reports are generated through a methodology based on scientific evidence, approved in Colombia by the National Government, and internationally recognized by the United Nations and Boku University (Rincón-Ruiz et al., 2016). They are publicly available on the source's website.

- Source: UNODC. Information: Monitoring reports of territories affected by illicit crops in Peru and Bolivia. **Evaluation: A1.** The source is an international organization of recognized trajectory, whose work is of worldwide reference and is based on the international drug control conventions described in the literature review, conventions against transnational organized crime and against corruption, and the international instruments against terrorism. It has proven to be reliable in all cases. The reports are generated through a methodology based on scientific evidence, approved in Peru and Bolivia by the National Government, and internationally recognized by the United Nations. They are publicly available on the source's website.

4.2.4 Collation/processing

As with the previous experiment, for the classification of potential areas linked to transnational environmental crimes (TEC) in the Amazon rainforest in remote sensing images using deep learning methods, it was first necessary to generate and label a training dataset for image classification tasks and then follow a workflow as illustrated in Figure 34.

FIGURE 100 - WORKFLOW EXPERIMENT 2



Source: (Author, 2022).

4.2.4.1 GEOINT data visualization

To ensure the correct identification of ground truth data and to automate the processing, selection, and downloading of satellite imagery, QGIS software, the GEE platform, and the GDAL Python package were used to visualize and process Sentinel-2 imagery and geospatial data.

4.2.4.2 Ground truth data

The dataset was named *AmazonCRIME*. It comprises six classes: Airstrips, Deforestation, Forest, Illegal Mining, Illicit Crops - Potential Coca Cultivation Area (PCCA), and Water. Initially, through QGIS geoprocessing tools, geospatial data (vectors) derived from the information sources used in this experiment were generated. Using the GEE plugin, the vectors were visualized in conjunction with the Sentinel-2 image collections described in the ICP, corresponding to the Amazon region. Subsequently, Table 25 described ground truth vectors (points) were selected for each class.

TABLE 25 - DESCRIPTION OF THE CLASSES THAT COMPOSE THE GROUND TRUTH DATA FROM THE *AMAZONCRIME* DATASET

Classes	Source	Acquisition methods
Airstrips	ANAC openAIP	– Identify 5,812 airstrips of all types (paved, unpaved, grass, dirt, airports, among others) in the 9 Amazonian countries. – Visual inspection to confirm the location and selection of airstrips located in the study area with rural characteristics. – Selection of 2,481 rural airstrips. – Visual detection and selection of 187 new airstrips with rudimentary characteristics and isolated from populated centers. – Final selection of 2,668 airstrips.
Deforestation	RAISG MapBiomas	Identification and selection of 5,500 representative points of this class.
Forest	WDPA MapBiomas	Identification and selection of 5,500 representative points of this class.
Illegal Mining	RAISG	Identification and selection of 7,304 representative points of this class.
Illicit Crops-PCCA	UNODC – Colombia UNODC – Peru UNODC – Bolivia	Georeferencing of the coca cultivation density maps generated in the monitoring reports of territories affected by illicit crops of: – Colombia 2016 and 2018 surveys. Identification and selection of 3,291 points. – Peru 2016 and 2017 surveys. Identification and selection of 1,709 points. – Bolivia 2016 and 2018 surveys. Identification and selection of 712 points. – Final selection of 5,712 points representative of this class.
Water	WDPA MapBiomas	Identification and selection of 5,500 representative points of this class.
The RAISG Amazon Forest vector file was used to delimit the study area The training samples were selected considering the four seasons of the year		

Source: (Author, 2022).

4.2.4.3 Data preparation in Google Earth Engine

GEE stores a large amount of global-scale satellite imagery, which includes data generated by the Copernicus Sentinel-2 mission. It provides programming tools and applications that enable the processing and analyzing large geospatial datasets (Gorelick et al., 2017). It currently offers Sentinel-2 products with processing levels 1C and 2A (GEE, 2022). Level 1C products are orthorectified in the WGS84 geographic coordinate geodetic system, UTM projection, with digital levels corresponding to values of apparent reflectance above the atmosphere (Top-Of-Atmosphere reflectance - TOA). Level 2A products are an evolution of level 1C in which atmospheric corrections are applied to provide orthoimage with digital levels expressed in real reflectance values at surface level (Bottom-Of-Atmosphere reflectance - BOA) (ESA, 2015). This platform was used to obtain and export 256 x 256 pixels image clippings, level 1C, in GeoTIFF format, for each class. Cloud coverage and acquisition temporality were considered criteria for generating image collections (mosaic) different from the study area (Amazon region).

In this regard, it is important to mention that GEE considers the cloud cover criterion based on the entire area of interest (mosaic) and not per individual image, which is why a generalized cloud criterion was not used for all temporal ranges. This was one of the challenges encountered in generating image mosaics with as little cloud cover as possible since, due to the climatic characteristics of the Amazon region (high temperatures and frequent rainfall), it is very difficult to generate cloud-free mosaics because the region remains cloudy practically all year round. Based on the ground truth vectors identified and described in Table 33, the following processes were carried out:

Airstrips. Four image collections were generated with the following criteria: for the years 2017 and 2018, with 1% cloud cover, and for the years 2016 and 2019, with 5% cloud cover. A total of 2,668 image clippings were exported each year, for a total of 10,672.

Illegal Mining. Two image collections were generated for the year 2017 with 5% cloud coverage and the year 2019 with 1% cloud coverage. From the ground truth vectors, 3,804 samples were exported for the year 2017 and 3,500 samples for the year 2019, obtaining a total of 7,304 image clippings for this class.

Illicit Crops-PCCA. Coca fields are characterized by different phenologies in one year and can produce between 4 and 5 harvests (SIMCI, 2019a). This particularity allows observing different spectral behaviors during this period (low/high leaf density and low/high soil reflectance). In addition to the different patterns and shapes of the fields used for this type of crop. Based on these variables, the following steps were carried out for the identification and selection of the samples:

- Georeferencing of coca cultivation density maps published in UNODC's monitoring reports of territories affected by illicit crops (Colombia, Peru, and Bolivia).
- Selection of samples only in the highest density areas and territories permanently affected during the last 10 years.
- Interpret spectral behavior in RGB and NIR combinations, tone, shape, texture, pattern, and geographical environment. These elements allowed highlighting the objects of interest (coca fields) and discriminating them from other coverages.
- Field experience.
- Criteria of the first law of geography. Areas of illicit coca cultivation are characterized by fields of land (spatial units) dedicated to this type of cultivation. These fields are geographically continuous, close together, and similar to distant ones. They have identifiable field boundaries. They are generally planted with the same type of species (coca) and group crops of the same age. However, some farmers also cultivate other licit agricultural species in the coca cultivation areas to avoid detection by aerial platforms (helicopters, remote sensing satellites, drones) and to create restrictions during eradication activities by security forces.
- For the years corresponding to the selected UNODC illicit crop monitoring reports, an image collection was generated for each season (summer, winter, autumn, and spring), with a cloud coverage of 5%, respectively. Bolivia and Colombia years 2016 and 2018, and Peru years 2016 and 2017.
- Samples selected. Bolivia: 712, Colombia: 3,291, Peru: 1,709. Total: 5,712 samples for this class.

Deforestation, Forest, and Water. Two image collections were generated for the year 2016 with 5% cloud cover and the year 2018 with 1% cloud cover. From the ground truth vectors, 2,250 samples were exported for each class per year, obtaining a total of 5,500 corresponding image clippings per class.

4.2.4.4 Exporting training samples

The images selected by each class were exported for local storage in GeoTIFF format, WGS-84 lat/long, level 1C, with a spatial resolution of 10 m, size of 256 x 256 pixels, and 13 multispectral bands, respectively.

4.2.4.5 Visual inspection

Subsequently, RGB image composites in JPG format were generated for each set of images/class. At this stage, a visual inspection was performed to make the final selection of the best 5,000 representative samples for each class.

4.2.4.6 Final structure dataset

Finally, the final selection of the samples was made, which allowed the generation of the *AmazonCRIME* dataset, made up of the following elements:

- *AmazonCRIME MS*, consisting of 5,000 image clippings for each class, for a total of 30,000 image clippings selected from 13 multispectral bands - georeferenced in GeoTIFF format, level 1C.
- The *AmazonCRIME.csv* file, with the dataset metadata (enumeration and label).
- *AmazonCRIME RGB* (derived version), consisting of bands 4,3,2 in JPG format.

The *AmazonCRIME* dataset, in its different versions, is publicly available in the repository: https://github.com/jp-geoAI/AmazonCRIME.git. This dataset is among the most significant results of this experiment. An overview and some examples are illustrated in Figure 35.

FIGURE 103 - SOME SAMPLE RGB IMAGE CLIPPINGS AND OVERVIEW OF THE *AMAZONCRIME* DATASET

Source: (Author, 2022).

4.2.4.7 Artificial intelligence model training (DenseNet architecture)

The CNNs have demonstrated their ability to solve image classification problems using hierarchical models, millions of parameters, and large datasets. In this context, the DenseNet-201 architecture was selected due to its capabilities in image classification tasks, as it allows for improving accuracy, promoting feature reuse, and significantly reducing the number of training parameters (Abdani & Zulkifley, 2019; Huang et al., 2017; Khan et al., 2021; Koh et al., 2021).

From the *AmazonCRIME* dataset, two models were trained from scratch with the DenseNet-201 architecture. A first model with the RGB band combinations (4,3,2) and a second model with the NIR band combinations (8,4,3). As in the previous experiment, data augmentation techniques were applied. The data set was divided into three subsets: 1) 80% for training data; 2) 10% for validation data; 3) 10% for test data. The training data are used to train the model. The validation data are used to evaluate the model to fit the hyperparameters during training. The test data are used to obtain an unbiased evaluation of the model at the end of the training, should be kept separate from the training process, and are used only once to evaluate the model performance. Table 26 specifies the hyperparameter settings and computational resources used.

TABLE 26 - HYPERPARAMETER CONFIGURATION AND COMPUTATIONAL RESOURCES FOR MODEL TRAINING WITH THE DENSENET-201 ARCHITECTURE

	DenseNet-201 architecture	
	First RGB Model	**Second NIR Model**
Dataset	*AmazonCRIME*	
Splitting	Train: 80% Validation: 10% Test: 10%	
Input shape	256 x 256 x 3	
Batch size	64	
Learning rate	0.001	
Optimizer	Adam	
Loss function	Categorical Cross-Entropy	
Training epoch	200	225
Hardware	Google Cloud Platform (1 GPU NVIDIA Tesla K80 / 4vCPUs, 15GB RAM)	
Programming language	Python 3.8	
Framework	TensorFlow 2.2	

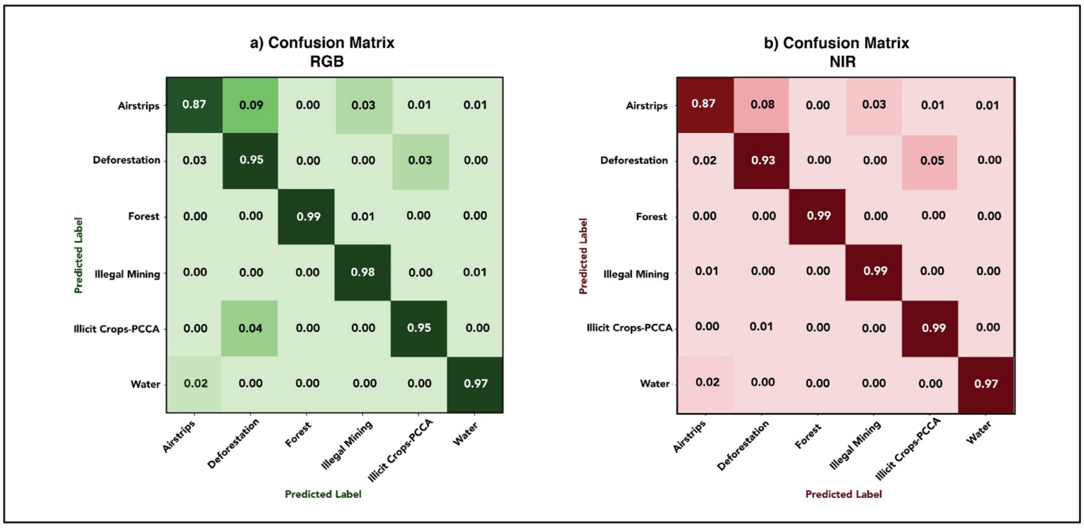
4.2.4.8 Model evaluation

For evaluating the models, the Confusion Matrix was calculated. This calculation allows evaluating the performance of a classification model by counting and visualizing the values of the predictions compared to the observed (real) values, showing when one class is confused with another. From this matrix, metrics describing the quality of the product (classification) can be calculated, such as: 1) Overall Accuracy, 2) Precision, and 3) Recall. The **Overall Accuracy** allows for measuring the percentage of cases in which the model has been correct in the classification about the total data. **Precision** provides a quality value relative to the total number of predictions made, and **Recall** provides a quality value relative to the total number of positive samples (Burkov, 2019). Table 27 describes the results obtained from the evaluation metrics used. Figure 36 shows the confusion matrices for each model.

TABLE 27 - EVALUATION METRICS

Evaluation Metrics	First RGB Model	Second NIR Model
Overall Accuracy	95.76 %	96.56 %
Precision	95.89 %	96.66 %
Recall	95.73 %	96.56 %

FIGURE 106 - CONFUSION MATRIX



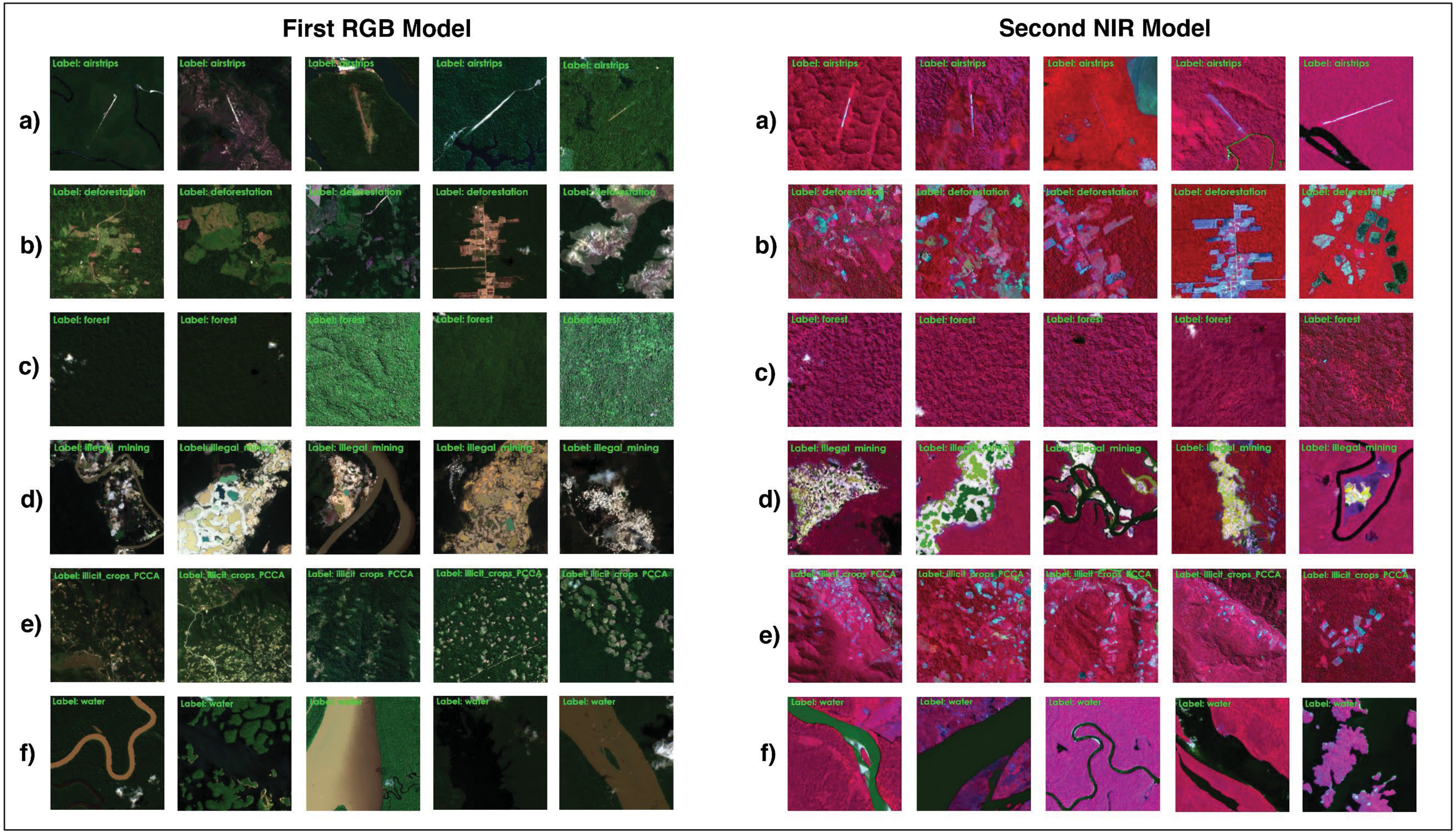
Source: (Author, 2022).

When comparing the values of the evaluation metrics, the second model presented a superior performance compared to the first model. These results prove the importance of including near-infrared spectral information in environmental monitoring and land cover disturbance detection studies in the Amazon region. The NIR band composition shows greater sensitivity to biomass discrimination and vegetation vigor detection in the infrared region of the electromagnetic spectrum. It also illustrates the strong absorption caused by the presence of chlorophyll in the visible region, especially in the red band. In this regard, the composition of NIR bands allowed a higher extraction of features during training since the objects of interest representing each class of the data set are dominantly influenced by the high presence of vegetation in the spatial context.

4.2.4.9 Visualizing results

Figure 37 shows some results obtained by the model. The model's capabilities to efficiently identify and classify the classes of interest can be appreciated. The results' explanation is extended in the analysis phase, and further inference tests are performed with new images.

FIGURE 109 - RESULTS OBTAINED WITH THE RGB AND NIR MODELS

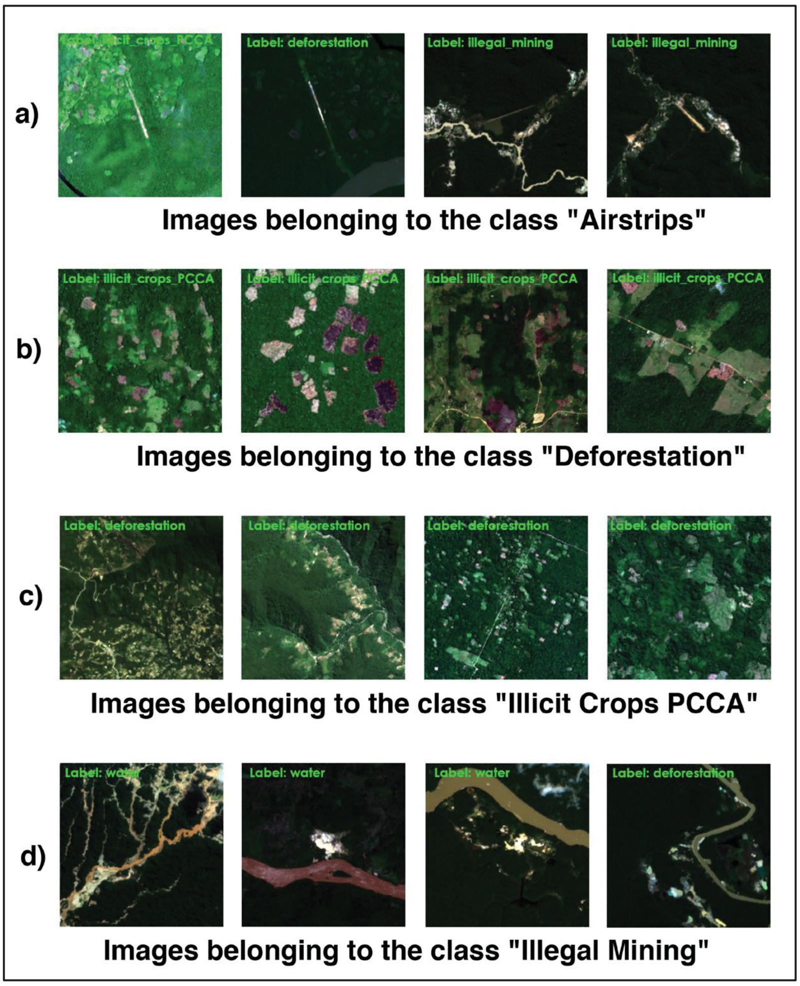


a) Airstrips; b) Deforestation; c) Forest; d) Illegal Mining; e) Illicit Crops PCCA, and f) Water. Source: (Author, 2022).

From the results obtained, it was observed that both models tend to confuse the classes “airstrips” and “illicit crops” with the class “deforestation,” probably because the common element between these classes is the absence of forest cover and the exposure of bare soil on the surface. In some of the image cropping of the dataset, it is practically inevitable that the presence of these three classes are found in the same image.

Similarly, this occurs with the “illegal mining” class, when confused with the “deforestation” class, and with the “water” class, since mining activities are most often carried out in the vicinity of river networks or bodies of water, generating strong degradation of vegetation cover and present similar pictomorphological elements (tone, texture, pattern, among others). Figure 38 shows some of the images the model confused when classifying.

FIGURE 112 - EXAMPLE OF INCORRECTLY CLASSIFIED IMAGES
THAT HAVE THE DEFORESTATION CLASS IN COMMON



(a) Images belonging to the airstrip class show in their geographical context loss of vegetation cover due to deforestation, illicit crops, and illegal mining; (b) Images belonging to the deforestation class incorrectly classified as illicit crops; (c) Images belonging to the illicit crops class were incorrectly classified as they also have spatial units and patterns corresponding to deforestation; (d) Images belonging to the illegal mining class were incorrectly classified as water and deforestation. Source: (Author, 2022).

4.2.5 Geospatial intelligence analysis

In this experiment, to demonstrate real-use applications and test the generalization capacity of the trained model, three natural protected areas in the Amazon region were selected in the inference process, which presents strong environmental impacts by organized crime groups; *Parque Nacional Cerro Yapacana* in Spanish (OAS, 2007), *Parque Nacional Natural La Paya* in Spanish (MinAmbiente, 1978) and *Floresta Nacional do Amana* in Portuguese (ICMBio, 2010). Subsequently, the intelligence layers technique was used for geospatial analysis.

4.2.5.1 Inference and intelligence layers

Following the methodology applied in the section 4.2.4.3 (Data Preparation in Google Earth Engine), three new Sentinel-2 image collections (multispectral, georeferenced in GeoTIFF format) were generated, with their respective enumeration for each class from 01/01/2020 to 07/31/2020, corresponding to each selected natural protected area, with a cloud coverage of 5%.

The *Parque Nacional Yapacana* area was divided into 464 image clippings, the *Parque Natural La Paya National* into 802 image clippings, and *Floresta Nacional do Amana* into 1,114 image clippings, all clippings with dimensions of 256 x 256 pixels. Subsequently, they were exported for local storage, and enumerated composites of RGB and NIR images were derived in JPG format.

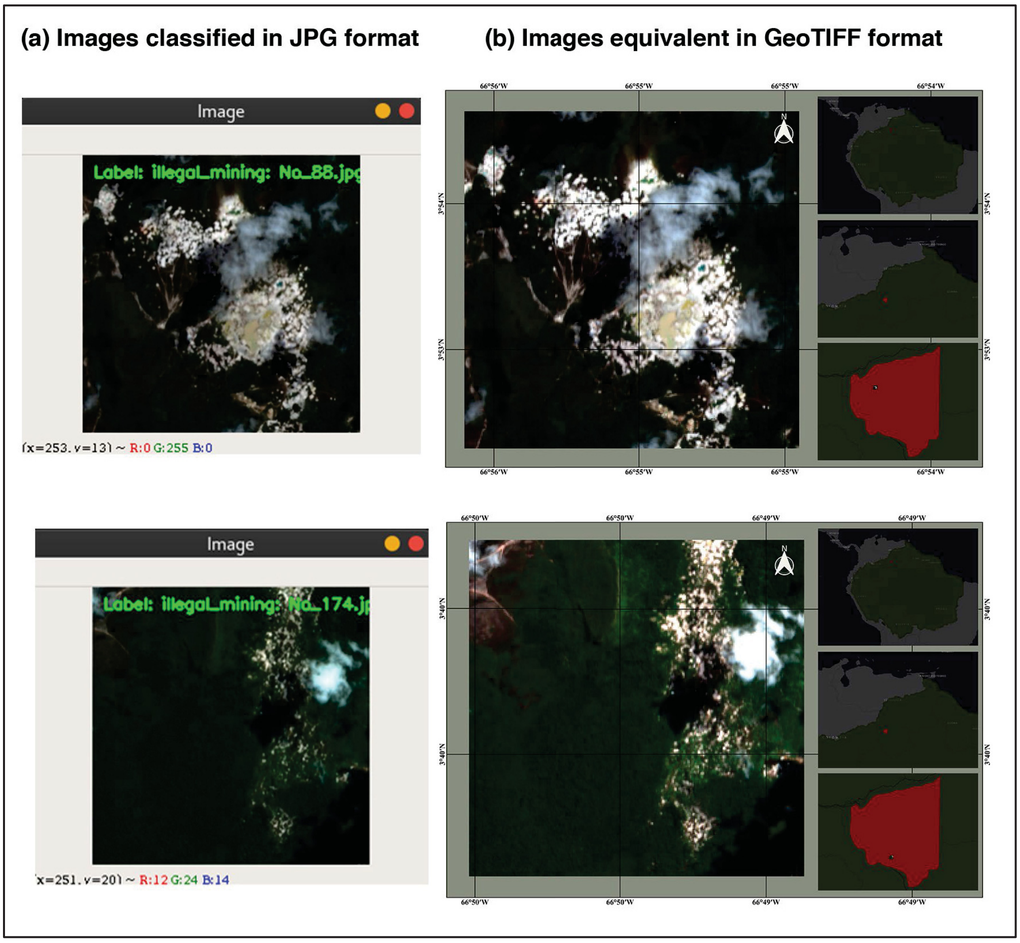
The trained models were then applied to the sets of RGB and NIR images (JPG format) that were derived, obtaining predictions that made it possible to recognize various areas affected by the TEC, as well as to identify the georeferenced image (GeoTIFF format) equivalent to the enumeration and obtain the geographic coordinates. In practice, this is the most interesting data to know to promote actions to mitigate the environmental impact and plan interdiction operations to combat DTOs-related activities. It is important to mention that *AmazonCRIME* was built with images from 2016, 2017, 2018, and 2019. Therefore, this set of images is totally unknown to the previously trained network. Table 28 specifies the results obtained during the inference process.

TABLE 28 - RESULTS OF THE INFERENCE PROCESS

Evaluation Metrics	First RGB Model	Second NIR Model
Overall Accuracy	91.74 %	93.68 %
Precision	91.85 %	93.77 %
Recall	91.69 %	93.68 %

Figure 39 shows the classification and recognition of areas affected by illegal mining in the *Parque Nacional Yapacana*. The park is located in the Amazonas state of Venezuela. It has an area of approximately 320,000 hectares, with a plateau-like relief, characteristic of the tepuis of the Venezuelan Amazon region (OAS, 2007). It is currently heavily threatened by illegal mining, which is exercised by illegal miners and controlled by armed guerrilla groups such as the ELN and FARC-EP dissidents, who have found in this ecosystem an economic source, to finance their activities linked to drug trafficking and legitimize the economic benefits they obtain from cocaine trafficking, illegal gold mining and other related crimes (INSIGHT CRIME, 2018; RAISG, 2019; SOS ORINOCO, 2020).

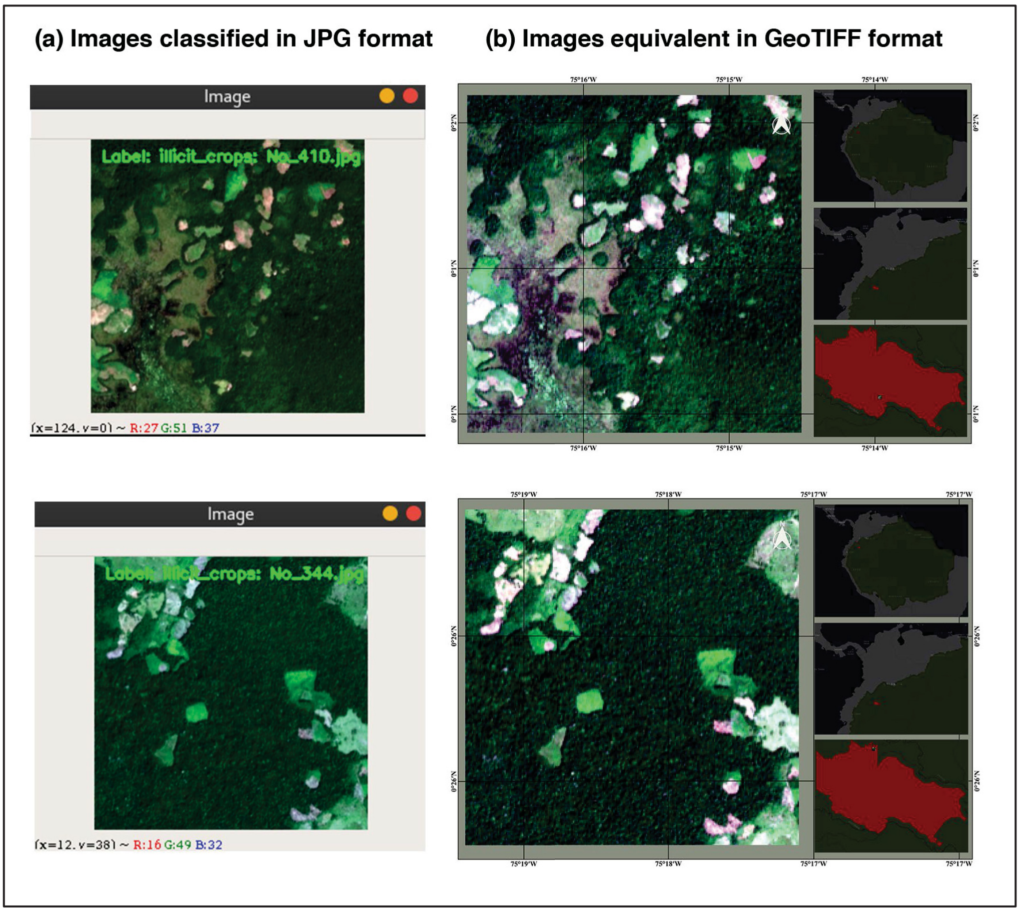
FIGURE 115 - CLASSIFICATION AND RECOGNITION OF AREAS AFFECTED BY ILLEGAL MINING IN THE *PARQUE NACIONAL YAPACANA*



(a) Examples of images in JPG format with their respective label and enumeration correctly classified as “illegal mining” during the inference process; (b) Representation of the equivalent georeferenced images of the classified JPG images. The location maps represent the Amazon region in South America (green polygon) and the *Parque Nacional Yapacana* (red polygon) in the Amazonas state, Venezuela. Source: (Author, 2022).

Another example is shown in Figure 40. By applying the trained model, it was possible to obtain predictions that made it possible to recognize several potential areas of illicit crops in the Parque Nacional Natural La Paya. This park, located in the department of Putumayo in southern Colombia, has an area of 422,000 hectares and is characterized by a dense water system and a variety of humid tropical vegetation. Among the most frequent anthropogenic activities are timber extraction, fishing, illegal mining, and illicit coca cultivation (FIP, 2020; Ministerio de la Defensa, 2020). This area is one of the most affected by deforestation caused by illegal armed groups involved in drug trafficking.

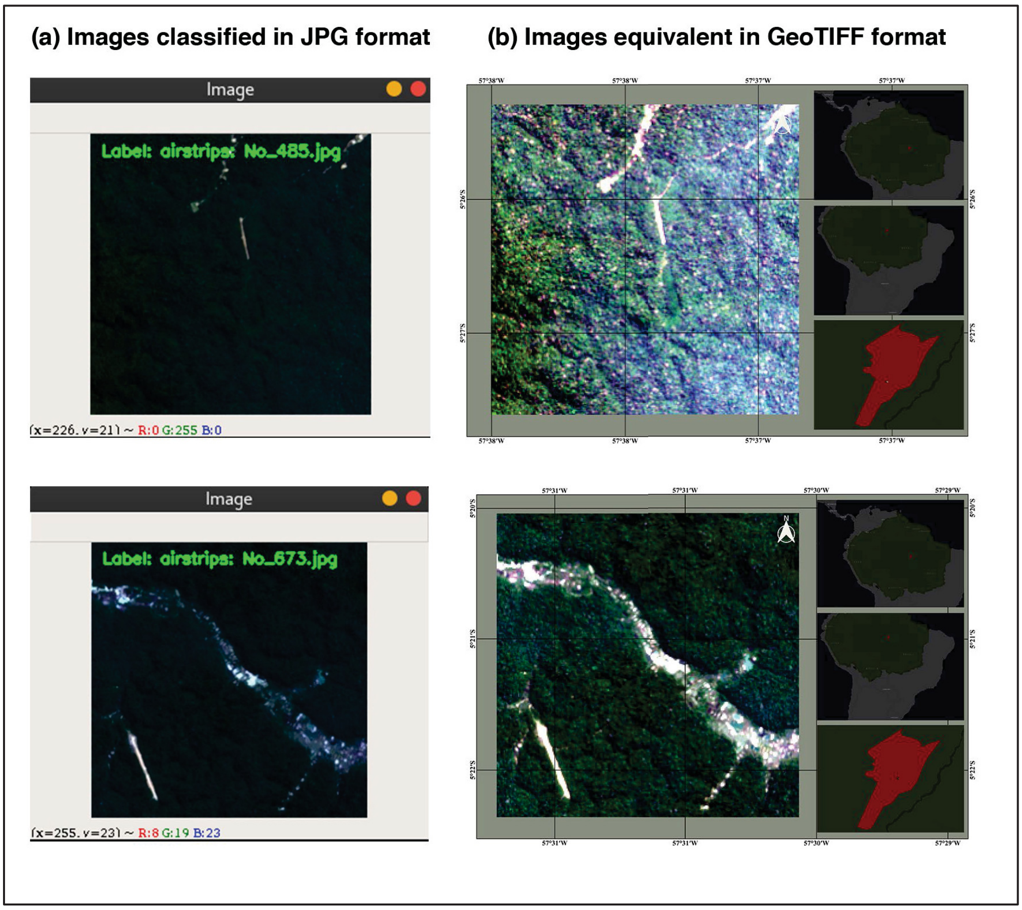
FIGURE 118 - CLASSIFICATION AND RECOGNITION OF POTENTIAL AREAS OF ILLICIT COCA CULTIVATION IN THE *PARQUE NACIONAL NATURAL LA PAYA*



(a) Examples of images in JPG format with their respective label and enumeration correctly classified as "illicit crops" during the inference process; (b) Representation of the equivalent georeferenced images of the classified JPG images. The location maps represent cartographically the Amazon region in South America (green polygon) and the *Parque Nacional Natural La Paya* (red polygon) in the department of Putumayo, Colombia. Source: (Author, 2022).

The *Floresta Nacional do Amana* is located in the state of Para, Brazil, has an approximate area of 540,417 hectares, and is characterized by dense vegetation, extensive hydrography, and varied diversity of flora and fauna. It was created to be a protected area with sustainable use of natural resources. However, the expansion of illegal mining and deforestation are the main threats in this environmental conservation unit (ICMBio, 2010; Oliveira, 2015). In this sense, by applying the trained model, the predictions managed to identify areas affected by natural resource mining and airstrips with rudimentary characteristics. In this particular, by superimposing the results with the ANAC geospatial data, an airstrip was identified that does not coincide with the official records. Some examples are shown in Figure 41.

FIGURE 121 - CLASSIFICATION AND RECOGNITION OF AIRSTRIPS IN THE *FLORESTA NACIONAL DO AMANA*



(a) Examples of images in JPG format with their respective label and enumeration correctly classified as "landing strips" during the inference process; (b) Representation of the equivalent georeferenced images of the classified JPG images. The location maps represent cartographically the Amazon region in South America (green polygon), and the Floresta Nacional do Amana (red polygon) in the state of Para, Brazil. Source: (Author, 2022).

4.2.6 Dissemination

For this experiment, Figures 35, 39, 40, and 41 are considered the main dissemination products.

4.3 EXPERIMENT 3. GEOSPATIAL INTELLIGENCE AND NATURAL LANGUAGE PROCESSING FOR ENVIRONMENTAL SCANNING TO IDENTIFY COCAINE TRAFFICKING ROUTES AND TRENDS IN BRAZIL[9]

4.3.1 Direction/tasking

4.3.1.1 Task definition

This experiment aims to generate GEOINT products to identify cocaine trafficking routes and trends in Brazil based on environmental scanning using open-source GEOINT data related to individual cocaine seizures (ICS). It will not cover identifying other forms of organized crime or collecting data from other sources or other types of illicit substances. The final products are expected to prove the proposed methodology's potential to contribute to formulating strategies against DTOs.

4.3.1.2 Study area (Brazilian territory)

Brazil is a Federative Republic organized politically and administratively in federative units or *Unidade Federativa* in Portuguese (UF), comprised of 26 states, one Federal District, and 5,568 municipalities (IBGE, 2022). It is considered an important transit and destination country for cocaine produced in the Andean region (UNODC 2022b; DOS, 2022). Some studies suggest it is the largest cocaine market in South America (UNODC, 2021b) and probably the second largest cocaine consumer worldwide (DOS, 2022).

For decades, Brazil's geostrategic location has played a relevant role in the global illicit drug trade, representing one of the main obstacles to combating organized crime and drug trafficking in the country (CoE-Brazil, 2021). This is due to its continental geographical setting, extensive maritime coasts, and land borders with 10 South American countries, each with specific dynamics in drug trafficking: cultivation, production, transit, distribution, consumption, and destination (OAS, 2013). Among them the main producers of coca and cocaine worldwide (Colombia, Peru, and Bolivia) (UNODC, 2022b), and Paraguay, which stands out for international arms smuggling, cultivation, and export of marijuana to the Southern Cone (SENAD, 2021). (Table 29).

[9] This experiment is based on an article currently under peer review.

TABLE 29 - COUNTRIES BORDERING BRAZIL

No	Country	Extension of Border (km)	Dynamics of licit drug trafficking	Twin City
1	Bolivia	3,423.2	Cultivation – Production – Transit – Exporter	*Brasiléia, Corumbá, Cáceres, Guajará-Mirim, Epitaciolândia*
2	Peru	2,995.3	Cultivation – Production – Transit – Exporter	*Tabatinga, Assis Brasil, Santa Rosa do Purus*
3	Venezuela	2,199.0	Transit - Exporter	*Pacaraima*
4	Colombia	1,644.2	Cultivation – Production – Exporter	*Tabatinga*
5	Guyana	1,605.8	Transit	*Bonfim*
6	Paraguay	1,365.4	Cultivation – Production – Transit – Exporter – Consumption	*Foz do Iguaçu, Bela Vista, Coronel Sapucaia, Mundo Novo, Paranhos, Ponta Porã, Porto Murtinho, Guaíra*
7	Argentina	1,261.3	Transit – Consumption	*Foz do Iguaçu, Uruguaiana, Barracão, Santo Antônio do Sudoeste, Itaqui, Porto Mauá, Porto Xavier, São Borja, Dionísio Cerqueira*
8	Uruguay	1,068.1	Transit	*Uruguaiana, Aceguá, Barra do Quaraí, Chuí, Jaguarão, Quaraí, Santana do Livramento*
9	French Guiana	730.4	Transit	*Oiapoque*
10	Suriname	593.0	Transit	--

Twin Cities: Border municipalities with more than 2,000 inhabitants characterized by economic, cultural, and social integration with another municipality in a neighboring country.

Source: (Diário Oficial da União, 2021; UNODC, 2022b; DOS, 2022; ITAMARATY, 2022).

The porous borders, as well as its vast transport infrastructure system (road, air, river, and maritime), offer numerous opportunities to reduce the risk of interdiction and to establish routes that cross the territory through five regions (North, Northwest, Center-West, Southeast, South) (UNODC, 2003). Cocaine generally enters Brazil by air (small aircraft), land (cars, trucks, and buses), and river (boats), where it subsequently supplies the domestic market and is shipped abroad using containers and aircrafts. This dynamic makes Brazil the main transit country for cocaine from LAC to international markets, mainly Europe and West Africa (UNODC, 2022b; DOS, 2022; EMCDDA, 2022a).

A strategic study that evaluated the impacts of drug trafficking in Brazil (CoE-Brazil, 2021) highlights the existence of multiple routes that connect border regions with the country's main population centers and seaports, especially the ports of Paranaguá (Paraná), Itajaí (Santa Catarina), Salvador (Bahia) and Santos (São Paulo), noting that these infrastructures are used as platforms for cocaine exports to Europe, Africa, and Asia. The study also suggests that the territory continues to be a strategic region for cocaine transit, with a strong capacity of DTOs to adapt and diversify trafficking routes and modalities. This dynamic of cocaine trafficking in Brazil and its high profitability have driven the expansion of DTOs in all regions of the territory (das Neves & Ludwig, 2022; Stahlberg, 2022). The country has approximately 53 organized crime groups operating in the national territory (FBSP, 2022).

The *Comando Vermelho* (CV), *Primeiro Comando da Capital* (PCC), *Bonde dos 13, Ifara,* and *Famila do Norte* (FDN) stand out as the main criminal organizations involved in drug trafficking, posing a serious threat to the Brazilian state (INSIGHT CRIME, 2020c; SENAD, 2021; FBSP, 2022; das Neves & Ludwig, 2022; Stahlberg, 2022). In this sense, understanding the geographic patterns of drug trafficking routes in Brazil is essential for the effective allocation of resources and decision-making aimed at improving drug interdiction and prevention policies.

4.3.1.3 Resources

Table 30 describes the data, information, software, and hardware used to develop this experiment.

TABLE 30 - RESOURCES USED FOR DEVELOPING THE RESEARCH – EXPERIMENT 3

Software
– ArcGIS Pro Intelligence 3.0.1 / Environmental Systems Research Institute (ESRI) – Anaconda Distribution/Python 3.8 – gdeltdoc Python package – goose3 Python package – trrex Python package – Jupyter Notebook – Windows 10 Operating System
Hardware
– Processor: Intel® Core™ i7-8750H CPU @ 2.20GHz – GPU: NVIDIA GeForce GTX 1060 – RAM: 16 GB – SSD: 250 GB – HDD: 2TB
Geospatial Information
– Vectors of basic cartography of Brazil (boundaries of countries, states, municipalities, hydrography, roads, populated centers, ports, aerodrome, among others)
Open Source GEOINT Data
– News websites related to cocaine seizures

4.3.2 Collection

Data were collected as described in the Information Collection Plan (ICP). (Table 31).

TABLE 31 - INFORMATION COLLECTION PLAN - EXPERIMENT 3

Geospatial Information		
Information/Requirement	**Description**	**Source of Information**
Vectors of basic cartography of Brazil	Georeferenced vectors (SIRGAS 2000) in shapefile format: boundaries of countries, states, municipalities, hydrography, roads, populated centers, ports, and airports, among others.	Brazilian Institute of Geography and Statistics (IBGE) (IBGE, 2022) National Transportation Infrastructure Department (DNIT) (DNIT, 2022)
Open Source GEOINT Data		
Information/Requirement	**Description**	**Source of Information**
News websites from the following domains: https://www.gov.br/pt-br https://noticias.r7.com/ https://g1.globo.com/	The gov.br domain was selected considering that the information corresponds to sources validated by the Brazilian government. The domains noticias.r7.com and g1.globo.com were selected based on a study conducted by the Reuter Institute and Oxford University on public trust in news. The results indicated that noticias.r7.com is the media with the highest confidence level in Brazil (68%), followed by O GLOBO with a 59% confidence index.	Brazilian Government (GOV.BR, 2021) Record News (Record News, 2021) O GLOBO (O GLOBO, 2021a) Reuters Institute (Reuters Institute, 2021)

4.3.2.1 URL collection

In this step, research was performed on the internet to locate URLs of news related to ICS in Brazil during 2021.

- The domain URLs https://www.gov.br/pt-br were manually selected using the built-in filtering tools provided by the website. This practice consisted of filtering content using the word "cocaine" between 01/01/2021 and 12/31/2021. A total of 1,458 URLs were obtained.
- The URLs of the domains https://noticias.r7.com/ and https://g1.globo.com/ were selected using jupyter Notebook, the Python programming language and the gdeltdoc Python package (Whitehead & Kleine, 2022). This is an application to obtain data from the Global Database of Events, Language, and Ton (GDELT Project) (Leetaru, 2013). The GDELT project monitors the web, print, and broadcast media in over 100 languages in all countries of the world. The database is 100% free and allows data to be downloaded for research. Its archives are updated every 15 minutes. To obtain the URLs, the filtering module provided by the gdeltdoc Python package was configured

according to the following parameters: a) keyword (cocaine, police, seizure); b) *start_date* (2021-01-01); c) *end_data* (2021-12-31); d) country (Brazil); e) domain (noticias.r7.com, g1.globo.com) and d) theme (DRUG_TRADE). We obtained 1,008 URLs for the domain https://noticias.r7.com/ and 2,009 URLs for https://g1.globo.com/

All the resulting URLs for the three domains were stored as a txt file named URL_COCAINE. There was no attempt to extract specific information at this stage. In total, 4,475 URLs of news related to ICS in Brazil during 2021 were collected.

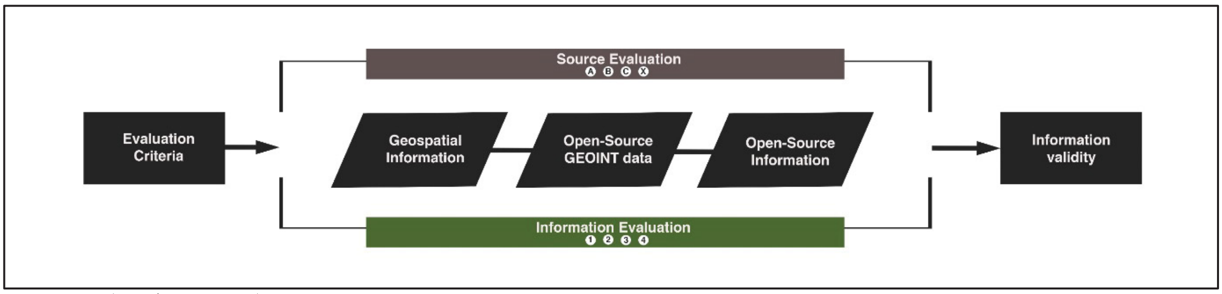
4.3.2.2 Data collection

Data were collected with web scraping techniques using the Python package goose3 (Mitchell, 2018; Grangier, 2022). The objective of this tool is to extract text, images, videos, among other metadata, from any news website from a URL. This process allowed us to collect the information automatically from the URLs in the URL_COCAINE file and convert them into structured text. The parameters were configured as described in the documentation (https://github.com/goose3/goose3), allowing the generation of a dataset with 4,475 records with the following variables: TEXT (the content of the main body of the article), TITLE (title of the article), DATE (date of publication), SOURCE (domain) and URL (access URL). This corpus was exported in a csv file named ARTICLE_EXTRACTOR_COCAINE.

4.3.3 Evaluation

The workflow applied to evaluate the sources and information used in this investigation is shown in Figure 42.

FIGURE 124 - WORKFLOW FOR EVALUATING SOURCES AND INFORMATION – EXPERIMENT 3



Source: (Author, 2022).

Based on the criteria described in section 3.3, the corresponding evaluation was assigned to each piece of the ICP.

4.3.3.1 Geospatial information

- Source: IBGE. Information: Basic mapping vectors of Brazil. **Evaluation: A1**. The source and information are official. Approved by the National Government. They are publicly available on the source's website.
- Source: DNIT. Information: Basic mapping vectors of Brazil. **Evaluation: A1**. The source and information are official. Approved by the National Government. They are publicly available on the source's website.

4.3.3.2 Open-source GEOINT data

- Source: Reuters Institute. Information: Reuter's Institute and Oxford University study public trust in news by source. **Evaluation: A2**. The Source is an internationally recognized research center of the University of Oxford. It conducts academic and professional research on issues affecting the media worldwide. It has proven to be consistently reliable and frequently generates information on trends in journalism and the media based on a robust scientific methodology. Publications are publicly available on the source's website.
- Source: Brazilian Government. Information: News and newspaper website of the https://www.gov.br/pt-br domain. **Evaluation: A2**. The source is a unified project of the digital channels of the Federal Government of Brazil. It integrates services and information from all areas and institutions of the government. It has demonstrated reliability and competence. It has an extensive history of publications related to FSPB's drug interdiction activities. Reports on IDS always provide the reference and contact of the primary source.
- Source: Record News. Information: News and newspaper website of the https://noticias.r7.com/ domain. **Evaluation: B2**. The source has proven to be reliable in most cases. A study by the Reuter Institute shows that it is the most trusted media outlet in Brazil (68%). It frequently publishes news about the FSPB's drug interdiction activities. Other sources of information can corroborate the information it publishes.
- Source: O GLOBO. Information: News and newspaper website of the https://g1.globo.com/ domain. **Evaluation: B2**. The source has proven to be reliable in most cases. Based on a study by the Reuter Institute, the media outlet has a 59% trust rating in Brazil. It frequently publishes news about the FSPB's drug interdiction activities. Other sources of information can corroborate the information it publishes.

4.3.3.3 Open-source information

- Source: Bibliographic references of the article. Information: Other publications. **Evaluation: A1, A2, or B2**. The references in this article are from reliable sources and open sources that have proven to be reliable in most cases. The information may or may not be personally known to the source but is corroborated by other reliable sources of information. The information is coherent, makes logical sense, and is based on scientific evidence in most cases. Access to this information can be consulted in the references of this research.

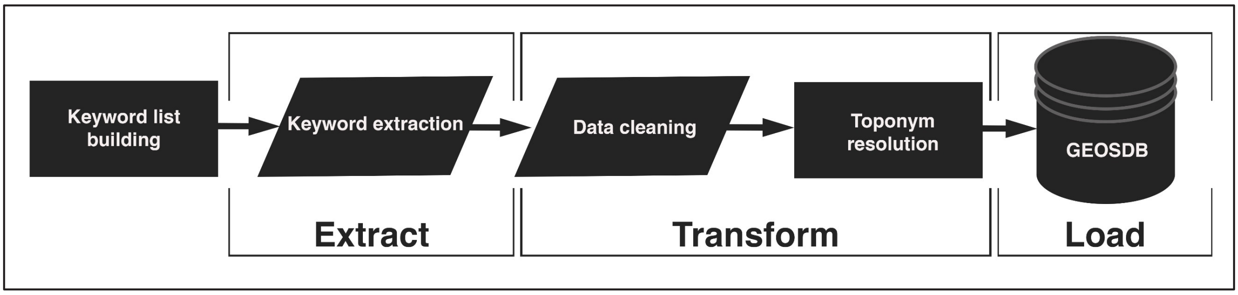
The competence of the sources proved to be consistently reliable. They frequently publish information on IDS conducted by FSPB and in other countries. In most cases, the wording and photographs of the occurrences cite the original source (FSPB making the seizure). We did not identify biased or sensationalist content. In the case of Record News and O GLOBO sources, in addition to considering the trust indexes of the study conducted by the Reuter Institute (Reuters Institute, 2021), we randomly selected 50 articles to corroborate the information based on other news websites.

4.3.4 Collation/processing

A natural language processing (NLP) algorithm was developed for extracting information related to cocaine trafficking from the dataset ARTICLE_EXTRACTOR_COCAINE. Due to the high costs of manual labeling, and because drug trafficking modalities, scenarios, geographic locations, quantities seized, criminal actors, among other variables, are framed in countless possibilities, and because the data generated do not allow to guarantee the balance in the number of training samples, we adopted an approach like the one applied by the European drug monitoring system (EMCDDA, 2019). This is based on regular expression rules for extracting information related to IDS.

This approach has shown consistent and favorable results in recognition of entities related to geographic locations (toponyms) on news websites (Lieberman, 2011), which is fundamental to the objectives of this research. Figure 43 specifies the workflow for the continuity of data processing. A list of keywords was created from domain knowledge and official sources. Then the dataset ARTICLE_EXTRACTOR_COCAINE undergoes an "Extract, Transform, Load" process for subsequent analysis.

FIGURE 127 - WORKFLOW OF THE COLLATION/PROCESSING STAGE – EXPERIMENT 3



Source: (Author, 2022).

4.3.4.1 Keyword list building

Twenty variables were defined, considering domain knowledge and IDS variables used by the UNODC (UNODC, 2022k) to evaluate international drug trafficking trends and patterns. For each variable, a list of keywords was generated combining different writing criteria: capitalization, lowercase, accents, acronyms, grammatical gender, and punctuation marks, among others, as displayed in Table 32. The lists were made manually using the Microsoft Excel spreadsheet software. Once the lists were generated, each one was copied into a TXT file, obtaining twenty keyword lists.

TABLE 32 - KEYWORD LISTS

No	Keyword lists/Variables	Total keywords	Description	Examples (In Portuguese)	Source
1	Security Forces	93	FSPB Names.	*Polícia Federal, PRF, PM, Receita Federal, polícia civil*	(Congresso Nacional, 1988)
2	Drug Interdiction	39	Activities conducted to divert, disrupt, disrupt, delay, intercept, interdict, board, detain, or destroy, under lawful authority, drug trafficking (US ARMED FORCES, 2016).	*Apreensão, flagrante, Operação Conjunta, abordagem policial*	Domain knowledge
3	UF	81	UF names and acronyms (*toponym).*	*Distrito Federal, Paraná, SP, mato-grosso, RS*	(IBGE, 2022)
4	Municipality	11,138	Names of municipalities (*toponym).*	*Curitiba, Ponta Porã, Tabatinga, Guaíra, Foz do Iguaçu*	(IBGE, 2022)
5	Drugs Mentioned	76	Main illicit drugs and consumer products in Brazil.	*Cocaína, maconha, ecstasy, lança-perfume, escama de peixe*	Domain knowledge

6	Cocaine Mentioned	13	Main cocaine products in Brazil.	*cocaína, Pasta Base, pasta base de cocaína, crack, cloridrato-de-cocaína*	Domain knowledge
7	Installation-Transportation	149	Place where the seizure was made. Means of transport used.	*Rodovia, favela, aeroporto, porto, Carro, caminhão*	Domain knowledge
8	Hiding Place	134	Place where the drug was hidden.	*Bagagem, Pneus, ao corpo, encomenda, tapete, Contêiner, tanque-de-combustível*	Domain knowledge
9	Packaging	84	Types of packaging.	*Tijolo, tablete, pedra. Barra, pino, trouxinhas*	Domain knowledge
10	Trafficker	75	Gender or nouns describing those involved.	*Homem, mulheres, rapaz, idoso, motorists, Caminhoneiro, piloto, garimpeiro, Traficante*	Domain knowledge
11	Trafficker Age	91	Age ranged from 10 to 100 years.	*de 18 anos, de 40 anos, de 12 anos*	Domain knowledge
12	Prejudice	2	Variable to identify the records that report the economic impact generated to the DTOs.	*prejuízo ao narcotráfico prejuízo*	Domain knowledge
13	Country Mentioned	199	Countries	*Australia, Colômbia, Estados Unidos, Venezuela, Alemanha, Bolívia, Paraguai*	(IBGE, 2022)
14	Continent Mentioned	17	Continents	*Europa, América do Norte, africano, América Central, Ásia*	(IBGE, 2022)
15	DTOs	196	Main DTOs in Brazil	*Primeiro Comando da Capital, Comando Vermelho, PCC, Terceiro Comando Puro, FDN*	Domain knowledge (FBSP, 2018; SENAD, 2021)
16	Cocaine	19,740,192	Combinations were created between the ranges 0.01 – 1,000 on the quantity of cocaine in weight units: *kg, Kg, KG, g, quilo*, and *quilos*. And combinations between 0 – 10,000 using packaging as a reference measurement.	*23,2 kg de cocaína 999,94 quilos de cocaína 326,54 g de cocaína 0,07 gramas de cocaína 250 pinos de cocaína, 30 tijolos de cocaína, 10 papelote, 2 trouxinhas, 7 tabletes*	Domain knowledge
17	Cocaine hydrochloride	19,740,192		*861,5 kg de cloridrato de cocaína 0,26 gramas de cloridrato de cocaína 500 quilos de cloridrato de cocaína*	Domain knowledge
18	PBC	19,740,192		*543,09 kg de pasta base de cocaína; 783,13 g de pasta base*	Domain knowledge

19	Crack	19,740,192		*13 kg de crack* *10 quilos de crack* *790,12 gramas de crack* *550 pedras de crack*	Domain knowledge
20	Drugs - Narcotics	19,200,192		*10 kg de drogas, 700 quilos de estupefacientes*	Domain knowledge

4.3.4.2 Keyword extraction

This phase allows us to identify and extract entities of interest for our domain, such as geographic names (toponyms), types of drugs, and quantities seized, among others. The NLP algorithm was developed using the Python package trrex (Mesejo, 2021). This tool contains a function to identify patterns in text fragments through rule-based information extraction methods, such as regular expressions. As described in the documentation (https://github.com/mesejo/trex), we established a set of rules based on regular expressions using the defined keyword lists. Subsequently, we implemented the proposed algorithm to the ARTICLE_EXTRACTOR_COCAINE dataset and efficiently extracted the keywords of interest corresponding to the twenty established variables. This process took approximately 60 minutes and generated a structured dataset with 4,475 records.

4.3.4.3 Data cleaning

Using the tools of the Anaconda Python distribution (https://www.anaconda.com/products/distribution), an interactive data cleansing process was developed, which ensured the following set of rules:

- remove duplicate titles and URLs;
- remove records with no content;
- replace acronyms with the corresponding names, e.g., "*SP*" should be replaced by "*São Paulo*";
- replace and correct toponyms without accent;
- remove white spaces, tabs, duplicates, and punctuation marks;
- remove all characters such as parenthesis, commas, and quotation marks;
- filter the data to keep only records of cocaine seizures and not of other types of drugs;
- unify the format of dates;

- remove the alphabetical characters of the variables “Cocaine,” “Cocaine hydrochloride,” “PBC,” and “Crack” in order to keep the numerical value corresponding to the quantity seized;
- assign to each record the corresponding code of the sources and information evaluation process.

Subsequently, a manual review was conducted to detect and correct any other inconsistent record and to avoid double counting any seizure. The results generated a database with 2,559 records, 18 context variables, and 2 toponym variables related to the ICS.

4.3.4.4 Toponym resolution

At this stage, the goal is geo-locate the identified geographic names (Hu, 2018). This procedure is essential to spatialize the text in geographic space since it allows mapping and automatically generating geospatial context to the text statements (Yuan, 2021). It consists of matching the place names in a text with their corresponding spatial references on the surface of the Earth (Hill, 2006; Leidner, 2007; Yuan, 2021). Its importance lies in that it allows for identifying spatial footprints (e.g., the interaction of DTOs in the geographical environment) and recording them as geographical coordinates (such as latitude and longitude) (Hu, 2018; Li et al., 2012). In this sense, ArcGIS Pro geoprocessing tools were used to generate the geographic coordinates of each ICS from the toponyms recognized and stored in the variables “UF” and “Municipality.” This method is commonly used in crime analysis (Ratcliffe, 2004; Santos, 2022) as it allows employing GIScience and geospatial reasoning in the geographic analysis of crime. This made it possible to complement the records with geospatial attributes and visualize them in a cartographic framework. (Figure 44).

FIGURE 130 - SPATIAL DISTRIBUTION AND CARTOGRAPHIC REPRESENTATION OF INDIVIDUAL COCAINE SEIZURE

Source: (Author, 2022).

4.3.4.5 GEOINT seizure database

Finally, a database was generated, called GEOSDB (GEOINT seizure database), with 39 variables and 2,559 records with geospatial attributes that have quantitative and qualitative data related to the ICS in Brazil - 2021. (Table 33).

TABLE 33 - GEOINT SEIZURE DATABASE VARIABLES

No	Variables	Description
1	Title	News article title
2	Security Forces	FSPB
3	Drug Interdiction	Interdiction activity in which the ICS was performed
4	Day	Day of publication
5	Month	Month of publication
6	Year	Year of publication
7	Federative Units	UF, where ICS was performed
8	Municipality	Municipality where the ICS was performed
9	X	Longitude (SIRGAS 2000)
10	Y	Latitude (SIRGAS 2000)
11	Drugs Mentioned	Drugs mentioned in the ICS
12	Cocaine Mentioned	Cocaine products mentioned in the ICS
13	Installation-Transportation	Place of ICS and means of transport used
14	Hiding Place	Place where the drug was concealed
15	Packaging	Types of packaging
16	Trafficker	Gender or nouns of those involved
17	Trafficker Age	Age of those involved
18	Prejudice	Variable to identify the financial impact
19	Country Mentioned	Countries mentioned in the ICS
20	Continent Mentioned	Continents mentioned in the ICS
21	DTOs	DTOs mentioned in the ICS
22	Source	Source of information (domain)
23	Evaluation	Evaluation code Source-Information
24	Cocaine_kg_1	Quantity in kilograms
25	Cocaine_kg_2	Quantity in kilograms In some records, two ICS are reported
26	Cocaine_Pinos	Quantity of *pinos*
27	Cocaine_Papelotes	Number of *papelotes*
28	Cocaine_Pacotes	Quantity of *pacotes*
29	Cocaine_Porções	Quantity of *porções*
30	Cocaine_Trouxinhas	Quantity of *trouxinhas*
31	Cocaine_Tijolos_Tabletes	Quantity of *tijolos/tabletes*
32	Cocaine Hydrochloride-kg	Quantity in kilograms
33	Cocaine_hydrochloride_Tijolos_Tabletes	Quantity of *tijolos/tabletes*
34	PBC_kg	Quantity in kilograms
35	PBC_Tijolos_Tabletes	Quantity of *tijolos/tabletes*
36	Crack_kg	Quantity in kilograms
37	Crack_Pedras	Quantity of *pedras*

38	Drugs_Narcotics_kg	Quantity in kilograms reported as drugs or narcotic drugs
39	URL	Information source (domain)

Source: (Author, 2022).

4.3.5 Geospatial intelligence analysis

In this experiment, geospatial analysis methods and cartographic techniques are applied to process GEOSDB data and produce geospatial intelligence, taking into account the following criteria:

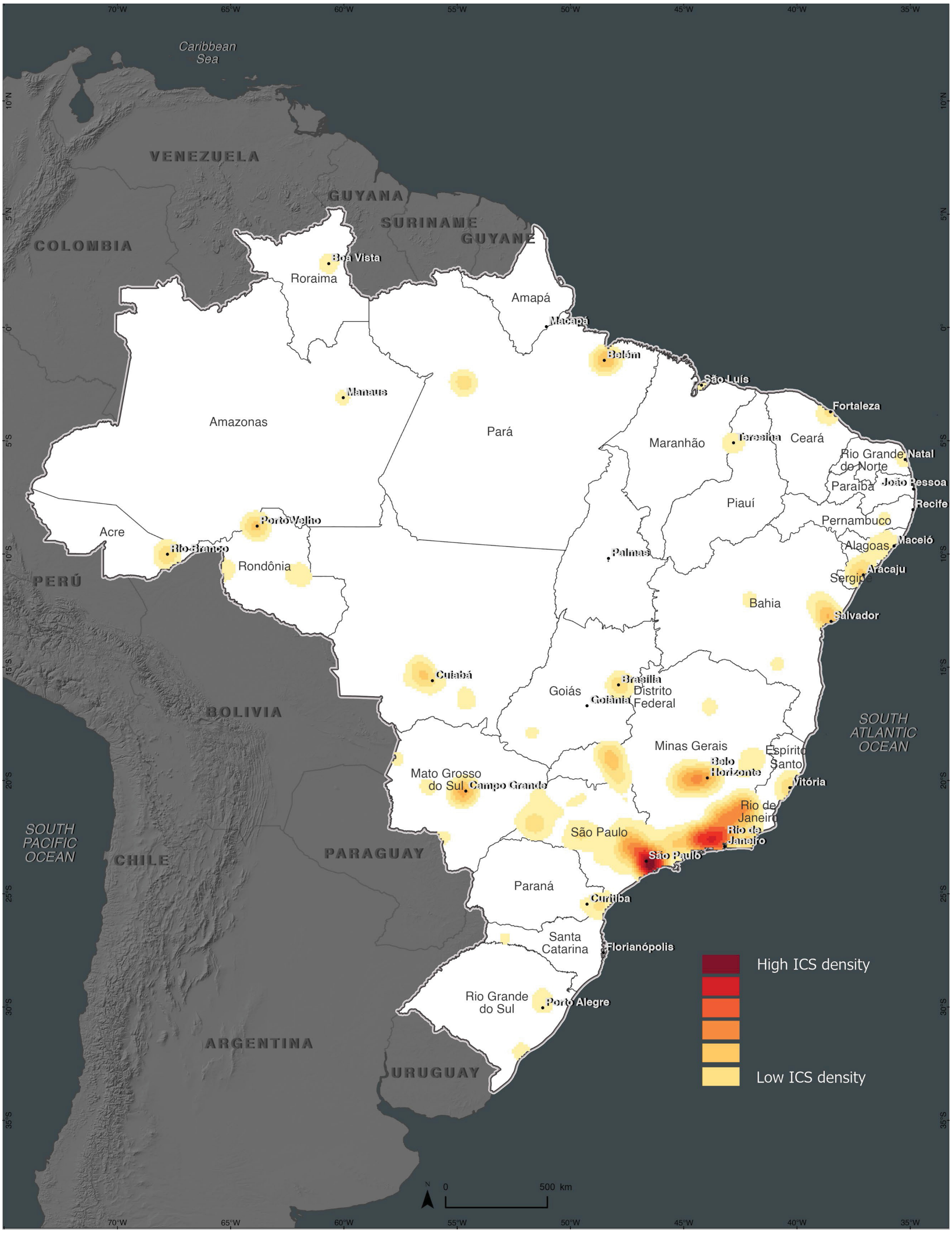
- As described in the conceptual basis described in the literature review, different cocaine consumption products can be presented in two chemical forms (base or salt), each with different particularities in terms of routes of administration, purity, cutting agents, price, names, and packaging, among others. For the analysis, we will use “cocaine” to refer to all types of cocaine registered in the GEOSDB.
- UNODC establishes a threshold of ≥ 100 grams to be considered a significant amount of cocaine seized (UNODC, 2022k). However, given that not all news reports provide this information, and that the methodology allows for the extraction of data on seizures below that threshold and data using packages as the unit of reference measure, all records were considered for the analyses.
- It discarded 38 records corresponding to incineration activities and general balances of the results. These were evaluated individually, and it was identified that these types of occurrences do not refer to ICS.
- The following questions were addressed to produce geospatial intelligence: (a) Where are the cocaine trafficking hotspots in Brazil? (b) What are the trends in the number of ICS? (c) Where are ICS with similar characteristics spatially clustered? (d) What are the places with significant ICS? (e) What are the countries involved in the dynamics of cocaine trafficking in Brazil? (f) What are the main routes and trends identified in the geographical space? Why?

The answers to these questions are of great interest to stakeholders and researchers, as they allow targeting specific geographic locations or trends to improve interdiction operations, decision-making, and resource allocation.

4.3.5.1 Kernel density estimation

The technique was executed using the KDE tool of ArcGIS Pro. This implements the kernel function based on Silverman's rule-of-thumb algorithm to calculate a predetermined bandwidth based on the standard distance of points (ESRI, 2021b; Silverman, 1986). (Figure 45).

FIGURE 133 - DYNAMICS OF INDIVIDUAL COCAINE SEIZURE HOT SPOTS



Source: (Author, 2022).

This approach avoids the "ring around the points" phenomenon that often occurs with sparse datasets is resistant to spatial outliers (ESRI, 2021b) and has been shown to perform efficiently compared to other methods (Heidenreich et al., 2013; Kim et al., 2020).

The distribution of the ICS kernel density estimated with KDE revealed where Brazil's main cocaine trafficking hotspots are located. It is observed that the southeast region of the country, specifically the UF of São Paulo and Rio de Janeiro, are the areas with the highest densities, followed by the cities of Belo Horizonte in Minas Gerais and Campo Grande in Mato Grosso do Sul. It is also observed that average densities are concentrated mainly in the capital cities bordering the Atlantic Ocean and the border strip with neighboring countries, with the cities of Aracaju, Belem, Boa Vista, Cuiabá, Curitiba, Fortaleza, Maceió, Manaus, Natal, Porto Alegre, Porto Velho, Rio Branco, Salvador, and Vitória standing out. These spatial patterns infer that these territories offer opportunities for DTOs to traffic cocaine and suggest that this is where the FSPB can focus interdiction and monitoring efforts.

4.3.5.2 Summarize individual cocaine seizure counts

The technique was used to identify the number of ICS in each UF and the impact on major highways and roads. Figures 46 and 47. Figure 46 shows the number of ICS per UF and reinforces the evidence of the patterns revealed in the KDE analysis, highlighting São Paulo, Minas Gerais, Rio de Janeiro, and Mato Grosso do Sul as the territories with the highest number of seizures. Figure 47 applied the technique using the vectors of the country's main highways (DNIT, 2022). Each geospatial object representing an ICS was configured with a search radius of 1 km, considering the average distance of the traffic modality known as *la Mosca* in Spanish, described in Table 4.

In Brazil, the nomenclature of highways is defined by the acronym BR, which means that the highway is federal, followed by three numbers, which identify the category and position concerning the Federal Capital (Brasília) and the country's boundaries (Ministério da Infraestrutura, 2020). Concerning the road network, BR-262 (MS), BR-356 (MG), BR-267 (MG), BR-050 (SP), BR-364 (RO), BR-262 (MG), BR-421 (RO), BR-494 (RJ), BR-070 (MT), BR-116 (SP), BR-163 (MT), BR-277 (PR), BR- 317 (AC), are visualized as road sections with high ICS numbers. Other road sections such as BR- 230 (PA), BR-116 (RS), BR-010 (PA), BR-158 (RS), BR-307 (AC), BR-324 (BA), and BR-287 (RS) present similar trends, as displayed in Table 34.

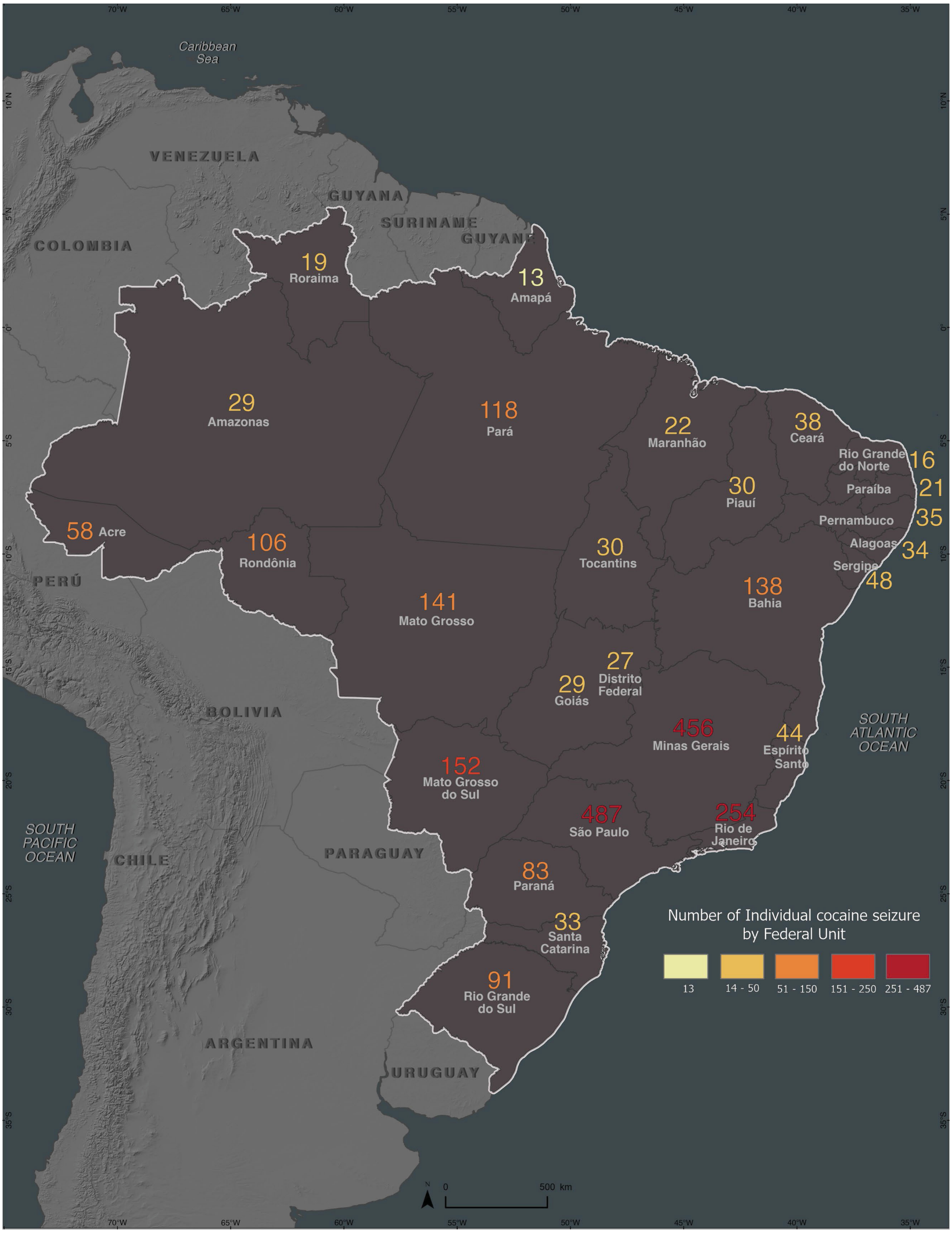
TABLE 34 - NUMBER OF ICS ON MAIN HIGHWAYS. (1-KM RADIUS)

N°	Highway	UF	Acronym	Count
1	BR-262	Mato Grosso do Sul	MS	36
2	BR-356	Minas Gerais	MG	36
3	BR-267	Minas Gerais	MG	36
4	BR-050	São Paulo	SP	30
5	BR-364	Rondônia	RO	29
6	BR-262	Minas Gerais	MG	27
7	BR-421	Rondônia	RO	23
8	BR-494	Rio de Janeiro	RJ	23
9	BR-070	Mato Grosso	MT	19
10	BR-116	São Paulo	SP	17
11	BR-163	Mato Grosso	MT	16
12	BR-277	Paraná	PR	13
13	BR-317	Acre	AC	13
14	BR-230	Pará	PA	12
15	BR-116	Rio Grande do Sul	RS	11
16	BR-010	Pará	PA	9
17	BR-158	Rio Grande do Sul	RS	8
18	BR-307	Acre	AC	7
19	BR-324	Bahia	BA	6
20	BR-287	Rio Grande do Sul	RS	6

Source: (Author, 2022).

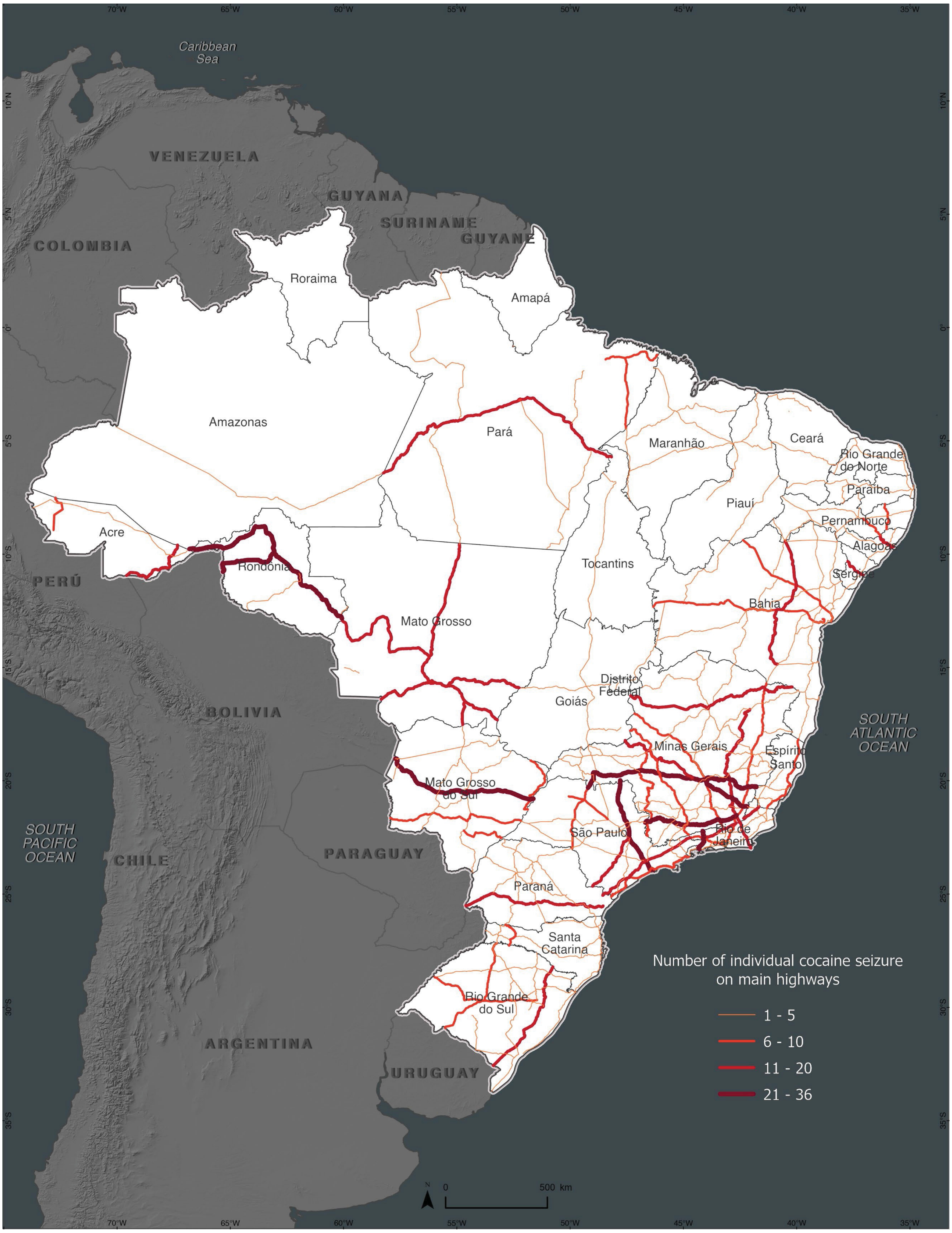
When the results obtained in Figures 46 and 47 are evaluated as a whole, a pattern emerges that reflects the impact of DTOs in the states bordering coca/cocaine and marijuana-producing countries (Acre, Rondônia, Mato Grosso, Mato Grosso do Sul, Paraná, Santa Catarina, and Rio Grande do Sul). Probably to use these territories as a route of entry and transit of these illicit substances to the country's interior. Similar behavior is observed in Pernambuco, Alagoas, Sergipe, Bahia, Minas Gerais, São Paulo, and Rio de Janeiro, geographical areas that, due to their proximity to the Atlantic Ocean and port infrastructure, are threatened by drug trafficking to be used as platforms for destinations to international markets.

FIGURE 136 - NUMBER OF ICS BY FEDERATION UNIT



Source: (Author, 2022).

FIGURE 139 - NUMBER OF ICS ON MAJOR ROADS



Each geospatial object representing an ICS has a defined search radius of 1 km. The thicker the strokes, the higher the concentration of ICS on the road segment. Source: (Author, 2022).

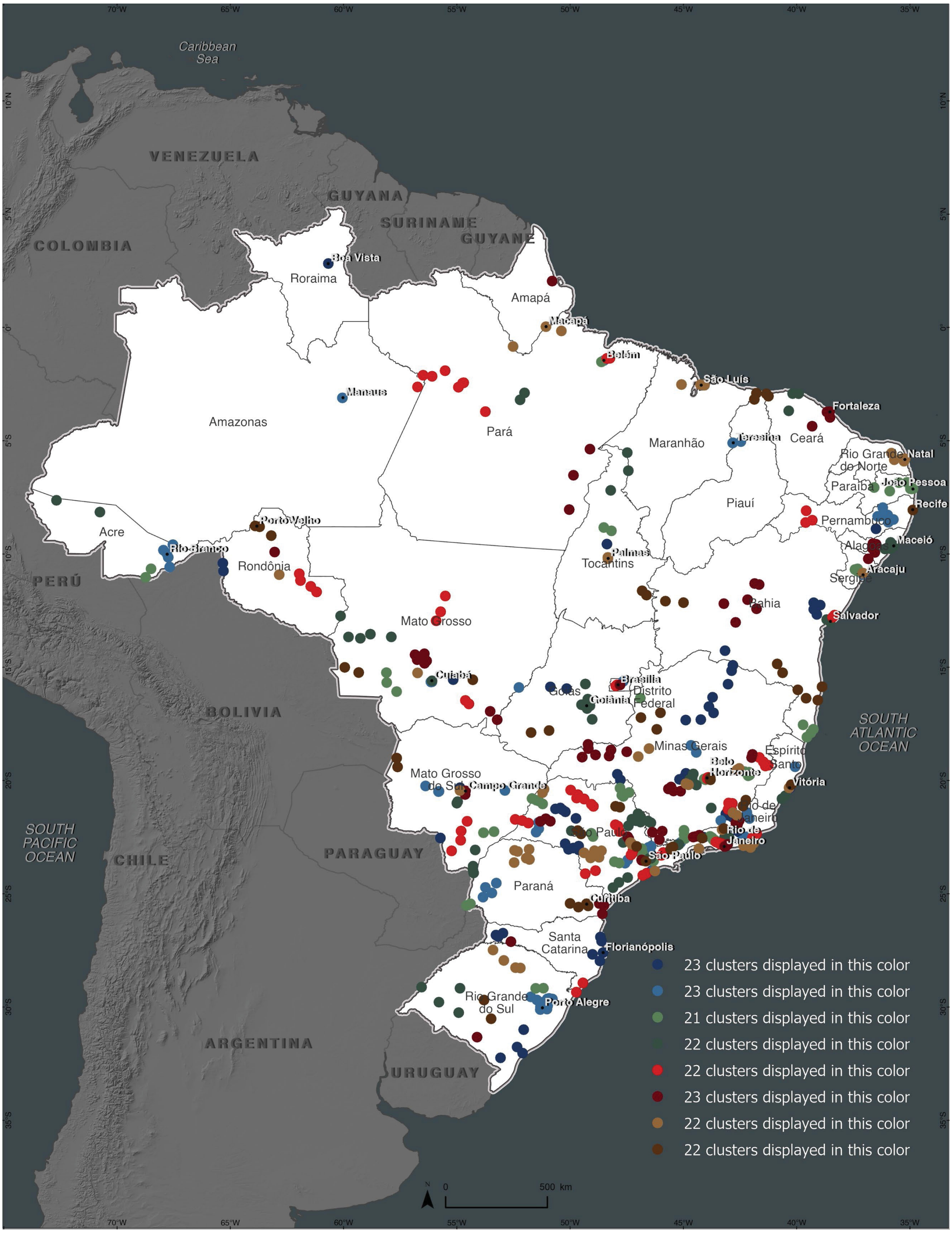
4.3.5.3 HDBSCAN

Due to the uneven distribution of ICS, these events can be considered to have an inherently geographic characteristic, i.e., they occur in a place with a specific geographic location (Chainey & Ratcliffe, 2005), some locations may offer more significant opportunities than others for drug trafficking (Wortley & Townsley, 2016), and the selection of routes is generally a rational and planned choice that considers the geographic context to reduce drug interdiction risks (Chainey, 2021; Labrousse, 2011).

As shown in Figure 48, HDBSCAN was applied from GEOSDB data. The algorithm's efficiency depends on the main parameter (minimum features per cluster - m_{fpc}) that determines the minimum number of points that will be considered a meaningful cluster. Clusters with fewer points than the m_{fpc} will be considered noise (McInnes, 2017; ESRI, 2021a). A 5 points m_{fpc} was selected, establishing as a criterion that the occurrence of five ICS concentrated in a geographic region is a pattern that suggests an alert to law enforcement agencies.

The results revealed interesting patterns, without the application of the algorithm, which would have been impossible to identify. It is possible to visualize how the clusters create patterns that allow the design of the routes. For example, it is observed how the clusters create linear patterns, which start in the border states with cocaine-producing countries and cross the territory to diversify the route towards the country's interior and the states with a sea coast. There are also a more significant number of critical clusters located in the southeast and south of the country, which illustrates the presence of more significant trafficking activity and are focal points that require more attention.

FIGURE 142 - SPATIAL DISTRIBUTIONS OF CLUSTERS DETECTED BY THE HDBSCAN ALGORITHM TO IDENTIFY ICS CONCENTRATIONS



The noise was discarded in the mapping representation. Source: (Author, 2022).

4.3.5.4 Proportional symbol maps

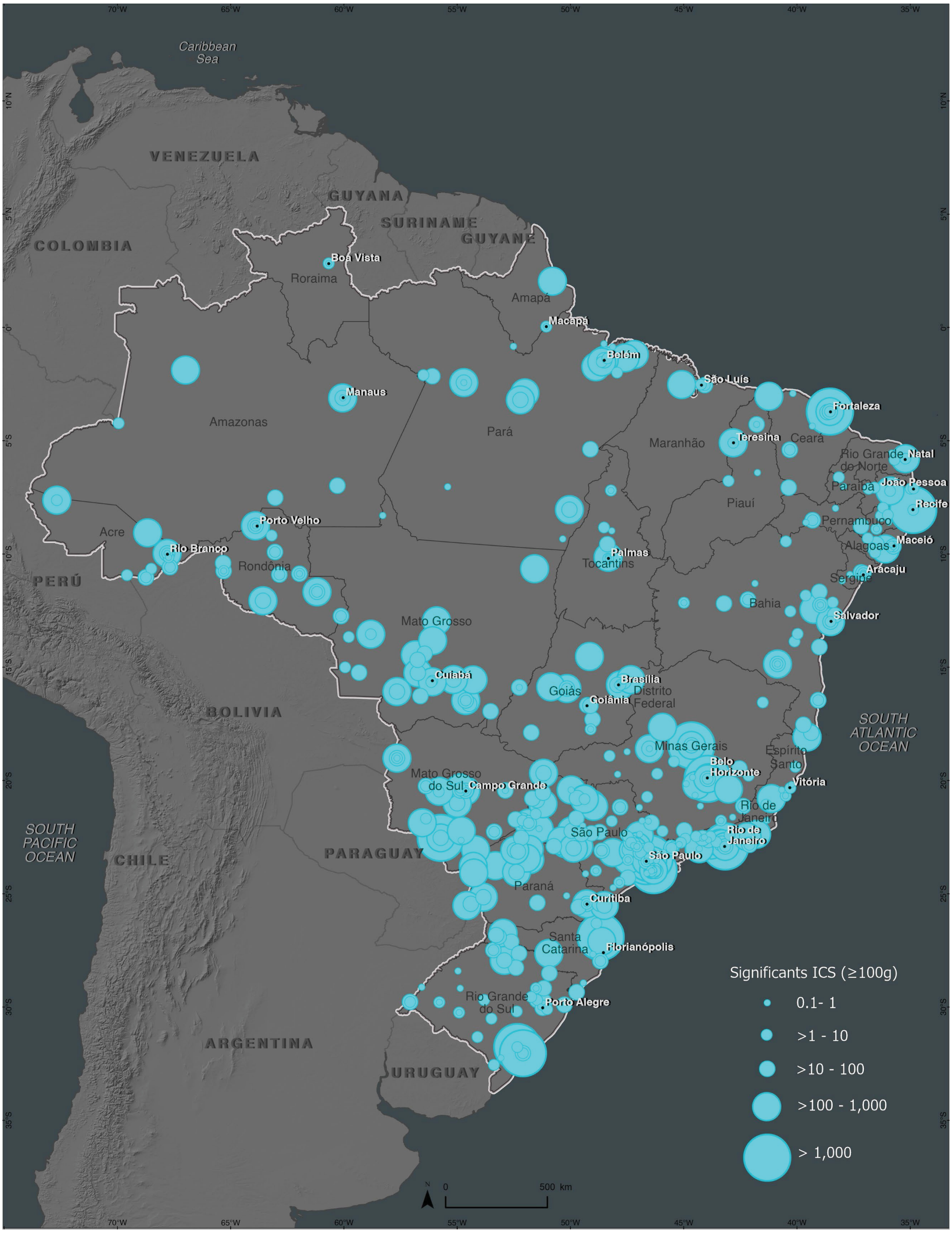
Although the representativeness of the data on the amounts of kg of cocaine (PBC, hydrochloride, and crack) is not found in all the records of the GEOSDB, those with this information are considered valuable for the analysis. In this sense, from the records with quantitative values in the Cocaine_kg_1 variable, a map of proportional symbols was generated to visualize the places with significant ICS (≥ 100 grams) and make numerical visual comparisons between symbols and identify possible patterns and trends. (Figure 49).

The symbols show how ICS concentrations create specific patterns in each state, mainly in the country's Northeast, Southeast, and South regions. In the North region, dispersed seizures are observed, concentrated mainly in the cities of Boa Vista, Manaus, Belem, Palmas, Rio Branco, Porto Velho, Tabatinga, Altamira, and Japurá. As for the Northeast region, there are ICS with different quantities, highlighting a seizure of 2,200 kg, 270 km off the coast of Recife (Pernambuco) (O GLOBO, 2021e).

In the Central-West and Southeast regions, Mato Grosso, Mato Grosso do Sul, São Paulo, Rio Janeiro, Minas Gerais, and Espírito Santo states, the visualization of the symbols reflects the occurrence of seizures in larger quantities. This geographical pattern evidences the Caipira route or Rota Caipira in Portuguese (de Abreu, 2018), one of the main international drug trafficking routes in Brazil that, due to its geostrategic characteristics, allows establishing clandestine routes and tracks, which connect the cocaine production areas of neighboring countries, with the country's drug consumption centers and port infrastructure, to be used as a destination platform towards European and African markets. Critical overlaps of symbols are visualized in Rio Janeiro and São Paulo, highlighting seizures of 5,000 kg (PF, 2021a), 1,854 kg, and 1,788 kg, respectively (O GLOBO, 2021c, d).

In the southern region, seizures are clustered in Foz do Iguaçu and Guaíra (Paraná - border with Paraguay), generating several concentrations between Curitiba and Florianópolis. A symbol representing 2,800 kg stands out in Itajaí, north coast of Santa Catarina, which was a seizure destined for Africa (O GLOBO, 2021b). Regarding Rio Grande do Sul, the spatial pattern highlights 2,700 kg in Pelotas, considered one of the largest cocaine seizures made in Rio Grande do Sul (PF, 2021b), and 1,116 kg in the port of Rio Grande (RF, 2021a). In general, the dynamics reflected in the symbols suggest that the geographic characteristics of the state (border region and proximity to the Atlantic Ocean) generate interest for DTOs to use the territory as a platform for international cocaine trafficking. This behavior coincides with previous studies that evidenced the existence of a new route or the increase in its use as an alternative to avoid interdiction efforts carried out in the maritime ports of the Northeast and Southeast of the country (CoE-Brazil, 2021).

FIGURE 145 - SPATIAL DISTRIBUTION OF SIGNIFICANT ICS (≥100G)



Source: (Author, 2022).

As described above, not all website reports provide information on the weight in mass units of the cocaine seized. However, the NLP techniques made it possible to extract data based on the number of units according to the type of packaging. Table 35 shows examples of how counting the containers in which cocaine is marketed can also add value and generate geospatial intelligence to identify possible trends.

TABLE 35 - NUMBER OF SEIZED UNITS BY THE TYPE OF PACKAGING

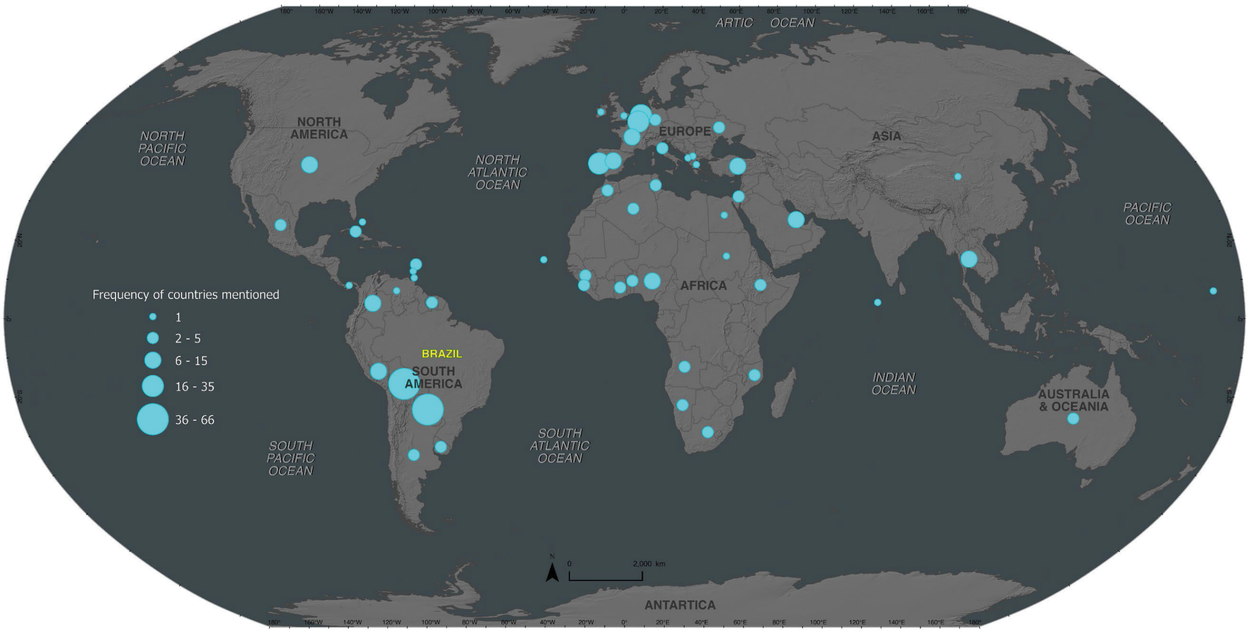
Cocaine type	Min	UF	Municipality	Max	UF	Municipality
Cocaine - Pinos	7	Minas Gerais	Juiz de Fora	6,605	Minas Gerais	Belo Horizonte
Cocaine -Papelote	4	Pará	Santarém	6,280	Minas Gerais	São João Nepomuceno
Cocaine - Pacotes	5	Pará	Santarém	245	Minas Gerais	Rio Novo
Cocaine - Porções	1	Minas Gerais	Juiz de Fora	5,250	São Paulo	Guarujá
Cocaine - Trouxinhas	10	Rio de Janeiro	Miguel Pereira	93	Acre	Rio Branco
Cocaine – Tijolos - Tablete	1	São Paulo	Guarulhos	1,200	Ceará	Fortaleza
Cocaine - hydrochloride – Tijolos -Tablete	3	São Paulo	Lavrinhas	548	Mato Grosso	Alto Garças
PBC – Tijolos - Tablete	2	São Paulo	Santa Isabel	440	Minas Gerais	Itapagipe
Crack - Pedras	11	Minas Gerais	Araguari	2,982	Rio de Janeiro	Araruama

Source: (Author, 2022).

Another example of the use of proportional symbol maps to examine the geographic manifestations and patterns of DTOs is shown in Figure 50. In this map, the variable “Country Mentioned” was used to visualize in a geographical context the countries that are frequently mentioned in the GEOSDB. We identified 53 countries in which reference was made to three main aspects: a) destination of the drug, b) the origin of the drug, and c) nationality of the traffickers.

The spatial pattern revealed by the symbols suggests that Bolivia (66), Paraguay (37), and the Netherlands (22) are the countries with the highest frequency of mentions, followed by Portugal (21), Belgium (18), Spain (13) and Colombia (11). (Table 36). From this map, the GEOSDB records mentioning countries can be evaluated individually, and the context of traffic dynamics can be analyzed in more detail.

FIGURE 148 - SPATIAL DISTRIBUTION AND FREQUENCY OF COUNTRIES MENTIONED IN THE GEOSDB



Source: (Author, 2022).

TABLE 36 - FREQUENCIES OF THE COUNTRIES MENTIONED IN THE GEOSDB

Countries	Frequency
Bolivia	66
Paraguay	37
Netherlands	22
Portugal	21
Belgium	18
Spain	13
Colombia	11
United States of America, French, Nigeria, Peru	8
Qatar, Thailand, Turkey	6
Ethiopia, Ghana, Guinea, Mozambique	5
South Africa, Germany, Namibia	4
Angola, Argentina, Israel, Italy, Uruguay	3
Australia, Algeria, Benin, Cuba, Morocco, Mexico, Saint Lucia, Sierra Leone, Suriname, Tunisia, Ukraine	2
Albania, The Bahamas, Cape Verde, People's Republic of China, Egypt, French Guiana, Grenada, Greece, Marshall Islands, Maldives, Panama, United Kingdom, Ireland, Republic of Macedonia, Sudan, Trinidad and Tobago, Venezuela	1

Overall, the map offers some interesting geographic patterns. For example, the high frequencies in Bolivia and Paraguay coincide with hypotheses about the impact and threat posed by DTOs to use the territory of border states as a cocaine entry and transit route to Brazil (UNODC, 2003; Tortato, 2017). Similarly, it illustrates the relationship between cocaine trafficking witch North America, Europe, and Africa, which corresponds with evidence documented by UNODC, EMCDDA, and DEA, among other international agencies (CIENA, 2021; UNODC 2022b, d; DOS, 2022; EMCDDA, 2022a).

Another relevant result of the GEOINT analysis is that it allowed capturing emerging patterns of spatial variation in cocaine prices and identifying destinations that are not usually visible along with the trafficking modality. This is an important indicator used in most countries for drug policy monitoring and evaluation (Singleton et al., 2018).

For example, Figure 57 shows that Australia has a frequency of two mentions. In this country, 1 kg of cocaine has an estimated price of $159,530; while in Bolivia, it costs $2,600 (UNODC, 2020b). This supports the theory that prices increase as a move away from the sources of production (Caulkins & Reuter, 1998), as overcoming geographic obstacles, country location, financial risks, and law enforcement policies are incorporated into prices (Labrousse, 2011; Benitez et al., 2019; Bergman, 2018).

In this sense, when evaluating those two records in the GEOSDB, it was identified that both occurrences corresponded to ICS of different dates (December 10 and 24, 2021) (RF, 2021b, c). These seizures had four elements in common: (a) geographic location (Port of Santos in São Paulo), (b) destination (Australia), (c) modus operandi (concealed in gypsum bags of an export shipment), and (d) similar quantities of cocaine, 40 kg, and 35.5 kg, respectively. From this information, in addition to identifying the route, it is also possible to measure the economic impact caused to the DTOs and create new interventions focused on greater control of drug trafficking.

4.3.5.5 Intelligence layers

This technique was applied, from the overlay of the geographic patterns observed in Figures 45, 47, 48, and 49, the tracings were made to represent cartographically the possible cocaine trafficking routes in Brazil identified in this research. It is important to consider that the vectors should be interpreted as simplifying a very complex reality. In practice, the routes used by the DTOs can hardly be accurately projected on a map.

Figure 51 shows that cocaine entering Brazil generally comes from Bolivia, Colombia, and Peru (UNODC, 2021b) and arrives by land, air, and river routes across borders. From Colombia, it enters through the Amazon (Tabatinga, Japurá, Iça, Solimões, Uaupés, Rio Negro), with the cities of Manaus, Macapá, Belém, São Luís, Teresina, Fortaleza, and the Northeast of the country as strategic points along the route. In the case of Boa Vista, a route is identified, probably with a flow coming from Venezuela and Colombia.

From Peru, it enters through the state of Acre, passing through the cities of Cruzeiro do Sul, Santa Rosa de Purus, Assis Brasil, Brasiléia, Epitaciolândia, Capixaba, Xapuri and Rio Branco, with a connection in the city of Porto Velho (Rondônia), probably to provide transit continuity and supply domestic consumption. From Bolivia, it enters through the states of Rondônia and Mato Grosso, mainly through the municipalities of Nova Mamoré, Guajará-Mirim, São Francisco do Guaporé, Vila Bela da Santíssima Trindade, Pontes e Lacerda, Cáceres and Corumbá. The cities of Cuiabá, Campo Grande, and Rondonópolis stand out as important points to connect the transit of cocaine with Goiás, Brasília, Minas Gerais, Espirito Santo, Rio de Janeiro Northeast, and South of the country.

From the borders of Argentina, Paraguay and Uruguay, cocaine enters Brazil through the cities of Porto Murtinho, Bela Vista, Ponta Porã, Coronel Sapucaia, Paranhos, Mundo Novo, Guaíra, Foz do Iguaçu, Lago Itaipu, Santa Terezinha de Itaipu, Iraceminha, São Borja, Itaqui, Uruguaiana, Barra do Quaraí, Santana do Livramento and Jaguarão. The cities of Céu Azul, Guarapuava, Ponta Grossa, Balsa Nova and Curitiba stand out in the route to take cocaine to the ports of Paranaguá and São Paulo. Itajaí, Porto Alegre, Pelotas and the Port of Rio Grande also illustrate relevance in connecting the route to local consumption and international markets. In this particular, these geographical areas belong to the Southern Cone, which is considered a transit zone for the movement of PBC and cocaine hydrochloride to the United States, Europe, and Africa (DEA, 2022).

Once the cocaine arrives in Brazil, GEOSDB data indicate that the country's transportation infrastructure is used by various criminal actors, with the PCC and CV being the most frequently mentioned criminal organizations. Cargo vehicles, private vehicles, buses, ports, and airports predominate as the main facilities used for trafficking. Among the modus operandi, luggage, false bottoms, containers, and hidden compartments are particularly relevant. The *tijolos* and *tabletes* are mentioned as the most frequent forms of packaging in which cocaine is transported. Rio de Janeiro and especially São Paulo and the Port of Santos stand out as the main destination points for cocaine entering Brazil.

FIGURE 151 - POTENTIAL COCAINE TRAFFICKING ROUTES IN BRAZIL, 2021

Routes may originate in other points of the geographic space and may deviate to other municipalities and states along the transit; there are also countless alternative routes, which may not be reflected on the map.
Source: (Author, 2022).

The overlapping geographical patterns observed suggest that all the routes identified have some connection with Rio de Janeiro and especially São Paulo and the port of Santos, standing out as the main destination points for cocaine entering Brazil and serving as a node connecting the illicit activities of the DTOs with the entire Brazilian territory. These results also reflect the importance of the port of Santos as a strategic platform for cocaine trafficking, which is one of the main maritime ports used to ship cocaine from South America to international markets (UNODC, 2022b).

4.3.6 Dissemination

For this experiment, Figures 44, 45, 46, 47, 48, 49, 50, 51 and Table 34, 35, and 36, are considered the main dissemination products. It should be noted that a map is a form of geographic representation par excellence. Information can be represented on the map to elaborate tactics and strategies (Lacoste, 2014). It is a scientific and powerful tool that improves decision-making and facilitates the construction of knowledge to control and manage conflicts that threaten territories.

5 RESULTS DISCUSSIONS

The illegality of drug trafficking, resilience[10], and convergence[11] with other organized crime activities such as illegal mining, makes it very difficult to gather direct and reliable information on illicit drug markets and supply chains. This becomes a challenge mainly for researchers and law enforcement agencies to generate knowledge on the structure, operation, location, trafficking routes, trends, and threats of DTOs related activities in order to develop effective policies to combat them.

In this sense, detecting geospatial objects linked to DTOs is a real challenge. In the case of infrastructures to produce cocaine hydrochloride and its derivatives, various institutions and law enforcement agencies have made efforts to facilitate their interdiction. However, it is not an easy task since identifying this type of infrastructure in the field and the dynamics that develop in their environment for the production processes of illicit substances generate very high risks and costs due to the conditions of uncertainty and insecurity of the affected areas, which armed groups of organized crime mainly control.

For example, in the border region between Venezuela and Colombia, the CPCC are in dense jungle environments that are difficult to access and take advantage of the geographical conditions of the terrain to hide and avoid detection from aerial means such as helicopters or remote sensing satellites. Concerning IFP-PBC, the proximity to coca cultivation areas, in some cases, facilitates detection during interdiction operations. However, despite this, there is the risk that security forces must assume, as these areas may be guarded by illegal armed groups and anti-personnel mines aimed at protecting illicit crops from manual eradication activities.[12] [13]

In addition, there is the possible confrontation with the inhabitants of the community, which are instrumentalized populations (used to commit crimes) by the DTOs, who act directly or indirectly in the planting of illicit coca crops, and cocaine production (PONAL, 2020), live

[10] For the purposes of this thesis, resilience is defined as the ability of DTOs to preserve existing levels in the illicit drug market despite external pressure from law enforcement agencies aimed at drug interdiction. Drug interdiction is defined as activities undertaken to divert, disrupt, disrupt trade, delay, interdict, intercept, board, detain or destroy, under lawful authority, drug trafficking.
[11] Crime convergence occurs when an organized crime group operates across multiple illicit business lines (INTERPOL, 2022a).
[12] https://ideaspaz.org/publicaciones/opinion/2019-03/los-costos-humanos-de-la-erradicacion-forzada-es-el-glifosato-la-solucion
[13] https://www.cgfm.mil.co/es/blog/en-tiempo-record-ejercito-nacional-ha-erradicado-mas-de-200-hectareas-de-cultivos-ilicitos-en.

illegally and offer strong resistance, act violently and use bladed weapons and blunt objects towards the physical integrity and means of transport of the security forces. [14] [15]

This situation increases the likelihood of excessive use of force, in view of the obligation to guarantee the human rights of the civilian population and peacekeeping in these operations. However, it is emphasized that incapacity, fear, tolerance, respect, or fear of criminals cannot impede the existence of impunity (Huertas & Torres, 2012).

The results of this thesis demonstrate that GEOINT and artificial intelligence are suitable methods to detect some of the geospatial objects linked to DTOs, such as illegal mining areas, clandestine airstrips, coca cultivation areas, routes, and potential IFP-PBC in territories affected by illicit coca cultivation. In practice, obtaining the location of these geospatial objects is of great importance, for example, (a) to increase the capacities of governments aimed at their interdiction and dismantling; (b) to identify the number of infrastructures linked to UPAC; (c) to estimate the density and distribution of geospatial objects linked to DTOs such as individual drug seizures, potential IFP-PBC, clandestine airstrips, among others; d) identify potential IFP-PBC or airstrips that, due to their location on the borderline, use the territory of both countries; e) supports the objectives of the UNODC Global Illicit Crop Monitoring Programme (ICMP); f) strengthen the plans and policies on drugs of the affected countries; g) contribute to the UNODC strategic vision for Latin America and the Caribbean 2022-2025; among others.

The model's generalization for object detection tasks was demonstrated to detect potential IFP-PBC in PlanetScope images of 5 m spatial resolution. However, some infrastructures of less than 3 pixels were inconsistently detected. An alternative to taking advantage of the features offered by PlanetScope images would be to use both types of resolutions (3 m and 5 m) to build the training dataset; this will evaluate if integrating these resolutions would improve the ability to detect potential IFP-PBC in satellite imagery.

Therefore, experiment 1 focused on detecting potential IFP-PBC located in the territories affected by coca cultivation, which allowed us to count and obtain the geographical coordinates of these infrastructures. The academic review in this research suggests that no study has yet been developed that attempts to solve the problem of detecting this type of infrastructure, integrating GEOINT techniques and artificial intelligence methods. For example, a baseline can be established. From the detection of new infrastructures in a multi-temporal analysis with other variables of the geographical environment, it will be possible to establish alerts, and infer with

[14] https://caracol.com.co/radio/2021/03/03/judicial/1614805490_980515.html
[15] https://www.eltiempo.com/colombia/otras-ciudades/tibu-retencion-ilegal-de-soldados-que-iban-a-erradicar-cultivos-de-coca-629060

greater precision the identification of illicit production units in the region, constituting an alternative to strengthen the work of monitoring and analysis of the dynamics of cocaine production.

It is important to note that not all rural infrastructures with zinc roofs in the territories affected by coca cultivation produce PBC or are exclusively dedicated to this illicit crop. Some are homes of peasant populations that use part of their land for licit agricultural activities other than coca production. However, due to the economic benefits it offers over other activities available in the regions (Marín et al., 2020), the territorial control exercised by the DTOs, weak licit market structures, the difficulty of accessible, safe, and efficient trade, and the lack of legal tenure of agricultural production units, these are vulnerable populations who are forced or manipulated to have some link with the cocaine hydrochloride production chain (coca cultivation, collection of coca leaves, extraction of PBC/BC and processing of its derivatives) (SIMCI, 2010). suggesting a high correlation between the location of coca crops and the IFP-PBC/BC (SIMCI, 2019).

Experiment 2 addresses the challenge of classifying satellite images of the Amazon rainforest by training deep learning models for image classification tasks. The predictions allowed the identification and classification of TEC in protected natural areas in the Amazon region.

As in experiment 1, the methodology for creating the training dataset is described. In experiment 2, the dataset is constructed from Sentinel-2 satellite images, which are freely available and provided by the Copernicus program of the European Union. The dataset is called *AmazonCRIME*; it consists of 6 classes, 5,000 images per class, for a total of 30,000 multispectral images of 13 bands, level 1C, labeled, enumerated, and georeferenced in GeoTIFF format. Additionally, a derivative version is offered, with RGB band combinations in JPG format, which was used to train one of the models of the DenseNet-201 architecture.

For this experiment, the review of related works suggests that the available datasets are mainly aimed at agricultural applications, land use, and land cover, and detection of common natural and cultural elements, scarce the availability of reference datasets for applications in the domain of interest of this thesis. In this sense, *AmazonCRIME* is presented as the first dataset aimed at generating artificial intelligence applications for the classification and detection of areas linked to transnational environmental crimes in the Amazon rainforest on a large scale, probably related to the activities of DTOs. This experiment highlights the importance of creating new datasets that prioritize the geographical representation of the Amazon region since most publicly available satellite image datasets are biased towards other regions of the world.

This is one of the main limitations of generating remote sensing applications in the Amazon, using geospatial intelligence and artificial intelligence methods.

The training of the deep learning models of this experiment allowed us to analyze the performance of the RGB (4,3,2) and NIR (8,4,3) spectral bands based on image clipping and scene classification tasks. In this regard, the NIR band combination achieved superior overall performance in the quality of the results compared to the RGB band combination. The results also demonstrated the generalization capability of the models trained with the *AmazonCRIME* dataset and the potential use for real applications when applied to new satellite images corresponding to areas of the Amazon region strongly threatened by transnational organized crime.

However, although the training samples were selected considering the four seasons of the year to obtain representative samples with different spectral behaviors, in some predictions, the models presented confusion in classifying the images, such as scenes of illegal mining with those of water bodies, probably due to the characteristics of this activity, which is generally carried out near river networks.

The same occurred with the areas of coca cultivation and deforested areas, probably because the spatial pattern presents some similarities with deforestation. In addition, upon further analysis of these inconsistencies, it was observed that the geographic patterns of coca cultivation practices present some differences between the countries from which the training samples were taken, which are adapted according to the terrain conditions and cultural customs, as in the case of Peru and Bolivia. In these countries, the indigenous populations have as a traditional practice the cultivation of coca (DEVIDA, 2020; EL PACCTO, 2022; Reuters, 2008) therefore, coca fields' spatial behavior, sizes, and shapes vary between countries.

As an alternative to improve the classification of these scenes, the size of the training image clippings can be reduced to prevent the algorithm from extracting and learning additional features from the geospatial context that may generate confusion, then perform the model training and evaluate the performance and quality of the classification.

In experiment 3, open-source data were collected from 4,475 news URLs related to cocaine seizures using web scraping techniques. An NLP algorithm was developed that, using regular expressions, keyword lists, and toponym resolution methods, facilitated the extraction of information and the consolidation of a database with 2,559 records with geospatial attributes related to ICS in Brazil for the year 2021. Subsequently, geospatial analysis methods and cartographic techniques were applied to generate geospatial intelligence to identify some routes and trends in the dynamics of cocaine trafficking.

A huge volume of relevant information can be extracted from open-source sources. However, because it is not in a structured form, it is poorly organized and isolated from the geographic context and, therefore, of little value. The methodology proposed in this thesis demonstrated that data from news website articles, when collected, evaluated, structured, and linked with geospatial attributes, provide valuable details. GIScience becomes relevant for more advanced tasks, generating information and creating knowledge to support decision-making and strengthen drug policies.

In this sense, the GEODSB demonstrates the dynamism of cocaine trafficking routes and modalities in Brazil and, in most cases, provides answers to the 5W1H (Who, What, Whom, When, Where, and How) about these illicit activities, considering the spatial dimension, and offers important contributions to help fill the knowledge gaps resulting from the scarcity or insufficiency of available data on cocaine trafficking.

For example, during the geospatial intelligence analysis process, it was identified that, in most of the records, ICS in Brazil are reported by the information sources as a single substance, "cocaine," without differentiating "coca paste" from "cocaine hydrochloride." In addition, different names are used to refer to the brick-shaped packages (e.g., *tijolos, barras*, or *tabletes*). In some cases, the photographs show that these packages have different sizes, which makes it confusing to infer the weight. For instance, in cocaine hydrochloride production complexes in South American countries, there is evidence of the use of molds, hydraulic presses, and weighing scales to generate 1 kg bricks of cocaine hydrochloride with their respective markings and logos, or *Marquillas* and *Logos* in Spanish. (Figure 52).

FIGURE 154 - MATERIALS USED IN THE PRODUCTION COMPLEXES FOR THE PACKAGING OF COCAINE HYDROCHLORIDE BRICKS

Venezuela-Colombia border. (a) 1 kg mold, (b) Hydraulic press and 1kg molds, (c) Weighing scales, (d) *Marquillas/Logos* (Author, 2017).

Similarly, the records suggest that the journalistic interest of news sources is focused on seizures ≥ 100 grams of cocaine. Only 1.6% of the records amounted to below that threshold. In several reports, cocaine is not quantified by weight units (kg or g) but by units concerning the type of packaging (e.g., 1,200 *tijolos*, 7 *pinos*, 40 *papelotes*). Crack is frequently reported by units (*pedras*) and not by quantities in weight. Generally, the way seizures are reported by information sources is like the police lexicon used to narrate this type of activity, so that news reports, in most cases, offer important information to extract data related to the 39 variables of interest present in the GEOSDB. In some reports, the account of more than one drug seizure was identified. They described the occurrence of seizures on different dates and places, or with different types of drugs, or the sum of several IDS as a joint result of the FSPB.

The geospatial analysis revealed interesting results that, without the application of GIScience, would have been very difficult to identify. This demonstrated the potential of geoscience to find answers to challenging questions and the cartographic representation in communicating those answers. The methodology applied in this experiment illustrates some potential advantages. From the perspective of illicit drug monitoring and research, the data extracted can provide contextual information on the dynamics of DTOs, for example, modus operandi, identifying where they operate, main destinations, routes, emerging trends, and geospatial context of trafficking, hot spots, among others. Similarly, it is possible to extract quantitative information on significant quantities of cocaine in weight and packaging units, allowing to fill existing gaps, given the limited access and integration of closed and classified national data.

From a public security perspective, the methodology could be used for environmental scanning and obtaining strategic alerts for detecting threats related to DTOs activities. For example, the identification of a new route or the geographic visualization of multiple seizures in a particular area would facilitate the detection of a focus of attention, which could be triangulated with other sources of information, and generate an early warning, which would support plans such as the Brazilian National Drug Policy (MJSP, 2021), Strategic Alliance against Transnational Organized Crime (MJSP, 2022a), promote scientific research to produce knowledge that can contribute to SDG #16 peace, justice, and strong institutions, and SDG #17 partnerships for the goals (UNDP, 2022), among others.

The proposed methodology enables quantifying and describing DTOs activities. As Thomson (1883) states, when something is not known and undefined, it cannot be measured; knowledge is scarce and unsatisfactory; but when it can be measured, expressed in numbers, and something is known about it, it can be managed. In other words, we cannot manage what we cannot measure (Morabito & Gaub, 2022). However, without data, there is little that can be done. Quantifying objects or individuals and measuring their characteristics is the basis of almost all studies (Grekousis, 2020). In scenarios where national-level (official - closed) data on IDS are unavailable or difficult to access, obtaining this information from open-source sources becomes an option to overcome these limitations. In practice, organizations such as UNODC, EMCDDA, OAS, INTERPOL, EUROPOL, and DEA use data from media reports as an alternative to complement analyses of drug trafficking at both the national and international levels (Reichel & Albanese, 2013; Lowenthal & Clark, 2015; EMCDDA, 2019; UNODC, 2021b, 2022l).

In Brazil, 95% of police forces are linked to the states, totaling at least 54 decentralized public security institutions. At the federal level, the Federal Police and the Federal Highway Police occupy 5% (Monteiro, 2022). Although each FSPB police agency has its own IDS system, this information is not shared, becoming an obstacle to analyzing drug trafficking dynamics in an integrated manner (CoE-Brazil, 2022, Gonçalves, 2004). It has been documented that open-source data can provide contextual information, fill knowledge gaps, and generate new information on threats and trends, resulting in a more complete intelligence picture (EMCDDA, 2019). Once evaluated, it can support strategic planning or contribute to ongoing operations or research.

In this sense, one of the main advantages of the proposed methodology, in the Brazilian context, is that it allows generating a national picture of the cocaine trafficking phenomenon in the country and becomes an alternative to collect information in a timely and detailed manner on the IDS. Table 37 describes some of the main strengths and limitations of the open source GEOINT data.

TABLE 37 - STRENGTHS AND LIMITATIONS OF OPEN SOURCE GEOINT DATA

Strengths	Limitations
– Provides quantitative and contextual information on IDS, allowing for the increased analytical potential for strategic, operational, and policy purposes. – It can be used as a substitute when official IDS data are not available. – They are obtained promptly through legal means and do not depend on a court order or security restriction for access. – They have the potential to consolidate a geo-referenced early warning system to identify threats related to IDS dynamics in Brazil, increasing the usefulness of these data both nationally and internationally. – They enable the identification, change detection, and monitoring of routes, emerging trends, modus operandi, and organized crime, among others. – They can be used for environmental scanning of the dynamics of other drugs (synthetic drugs, NPS, marijuana, heroin, among others). – Combining these data with official information would further strengthen the analysis for public policy formulation. – Open-source information is considered the source of the first resource for the intelligence community and complements other sources of information. – They make it possible to generate GEOINT products that facilitate the identification of patterns and trends through geospatial reasoning: route maps, hot spot analysis, summarize individual cocaine seizure counts, density-based clustering, proportional symbol maps, thematic maps, and dashboard, among others. – No large operational budgets are required to support the logistical infrastructure (hardware and software).	– The amount of information accessed is considerably large, so data cleaning processes are time-consuming. – The nature of this data is inherently biased. Each source of information needs to be understood and analyzed. Criteria must be established to evaluate sources and information based on the source's reliability, validity of the information, and frequency with which the source reports. – The data reported on IDS is influenced by the activities and priorities of law enforcement agencies, so the information will only represent the seizures that the FSPB may wish to disclose. – Qualified human resources (analysts) are required to extract these data and evaluation through the methods recognized and used by law enforcement agencies. – Not all IDS reports offered by the media provide all the variables of interest suggested in Table 9 of this research. – In addition to using automated techniques through programming languages such as Python to clean the data and discard duplicates, a manual inspection phase is still necessary, as some information sources may repeat the same occurrence using different dates, titles, and wording. – The wording of articles may have misspelled words. This limits the NLP algorithm for extracting the information.

Source: (Author, 2022).

This thesis describes a methodology based on the intelligence cycle, in which, in addition to integrating deep learning methods, NLP, and GIScience techniques in the processing phase, it uses source and information evaluation methods that are internationally recognized by the security forces, which allow providing reliability and accuracy parameters of the intelligence generated for complex decision-making.

As shown in Table 38, sources and information were evaluated as A1, A2, and B2. Most were from official sources, international organizations, law enforcement agencies, news and newspaper website, data collected directly in the field, academic research with a solid scientific basis, and sources confirmed by other independent and reliable sources, whose information has demonstrated a high degree of relevance, validity, and accuracy.

TABLE 38 - EVALUATION PROCESS RESULTS

Satellite Images

Source	Information	Evaluation
Planet Labs Education and Research Program	PlanetScope Images	**A1**
European Space Agency. Google Earth Engine	Sentinel-2 Images	**A1**

Geospatial Information

Source	Information	Evaluation
IGAC	Basic vector maps of Colombia	**A1**
SIMCI - UNODC	Coca Crop Density Vectors 2020 - Colombia	**A1**
IGVSB	Basic vector maps of Venezuela	**A1**
IBGE	Basic vector maps of Brazil	**A1**
DNIT	Basic vector maps of Brazil	**A1**
RAISG	Vectors of the Amazon rainforest	**A2**
Mapbiomas	Vectors of the Amazon rainforest	**A2**
WDPA	Vectors of the Amazon rainforest	**A2**

Open-source GEOINT data

Source	Information	Evaluation
Reuters Institute	Reuter's Institute and Oxford University study on public trust in news by source	**A2**
Brazilian Government	News and newspaper website of the https://www.gov.br/pt-br domain.	**B2**
Record News	News and newspaper website of the https://noticias.r7.com/ domain.	**B2**
O GLOBO	News and newspaper website of the https://g1.globo.com/ domain	**B2**
ANAC	Airstrip geographic coordinates	**A1**
openAIP	Airstrip geographic coordinates	**A2**

Ground Truth Data

Source	Information	Evaluation
Sierra XXIV - 2014 *Raspaculo - 2015* *Catatumbo Sur - 2015* *Caño Motilon Sur - 2016* *Rio Tarra - 2016* *Paso del Tornado - 2017* *Sierra - 2017* *Parque Nacional Yapacana*	Geographical coordinates of the areas of coca crops eradicated in Venezuelan territory	**A1**
	Photographs of plantations of illicit coca crops in Venezuelan territory	**A1**
	Photographs of IFP-PBC in Venezuelan territory	**A1**
	Photographs of CPCC in Venezuelan territory	**A1**
	Photographs of clandestine airstrips	**A1**
	Photographs of illegal mining in the Amazon rainforest	**A1**

Open-Source Information

Source	Information	Evaluation
SIMCI - UNODC	Monitoring reports of territories affected by illicit crops in Colombia	**A1**
UNODC	Monitoring reports of territories affected by illicit crops in Peru and Bolivia	**A1**
CIENA	Bulletin: Infrastructures for the Processing of Illicit Drugs and Artisanal Chemicals	**A1**
	Bulletin: Cocaine Market Analysis 2020	**A1**
Colombian Drug Observatory, SIMCI - UNODC	Regional characterization of the problems associated with illicit drugs in the department of Norte de Santander	**A1**
Central University of Venezuela	Master's Thesis. Characterization of activities associated with illicit drug trafficking in Venezuela's border area with Colombia, using remote sensing techniques	**A1**
Bolivarian National Armed Forces National Anti-Drug Command	Magazine: National Anti-Drug Command Operational Vanguard 2016	**A1**
Ministry of People's Power for Internal Relations, Justice and National Peace Anti-Drug Superintendence	News Operation *Ave Fenix IV - 2021* News Operation *Febrero Rebelde - 2022*	**A1**
Bibliographic references of the article	Other publications	**A1, A2, or B2**

A1: There are no doubts about the reliability and competence of the source. The source has proven to be reliable in all cases. There are no doubts about the accuracy of the information. **A2:** There are no doubts about the reliability and competence of the source. The source has proven to be reliable in all cases. The information is personally known to the source but not to the official transmitting it. **B2**: The source has proven to be reliable in most cases. The information is personally known to the source but not to the official transmitting it. Source: (Author, 2022).

In general, the results of this research advance the generation of knowledge on the control of illicit drugs using geospatial intelligence and artificial intelligence since they offer alternatives to obtain direct measurements of activities related to DTOs, whose information is generally of limited access and difficult to obtain due to its nature and sensitivity. In addition, it has been identified that most research focuses on prevention and treatment and that aimed at providing tools to strengthen law enforcement strategies has been considerably under-researched (Caulkins, 2017; Reuter, 2001).

6 CONCLUSIONS

6.1 MAIN FINDINGS

GEOINT, combined with artificial intelligence methods (machine learning, deep learning, natural language processing), big data processing, and open-source information, offers the potential to generate significant contributions to efforts against drug trafficking and organized crime. It allows the identification of the "what," "when," and "where" of a given target, as well as the detection of emerging patterns and trends in a Spatio-temporal context.

The dynamics of drug trafficking involve stages with specific actors. From a geospatial context, they take advantage of the geography of a given territory to commit illicit activities and reduce the risk of law enforcement interdiction. Identifying the geographic location of geospatial objects linked to DTOs and knowing their geospatial distribution becomes valuable strategic information that allows policymakers and researchers to strengthen decision-making aimed at interdiction and prevention against illicit drugs.

However, due to the intrinsic illegal nature of DTOs and the sensitivity of the information on the activities of these criminal organizations, the availability of this type of data, and especially data with geospatial attributes, is considerably limited or non-existent, being the main challenge to address them.

This thesis proposes a methodology based on the intelligence cycle, which is internationally recognized by several organizations and researchers for its ability to identify and analyze criminal phenomena based on transparent, reliable, and reproducible scientific methods. Geospatial intelligence techniques and artificial intelligence methods were used to detect geospatial objects linked to DTOs and obtain their geographic coordinates, specifically the detection of potential primary production infrastructures to produce coca paste (IFP-PBC), airstrips, illegal mining areas, coca cultivation areas, deforested areas, individual cocaine seizures and routes associated with drug trafficking.

In this sense, three experiments are conducted where the challenge of generating datasets for training deep learning models and environment scanning using NLP techniques is addressed. These are built from remote sensing images, field collected data, open source GEOINT data, and open-source information sources. The reliability of the sources and the validity of the information used in this thesis were assessed as A1, A2, and B2 using evaluation methods internationally recognized by law enforcement agencies.

In the first experiment, the dataset is generated from PlanetScope level 3B satellite imagery evaluated at NIIRS level 3. This dataset, named *CocaPaste-PI-DETECTION*, consists of 16,778 training samples labeled to detect the location of potential IFP-PBC in remotely sensed images of areas affected by illicit coca cultivation.

Using *CocaPaste-PI-DETECTION*, an advanced deep learning model with the Faster R-CNN architecture was trained to detect possible IFP-PBC, in which a mAP of 90.07% was obtained. The performance of the model was analyzed, and different tests were performed, which showed: (a) that the model performs well on PlanetScope satellite images totally unknown to the network and of different spatial resolution; (b) that it can obtain the geographic location of potential IFP-PBC automatically, without the need for manual selection and with a detection speed much faster than that of a human operator, becoming a much more efficient alternative that saves time, resources and reduces risks; (c) the efficiency of PlanetScope imagery to support geospatial intelligence; and (d) how the proposed methodology, through real applications, can contribute to public policies and strategic analysis aimed at strengthening monitoring, analysis and intervention strategies against drug trafficking.

Similarly, the second experiment was developed. In this one, the dataset is called *AmazonCRIME*, built from Sentinel-2 images, using the cloud processing capabilities of the Google Earth Engine platform. It consists of 6 classes, 5,000 images per class, for a total of 30,000 multispectral images of 13 bands, level 1C, evaluated at NIIRS level 1, labeled to classify images of areas linked to transnational environmental crimes in the Amazon rainforest. With *AmazonCRIME*, two deep learning models were trained with the DenseNet-201 architecture, specialized in image classification tasks, being possible to obtain an overall classification accuracy of 96.56%. In both datasets, *CocaPaste-PI-DETECTION* and AmazonCRIME, the images are georeferenced in GeoTIFF format.

In the third experiment, the database was built through an NLP algorithm capable of extracting open source GEOINT data from news about drug seizures, allowing conversion from unstructured text to a new database called GEOSDB. It consists of 39 variables and 2,559 records, with geospatial attributes that have quantitative and qualitative data related to individual cocaine seizures in Brazil during the year 2021.

In this experiment, natural language processing techniques and geospatial intelligence were applied to demonstrate: (a) the ability of the proposed methodology to extract meaningful data that allow environment scanning with a strategic approach and generate a more complete intelligence picture to identify routes and trends about the dynamics of cocaine trafficking in Brazil; (b) the potential value of open source GEOINT data to provide information promptly, with high value, offering relevant opportunities for research and formulation of public policies aimed at reducing the supply of illicit drugs; (c) how data with geospatial attributes enable the discovery of new knowledge and the consolidation of evidence; (d) the importance of integrating information in a geospatial context to create effective tools to support strategies aimed at impacting drug trafficking activities. All datasets developed in this thesis were made available to the scientific and academic community for research purposes.

Research on this front still has significant challenges to address. Most of the work driven by artificial intelligence is devoted to data preparation (labeling) and model training. The results (output) obtained through the processes of transforming raw data into information will largely depend on the quality and quantity of data used for training (input).

Additionally, it must be considered that training deep learning models is a computationally demanding task due to the innumerable parameters and hyperparameters used by artificial neural networks during the learning process. Therefore, it is necessary to use high-performance computers with dedicated architectures such as GPU to train and run the models.

The detection of geospatial objects linked to DTOs from remote sensing images is not an easy task since the geographic environment of these objects is influenced by a mixture of common elements, both cultural (houses, roads, airstrips) and natural (soil, vegetation, water), which are not necessarily related to organized crime activities. They are also affected by the atmospheric conditions and particular geographic characteristics of each study area.

Concerning open-source information, the main criticism concerns the source's reliability and the risk that the information, being a secondary source, may undergo changes or be biased. Therefore, as with other sources of information, it is very important to apply evaluation criteria and methods that allow distinguishing and validating objective information and discarding that which lacks credibility.

Therefore, the success in the detection of geospatial objects related to organized crime will be directly proportional to the degree of knowledge about the dynamics of DTOs, the geographic space of interest, and the mastery of the technical and theoretical foundations that are used for the processing of remote sensing images and geospatial data, using geospatial intelligence techniques and artificial intelligence methods.

6.2 THESIS CONTRIBUTIONS

This thesis explores the potential of geospatial intelligence and artificial intelligence as a tool for geospatial object detection and intelligent information gathering linked to the activities of DTOs. Within this perspective, the following contributions stand out:

- The methodology to create training datasets composed of georeferenced multispectral images from Sentinel-2 and PlanetScope satellites to train advanced deep learning models, specialized in image classification and detection of geospatial objects linked to DTOs, is described.
- The methodology for data collection and processing and extracting information (contextual and geographic) on individual cocaine seizures from open-source information and natural language processing methods, is described.
- To address the engineering practice, from the data sets generated, a series of experiments are conducted, which, through the training of deep learning models specialized in object detection, image classification, and development of natural language processing algorithms, geospatial objects linked to DTOs are detected in three major study areas: a) Border region of Venezuela and Colombia; b) Amazon rainforest; and c) Brazilian territory. The results generate predictions whose evaluation metrics are higher than 90%.
- Different GEOINT products are generated to illustrate the potential offered by the proposed methodology for research and decision-making.
- It demonstrates the practical potential of open-source information to generate knowledge on the dynamics of transnational drug trafficking and environmental crimes. The academic review suggested that there are no publicly available reference datasets for the domain of interest of this research. In this sense, they are the first datasets available for research purposes and are made available to the scientific and academic community through the following links:
  AmazonCRIME[16]
  CocaPaste-PI-DETECTION[17]
  GEOSDB[18]

[16] https://github.com/jp-geoAI/AmazonCRIME.git
[17] https://doi.org/10.17632/gmhsjwr24n.1
[18] https://figshare.com/s/4822ee0e1cb9d62139b4

- Based on operational experiences in drug interdiction and academic literature, a conceptual bases for understanding the dynamics of DTOs and cocaine hydrochloride production processes in complex border regions is described. From a law enforcement perspective, concepts related to artificial intelligence applied in remote sensing and geospatial intelligence are also defined.
- Finally, a methodology based on the intelligence cycle is proposed to detect geospatial objects linked to drug trafficking organizations.

Some of the contents and results of this thesis were published or submitted for publication. The following list provides the references:

- Pinto, J., and Centeno, J.A.S. (2022). *Geospatial Intelligence and Artificial Intelligence for detecting potential coca paste production infrastructure in the border region of Venezuela and Colombia*. **Journal of Applied Security Research.** DOI: https://doi.org/10.1080/19361610.2022.2111184.

- Pinto, J., and Centeno, J.A.S. (2022). *AmazonCRIME: a Geospatial Artificial Intelligence dataset and benchmark for the classification of potential areas linked to Transnational Environmental Crimes in the Amazon Rainforest*. **Revista de Teledetección**. DOI: https://doi.org/10.4995/raet.2022.15710. (Published in Spanish).

- Pinto, J., and Centeno, J.A.S. (2022). *Geospatial intelligence and natural language processing for environmental scanning to identify cocaine trafficking routes and trends in Brazil*. (Submitted for publication).

6.3 FUTURE RESEARCH

Although the experiments conducted in this thesis deal with specific cases, mainly focused on cocaine trafficking, the proposed methodology can be applied to help solve other problems and detect other geospatial objects linked to organized crime. Thus, using and evaluating the methodology introduced in this research in other areas is strongly recommended.

For example, to train deep learning algorithms specialized in detecting rafts used for illegal mining in the Amazon region, clandestine ports used for drug trafficking and smuggling of goods in border regions such as the state of Paraná (Brazil) and Paraguay, clandestine airstrips that are located in border states used for trafficking drugs, weapons, mineral resources, and wildlife; detection of illicit crop fields, such as coca, marijuana and opium poppy, among others.

The methodology can also be leveraged to detect geospatial objects linked to DTOs using other band combinations, other sensors with higher spatial resolution, or exploiting the capabilities of SAR sensors, including amplitude, frequency, phase, and polarization information.

For example, in the case of the detection of potential IFP-PBC, in future research, the number of training samples can be increased and balanced by using optical satellite imagery that qualifies at a NIIRS level higher than 3, e.g., SkySat imagery of 0.5 m spatial resolution. This would improve the feature extraction capability and likely allow the identification of open sky infrastructure with black plastic-covered roofs or dry vegetation. Also, the possibility of employing high-resolution SAR imagery such as Capella's SAR products to assess whether potential IFP-PBC features are better identified with this type of sensor, in regions where frequent cloud coverage is observed.

The methodology can also be applied to generate NLP algorithms based on rules and machine learning or build hybrid models to extract information related to other illicit drugs, such as amphetamine-type stimulants (ATS) and marijuana. It could be extended to extract information from infrastructures of interest, such as a port or an airport, and perform a risk analysis of the facilities from the extracted data.

It can be applied to identify potential trends in firearms and ammunition trafficking, seizures of chemicals used for producing and adulterating cocaine hydrochloride, and identification of organized crime groups in different UF, among others. The methodology can monitor incidents related to interdiction of clandestine airstrips or clandestine aircraft entering the airspace. This would allow for to extraction of information on the quantities of cocaine, origin, destinations, and involved, among other variables. It is also possible to adjust the domain of interest to identify signs of health threats associated with NPS; this will allow, for example, to support the Brazilian Drug Early Warning Subsystem.

Similarly, from the extracted open source GEOINT data, a national database could be created that consolidates and integrates data on the dynamics of drug trafficking in Brazil. For example, through an interactive platform that offers access to this information for all FSPB and qualified researchers and enables the integration of official data from the IDS conducted in each Federal Unit. There are successful experiences based on a similar idea, for example, the Consolidated Counter Drug Database (CCDB) of the United States government (McSweeney, 2020) and the EMCDDA drug supply monitoring system (EMCDDA, 2017).

The results of this thesis demonstrated how deep learning methods, specifically CNN, applied to remote sensing data, can accelerate Big Data analysis, to automatically recognize objects that allow to interpret and understand the physical characteristics and georeferenced activities of the Earth, generating geospatial patterns and trends that cannot be identified manually; being this information useful in decision-making processes and further policy actions.

The practical potential of environment scanning through open source GEOINT data was illustrated, which allowed us to identify some signals about cocaine trafficking routes and trends in Brazil and generate knowledge about this illicit market's dynamics. The results revealed to coincide with the existing literature on organized crime and drug trafficking, widely documented by other sources of information, which have demonstrated competence and reliability. [19] [20] [21] [22]

It is hoped that the contributions of this thesis will foster the development of innovative research and the integration of new data sources to understand the dynamics of DTOs and create proactive actions to strengthen intervention strategies against organized crime. The strong relationship between illegal mining, deforestation, and other illegal economies, such as drug trafficking, becomes a threat that requires urgent actions, comprehensive approaches, and technological tools to mitigate the environmental impact and restore the ecological balance in the world's largest rainforest. Although the methodology was applied in three large specific study areas, it is considered that the methodology can be adapted to other countries, regions,

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[19] World Drug Report 2022. United Nations Office on Drugs and Crime, 2022. https://www.unodc.org/unodc/en/data-and-analysis/world-drug-report-2022.html

[20] Covid-19 and drug trafficking in Brazil: the adaptation of organized crime and the role of police forces in the pandemic. Centre of Excellence for Illicit Drug Supply Reduction. United Nations Office on Drugs and Crime, 2021. https://www.cdebrasil.org.br/estudos/

[21] EU Drug Market: Cocaine. European Monitoring Centre for Drugs and Drug Addiction, 2022. https://www.emcdda.europa.eu/publications/eu-drug-markets/cocaine_en#box_cocaine

[22] Rutas y destinos del tráfico de sustancias ilícitas. Centro Internacional de Estudios Estratégicos Contra el Narcotráfico, 2021. https://www.policia.gov.co/centro-estudios-narcotrafico/productos

and geographic levels that, due to their geostrategic characteristics, may be attractive for DTOs activities.

We believe that intelligence, interdiction, and prevention processes, supported by technology and geographic information sciences, can contribute to and generate impacts on the manifestations of organized crime. These strategies require data, both objective and subjective information. Cooperation between public security forces and investigators is essential to establish mechanisms to improve the promotion of the Rule of Law, the consolidation of the SDGs, and current preventive and repressive strategies in the face of the threats and challenges that DTOs represent society.

In this sense, intelligence processes, interdiction, and prevention efforts, supported by geospatial intelligence and artificial intelligence, can contribute to and generate impacts on the manifestations of organized crime. These strategies require precise and measurable data, both objective and subjective information, especially when the targets of interest are located in territories that safeguard strategic environmental assets such as the Amazon; or countries with continental dimensions such as Brazil, or are located in remote and difficult to access areas, such as the border region of Venezuela and Colombia, which share a continuous border of approximately 2,219 km, characterized by a complex dynamic and strongly threatened by armed drug trafficking groups.

7 REFERENCES

ABDANI, S. R.; ZULKIFLEY, M. A. DenseNet with Spatial Pyramid Pooling for Industrial Oil Palm Plantation Detection. **2019 International Conference on Mechatronics, Robotics and Systems Engineering (MoRSE)**. p.134–138, 2019.

ABIN. **Atividade de inteligência no Brasil**. Brasília: Agência Brasileira de Inteligência. Cadernos de Legislação da Abin, n. 3., 2020. Available at: <https://www.gov.br/abin/pt-br/centrais-de-conteudo/publicacoes/Col3v3.pdf>.

ADDERLEY, R.; SEIDLER, P.; BADII, A.; et al. Semantic mining and analysis of heterogeneous data for novel intelligence insights. **Proceedings of The Fourth International Conference on Advances in Information Mining and Management**, IARIA, p.36–40, 2014.

AKHGAR B, BAYERL P, SAMPSON, F. **Open source intelligence investigation: From strategy to implementation**. Springer, 2017.

ALBANESE, J. **Organized crime: From the mob to transnational organized crime**. Routledge, 2015.

ALBANESE, J. Why organized crime seeks new criminal markets. **Illegal Mining. Organized Crime, Corruption, and Ecocide in a Resource-Scarce World**. p.31–42, 2020. Springer.

ALIPRANDI, C.; ARRAIZA IRUJO, J.; CUADROS, M.; et al. CAPER: Collaborative Information, Acquisition, Processing, Exploitation and Reporting for the Prevention of Organised Crime. In: C. Stephanidis (Ed.); HCI International 2014 - Posters' Extended Abstracts. **Anais.**. p.147–152, 2014. Cham: Springer International Publishing.

ALLEN, C. **An industrial geography of cocaine.** Routledge, 2013.

AMERIPOL. **La verdadera dimensión de las drogas. Una nueva forma de analizar el problema**. AMERIPOL - Comunidad de Policías de América, 2012. Avaiable at: < http://www.ameripol.org/portalAmeripol/ShowBinary?nodeId=/WLP%20Repository/52139//archivo>.

ANAC. **Dados Abertos**. Agência Nacional de Aviação Civil, 2020. Available at:<https://www.anac.gov.br/acesso-a-informacao/dados-abertos>.

ANTIDROGAS-GNB. **Vanguardia Operativa - Lucha Frontal contra el Tráfico Ilícito de Drogas**. Comando Nacional Antidrogas. Guardia Nacional Bolivariana, 2016. Available at: < https://osf.io/y8v45/?view_only=93be77b41b994ce08e2e7b655aff51c7>.

ANTONOPOULOS, G. A.; PAPANICOLAOU, G. **Organized crime: a very short introduction**. Oxford University Press, 2018.

ARESINFOSERVICE. **Helicóptero persigue avión narco escape pista clandestina Nicaragua**. Available at:<https://www.youtube.com/shorts/EgeWNYhhnNY>.
Available at:< https://www.unodc.org/unodc/en/data-and-analysis/the-cocaine-market.html >.

AZAVEA. **Raster Vision**, 2021. Available at:<https://rastervision.io/>.

24 HORAS. **Amazonas: Agentes de la policía destruye pista de aterrizaje clandestina**. Available at:<https://www.youtube.com/watch?v=f-Nfz8hq0Ko>.

BABER, M. Geospatial Intelligence and National Security. **The Geographic Information Science & Technology Body of Knowledge**, 2018. Available at:<https://gistbok.ucgis.org/bok-topics/geospatial-intelligence-and-national-security>.

BACASTOW, T. S.; BELLAFIORE, D. Redefining Geospatial Intelligence. **American Intelligence Journal**, v. 27, n. 1, p. 38–40, 2009. National Military Intelligence Foundation. Available at:<http://www.jstor.org/stable/44327109>.

BAGLEY, B. M. **Drug trafficking and organized crime in the Americas: major trends in the twenty-first century**. Woodrow Wilson International Center for Scholars, Latin American Program, 2012. Available at: < https://www.wilsoncenter.org/sites/default/files/media/documents/publication/BB%20Final.pdf>.

BAPTISTA, G; NASCIMENTO, N. **O que é possível saber sobre o tráfico de drogas ilícitas: intersecções entre estatísticas para as políticas de segurança pública e sobre drogas**. Fórum Brasileiro de Segurança Pública, 2022. Available at:< https://forumseguranca.org.br/publicacoes_posts/estatisticas-de-seguranca-publica-producao-e-uso-de-dados-criminais-no-brasil/>.

BASU, S.; GANGULY, S.; MUKHOPADHYAY, S.; et al. DeepSat: A Learning Framework for Satellite Imagery. **Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems**. SIGSPATIAL '15., 2015. New York, NY, USA: Association for Computing Machinery. Available at:<https://doi.org/10.1145/2820783.2820816>.

BAYDIN, A. G.; PEARLMUTTER, B. A.; RADUL, A. A.; SISKIND, J. M. Automatic Differentiation in Machine Learning: A Survey. **Journal of Machine Learning Research**, v. 18, n. 1, p. 1–43, 2018. JMLR.org. Available at:<https://www.jmlr.org/papers/volume18/17-468/17-468.pdf>.

BENGIO, Y. Learning Deep Architectures for AI. **Foundations and Trends® in Machine Learning**, v. 2, n. 1, p. 1–127, 2009. Available at:<http://dx.doi.org/10.1561/2200000006>.

BENÍTEZ, G. J.; CHANDRA, S.; CUADROS VELOZA, T. C. L. W.; DÍAZ CÁRDENAS, I. J. D. Following the price: identifying cocaine trafficking networks in Colombia. **Global Crime**, v. 20, n. 2, p. 90–114, 2019. Routledge. Available at:<https://doi.org/10.1080/17440572.2019.1588116>.

BERGMAN, M. **Illegal drugs, drug trafficking and violence in Latin America**. Springer, 2018.

BILTGEN, P.; RYAN, S. **Activity-based intelligence: principles and applications**. Artech House, 2016.

BINGHAM, H. C.; JUFFE BIGNOLI, D.; LEWIS, E.; et al. Sixty years of tracking conservation progress using the World Database on Protected Areas. **Nature Ecology & Evolution**, v. 3, n. 5, p. 737–743, 2019. Available at:<https://doi.org/10.1038/s41559-019-0869-3>.

BISHOP, C. M.; NASRABADI, N. M. **Pattern recognition and machine learning**. Springer, 2006.

BLANCO, J. M.; COHEN, J. Macro-environmental factors driving organised crime. **Using Open Data to Detect Organized Crime Threats**. p.137–166, 2017. Springer.

BOGUSZEWSKI, A.; BATORSKI, D.; ZIEMBA-JANKOWSKA, N.; DZIEDZIC, T.; ZAMBRZYCKA, A. LandCover. ai: Dataset for automatic mapping of buildings, woodlands, water and roads from aerial imagery. **Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition**. p.1102–1110, 2021.

BOUCHARD, M. On the Resilience of Illegal Drug Markets. **Global Crime**, v. 8, n. 4, p. 325–344, 2007. Routledge. Available at:<https://doi.org/10.1080/17440570701739702>.

BREWSTER, B.; ANDREWS, S.; POLOVINA, S.; HIRSCH, L.; AKHGAR, B. Environmental Scanning and Knowledge Representation for the Detection of Organised Crime Threats. In: N. Hernandez; R. Jäschke; M. Croitoru (Eds.); **Graph-Based Representation and Reasoning**, p.275–280, 2014. Cham: Springer International Publishing.

BRIGHT, D. A.; HUGHES, C. E.; CHALMERS, J. Illuminating dark networks: a social network analysis of an Australian drug trafficking syndicate. **Crime, Law and Social Change**, v. 57, n. 2, p. 151–176, 2012. Available at:<https://doi.org/10.1007/s10611-011-9336-z>.

BROWN, S.; HERMANN, M.; SOVEREIGNTY, R. **Transnational Crime and Black Spots**. Springer, 2020.

BROWNLEE, J. **Deep learning with Python: develop deep learning models on Theano and TensorFlow using Keras**. Machine Learning Mastery, 2016.

BUDAK, Ü.; ŞENGÜR, A.; HALICI, U. Deep convolutional neural networks for airport detection in remote sensing images. **2018 26th Signal Processing and Communications Applications Conference (SIU)**, p.1–4, 2018.

BURKOV, A. **The hundred-page machine learning book**. Andriy Burkov Quebec City, QC, Canada, 2019.

BUTT, U; LETCHMUNAN, S; HASSAN, F; ALI, M; BAQIR, A; KOH, T; SHERAZI, H. Spatio-temporal crime predictions by leveraging artificial intelligence for citizens security in smart cities. **IEEE Access**, 2021. Available at: < https://doi.org/10.1109/ACCESS.2021.3068306>.

CAF. La riqueza natural de la Amazonía como base del desarrollo sostenible regional. **Banco de Desarrollo de América Latina**, 2019. Available at:<https://www.caf.com/es/conocimiento/visiones/2019/09/la-riqueza-natural-de-la-amazonia-como-base-del-desarrollo-sostenible-regional/>.

CAI, X; WU, Z; CHENG, J. Using kernel density estimation to assess the spatial pattern of road density and its impact on landscape fragmentation. **International Journal of Geographical Information Science**, 27(2), 222-230, 2013. Available at: < https://doi.org/10.1080/13658816.2012.663918>.

CAISSE, A. **Pedestrian detection and monitoring with high spatial resolution images using convolutional neural networks and Image processing**, 2020. Doctoral Thesis, Curitiba: Universidade Federal do Paraná.

CAMPELLO, R. J. G. B.; MOULAVI, D.; ZIMEK, A.; SANDER, J. Hierarchical Density Estimates for Data Clustering, Visualization, and Outlier Detection. **ACM Trans. Knowl. Discov. Data**, v. 10, n. 1, 2015. New York, NY, USA: Association for Computing Machinery. Available at:<https://doi.org/10.1145/2733381>.

CAMPS-VALLS, G.; TUIA, D.; ZHU, X. X.; REICHSTEIN, M. **Deep learning for the Earth Sciences: A comprehensive approach to remote sensing, climate science and geosciences**. John Wiley & Sons, 2021.

CARACOL. **Choques entre Ejército y pobladores por labores de erradicación en Chocó**. Caracol, 2021. Available at:<https://caracol.com.co/radio/2021/03/03/judicial/1614805490_980515.html>.

CARNAZ, G.; ANTUNES, M.; NOGUEIRA, V. B. An Annotated Corpus of Crime-Related Portuguese Documents for NLP and Machine Learning Processing. **Data**, v. 6, n. 7, p. 71, 2021. MDPI.

CARTER, D. **Law Enforcement Intelligence: A Guide for State, Local, and Tribal Law Enforcement Agencies.** Third Edition ed. Justice Information Sharing, 2021. Available at: <https://bja.ojp.gov/library/publications/law-enforcement-intelligence-guide-state-local-and-tribal-law-enforcement>.

CASANOVAS, P.; IRUJO, J. A.; MELERO, F.; et al. Fighting Organized Crime Through Open-Source Intelligence: **Regulatory Strategies of the CAPER Project. JURIX**, 2014.

CAULKINS, J. Improving research on drug law enforcement. **International Journal of Drug Policy**, 41 (2017), pp. 158-159, 2017. Available at: <https://doi.org/10.1016/j.drugpo.2017.01.002>.

CAULKINS, J; REUTER, P. What Price Data Tell Us about Drug Markets. **Journal of Drug Issues**, 28(3), 593–612, 1998. Available at: <https://doi.org/10.1177/002204269802800302>.

CEOFANB. Desmantelados dos campamentos con más de 5.000 kilos de cocaína colombiana. **Comando Estratégico Operacional de la Fuerza Armada Nacional Bolivariana,** 2021. Available at:<https://ceofanb.mil.ve/desmantelados-dos-campamentos-con-mdesmantelados-dos-campamentos-con-mas-de-5-000-kilos-de-cocaina-colombianaas-de-5-000-kilos-de-cocaina-colombiana/>.

CEOFANB. FANB inutiliza la pista TANCOL número 50. **Comando Estratégico Operacional de la Fuerza Armada Nacional Bolivariana,** 2022a. Available at:<https://ceofanb.mil.ve/fanb-inutiliza-la-pista-tancol-numero-50/>.

CEOFANB. FANB localizó dos aviones TANCOL en el Zulia. **Comando Estratégico Operacional de la Fuerza Armada Nacional Bolivariana,** 2022b. Available at:<https://ceofanb.mil.ve/fanb-localizo-dos-aviones-tancol/>.

CGFM. **En tiempo récord Ejército Nacional ha erradicado más de 200 hectáreas de cultivos ilícitos en Guaviare**. Comando General de las Fuerzas Militares de Colombia, 2022. Available at:<https://www.cgfm.mil.co/es/blog/en-tiempo-record-ejercito-nacional-ha-erradicado-mas-de-200-hectareas-de-cultivos-ilicitos-en>.

CHAINEY, S. **Understanding crime: Analyzing the geography of crime**. Esri Press, 2021.

CHAINEY, S; ALONSO, A. A structured methodical process for populating a crime script of organized crime activity using OSINT. **Trends in Organized Crime**, 2021. Available at:<https://doi.org/10.1007/s12117-021-09428-9>.

CHAINEY, S; RATCLIFFE, J. **GIS and Crime Mapping**. London: Wiley, 2005.

CHAINEY, S; UHLIG, S. The utility of hotspot mapping for predicting spatial patterns of crime. **Security journal**, 2008. Available at: <https://doi.org/10.1057/palgrave.sj.8350066>.

CHEN, H.; CHUNG, W.; XU, J. J.; et al. Crime data mining: a general framework and some examples. **Computer**, v. 37, n. 4, p. 50–56, 2004.

CHEN, P; SHI, W; ZHOU, X; LIU, Z; FU, X. STLP-GSM: a method to predict future locations of individuals based on geotagged social media data. **International Journal of Geographical Information Science**, 2019. Available at: <10.1080/13658816.2019.1630630>.

CHENG, G.; HAN, J. A survey on object detection in optical remote sensing images. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 117, p. 11–28, 2016. Available at:<https://www.sciencedirect.com/science/article/pii/S0924271616300144>.

CHENG, G.; HAN, J.; LU, X. Remote Sensing Image Scene Classification: Benchmark and State of the Art. **Proceedings of the IEEE**, v. 105, n. 10, p. 1865–1883, 2017.

CHENG, G.; XIE, X.; HAN, J.; GUO, L.; XIA, G.-S. Remote Sensing Image Scene Classification Meets Deep Learning: Challenges, Methods, Benchmarks, and Opportunities. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 13, p. 3735–3756, 2020.

CHIU, M. T.; XU, X.; WEI, Y.; et al. Agriculture-vision: A large aerial image database for agricultural pattern analysis. **Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.** p.2828–2838, 2020.

CHOLLET, F. **Deep learning with Python**. Second Edition. Simon and Schuster, 2021.

CHUVIECO, E. **Fundamentals of Satellite Remote Sensing: An Environmental Approach**. 3rd ed ed. CRC press, 2020.

CIENA. **COCA: Deforestación, contaminación y pobreza**. Centro Internacional de Estudios Estratégicos Contra el Narcotráfico. Policía Nacional de Colombia. Dirección de Antinarcóticos, 2014. Available at: < https://www.policia.gov.co/centro-estudios-narcotrafico/productos>.

CIENA. **Infraestructuras para el procesamiento de drogas ilícitas y sustancias químicas artesanales**. Centro Internacional de Estudios Estratégicos Contra el Narcotráfico. Policía Nacional de Colombia. Dirección de Antinarcóticos, 2018. Available at: < https://www.policia.gov.co/centro-estudios-narcotrafico/productos>.

CIENA. **Análisis del mercado de cocaína 2020**. Centro Internacional de Estudios Estratégicos Contra el Narcotráfico. Policía Nacional de Colombia. Dirección de Antinarcóticos, 2020. Available at: <https://www.policia.gov.co/centro-estudios-narcotrafico/productos>.

CIENA. **Rutas y destinos del tráfico de sustancias ilícitas**. Centro Internacional de Estudios Estratégicos Contra el Narcotráfico. Policía Nacional de Colombia. Dirección de Antinarcóticos, 2021. Available at: <https://www.policia.gov.co/centro-estudios-narcotrafico/productos>.

CLARK, R. M. **Geospatial Intelligence: Origins and Evolution**. Georgetown University Press, 2020.

CLARK, R. M. **Intelligence analysis: a target-centric approach**. CQ press, 2019.

CLARK, R. M. **Intelligence collection**. CQ Press, 2014.

COE-BRAZIL. **Covid-19 and drug trafficking in Brazil: the adaptation of organized crime and the role of police forces in the pandemic**. Centre of Excellence for Illicit Drug Supply Reduction. United Nations Office on Drugs and Crime, 2021. Available at: < https://www.cdebrasil.org.br/estudos/>.

COE-BRAZIL. **About the CoE**. Centre of Excellence for Illicit Drug Supply Reduction. United Nations Office on Drugs and Crime, 2022a. Available at:<https://www.cdebrasil.org.br/en/sobre/>.

COE-BRAZIL. **Monitoramento de Preços de Drogas Ilícitas. Lições aprendidas na Colômbia e possíveis desafios no Brasil**. Centre of Excellence for Illicit Drug Supply Reduction. United Nations Office on Drugs and Crime, 2022b. Available at: < https://www.cdebrasil.org.br/estudos/>.

COE-MEXICO. **Measuring OC in Latin America - A methodology for developing and validating scores and composite indicators for measuring OC at national and subnational level**. Centre of Excellence for Illicit Drug Supply Reduction. United Nations Office on Drugs and Crime, 2014. Available at: <https://www.cdeunodc.inegi.org.mx/unodc/articulos/doc/measuringfinalTRANSCRIME.pdf>.

CONGRESSO NACIONAL. **Constituição Federal**, 1998. Available at:<https://www.gov.br/planalto/pt-br/conheca-a-presidencia/acervo/constituicao-federal>.

COOREY, R. S. The Evolution of Geospatial Intelligence. **Australian Contributions to Strategic and Military Geography**. p.143–151, 2018. Springer.

CRESSON, R. **OTBTF. A framework for remote sensing images processing using deep learning techniques**, 2018. Available at:<https://github.com/remicres/otbtf>.

CUI, X; QUAN, Z; CHEN, X; ZHANG, Z; ZHOU, J; LIU, X; CHEN, J; CAO, X; GUO, L. GPR-Based Automatic Identification of Root Zones of Influence Using HDBSCAN. **Remote Sensing**. 2021. Available at: <https://doi.org/10.3390/rs13061227>.

DAS NEVES, A. J.; LUDWIG, F. J. A expansão das organizações criminosas nas fronteiras da América do Sul e as iniciativas do Estado brasileiro. **Coleção Meira Mattos: revista das ciências militares**, v. 16, n. 55, p. 1–24, 2022.

DAS, P.; DAS, A. K.; NAYAK, J.; PELUSI, D. A framework for crime data analysis using relationship among named entities. **Neural Computing and Applications**, v. 32, n. 12, p. 7671–7689, 2020. Available at:<https://doi.org/10.1007/s00521-019-04150-8>.

DAVIES, E. R. **Computer vision: principles, algorithms, applications, learning**. Academic Press, 2017.

DE ABREU, A. **Cocaína: a rota caipira: o narcotráfico no principal corredor de drogas do Brasil**. Editora Record, 2018.

DEA. **2020 National Drug Threat Assessment**. United States Drug Enforcement Administration, 2021. Available at: https://www.dea.gov/documents/2021/03/02/2020-national-drug-threat-assessment

DEA. **Southern Cone**. United States Drug Enforcement Administration, 2022. Available at:<https://www.dea.gov/foreign-offices/southern-cone#:~:text=The%20Southern%20Cone’s%20geographical%20area,%2C%20Paraguay%2C%20Peru%20and%20Uruguay>.

DEITEL, P.; DEITEL, H. **Intro to Python for Computer Science and Data Science**. Pearson Education, 2020.

DEL ROSSO, M. P.; SEBASTIANELLI, A.; ULLO, S. L. **Artificial Intelligence Applied to Satellite-based Remote Sensing Data for Earth Observation**. Institution of Engineering and Technology, 2021.

DEMIR, I.; KOPERSKI, K.; LINDENBAUM, D.; et al. **DeepGlobe 2018: A Challenge to Parse the Earth through Satellite Images**. 2018.

DENG, Z.; SUN, H.; ZHOU, S.; ZHAO, J.; ZOU, H. Toward Fast and Accurate Vehicle Detection in Aerial Images Using Coupled Region-Based Convolutional Neural Networks. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 10, n. 8, p. 3652–3664, 2017.

DEVIDA. **Informe sobre la demanda de hoja de coca para fines tradicionales e industriales**. Comisión Nacional para el Desarrollo y Vida sin Drogas – DEVIDA, Lima, 2020. Available at: < https://cdn.www.gob.pe/uploads/document/file/1348630/Informe%20-%20Demanda%20Hoja%20de%20Coca.pdf>.

DIÁRIO OFICIAL DA UNIÃO. PORTARIA Nº 2.507, DE 5 DE OUTUBRO DE 2021. Available at:<https://www.in.gov.br/en/web/dou/-/portaria-n-2.507-de-5-de-outubro-de-2021-350617155>.

DNIT. **DNITGeo - Geotecnologias Aplicadas**. Departamento Nacional de Infraestrutura de Transportes , 2022. Available at:<https://www.gov.br/dnit/pt-br/assuntos/planejamento-e-pesquisa/dnit-geo>.

DOLD, J; GROOPMAN, J. The future of geospatial intelligence. **Geo-Spatial Information Science**, 20(2), 151–162, 2017. Available at: < https://doi.org/10.1080/10095020.2017.1337318>.

DOS. **International Narcotics Control Strategy Report. Volume I: Drug and Chemical Control**. United States Department of State, 2022. Available at: <https://www.state.gov/2022-international-narcotics-control-strategy-report-2/#:~:text=The%202022%20International%20Narcotics%20Control,trade%20in%20Calendar%20Year%202021>.

DUGATO, M.; AZIANI, A. Measuring (Transnational) Organized Crime as an Indicator of Global Justice. **Fudan Journal of the Humanities and Social Sciences**, v. 13, n. 2, p. 211–231, 2020. Available at:<https://doi.org/10.1007/s40647-020-00279-2>.

ECK, J; CHAINEY, S; CAMERON, J; WILSON, R. **Mapping crime: Understanding hotspots**. Washington, DC: National Institute of Justice, 2005.

EL DEBER. El 84% de pistas destruidas a narcos operaba en Beni y Santa Cruz; Tarija es otra ruta. **EL DEBER**, 2022. Available at:<https://eldeber.com.bo/pais/el-84-de-pistas-destruidas-a-narcos-operaba-en-beni-y-santa-cruz-tarija-es-otra-ruta_262884>.

EL PACCTO. **Los delitos Ambientales en la Cuenca del Amazonas: el rol del crimen organizado en la minería**. Programa de Asistencia contra el Crimen Transnacional Organizado, 2019. Available at: <https://www.elpaccto.eu/wp-content/uploads/2019/05/Los-Delitos-Ambientales-en-la-Cuenca-del-Amazonas-comprimido.pdf >.

EL PACCTO. **Análisis del Impacto del Crimen Transnacional Organizado en las comunidades indígenas de América Latina: El caso de Bolivia**. Programa de Asistencia contra el Crimen Transnacional Organizado, 2022. Available at: https://www.elpaccto.eu/wp-content/uploads/2022/04/Comunidades-Indigenas-Bolivia.pdf

EL TIEMPO. Horas de tensión en el Catatumbo por plan de erradicación de coca. **El Tiempo**, 2021. Available at:<https://www.eltiempo.com/colombia/otras-ciudades/tibu-retencion-ilegal-de-soldados-que-iban-a-erradicar-cultivos-de-coca-629060>.

ELGENDY, M. **Deep learning for vision systems**. Simon and Schuster, 2020.

ELLIOTT, L.; SCHAEDLA, W. H. **Handbook of transnational environmental crime**. Edward Elgar Publishing, 2016.

EMCDDA. **An overview of recent changes in cocaine trafficking routes into Europe**. European Monitoring Centre for Drugs and Drug Addiction, 2016. Available at: https://www.emcdda.europa.eu/system/files/attachments/12066/EDMR2016%20Background%20paper_Eventon%20and%20Bewley-Taylor_Cocaine%20trafficking%20to%20Europe.pdf

EMCDDA. **Developing drug supply monitoring in Europe: current concepts**. European Monitoring Centre for Drugs and Drug Addiction, 2017. Available at: <https://doi.org/10.2810/56933>.

EMCDDA. **Using open-source information to improve the European drug monitoring system**. European Monitoring Centre for Drugs and Drug Addiction, 2019. Available at: < https://www.emcdda.europa.eu/publications/emcdda-papers/using-open-source-information_en>.

EMCDDA. **EU Drug Market: Cocaine**. European Monitoring Centre for Drugs and Drug Addiction, 2022a. Available at: <https://www.emcdda.europa.eu/publications/eu-drug-markets/cocaine_en#box_cocaine>.

EMCDDA. **Drug trafficking**. European Monitoring Centre for Drugs and Drug Addiction, 2022b. Available at:< https://www.emcdda.europa.eu/topics/drug-trafficking_en>.

EMCDDA. **European Drug Report 2022: Trends and Developments**. European Monitoring Centre for Drugs and Drug Addiction, 2022c. Available at: https://www.emcdda.europa.eu/publications/edr/trends-developments/2022_en

ESA. **Sentinel-2 User Handbook**. European Space Agency, 2015. Available at:<https://sentinels.copernicus.eu/web/sentinel/user-guides/document-library/-/asset_publisher/xlslt4309D5h/content/sentinel-2-user-handbook>.

ESRI. **Crime Analysis Solution: Tactical and Strategic Analysis**. Web Course. Environmental Systems Research Institute, 2021a. Available at: <https://www.esri.com/training/catalog/5bd8cd26166cf041da814dea/crime-analysis-solution%3A-tactical-and-strategic-analysis/>.

ESRI. **How Kernel Density works**. Environmental Systems Research Institute, 2021b. Available at: <https://desktop.arcgis.com/en/arcmap/latest/tools/spatial-analyst-toolbox/how-kernel-density-works.htm#>.

ESRI. **Geospatial deep learning with arcgis.learn**. Environmental Systems Research Institute, 2022. Available at:<https://developers.arcgis.com/python/guide/geospatial-deep-learning/>.

EUROPEAN UNION. **Cocaine Route Programme Newsletter N°17**. European Union, 2020. Available at:<https://illicitflows.eu/cocaine-route-programme-newsletter-issue-17/>.

EUROPOL. **OCTA 2011: EU Organised Crime Threat Assessment**. Publications Office of the European Union, 2011. Available at: < https://www.europol.europa.eu/publications-events/main-reports/octa-2011-eu-organised-crime-threat-assessment>.

EUROPOL. **European Union serious and organised crime threat assessment, A corrupting influence: the infiltration and undermining of Europe's economy and society by organised crime**. Luxembourg: Publications Office of the European Union, 2021. Available at: < https://www.europol.europa.eu/publication-events/main-reports/european-union-serious-and-organised-crime-threat-assessment-socta-2021>.

EUROPOL. **ENVIRONMENTAL CRIME. Threat assessment 2022 in the age of climate change**. Publications Office of the European Union, 2022. Available at: < https://www.europol.europa.eu/cms/sites/default/files/documents/Environmental%20Crime%20in%20the%20Age%20of%20Climate%20Change%20-%20Public%20report_5.pdf>.

EVANS-BROWN, M.; SEDEFOV, R. Responding to New Psychoactive Substances in the European Union: Early Warning, Risk Assessment, and Control Measures. In: H. H. Maurer; S. D. Brandt (Eds.); **New Psychoactive Substances: Pharmacology, Clinical, Forensic and Analytical Toxicology**. p.3–49, 2018. Cham: Springer International Publishing. Available at:<https://doi.org/10.1007/164_2018_160>.

EXÉRCITO BRASILEIRO. OPERAÇÃO CURARE IX - INTERDIÇÃO DE PISTA DE POUSO CLANDESTINA. **EXÉRCITO BRASILEIRO**, 2018. Available at:<http://www.eb.mil.br/o-exercito?p_p_id=101&p_p_lifecycle=0&p_p_state=maximized&p_p_mode=view&_101_struts_action=%2Fasset_publisher%2Fview_content&_101_returnToFullPageURL=%2Fo-exercito%3Fp_p_auth%3DP8IY3MqU%26p_p_id%3D3%26p_p_lifecycle%3D0%26p_p_state%3Dmaximized%26p_p_mode%3Dview%26_3_struts_action%3D%252Fs&_101_assetEntryId=9135725&_101_type=content&_101_groupId=8357041&_101_urlTitle=no-contexto-da-operacao-curare-ix-1-brigada-infantaria-de-selva-realiza-interdicao-de-pista-de-pouso-clandestina-&inheritRedirect=true>.

FAS. **National Imagery Interpretability Rating Scale (NIIRS).** Federation of American Scientists, 1998. Available at:<https://irp.fas.org/imint/niirs.htm>.

FBSP. **Anuário Brasileiro de Segurança Pública 2018**. Fórum Brasileiro de Segurança Pública, 2018. Available at: <https://forumseguranca.org.br/wp-content/uploads/2019/03/Anuario-Brasileiro-de-Seguranc%CC%A7a-Pu%CC%81blica-2018.pdf>.

FBSP. **Anuário Brasileiro de Segurança Pública Edição Especial 2022**. Fórum Brasileiro de Segurança Pública, 2022. Available at: < https://forumseguranca.org.br/anuario-edicao-especial-2022/>.

FERREIRA, A.; FELIPUSSI, S. C.; PIRES, R.; et al. Eyes in the Skies: A Data-Driven Fusion Approach to Identifying Drug Crops From Remote Sensing Images. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 12, n. 12, p. 4773–4786, 2019.

FIELD, K. **Cartography**. Esri Press, 2018.

FIP. **Cultivos ilícitos y áreas protegidas del Sistema de Parques Nacionales Naturales**. Fundación Ideas para la Paz, 2020. Available at: < https://multimedia.ideaspaz.org/media/website/FIP_NE_PNNCultivosilicitos_web_Corregido_Final.pdf >.

GARDNER, D.; NICHOLS, D. **Multi-label classification of satellite images with deep learning**. Stanford Univ., Stanford, CA, USA, Tech. Rep, 2017. Available at: < http://cs231n.stanford.edu/reports/2017/pdfs/908.pdf>.

GARZÓN, J.; GELVEZ, J.; SILVA, Á. **Los costos humanos de la erradicación forzada ¿es el glifosato la solución?** Fundación Ideas para la Paz, 2019. Available at:<https://www.ideaspaz.org/publications/posts/1734>.

GEE. **Sentinel-2**. Google Earth Engine, 2022. Available at:<https://developers.google.com/earth-engine/datasets/catalog/sentinel-2>.

GEFRON. **Grupo Especial de Segurança de Fronteira - GEFRON 20 ANOS**. Cuiabá: Grupo Especial de Segurança de Fronteira , 2022.

GFI. **Transnational Crime and the Developing World**. Global Financial Integrity, 2017. Available at:< https://gfintegrity.org/report/transnational-crime-and-the-developing-world/>.

GIRSHICK, R. Fast R-CNN. **2015 IEEE International Conference on Computer Vision (ICCV)**, p.1440–1448, 2015. Available at: < doi: 10.1109/ICCV.2015.169>.

GIRSHICK, R.; DONAHUE, J.; DARRELL, T.; MALIK, J. Rich feature hierarchies for accurate object detection and semantic segmentation. **Proceedings of the IEEE conference on computer vision and pattern recognition**, p.580–587, 2014.

GLOBAL INITIATIVE. **Organized Crime and Illegally Mined Gold in Latin America**. Global Initiative, 2016. Available at: < https://globalinitiative.net/analysis/organized-crime-and-illegally-mined-gold-in-latin-america/>.

GLOBAL INITIATIVE. **Environmental crime: The not-so-hidden obstacle to combat climate change.** Global Initiative, 2021. Available at: < https://globalinitiative.net/analysis/environmental-crime-climate-change/>.

GNB. **Operación paso del Tornado – 2017**. Guardia Nacional Bolivariana, 2017. Available at:<https://www.youtube.com/watch?v=gKIKdJKzXUA>.

GONÇALVES, J. A inteligência contra o crime organizado. **Senatus : cadernos da Secretaria de Informação e Documentação**, 2004. Available at:<https://www2.senado.leg.br/bdsf/handle/id/99837>.

GOODFELLOW, I.; BENGIO, Y.; COURVILLE, A. **Deep learning**. MIT press, 2016.

GORE, M. L.; BRASZAK, P.; BROWN, J.; et al. Transnational environmental crime threatens sustainable development. **Nature Sustainability**, v. 2, n. 9, p. 784–786, 2019. Available at:<https://doi.org/10.1038/s41893-019-0363-6>.

GORELICK, N.; HANCHER, M.; DIXON, M.; et al. Google Earth Engine: Planetary-scale geospatial analysis for everyone. **Remote sensing of Environment**, v. 202, p. 18–27, 2017. Elsevier. Available at: < https://doi.org/10.1016/j.rse.2017.06.031>.

GOV.BR. **Governo do Brasil, 2021**. Available at:<https://www.gov.br/pt-br>.

GOYAL, A.; GUPTA, V.; KUMAR, M. Recent Named Entity Recognition and Classification techniques: A systematic review. **Computer Science Review**, v. 29, p. 21–43, 2018. Available at:<https://www.sciencedirect.com/science/article/pii/S1574013717302782>.

GRAHAM, B.; MARGUERAT, A. Using Natural Language Processing to Search for Textual References. In: D. Hamidović; C. Clivaz; S. B. Savant (Eds.); **Ancient Manuscripts in Digital Culture**, Visualisation, Data Mining, Communication. v. 3, p.115–132, 2019. Brill. Available at:<http://www.jstor.org/stable/10.1163/j.ctvrxk44t.11>.

GRANGIER, X. Goose3 - Article Extractor, 2022. Apache 2.0 license. Available at:<https://github.com/goose3/goose3>.

GREKOUSIS, G. **Spatial analysis methods and practice: describe–explore–explain through GIS**. Cambridge University Press, 2020.

GU, Y.; WANG, Y.; LI, Y. A Survey on Deep Learning-Driven Remote Sensing Image Scene Understanding: Scene Classification, Scene Retrieval and Scene-Guided Object Detection. **Applied Sciences**, v. 9, n. 10, 2019. Available at:<https://www.mdpi.com/2076-3417/9/10/2110>.

GUO, W.; YANG, W.; ZHANG, H.; HUA, G. Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network. **Remote Sensing**, v. 10, n. 1, 2018. Available at:<https://www.mdpi.com/2072-4292/10/1/131>.

HAENLEIN, M.; KAPLAN, A. A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. **California Management Review**, v. 61, n. 4, p. 5–14, 2019. Available at:<https://doi.org/10.1177/0008125619864925>.

HASSABALLAH, M.; AWAD, A. I. **Deep learning in computer vision: principles and applications**. CRC Press, 2020.

HASSAN, A.; HUSSEIN, W. M.; SAID, E.; HANAFY, M. E. A Deep Learning Framework for Automatic Airplane Detection in Remote Sensing Satellite Images. **2019 IEEE Aerospace Conference**. p.1–10, 2019.

HE, K.; GKIOXARI, G.; DOLLÁR, P.; GIRSHICK, R. **Mask R-CNN**, 2017. Available at:<https://arxiv.org/abs/1703.06870>.

HE, K.; ZHANG, X.; REN, S.; SUN, J. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. **IEEE Transactions on Pattern Analysis and Machine Intelligence**, v. 37, n. 9, p. 1904–1916, 2015.

HEIDENREICH, N; SCHINDLER A; SPERLICH S. Bandwidth selection for kernel density estimation: a review of fully automatic selectors. **AStA Advances in Statistical Analysis**, 97(4), 403-433, 2013. Available at: < https://doi.org/10.1007/s10182-013-0216-y>.

HELBER, P.; BISCHKE, B.; DENGEL, A.; BORTH, D. EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 12, n. 7, p. 2217–2226, 2019.

HILL, L. **Georeferencing: The geographic associations of information**. Mit Press, 2006. Available at: https://doi.org/10.7551/mitpress/3260.001.0001

HOBBS, C.; MORAN, M.; SALISBURY, D. **Open source intelligence in the twenty-first century: new approaches and opportunities**. Palgrave Macmillan London, 2014.

HOESER, T.; KUENZER, C. Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends. **Remote Sensing**, v. 12, n. 10, 2020. Available at:<https://www.mdpi.com/2072-4292/12/10/1667>.

HOWARD, J.; GUGGER, S. **Deep Learning for Coders with Fastai and Pytorch: AI Applications Without a PhD**. O'Reilly Media, 2020.

HRW. **The War in Catatumbo. Abuses by Armed Groups Against Civilians Including Venezuelan Exiles in Northeastern Colombia**. Human Rights Watch, 2019. Available at: <https://www.hrw.org/report/2019/08/08/war-catatumbo/abuses-armed-groups-against-civilians-including-venezuelan-exiles>.

HU, F.; XIA, G.-S.; HU, J.; ZHANG, L. Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery. **Remote Sensing**, v. 7, n. 11, p. 14680–14707, 2015. Available at:<https://www.mdpi.com/2072-4292/7/11/14680>.

HU, Y. Geo-text data and data-driven geospatial semantics. **Geography Compass**, v. 12, n. 11, p. e12404, 2018. John Wiley & Sons, Ltd. Available at:<https://doi.org/10.1111/gec3.12404>.

HUANG, G.; LIU, Z.; VAN DER MAATEN, L.; WEINBERGER, K. Q. Densely connected convolutional networks. **Proceedings of the IEEE conference on computer vision and pattern recognition**, p.4700–4708, 2017.

HUBEL, D.; WIESEL, T. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. **The Journal of physiology**, v. 160, n. 1, p. 106–154, 1962. Available at:<https://pubmed.ncbi.nlm.nih.gov/14449617>.

HUDSON, R. Thinking through the relationships between legal and illegal activities and economies: Spaces, flows and pathways. **Journal of Economic Geography**, Volume 14, Issue 4, July 2014, Pages 775–795, 2014. Available at: <https://doi.org/10.1093/jeg/lbt017>.

HUERTAS, O; TORRES, H. **El principio de jurisdicción o justicia universal : instrumento jurídico para combatir la impunidad en delitos de extrema gravedad en el ámbito internacional**. Bogotá: Grupo Editorial Ibáñez, 2012.

HULNICK, A. S. The Downside of Open Source Intelligence. **International Journal of Intelligence and CounterIntelligence**, v. 15, n. 4, p. 565–579, 2002. Routledge. Available at:<https://doi.org/10.1080/08850600290101767>.

HUNT, J. **Advanced Guide to Python 3 Programming**. Springer, 2019.

IACA. **Exploring Crime Analysis: Readings on Essential Skills**. Third. Ed. ed. International Association of Crime Analysts, 2017.

IBGE. R.PR 01/2015 – **SIRGAS2000**. Instituto Brasileiro de Geografia e Estatística, 2015. Available at: <https://geoftp.ibge.gov.br/metodos_e_outros_documentos_de_referencia/normas/rpr_01_2015_sirgas2000.pdf>.

IBGE. **Atlas Geográfico Escolar - 8ª edição**. Instituto Brasileiro de Geografia e Estatística, 2018. Available at: <https://atlasescolar.ibge.gov.br/conceitos-gerais/o-que-e-cartografia/as-projec-o-es-cartogra-ficas.html>.

IBGE. **Instituto Brasileiro de Geografia e Estatística**, 2022. Available at:<https://www.ibge.gov.br/pt/inicio.html>.

ICMBIO. **Floresta Nacional do Amana. Plano de Manejo**. Instituto Chico Mendes de Conservação da Biodiversidade, 2010. Available at: <https://www.gov.br/icmbio/pt-br/assuntos/biodiversidade/unidade-de-conservacao/unidades-de-biomas/amazonia/lista-de-ucs/flona-do-amana>.

IGAC. **Tibú, Municipio del Norte de Santander en donde renacerá la paz**. Instituto Geográfico Agustín Codazzi, 2016. Available at:<https://www.igac.gov.co/es/noticias/tibu-municipio-del-norte-de-santander-en-donde-renacera-la-paz>.

IGAC. **GEOPORTAL**. Instituto Geográfico Agustín Codazzi, 2021. Available at:<https://geoportal.igac.gov.co/contenido/datos-abiertos-cartografia-y-geografia>.

IGARAPÉ-INTERPOL. **Guía práctica para combatir los delitos ambientales: Lecciones de la minería ilegal de oro en la Cuenca Amazónica**. Instituto Igarapé - INTERPOL, 2021. Available at: <https://igarape.org.br/guia-practica-para-combatir-los-delitos-ambientales-lecciones-de-la-mineria-ilegal-de-oro-en-la-cuenca-amazonica/>.

IGVSB. **Geoportal Nacional Simón Bolívar**. Instituto Geográfico de Venezuela Simón Bolívar, 2012. Available at:<http://www.igvsb.gob.ve/>.

INCB. **Report of the International Narcotics Control Board for 2019**. International Narcotics Control Board, 2020. Available at: < https://www.incb.org/incb/en/publications/annual-reports/annual-report-2019.html>.

INCB. **Yellow List - List of Narcotic Drugs Under International Control**. International Narcotics Control Board, 2021a. Available at: < https://www.incb.org/incb/en/narcotic-drugs/Yellowlist/yellow-list.html>.

INCB. **Green List - List of Psychotropic Substances Under International Control**. International Narcotics Control Board, 2021b. Available at: <https://www.incb.org/incb/en/psychotropics/green-list.html>.

INCB. **Red List**. International Narcotics Control Board, 2022. Available at: < https://www.incb.org/incb/es/precursors/Red_Forms/red-list.html>.

INE. **Informe Geoambiental del estado Zulia**. Instituto Nacional de Estadística, 2011. Available at:<http://www.ine.gob.ve/documentos/Ambiental/PrincIndicadores-/pdf/Informe_Geoambiental_Zulia.pdf>.

INGLE, T.; STANIFORTH, A. Horizon scanning for law enforcement agencies: identifying factors driving the future of organized crime. **Using Open Data to Detect Organized Crime Threats**. p.119–136, 2017. Springer.

INPE. **TerraBrasilis**. Instituto Nacional de Pesquisas Espaciais, 2020. Available at: <http://terrabrasilis.dpi.inpe.br/en/home-page/>.

INSIGHT CRIME. Disidencia de la guerrilla colombiana penetra el Amazonas venezolano. **Insight Crime**, 2018. Available at:<https://es.insightcrime.org/noticias/analisis/disidencia-de-la-guerrilla-colombiana-penetra-el-amazonas-venezolano/>.

INSIGHT CRIME. Clandestine Airstrips, Drug Flights Becoming More Frequent Across Venezuela. **Insight Crime**, 2020a. Available at:<https://insightcrime.org/news/brief/airstrips-drug-flights-venezuela/>.

INSIGHT CRIME. ELN in Venezuela. **Insight Crime**, 2020b. Available at:<https://insightcrime.org/venezuela-organized-crime-news/eln-in-venezuela/>.

INSIGHT CRIME. Brazil Profile. **Insight Crime**, 2020c. Available at:<https://insightcrime.org/brazil-organized-crime-news/brazil-profile/>.

INSIGHT CRIME. **The Cocaine Pipeline to Europe**. Insight Crime, 2021a. Available at: < https://insightcrime.org/investigations/cocaine-pipeline-europe/>.

INSIGHT CRIME. Ex-FARC Mafia in Venezuela. **Insight Crime**, 2021b. Available at:<https://insightcrime.org/venezuela-organized-crime-news/farc-in-venezuela/>.

INSIGHT CRIME. **Coca Growing, Cocaine Production Reach New Heights in Honduras**. Insight Crime, 2022. Available at:<https://insightcrime.org/news/coca-growing-cocaine-production-reach-new-heights-in-honduras/>.

INTERPOL. **Introduction to Criminal Intelligence Analysis** (VA-2-050-EN). INTERPOL E-Learning Course. International Criminal Police Organization, 2014a.

INTERPOL. **Criminal Intelligence Analysis**. International Criminal Police Organization, 2014b. Available at:<https://www.interpol.int/en/How-we-work/Criminal-intelligence-analysis>.

INTERPOL. **World atlas of illicit flows**. International Criminal Police Organization, 2018a. Available at: <https://www.interpol.int/ar/content/download/14080/file/World%20Atlas%20of%20Illicit%20Flows-1.pdf>.

INTERPOL. **Open Source Intelligence in investigations** (EN-2-932). INTERPOL e-learning Course. International Criminal Police Organization, 2018b.

INTERPOL. **Illegal Mining and Associated Crimes - A Law Enforcement Perspective On One Of the Most Lucrative Crimes**. International Criminal Police Organization, 2022a. Available at:< https://www.interpol.int/content/download/17495/file/ILM%20-%20Illegal%20mining%20-%20Report.pdf >.

INTERPOL. **Drug trafficking**. International Criminal Police Organization, 2022b. Available at:<https://www.interpol.int/Crimes/Drug-trafficking>.

INTERPOL. **Artificial Intelligence and Policing: Threat, Tool and Source of Evidence**. International Criminal Police Organization, 2022c.

ITAMARATY. Comissão Brasileira Demarcadora de Limites, 2022. Available at:<http://pcdl.itamaraty.gov.br/pt-br/>.

JANES. **Tradecraft**. Janes, 2022. Available at:<https://www.janes.com/about-janes/janes-defence-intelligence-tradecraft>.

JANOWICZ, K.; GAO, S.; MCKENZIE, G.; HU, Y.; BHADURI, B. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. **International Journal of Geographical Information Science**, v. 34, n. 4, p. 625–636, 2020. Taylor & Francis. Available at:<https://doi.org/10.1080/13658816.2019.1684500>.

JENSEN, J. R. **Remote sensing of the environment: An earth resource perspective 2/e**. Pearson Education India, 2009.

JOHNSON, L. K. **The Oxford handbook of national security intelligence**. Oxford University Press, 2010.

KARIMI H, KARIMI B. **Geospatial data science techniques and applications**. CRC Press, 2017.

KELLEHER, J. **Deep Learning**. London: The MIT Press Essential Knowledge Series, 2019.

KELLEHER, J.; MAC NAMEE, B.; D'ARCY, A. **Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies**. MIT press, 2020.

KHAN, M. A.; HUSSAIN, N.; MAJID, A.; et al. Classification of positive COVID-19 CT scans using deep learning. **CMC-COMPUTERS MATERIALS & CONTINUA**, v. 66, p. 2923–2938, 2021. TECH SCIENCE PRESS.

KHAN, S.; RAHMANI, H.; SHAH, S. A. A.; BENNAMOUN, M. A guide to convolutional neural networks for computer vision. **Synthesis lectures on computer vision**, v. 8, n. 1, p. 1–207, 2018. Morgan & Claypool Publishers.

KIM, Y; KIM, G; LEE, Y; JANG, K. Bandwidth Selection of Kernel Density Estimation for GIS-based Crime Occurrence Map Visualization. **In 2020 International Conference on Information and Communication Technology Convergence**, 2020. Available at: 10.1109/ICTC49870.2020.9289633

KLUYVER, T; RAGAN-KELLEY, B; PÉREZ, F; GRANGER, E; BUSSONNIER, M; FREDERIC, J; KELLEY, K; HAMRICK, J; GROUT, J; CORLAY, S; IVANOV, P; AVILA, D; ABDALLA, S; WILLING, C. Jupyter Notebooks - a publishing format for reproducible computational workflows. **Positioning and Power in Academic Publishing: Players, Agents and Agendas**. IOS Press. pp. 87-90, 2016. Available at: < doi:10.3233/978-1-61499-649-1-87>.

KOH, J. C. O.; SPANGENBERG, G.; KANT, S. Automated Machine Learning for High-Throughput Image-Based Plant Phenotyping. **Remote Sensing**, v. 13, n. 5, 2021. Available at:<https://www.mdpi.com/2072-4292/13/5/858>.

KRESSE W; DANKO D. **Springer handbook of geographic information**. 2nd Edition. Springer Cham, 2022.

KRUSE, M.; SVENDSEN, A. D. M. Foresight and the future of crime: Advancing environmental scanning approaches. **Using Open Data to Detect Organized Crime Threats**. p.73–101, 2017. Springer.

KUSSUL, N.; LAVRENIUK, M.; SKAKUN, S.; SHELESTOV, A. Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. **IEEE Geoscience and Remote Sensing Letters**, v. 14, n. 5, p. 778–782, 2017.

LABELBOX. **Labelbox**, 2022. Available at:<https://labelbox.com/>.

LABROUSSE, A. **Géopolitique des drogues**. Presses universitaires de France, 2011.

LACOSTE, Y. **La géographie, ça sert, d'abord, à faire la guerre**. La découverte, 2014.

LARSEN, H; BLANCO, J; PASTOR, R; YAGER, R. **Using Open Data to Detect Organized Crime Threats: Factors Driving Future Crime**. Springer, 2017.

LECUN, Y.; BENGIO, Y.; HINTON, G. Deep learning. **Nature**, v. 521, n. 7553, p. 436–444, 2015. Available at:<https://doi.org/10.1038/nature14539>.

LECUN, Y; BOTTOU, L O. G. B. AND M. K.-R. Efficient BackProp. In: G. B. and M. K.-R. Montavon Grégoire and Orr (Ed.); **Neural Networks: Tricks of the Trade: Second Edition**. p.9–48, 2012. Berlin, Heidelberg: Springer Berlin Heidelberg. Available at:<https://doi.org/10.1007/978-3-642-35289-8_3>.

LEETARU, K. The GDELT Project - Watching Our World Unfold, 2013. Available at:<https://www.gdeltproject.org/>.

LEIDNER, J. **TOPONYM RESOLUTION IN TEXT ANNOTATION**. Evaluation and Applications of Spatial Grounding of Place Names, 2007. Doctoral Thesis, University of Edinburgh. School of Informatics. Available at: https://era.ed.ac.uk/handle/1842/1849

LI, K.; WAN, G.; CHENG, G.; MENG, L.; HAN, J. Object detection in optical remote sensing images: A survey and a new benchmark. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 159, p. 296–307, 2020. Available at:<https://www.sciencedirect.com/science/article/pii/S0924271619302825>.

LI, L; GOODCHILD, F. Constructing places from spatial footprints. In Proceedings of the 1st Association for Computing Machinery. **SIGSPATIAL international workshop on crowdsourced and volunteered geographic information**, 2012. Available at: < https://doi.org/10.1145/2442952.2442956>.

LI, S.; DRAGICEVIC, S.; CASTRO, F. A.; et al. Geospatial big data handling theory and methods: A review and research challenges. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 115, p. 119–133, 2016. Available at:<https://www.sciencedirect.com/science/article/pii/S0924271615002439>.

LIEBERMAN M, SAMET H. Multifaceted toponym recognition for streaming news. **Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval (SIGIR '11).** Association for Computing Machinery, New York, NY, USA, 843–852, 2011. Available at: < https://doi.org/10.1145/2009916.2010029>.

LIM, K. Big Data and Strategic Intelligence. **Intelligence and National Security**, v. 31, n. 4, p. 619–635, 2016. Routledge. Available at:<https://doi.org/10.1080/02684527.2015.1062321>.

LIN, T.-Y.; GOYAL, P.; GIRSHICK, R.; HE, K.; DOLLÁR, P. Focal loss for dense object detection. **Proceedings of the IEEE international conference on computer vision**, p.2980–2988, 2017.

LIU WEI & ANGUELOV, D. AND E. D. AND S. C. AND R. S. AND F. C.-Y. AND B. A. C. SSD: Single Shot MultiBox Detector. **In: J. and S. N. and W. M. Leibe Bastian and Matas (Ed.); Computer Vision – ECCV 2016**, p.21–37, 2016. Cham: Springer International Publishing.

LIU, R.; YU, Z.; MO, D.; CAI, Y. An Improved Faster-RCNN Algorithm for Object Detection in Remote Sensing Images. **2020 39th Chinese Control Conference (CCC),** p.7188–7192, 2020.

LIU, S.; QI, L.; QIN, H.; SHI, J.; JIA, J. Path aggregation network for instance segmentation. **Proceedings of the IEEE conference on computer vision and pattern recognition**. p.8759–8768, 2018.

LIU, X.; TIAN, Y.; YUAN, C.; ZHANG, F.; YANG, G. Opium Poppy Detection Using Deep Learning. **Remote Sensing**, v. 10, n. 12, 2018. Available at:<https://www.mdpi.com/2072-4292/10/12/1886>.

LIU, X.; ZHOU, Y.; ZHAO, J.; et al. Siamese Convolutional Neural Networks for Remote Sensing Scene Classification. **IEEE Geoscience and Remote Sensing Letters**, v. 16, n. 8, p. 1200–1204, 2019.

LOCH, J. **National Security Intelligence**. 2nd Edition ed. Wiley, 2017.

LÓPEZ-JIMÉNEZ, E.; VASQUEZ-GOMEZ, J. I.; SANCHEZ-ACEVEDO, M. A.; HERRERA-LOZADA, J. C.; URIARTE-ARCIA, A. V. Columnar cactus recognition in aerial images using a deep learning approach. **Ecological Informatics**, v. 52, p. 131–138, 2019. Available at:<https://www.sciencedirect.com/science/article/pii/S1574954119300895>.

LOWENTHAL, M. M. **Intelligence: From secrets to policy**. CQ press, 2019.

LOWENTHAL, M. M.; CLARK, R. M. **The five disciplines of intelligence collection**. Sage, 2015.

MA, L.; LIU, Y.; ZHANG, X.; et al. Deep learning in remote sensing applications: A meta-analysis and review. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 152, p. 166–177, 2019. Available at:<https://www.sciencedirect.com/science/article/pii/S0924271619301108>.

MAGLIOCCA, N. R.; MCSWEENEY, K.; SESNIE, S. E.; et al. Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. **Proceedings of the National Academy of Sciences**, v. 116, n. 16, p. 7784–7792, 2019. Available at:<https://doi.org/10.1073/pnas.1812459116>.

MAPBIOMAS. **Mapas e Dados**. MapBiomas, 2020. Available at:<https://mapbiomas.org/>.

MARETTO, R. **Automating Land Cover Change Detection: A Deep Learning Based Approach to Map Deforested Areas**, 2020. Doctoral Thesis, Instituto Nacional de Pesquisas Espaciais (INPE). Available at:<http://urlib.net/sid.inpe.br/mtc-m21c/2020/06.09.11.59>.

MARÍN, M.; MACHUCA, D.; ACERO, C. **El PNIS en Terreno: Voces del campesinado cocalero**. Observatorio de restitución y regulación de los derechos de propiedad rural. IEPRI, 2020. Available at: < https://www.observatoriodetierras.org/wp-content/uploads/2020/05/El-PNIS-en-Terreno_-Voces-del-campesinado-cocalero.pdf>.

MAYBIR, J.; CHAPMAN, B. Web scraping of ecstasy user reports as a novel tool for detecting drug market trends. **Forensic Science International: Digital Investigation**, v. 37, p. 301172, 2021. Available at:<https://www.sciencedirect.com/science/article/pii/S2666281721000809>.

MCCARTHY, J. **What is artificial intelligence?** 2007. Available at:<http://jmc.stanford.edu/articles/whatisai.html>.

MCCULLOCH, W. S.; PITTS, W. A logical calculus of the ideas immanent in nervous activity. **The bulletin of mathematical biophysics**, v. 5, n. 4, p. 115–133, 1943. Available at:<https://doi.org/10.1007/BF02478259>.

MCINNES, L; HEALY, J; ASTELS, S. Hdbscan: Hierarchical density based clustering, **Journal of Open Source Software**, 2(11), 205, 2017. Aailable at: < https://doi.org/10.21105/joss.00205>.

MCSWEENEY, K. Reliable drug war data: The Consolidated Counterdrug Database and cocaine interdiction in the “Transit Zone.” **International Journal of Drug Policy**, v. 80, p. 102719, 2020. Available at:< https://doi.org/10.1016/j.drugpo.2020.102719>.

MEILLÓN, S. Geospatial Intelligence and Geospatial Information Systems. **NPS-Naval Postgraduation School: Monterey, CA, USA**, 2008.

MESEJO, D. tr.rex - **Efficient keyword extraction with regex**, 2021. MIT license. Available at:<https://github.com/mesejo/trex>.

MICROSOFT. **Evaluate automated machine learning experiment results**. MICROSOFT, 2022. Available at:<https://docs.microsoft.com/en-us/azure/machine-learning/how-to-understand-automated-ml>.

MINAMBIENTE. **Parques Nacionales Naturales de Colombia. Plan de Manejo del Parque Nacional Natural La Paya**. Ministerio del Ambiente, 1978. Available at: < https://www.parquesnacionales.gov.co/portal/wp-content/uploads/2020/10/plan-de-manejo-pnn-la-paya.pdf>.

MINETTO, R.; PAMPLONA SEGUNDO, M.; SARKAR, S. Hydra: An Ensemble of Convolutional Neural Networks for Geospatial Land Classification. **IEEE Transactions on Geoscience and Remote Sensing**, v. 57, n. 9, p. 6530–6541, 2019.

MINISTÉRIO DA INFRAESTRUTURA. **Nomenclatura das rodovias federais**. Ministério da Infraestrutura, 2020. Available at:<https://www.gov.br/dnit/pt-br/rodovias/rodovias-federais/nomeclatura-das-rodovias-federais>.

MINISTERIO DE LA DEFENSA. **Medio Ambiente**. 2020. Available at: < https://www.mindefensa.gov.co/irj/go/km/docs/Mindefensa/Documentos/descargas/Documentos_Descargables/espanol/Medio%20Ambiente.pdf >.

MITCHELL, R. **Web scraping with Python: Collecting more data from the modern web**. “ O’Reilly Media, Inc.,” 2018.

MJD-UNODC. **Caracterización Regional Norte de Santander**. Ministerio de Justicia y del Derecho - Oficina de las Naciones Unidas contra la Droga y el Delito, 2016. Available at: < https://www.minjusticia.gov.co/programas-co/ODC/Paginas/Publicaciones-ODC.aspx>.

MJD. **Densidad de Cultivos de Coca 2020**. Ministerio de Justicia y del Derecho, 2021. Available at:<https://www.datos.gov.co/Justicia-y-Derecho/Densidad-de-Cultivos-de-Coca-2020-Subdirecci-n-Est/ihhp-t7zk>.

MJSP. **Política Nacional sobre Drogas. Redução da Oferta de Drogas**. Ministério da Justiça e Segurança Pública, 2021. Available at: <https://www.gov.br/mj/pt-br/assuntos/sua-protecao/politicas-sobre-drogas/subcapas-senad/reducao-da-oferta-de-drogas/view>.

MJSP. Aliança Estratégica contra o Crime Organizado Transnacional. **Ministério da Justiça e Segurança Pública**, 2022a. Available at:<https://www.gov.br/mj/pt-br/assuntos/noticias/brasil-anuncia-no-paraguai-alianca-internacional-contra-crime-organizado-no-cone-sul>.

MJSP. **Subsistema de Alerta Rápido sobre Drogas**. Ministério da Justiça e Segurança Pública, 2022b. Available at:<https://www.gov.br/mj/pt-br/assuntos/sua-protecao/politicas-sobre-drogas/subsistema-de-alerta-rapido-sobre-drogas-sar/subsistema-de-alerta-rapido-sobre-drogas>.

MONTEIRO, C. **A GOVERNANÇA DAS POLÍCIAS NO BRASIL E MÉXICO: Estratégias para o desenvolvimento de planos no campo da segurança pública**, 2022. Doctoral Thesis, Porto Alegre: Universidade Federal do Rio Grande do Sul. Available at: < https://lume.ufrgs.br/handle/10183/249792>.

MORABITO, M. S.; GAUB, J. E. You can’t manage what you can’t measure: the importance of data in policing. **Police Practice and Research**, v. 23, n. 4, p. 397–399, 2022. Routledge. Available at:<https://doi.org/10.1080/15614263.2022.2066781>.

NATO. **Allied Joint Doctrine for Intelligence Procedures AJP-2.1**. Brussels, Belgium: North Atlantic Treaty Organization, 2016.

NEGRET, P. J.; SONTER, L.; WATSON, J. E. M.; et al. Emerging evidence that armed conflict and coca cultivation influence deforestation patterns. **Biological Conservation**, v. 239, p. 108176, 2019. Available at:<https://www.sciencedirect.com/science/article/pii/S0006320718318779>.

NEWSAVIA. **Uma descolagem inacreditável**. **Kamikazes Garimpeiros**. Available at:<https://www.youtube.com/watch?v=K64bBAZlMRM>.

NG, ANDREW. **What Data Scientists Should Know about Deep Learning**, 2015. Available at:<https://www.slideshare.net/ExtractConf>.

NGA. **Geospatial Intelligence (GEOINT) Basic Doctrine**. National Geospatial-Intelligence Agency, 2018. Available at:<https://www.nga.mil/resources/GEOINT_Basic_Doctrine_Publication_10_.html>.

NIELSEN, M. A. **Neural networks and deep learning**. Determination press San Francisco, CA, USA, 2015.

NOGUEIRA, K.; DOS SANTOS, J. A.; FORNAZARI, T.; et al. Towards vegetation species discrimination by using data-driven descriptors. **2016 9th IAPR Workshop on Pattern Recogniton in Remote Sensing (PRRS)**. p.1–6, 2016.

NVIDIA. **DEEP LEARNING**. Nvidia Developer, 2022. Available at:<https://developer.nvidia.com/deep-learning>.

O GLOBO. O GLOBO. **O Portal de Noticias da Globo**. 2021a. Available at:<https://www.globo.com/>.

O GLOBO. Empresário foragido é apontado pela PF como intermediador do esquema de envio de cocaína de SC para África. **O portal de notícias da Globo**, 2021b. Available at:<https://g1.globo.com/sc/santa-catarina/noticia/2021/09/16/empresario-foragido-e-apontado-pela-pf-como-intermediador-do-esquema-de-envio-de-cocaina-de-sc-para-africa.ghtml>.

O GLOBO. Receita Federal localiza quase 2 toneladas de cocaína em sacas de açúcar no Porto de Santos, SP. **O portal de notícias da Globo**, 2021c. Available at:<https://g1.globo.com/sp/santos-regiao/porto-mar/noticia/2021/07/23/receita-federal-localiza-quase-2-toneladas-de-cocaina-em-sacas-de-acucar-no-porto-de-santos-sp.ghtml>.

O GLOBO. Receita localiza 1,7 tonelada de cocaína escondida em carga de tapioca no Porto de Santos, SP. **O portal de notícias da Globo**, 2021d. Available at:<https://g1.globo.com/sp/santos-regiao/porto-mar/noticia/2021/02/25/receita-localiza-17-tonelada-de-cocaina-escondida-em-carga-de-tapioca-no-porto-de-santos-sp.ghtml>.

O GLOBO. Veleiro com 2,2 toneladas de cocaína é interceptado a 270 quilômetros da costa do Recife e cinco pessoas são presas. **O portal de notícias da Globo**, 2021e. Available at:<https://g1.globo.com/pe/pernambuco/noticia/2021/02/15/veleiro-carregado-com-cocaina-e-interceptado-a-270-quilometros-da-costa-do-recife-e-cinco-pessoas-sao-presas.ghtml>.

O GLOBO. Operação da PF prende quadrilha que mantinha laboratório do narcotráfico na fronteira com a Bolívia. **O portal de notícias da Globo**, 2022. Available at:<https://g1.globo.com/mt/mato-grosso/noticia/2022/03/01/operacao-da-pf-prende-quadrilha-que-mantinha-laboratorio-do-narcotrafico-na-fronteira-com-a-bolivia.ghtml>.

OAS. **Conservation Status of Yapacana National Park**. Organization of American States, 2007. Available at: < https://www.oas.org/dsd/AAPAD2/Docs/(iii)%20Yapacana%20NP%20Special%20Report%20(Venezuela).pdf>.

OAS. **The Drug Problem in the Americas. Drugs and Security**. Organization of American States. Inter-American Drug Abuse Control Commission, 2013. Available at: < http://www.cicad.oas.org/Main/Template.asp?File=/drogas/elinforme/default_eng.asp>.

OAS. **Características e intervención a las infraestructuras clandestinas se producción ilícita de drogas de origen natural**. Organization of American States. Inter-American Drug

Abuse Control Commission, 2018. Available at: < http://www.cicad.oas.org/apps/Document.aspx?Id=4703>.

OECD. **Illegal Trade in Environmentally Sensitive Goods**. Organisation for Economic Co-operation and Development, 2012. Available at: < https://www.oecd.org/env/illegal-trade-in-environmentally-sensitive-goods-9789264174238-en.htm#:~:text=Illegal%20trade%20in%20environmentally%20sensitive%20goods%2C%20such%20as%20threatened%20wildlife,international%20trade%20and%20environment%20agenda. >.

OECD. **AI Principles overview**. Organisation for Economic Co-operation and Development, 2022. Available at:<https://oecd.ai/en/ai-principles>.

OLIVEIRA, D. **Atividade garimpeira na região do Tapajós (PA): o caso na Flona do Amana**, 2015. Monografia (Especialização em Análise Ambiental e Desenvolvimento Sustentável), Brasília: Instituto CEUB de Pesquisa e Desenvolvimento, Centro Universitário de Brasília. Available at:<https://repositorio.uniceub.br/jspui/handle/235/11514>.

OPENAIP. **Free Worldwide Aviation Database**. OpenAIP, 2020. Available at:<https://www.openaip.net/>.

OSCE. **Guidebook Intelligence-Led Policing**. Organization for Security and Co-operation in Europe, 2017. Available at: < https://www.osce.org/chairmanship/327476>.

OSTANKOVICH, V.; AFANASYEV, I. Illegal Buildings Detection from Satellite Images using GoogLeNet and Cadastral Map. **2018 International Conference on Intelligent Systems (IS),**. p.616–623, 2018.

PASTOR, R. P.; LARSEN, H. L. Scanning of open data for detection of emerging organized crime threats—the ePOOLICE project. **Using Open Data to Detect Organized Crime Threats**. p.47–71, 2017. Springer.

PEDRYCZ, W.; CHEN, S.-M. **Deep learning: Concepts and architectures**. Springer, 2020.

PENATTI, O. A. B.; NOGUEIRA, K.; DOS SANTOS, J. A. Do deep features generalize from everyday objects to remote sensing and aerial scenes domains? **Proceedings of the IEEE conference on computer vision and pattern recognition workshops**, p.44–51, 2015.

PENNSYLVANIA STATE UNIVERSITY. **Geographic Foundations of Geospatial Intelligence MOOC**. Pennsylvania State University, 2020a. Available at: <https://www.e-education.psu.edu/geog882/node/1952>.

PENNSYLVANIA STATE UNIVERSITY. **Geospatial Intelligence and the Geospatial Revolution MOOC**. Pennsylvania State University, 2020b. Available at:< https://www.e-education.psu.edu/geointmooc/>.

PENNSYLVANIA STATE UNIVERSITY. **Advanced Analytic Methods in Geospatial Intelligence MOOC.** Pennsylvania State University, 2020c. Available at:< https://roam.libraries.psu.edu/node/1355>.

PERAZZONI, F. **INFORMAÇÃO GEOGRÁFICA, SUSTENTABILIDADE E AMAZÔNIA: Geointeligência aplicada à avaliação de Manejos Florestais Sustentáveis no Sul do Amazonas**, 2021. Doctoral Thesis, Portugal: UNIVERSIDADE ABERTA. Available at:<https://repositorioaberto.uab.pt/handle/10400.2/10661>.

PF. PF apreende cinco toneladas de cocaína no Porto do Rio de Janeiro. **Polícia Federal. Portal Gov.br- Ministério da Justiça e Segurança Pública**, 2021a. Available at:<https://www.gov.br/pf/pt-br/assuntos/noticias/2021/10/pf-apreende-cinco-toneladas-de-cocaina-no-porto-do-rio-de-janeiro>.

PF. PF realiza a maior apreensão de cocaína do Rio Grande do Sul. **Polícia Federal. Portal Gov.br- Ministério da Justiça e Segurança Pública**, 2021b. Available at:<https://www.gov.br/pf/pt-br/assuntos/noticias/2021/11/pf-realiza-a-maior-apreensao-de-cocaina-do-rio-grande-do-sul>.

PINTO, J.; JORDÁN, J. **Propuesta metodológica para el monitoreo ambiental de la Amazonia venezolana utilizando técnicas de percepción remota. Caso: sector noreste de la Reserva Forestal El Caura, estado Bolívar – Amazonía venezolana**, 2013. Especialización en Cartografía Militar, Caracas: Universidad Nacional Experimental Politécnica de la Fuerza Armada.

PINTO, J. **Caracterización de las actividades asociadas con el tráfico ilícito de drogas en la zona fronteriza de Venezuela con Colombia, utilizando técnicas de percepción remota**, 2017. Master's Thesis, Caracas: Universidad Central de Venezuela. Available at:<https://osf.io/59grz/?view_only=420d198eb7ae4730935106f4d9428c83>.

PINTO, J. **CocaPaste-PI-DETECTION_dataset**., 2022. Mendeley Data. Available at:<https://data.mendeley.com/datasets/gmhsjwr24n/1>.

PINTO, J.; CENTENO, J. Geospatial Intelligence and Artificial Intelligence for Detecting Potential Coca Paste Production Infrastructure in the Border Region of Venezuela and Colombia. **Journal of Applied Security Research**, 2022a. DOI: https://doi.org/10.1080/19361610.2022.2111184.

PINTO, J.; CENTENO, J. AmazonCRIME: a Geospatial Artificial Intelligence dataset and benchmark for the classification of potential areas linked to Transnational Environmental Crimes in the Amazon Rainforest. **Revista de Teledeteccion**, 2022b. DOI: https://doi.org/10.4995/raet.2022.15710.

PIZA, E.; BAUGHMAN, J. **Modern Policing Using ArcGIS Pro**. Esri Press, 2021.

PLANEPHD. **CESSNA 441 Conquest II. Performance specifications**. Planephd, 2022a. Available at:<https://planephd.com/wizard/details/615/CESSNA-441-Conquest-II-specifications-performance-operating-cost-valuation?csrfmiddlewaretoken=vICgPDjXy7IxcLNDvWCXuHaqCE144ZjODYmw9aqBzNkFSKe2A0RTMIvYngRDCtdR&query=Beechcraft+Duke>.

PLANEPHD. **BEECHCRAFT B60 Duke. Performance specifications**. Planephd, 2022b. Available at:<https://planephd.com/wizard/details/80/BEECHCRAFT-B60-Duke-

specifications-performance-operating-cost-valuation?annual_hrs=100&selected_yearmfr=1978>.

PLANET TEAM. **Planet Application Program Interface: In Space for Life on Earth**, 2017. San Francisco, CA. Available at:<https://api.planet.com>.

PLANET. **Planet: Understanding the Amazon from Space**. Use satellite data to track the human footprint in the Amazon rainforest. Planet, 2017. Available at:<https://www.kaggle.com/c/planet-understanding-the-amazon-from-space>.

PONAL. **Sistema de las Drogas Ilícitas (SDI)**. Bogotá D.C: Policía Nacional de Colombia. Dirección de Antinarcóticos, 2020.

PRITT, M.; CHERN, G. Satellite Image Classification with Deep Learning. **2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR),** p.1–7, 2017. Available at: < doi: 10.1109/AIPR.2017.8457969>.

PRUNCKUN, H. **Methods of inquiry for intelligence analysis**. Rowman & Littlefield, 2019.

RAISG. ¡Imperdonable! Parque nacional en Amazonas es devastado por la minería ilegal que dirige el ELN. **Red Amazónica de Información Socioambiental Georreferenciada**, 2019. Available at:<https://www.amazoniasocioambiental.org/es/radar/imperdonable-parque-nacional-en-amazonas-es-devastado-por-la-mineria-ilegal-que-dirige-el-eln/>.

RAISG. **Datos cartográficos. Visualización de información geoespacial sobre la Amazonía**. Red Amazónica de Información Socioambiental Georreferenciada, 2020a. Available at:<https://www.raisg.org/es/mapas/>.

RAISG. **Atlas Amazonía Bajo Presión 2020**. Red Amazónica de Información Socioambiental Georreferenciada, 2020b. Available at: < https://www.amazoniasocioambiental.org/es/publicacion/amazonia-bajo-presion-2020/>.

RAMWELL, S.; DAY, T.; GIBSON, H. Use cases and best practices for LEAs. **Open Source Intelligence Investigation**. p.197–211, 2016. Springer.

RATCLIFFE J. **Crime Mapping: Spatial and Temporal Challenges**. Handbook of Quantitative Criminology. Springer, New York, NY, 2010.

RECORD NEWS. **Noticias Record News**. Record News, 2021. Available at: < https://www.r7.com/>.

REDMON, J.; DIVVALA, S.; GIRSHICK, R.; FARHADI, A. You only look once: Unified, real-time object detection**. Proceedings of the IEEE conference on computer vision and pattern recognition**, p.779–788, 2016.

REDRADIOVE. GNB localiza pista clandestina para narcotráfico en Anzoátegui. **REDRADIOVE**, 2020. Available at:<https://redradiove.com/gnb-localiza-pista-clandestina-para-narcotrafico-en-anzoategui/>.

REICHEL, P.; ALBANESE, J. **Handbook of transnational crime and justice**. SAGE publications, 2013.

REN, S.; HE, K.; GIRSHICK, R.; SUN, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In**: C. Cortes; N. Lawrence; D. Lee; M. Sugiyama; R. Garnett (Eds.); Advances in Neural Information Processing Systems**. v. 28, 2015. Curran Associates, Inc. Available at:<https://proceedings.neurips.cc/paper/2015/file/14bfa6bb14875e45bba028a21ed38046-Paper.pdf>.

REUTER, P. Why does research have so little impact on American drug policy?. **Addiction**, 96(3), 373-376, 2001. Available at: <https://doi.org/10.1046/j.1360-0443.2001.9633731.x>.

REUTER, P.; GREENFIELD, V. Measuring global drug markets. **World economics**, v. 2, n. 4, p. 159–173, 2001. World Economics, 1 Ivory Square, Plantation Wharf, London, United Kingdom.

REUTERS INSTITUTE. **Overcoming indifference: what attitudes towards news tell us about building trust**. Reuters Institute, 2021. Available at: < https://reutersinstitute.politics.ox.ac.uk/overcoming-indifference-what-attitudes-towards-news-tell-us-about-building-trust#methodology>.

REUTERS. Perú defiende uso tradicional de hoja de coca por indígenas. **Reuters**, 2008. Available at:<https://www.reuters.com/article/latinoamerica-peru-coca-onu-sol-idLTAN054618120080306>.

RF. Receita Federal apreende 1.116 kg de cocaína no Porto de Rio Grande/RS. **Receita Federal. Portal Gov.br- Ministério da Economia**, 2021a. Available at:<https://www.gov.br/receitafederal/pt-br/assuntos/noticias/2021/junho/receita-federal-apreende-1-116-kg-de-cocaina-no-porto-de-rio-grande-rs>.

RF. Receita Federal apreende 35,5 kg de cocaína destinados à Austrália. **Receita Federal. Portal Gov.br- Ministério da Economia**, 2021b. Available at:<https://www.gov.br/receitafederal/pt-br/assuntos/noticias/2021/dezembro/receita-federal-apreende-35-5-kg-de-cocaina-destinados-a-australia>.

RF. Receita Federal apreende 40 kg de cocaína destinados à Austrália. **Receita Federal. Portal Gov.br- Ministério da Economia**, 2021c. Available at:<https://www.gov.br/receitafederal/pt-br/assuntos/noticias/2021/dezembro/receita-federal-apreende-40-kg-de-cocaina-destinados-a-australia>.
RINCÓN-RUIZ, A.; CORREA, H. L.; LEÓN, D. O.; WILLIAMS, S. Coca cultivation and crop eradication in Colombia: The challenges of integrating rural reality into effective anti-drug policy. **International Journal of Drug Policy**, v. 33, p. 56–65, 2016. Elsevier.

ROBINSON, A; DEMŠAR, U; MOORE, A; BUCKLEY. A; JIANG, B; FIELD, K; KRAAK, M; CAMBOIM, S; SLUTER, C. Geospatial big data and cartography: research challenges and opportunities for making maps that matter. **International Journal of Cartography**, 2017. Available at: <https://doi.org/10.1080/23729333.2016.1278151>.

ROSEBROCK, A. **Deep Learning for Computer Vision with Python**. 3rd Edition ed. Pyimagesearch, 2019.

ROSENBLATT, F. **The Perceptron. A Perceiving and Recognizing Automaton Project PARA**. Cornell Aeronautical Laboratory,1957. Available at: < https://blogs.umass.edu/brain-wars/files/2016/03/rosenblatt-1957.pdf>.

RUMELHART, D. E.; HINTON, G. E.; WILLIAMS, R. J. Learning representations by back-propagating errors. **Nature**, v. 323, n. 6088, p. 533–536, 1986. Available at:<https://doi.org/10.1038/323533a0>.

RUSSELL, S.; NORVIG, P. **Artificial Intelligence: A Modern Approach**. 4th Edition ed. Pearson, 2020.

SAMPÓ, C.; TRONCOSO, V. Cocaine trafficking from non-traditional ports: examining the cases of Argentina, Chile and Uruguay. **Trends in Organized Crime**, 2022. Available at:<https://doi.org/10.1007/s12117-021-09441-y>.

SANTOS, R. B. **Crime analysis with crime mapping**. 4th ed. Sage publications, 2022.

SARAWAGI, S. Information extraction. **Foundations and Trends® in Databases**, v. 1, n. 3, p. 261–377, 2008. Now Publishers, Inc.

SCHARRE, P.; HOROWITZ, M. C.; WORK, R. O. **What is Artificial Intelligence?** Center for a New American Security, 2018. Available at: < https://www.jstor.org/stable/resrep20447.5>.

SCHMITT, M.; HUGHES, L. H.; QIU, C.; ZHU, X. X. SEN12MS-A CURATED DATASET OF GEOREFERENCED MULTI-SPECTRAL SENTINEL-1/2 IMAGERY FOR DEEP LEARNING AND DATA FUSION. **ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences**, 2019. Available at:<https://doi.org/10.5194/isprs-annals-IV-2-W7-153-2019>.

SENAD. **Fundamentos para Repressão ao Narcotráfico e ao Crime Organizado - Curso FRONT**. Secretaria Nacional de Políticas sobre Drogas e Gestão de Ativos - Universidade Federal de Santa Catarina, 2021.

SHAH, N.; LI, J.; MACKEY, T. K. An unsupervised machine learning approach for the detection and characterization of illicit drug-dealing comments and interactions on Instagram. **Substance Abuse**, v. 43, n. 1, p. 273–277, 2022. Taylor & Francis. Available at:<https://doi.org/10.1080/08897077.2021.1941508>.

SHARMA, A.; AMRITA; CHAKRABORTY, S.; KUMAR, S. Named Entity Recognition in Natural Language Processing: A Systematic Review. In: D. Gupta; A. Khanna; V. Kansal; G. Fortino; A. E. Hassanien (Eds.); **Proceedings of Second Doctoral Symposium on Computational Intelligence**, p.817–828, 2022. Singapore: Springer Singapore.

SHENDRYK, I.; RIST, Y.; LUCAS, R.; THORBURN, P.; TICEHURST, C. Deep Learning - a New Approach for Multi-Label Scene Classification in Planetscope and Sentinel-2 Imagery. **IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium**. p.1116–1119, 2018.

SILVERMAN, B. **Density Estimation for Statistics and Data Analysis**. New York: Chapman and Hall, 1986.

SIMCI. **Características agroculturales de los cultivos de Coca en Colombia 2005-2010**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2010. Available at: <https://www.minjusticia.gov.co/programas-co/ODC/Paginas/Publicaciones-ODC.aspx>.

SIMCI. **Monitoreo de territorios afectados por cultivos ilícitos 2017**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2017. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

SIMCI. **Informe de Monitoreo de Precios de Drogas – 2017**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2018.

SIMCI. **Monitoreo de territorios afectados por cultivos ilícitos 2018**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2019. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

SIMCI. **Monitoreo de territorios afectados por cultivos ilícitos 2020**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2020. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

SIMCI. **Monitoreo de territorios afectados por cultivos ilícitos 2021**. Integrated System for Monitoring Illicit Crop. United Nations Office on Drugs and Crime, 2021. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

SINGLETON, N.; CUNNINGHAM, A.; GROSHKOVA, T.; ROYUELA, L.; SEDEFOV, R. Drug supply indicators: Pitfalls and possibilities for improvements to assist comparative analysis. **International Journal of Drug Policy**, v. 56, p. 131–136, 2018. Available at:<https://www.sciencedirect.com/science/article/pii/S0955395918300380>.

SKALSKI, P. **MAKE SENSE**, 2019. Available at:<https://github.com/SkalskiP/make-sense/>.

SLOCUM, T; MCMASTER, R; KESSLER, F; HOWARD, H. **Thematic cartography and geovisualization**. CRC Press, 2022.

SOS ORINOCO. **La Minería Aurífera en el Parque Nacional Yapacana, Amazonas Venezolano | Un caso de extrema urgencia ambiental y geopolítica, nacional e internacional**. SOS Orinoco, 2020. Available at: < https://sosorinoco.org/es/informes/la-mineria-aurifera-en-el-parque-nacional-yapacana-amazonas-venezolano-un-caso-de-extrema-urgencia-ambiental-y-geopolitica-nacional-e-internacional-actualizacion-al-2020/>.

SOUTHCOM. **Adm. Tidd prepared remarks: GEOINT 2017 Keynote Address**. U.S. Southern Command, 2017. Available at:<https://www.southcom.mil/Media/Speeches-Transcripts/Article/1205833/adm-tidd-prepared-remarks-geoint-2017-keynote-address/>.

SOUZA, C. M.; Z. SHIMBO, J.; ROSA, M. R.; et al. Reconstructing Three Decades of Land

SRINIVASA, K.; THILAGAM, P. Crime base: Towards building a knowledge base for crime entities and their relationships from online news papers. **Information Processing & Management**, v. 56, n. 6, p. 102059, 2019. Available at:<https://www.sciencedirect.com/science/article/pii/S0306457318306885>.

STAHLBERG, S. G. From prison gangs to transnational mafia: the expansion of organized crime in Brazil. **Trends in Organized Crime**, 2022. Available at:<https://doi.org/10.1007/s12117-022-09453-2>.

STANFORD UNIVERSITY. **CS231n: Deep Learning for Computer Vision**. Stanford University, 2022. Available at:<http://cs231n.stanford.edu/>.

STEFANIDIS, A.; CROOKS, A.; RADZIKOWSKI, J.; CROITORU, A.; RICE, M. Social media and the emergence of open-source geospatial intelligence. **Human Geography: Socio-Cultural Dynamics and Global Security, US Geospatial Intelligence Foundation, Herndon, VA**, v. 1, p. 109–123, 2014.

STOCK, K; JONES, B; RUSSELL, S; RADKE, M; DAS, P; AFLAKI, N. Detecting geospatial location descriptions in natural language text. **International Journal of Geographical Information Science**, 36(3), 547-584, 2022. Available at: <10.1080/13658816.2021.1987441>.

SUMBUL, G.; CHARFUELAN, M.; DEMIR, B.; MARKL, V. Bigearthnet: A Large-Scale Benchmark Archive for Remote Sensing Image Understanding. **IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium**. p.5901–5904, 2019.

SUNAD. **Operación Sierra XXV-2017**. Superintendencia Nacional Antidrogas, 2017. Available at:<https://twitter.com/SUNADoficial/status/931684083238916101?s=20>.

SUNAD. **Destruidos 2 campamentos y 8 laboratorios con 13 toneladas de drogas en el Zulia**. Superintendencia Nacional Antidrogas, 2021a. Available at:<https://www.sunad.gob.ve/destruidos-2-campamentos-y-8-laboratorios-con-13-toneladas-de-drogas-en-el-zulia/>.

SUNAD. **Desmantelados 15 laboratorios y destruidas 6 pistas utilizadas para el tráfico de drogas en Zulia**. Superintendencia Nacional Antidrogas, 2021b. Available at:<https://www.sunad.gob.ve/desmantelados-15-laboratorios-y-destruidas-6-pistas-utilizadas-para-el-trafico-de-drogas-en-zulia/>.

SUNAD. **Desmantelan campamento con 8.058,00 Kg de drogas en el Zulia**. Superintendencia Nacional Antidrogas, 2022a. Available at:<https://www.sunad.gob.ve/desmantelan-campamento-con-8-05800-kg-de-drogas-en-el-zulia/>.

SUNAD. **Duro golpe al tráfico ilícito de drogas con la operación Mano de Hierro**. Superintendencia Nacional Antidrogas, 2022b. Available at:<https://www.sunad.gob.ve/duro-golpe-al-trafico-ilicito-de-drogas-con-la-operacion-mano-dura-de-hierro/>.

TAYLOR, J. S.; JASPARRO, C.; MATTSON, K. Geographers And Drugs: A Survey Of The Literature. **Geographical Review**, v. 103, n. 3, p. 415–430, 2013. Routledge. Available at:<https://doi.org/10.1111/j.1931-0846.2013.00007.x>.

TELESUR. **Asesta Venezuela duro golpe al narcotráfico gracias a Operación Sierra**. Telesur, 2014. Available at:<https://www.youtube.com/watch?v=a7p5kEw1Yng>.

TELLMAN B, SESNIE E, MAGLIOCCA R, NIELSEN A, DEVINE A, MCSWEENEY K, JAIN M, WRATHALL D, DÁVILA A, BENESSAIAH K, AGUILAR-GONZALEZ B. Illicit drivers of land use change: Narcotrafficking and forest loss. **Central America. Global Environmental Change**, 63, 2020. Available at: < https://doi.org/10.1016/j.gloenvcha.2020.102092>.

THOMSON, W. Popular Lectures and Addresses vol. 1 (1889) 'Electrical Units of Measurement' delivered 3 May 1883. **Electrical Units of Measurement**, 1883. Available at:<https://archive.org/details/popularlecturesa01kelvuoft/page/73/mode/2up?view=theater>.

TOBLER, W. A computer movie simulating urban growth in the Detroit region. **Economic geography**, v. 46, p. 234–240, 1970. Available at:<https://doi.org/10.2307/143141>.

TOMES R, MURDOCK D, TUCKER K**. Human Geography: Socio-cultural Dynamics and Challenges to Global Security**. United States Geospatial Intelligence Foundation, 2014.

TORRES, J. **Python deep learning: introducción práctica con Keras y TensorFlow 2**. Marcombo, 2020.

TORTATO, M. O elevado índice de apreensões de drogas em Mato Grosso. **VGN -Jornalismo com credibilidade**, 2017. Available at:<https://www.vgnoticias.com.br/artigos/o-elevado-indice-de-apreensoes-de-drogas-em-mato-grosso/40231>.

TRASK, A. **grokking Deep Learning**. Manning Publications, 2019.

TZUTALIN. **LabelImg,** 2015. Available at:<https://github.com/heartexlabs/labelImg>.

U.S. DEPARTMENT OF JUSTICE. **Drug Trafficking Organizations,** 2010. Available at:https://www.justice.gov/archive/ndic/pubs38/38661/dtos.htm

UNDP. **Catatumbo: Análisis de la Conflictividades y Construcción de Paz**. United Nations Development Programme, 2014. Available at: < https://www.undp.org/es/colombia/publications/catatumbo-analisis-de-conflictividades-y-construccion-de-paz>.

UNDP. **The SDGs in Action**. United Nations Development Programme, 2022. Available at: <https://www.undp.org/latin-america/sustainable-development-goals>.

UNEP. **Transnational Environmental Crime - a common crime in need of better enforcement**. United Nations Environment Programme, 2012. Available at: < https://wedocs.unep.org/rest/bitstreams/14319/retrieve>.

UNEP. **The Environmental Crime Crisis – Threats to Sustainable Development from Illegal Exploitation and Trade in Wildlife and Forest Resources**. United Nations Environment Programme, 2014. Available at: < https://wedocs.unep.org/handle/20.500.11822/9120>.

UNEP-WCMC. **World Database on Protected Areas**. United Nations Environment Programme, 2020. Available at:<https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA>.

UNGAR, M. **The 21st Century Fight for the Amazon**. Palgrave Macmillan Cham, 2018.

UN-GGIM. **Future Trends in geospatial information management: the five to ten year vision**. Third Edition ed. United Nations Committee of Experts on Global Geospatial Information Management, 2020. Available at: <https://ggim.un.org/meetings/GGIM-committee/10th-Session/documents/Future_Trends_Report_THIRD_EDITION_digital_accessible.pdf>.

UNHRC. **Detailed findings of the independent international factfinding mission on the Bolivarian Republic of Venezuela. Agenda item 4. Human rights situations that require the Council's attention**. United Nations Human Rights Council, 2020. Available at: < https://www.ohchr.org/Documents/HRBodies/HRCouncil/FFMV/A_HRC_45_CRP.11.pdf>.

UNHRC. **Venezuela: new UN report details responsibilities for crimes against humanity to repress dissent and highlights situation in remotes mining areas**. United Nations Human Rights Council, 2022. Available at: < https://www.ohchr.org/en/press-releases/2022/09/venezuela-new-un-report-details-responsibilities-crimes-against-humanity

UNICRI. **Artificial Intelligence: an overview of state initiatives**. Centre for Artificial Intelligence and Robotics of the United Nations Interregional Crime and Justice Research Institute, 2019. Available at: <http://www.unicri.it/artificial-intelligence-overview-state-initiatives>.

UNICRI. **Artificial Intelligence and Robotics for Law Enforcement**. Centre for Artificial Intelligence and Robotics of the United Nations Interregional Crime and Justice Research Institute, 2020a. Avalilable at: <http://www.unicri.it/News/Artificial%20Intelligence%20Collection>.

UNICRI. **Special Collection on Artificial Intelligence**. Centre for Artificial Intelligence and Robotics of the United Nations Interregional Crime and Justice Research Institute, 2020b. Available at: <https://unicri.it/News/Artificial%20Intelligence%20Collection>.

UNICRI. **Towards Responsible Artificial Intelligence Innovation**. Centre for Artificial Intelligence and Robotics of the United Nations Interregional Crime and Justice Research Institute, 2020c. Available at: <https://unicri.it/index.php/towards-responsible-artificial-intelligence-innovation>.

UNICRI. **Countering Terrorism Online with Artificial Intelligence - An Overview for Law Enforcement and Counter-Terrorism Agencies in South Asia and South-East Asia**. Centre for Artificial Intelligence and Robotics of the United Nations Interregional Crime and Justice

Research Institute, 2021. Available at: <https://unicri.it/Publications/Countering-Terrorism-Online-with-Artificial-Intelligence-%20SouthAsia-South-EastAsia>.

UNITED NATIONS. **Mapping for a Sustainable World**. United Nations, 2021. Available at: < https://www.un-ilibrary.org/content/books/9789216040468>.

UNITED NATIONS. **Single Convention on Narcotic Drugs of 1961**. United Nations, 2022a. Available at: < https://www.unodc.org/unodc/en/commissions/CND/conventions.html>.

UNITED NATIONS. **Convention on Psychotropic Substances of 1971**. United Nations, 2022b. Available at: < https://www.unodc.org/unodc/en/commissions/CND/conventions.html>.

UNITED NATIONS. **United Nations Convention against Illicit Traffic in Narcotic Drugs and Psychotropic Substances of 1988**. United Nations, 2022c. Available at: < https://www.unodc.org/unodc/en/commissions/CND/conventions.html>.

UNITED NATIONS. **What is Rule of Law?.** United Nations, 2022d. Available at:<https://www.un.org/ruleoflaw/what-is-the-rule-of-law/>.

UNITED NATIONS. **Big Data for Sustainable Development**. United Nations, 2022e. Available at: <https://www.un.org/en/global-issues/big-data-for-sustainable-development>.

UNITED NATIONS. **Open SDG Data Hub. Explore Geospatially Referenced Data by Goal**. United Nations, 2022f. Available at: < https://unstats-undesa.opendata.arcgis.com/#about>.

UNODC. **Brazil - Country profile**. United Nations Office on Drugs and Crime, 2003. Available at: < https://www.unodc.org/pdf/brazil/brazil_country_profile.pdf>.

UNODC. **United Nations Convention against Transnational Organized Crime and the Protocols Thereto**. United Nations Office on Drugs and Crime, 2004. Available at: < https://www.unodc.org/unodc/en/organized-crime/intro/UNTOC.html>.

UNODC. **Ecuador Monitoreo de Cultivos de Coca 2009**. United Nations Office on Drugs and Crime, 2010a. Available at: < https://www.unodc.org/documents/crop-monitoring/Ecuador/Ecu09_Coca_Survey_es.pdf>.

UNODC. **Guidance on the preparation and use of serious and organized crime threat assessments. The SOCTA Handbook**. United Nations Office on Drugs and Crime, 2010b. Available at: < https://www.unodc.org/documents/organized-crime/SOCTA_Handbook.pdf>.

UNODC. **Criminal Intelligence Manual for Analysts**. United Nations Office on Drugs and Crime, 2011. Available at: < https://www.unodc.org/unodc/en/drug-trafficking/crimjust/tools-and-publications.html>.

UNODC. **Transnational organized crime in Central America and the Caribbean: A threat assessment**. United Nations Office on Drugs and Crime, 2012a. Available at: <https://www.unodc.org/toc/en/reports/TOCTACentralAmerica-Caribbean.html>.

UNODC. **Digest of Organized Crime Cases. A compilation of cases with commentaries and lessons learned**. United Nations Office on Drugs and Crime, 2012b. Available at:< https://www.unodc.org/unodc/en/organized-crime/digest-of-organized-crime-cases.html>.

UNODC. **World Drug Report 2015**. United Nations Office on Drugs and Crime, 2015. Available at:<https://www.unodc.org/unodc/en/data-and-analysis/wdr-2022---previous-reports.html >.

UNODC. **World Drug Report 2017**. United Nations Office on Drugs and Crime, 2017a. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/wdr-2022---previous-reports.html >.

UNODC. **Perú Monitoreo de Cultivos de Coca 2016**. United Nations Office on Drugs and Crime, 2017b. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

UNODC. **Estado Plurinacional de Bolivia. Monitoreo de Cultivos de Coca 2016**. United Nations Office on Drugs and Crime, 2017c. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

UNODC. **Terminology and Information on Drugs**. United Nations Office on Drugs and Crime, 2018a. Available at: <https://www.unodc.org/unodc/en/scientists/terminology-and-information-on-drugs_new.html>.

UNODC. **Comunidad, bosque y coca: un camino para la acción**. United Nations Office on Drugs and Crime, 2018b. Available at: < https://www.gpdpd.org/fileadmin/media/publikationen/deforestation_comunidad__bosque_y_coca_con_insertos__2_.pdf>.

UNODC. **Perú Monitoreo de Cultivos de Coca 2017**. United Nations Office on Drugs and Crime, 2018c. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

UNODC. **World Drug Report 2019**. United Nations Office on Drugs and Crime, 2019a. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/wdr-2022---previous-reports.html >.

UNODC. **Ministerial Declaration Ministerial Declaration**. United Nations Office on Drugs and Crime, 2019b. Available at: < https://www.unodc.org/documents/commissions/CND/2019/19-06699_E_ebook.pdf>.

UNODC. **Estado Plurinacional de Bolivia. Monitoreo de Cultivos de Coca 2018**. United Nations Office on Drugs and Crime, 2019c. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

UNODC. **University Module Series. Organized Crime**. United Nations Office on Drugs and Crime, 2020a. Available at: <https://www.unodc.org/e4j/en/tertiary/organized-crime.html>.

UNODC. **Wholesale drug price and purity**. United Nations Office on Drugs and Crime, 2020b. Available at: <https://dataunodc.un.org/dp-drug-prices>.

UNODC. **Cocaine Insights 1. The illicit trade of cocaine from Latin America to Europe – from oligopolies to free-for-all?** United Nations Office on Drugs and Crime, 2021a. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/the-cocaine-market.html >.

UNODC. **World Drug Report 2021**. United Nations Office on Drugs and Crime, 2021b. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/wdr-2022---previous-reports.html >.

UNODC. **Cocaine Insights 2. Cocaine: A spectrum of products**. United Nations Office on Drugs and Crime, 2021c. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/the-cocaine-market.html >.

UNODC. **Colombia Explotación de oro de aluvión Evidencias a partir de percepción remota 2021**. United Nations Office on Drugs and Crime, 2022a. Available at:< https://www.biesimci.org/index.php?id=139 >.

UNODC. **World Drug Report 2022**. United Nations Office on Drugs and Crime, 2022b. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/world-drug-report-2022.html>.

UNODC. **UNODC Strategic Vision for Latin America and the Caribbean 2022-2025**. United Nations Office on Drugs and Crime, 2022c. Available at: <https://www.unodc.org/res/strategy/STRATEGIC_VISION_LATIN_AMERICA_AND_THE_CARIBBEAN_2022_2025_ENE17_EDsigned.pdf>.

UNODC. **Cocaine Insights 4. Brazil in the regional and transatlantic cocaine supply chain: The impact of COVID-19**. United Nations Office on Drugs and Crime, 2022d. Available at:< https://www.unodc.org/unodc/en/data-and-analysis/the-cocaine-market.html >.

UNODC. **Sistema Integrado de Monitoreo de Cultivos Ilícitos – SIMCI**. United Nations Office on Drugs and Crime, 2022e. Available at:< https://www.unodc.org/colombia/es/simci/simci.html>.

UNODC. **Drug trafficking**. United Nations Office on Drugs and Crime, 2022f. Available at: < https://www.unodc.org/unodc/en/drug-trafficking/index.html>.

UNODC. **Legal Framework for Drug Trafficking**. United Nations Office on Drugs and Crime, 2022g. Available at: < https://www.unodc.org/unodc/en/drug-trafficking/legal-framework.html>.
UNODC. **data UNODC**. United Nations Office on Drugs and Crime, 2022h. Available at: < https://dataunodc.un.org/>.

UNODC. **Methodological Guidelines For Monitoring the Prices of Illicit Drugs**. Side Event Session 65th of the Commission on Narcotic Drugs. United Nations Office on Drugs and Crime, 2022i. Available at:<https://www.youtube.com/watch?v=fSD-VWr7nfk>.

UNODC. **CRIMJUST holds Regional Investigative Case Forum to tackle Drug Trafficking via General Aviation in Latin America**. United Nations Office on Drugs and Crime, 2022j. Available at: < https://www.unodc.org/unodc/drug-trafficking/crimjust/news/crimjust-holds-regional-investigative-case-forum-to-tackle-drug-trafficking-via-general-aviation-in-latin-america.html>.

UNODC. **Individual Drug Seizures (IDS) data collection**. United Nations Office on Drugs and Crime, 2022k. Available at: <https://www.unodc.org/unodc/en/data-and-analysis/statistics/drugs/seizures_cases.html>.

UNODC. **Drugs Monitoring Platform**. United Nations Office on Drugs and Crime, 2022l. Available at: < https://dmp.unodc.org/>.

UNODC. **UNODC and illicit crop Monitoring**. United Nations Office on Drugs and Crime, 2022m. Available at: < https://www.unodc.org/unodc/en/crop-monitoring/index.html>.

UNODC. **Organized Crime Strategy Toolkit for Developing High-Impact Strategies**. United Nations Office on Drugs and Crime, 2022n. Available at: <https://sherloc.unodc.org/cld/en/st/strategies/strategy-toolkit.html#:~:text=The%20Organized%20Crime%20Strategy%20Toolkit,prevent%20and%20combat%20organized%20crime>.

US ARMED FORCES. **Joint Publication 1-02, Dictionary of Military and Associated Terms**. United States Armed Forces, 2016. Available at: <https://irp.fas.org/doddir/dod/jp1_02.pdf>.

US ARMED FORCES. **Joint Publication 2-03, Geospatial Intelligence Support to Joint Operations.** United States Armed Forces, 2017. Available at: <https://www.jcs.mil/Doctrine/Joint-Doctrine-Pubs/2-0-Intelligence-Series/>.

Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. **Remote Sensing**, v. 12, n. 17, 2020. Available at:<https://www.mdpi.com/2072-4292/12/17/2735>.

USGS. **Map Projections Poster**. U.S. Geological Survey, 2019. Available at: <https://www.usgs.gov/media/files/map-projections-poster>.

VOPHAM, T.; HART, J. E.; LADEN, F.; CHIANG, Y.-Y. Emerging trends in geospatial artificial intelligence (geoAI): potential applications for environmental epidemiology. **Environmental Health**, v. 17, n. 1, p. 40, 2018. Available at:<https://doi.org/10.1186/s12940-018-0386-x>.

WANG, C.; WANG, Q.; WU, H.; et al. Low-Altitude Remote Sensing Opium Poppy Image Detection Based on Modified YOLOv3. **Remote Sensing**, v. 13, n. 11, 2021. Available at:<https://www.mdpi.com/2072-4292/13/11/2130>.

WEXLER, P. **Encyclopedia of Toxicology**. 3rd Edition ed. Academic Press, 2014.

WHITE, R. **Transnational environmental crime: Toward an eco-global criminology**. Willan, 2018.

WHITEHEAD, A.; KLEINE, F. Python client for the GDELT 2.0 Doc API, 2022. MIT license. Available at:<https://github.com/alex9smith/gdelt-doc-api>.

WORTLEY, R; TOWNSLEY, M. **Environmental Criminology and Crime Analysis**. Routledge, 2016.

WRATHALL, D. J.; DEVINE, J.; AGUILAR-GONZÁLEZ, B.; et al. The impacts of cocaine-trafficking on conservation governance in Central America. **Global Environmental Change**, v. 63, p. 102098, 2020. Available at:<https://www.sciencedirect.com/science/article/pii/S0959378019310076>.

WU, X.; SAHOO, D.; HOI, S. C. H. Recent advances in deep learning for object detection. **Neurocomputing**, v. 396, p. 39–64, 2020. Elsevier. Available at: < https://doi.org/10.1016/j.neucom.2020.01.085>.

XIA, G.-S.; BAI, X.; DING, J.; et al. DOTA: A large-scale dataset for object detection in aerial images. **Proceedings of the IEEE conference on computer vision and pattern recognition**. p.3974–3983, 2018.

XIANG ZHU, X.; MEMBER, S.; HU, J.; et al. So2Sat LCZ42: A Benchmark Dataset for Global Local Climate Zones Classification. **IEEE Geoscience and Remote Sensing Magazine**, 2019. Available at:<http://doi.org/10.14459/2018mp1483140.>.

YANG, Y.; NEWSAM, S. Bag-of-Visual-Words and Spatial Extensions for Land-Use Classification. **Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems**. GIS '10. p.270–279, 2010. New York, NY, USA: Association for Computing Machinery. Available at:<https://doi.org/10.1145/1869790.1869829>.

YAO, Y.; JIANG, Z.; ZHANG, H.; ZHAO, D.; CAI, B. Ship detection in optical remote sensing images based on deep convolutional neural networks. **Journal of Applied Remote Sensing**, v. 11, n. 4, p. 1 – 12, 2017. SPIE. Available at:<https://doi.org/10.1117/1.JRS.11.042611>.

YIN, S.; LI, H.; TENG, L. Airport Detection Based on Improved Faster RCNN in Large Scale Remote Sensing Images. **Sensing and Imaging**, v. 21, n. 1, p. 49, 2020. Available at:<https://doi.org/10.1007/s11220-020-00314-2>.

YU, X.; WU, X.; LUO, C.; REN, P. Deep learning in remote sensing scene classification: a data augmentation enhanced convolutional neural network framework. **GIScience & Remote Sensing**, v. 54, n. 5, p. 741–758, 2017. Taylor & Francis. Available at:<https://doi.org/10.1080/15481603.2017.1323377>.

YUAN, M. **Spatializing text for deep mapping**. In Making Deep Maps (pp. 50–64). Routledge, 2021.

ZABYELINA, Y.; VAN UHM, D. **Illegal Mining: Organized Crime, Corruption, and Ecocide in a Resource-Scarce World**. Springer Nature, 2020.

ZHANG, G. (2022) Detecting and Visualizing Observation Hot-Spots in Massive Volunteer-Contributed Geographic Data across Spatial Scales Using GPU-Accelerated Kernel Density Estimation. **ISPRS International Journal of Geo-Information,** 11(1), 55, 2022. Available at: < https://doi.org/10.3390/ijgi11010055>.

ZHANG, J.; LU, C.; LI, X.; KIM, H.-J.; WANG, J. A full convolutional network based on DenseNet for remote sensing scene classification. **Mathematical Biosciences and Engineering**, v. 16, n. 5, p. 3345–3367, 2019. Available at:<https://www.aimspress.com/article/doi/10.3934/mbe.2019167>.

ZHANG, L.; XIA, G.-S.; WU, T.; LIN, L.; TAI, X. C. Deep Learning for Remote Sensing Image Understanding. **Journal of Sensors**, v. 2016, p. 7954154, 2016. Hindawi Publishing Corporation. Available at:<https://doi.org/10.1155/2016/7954154>.

ZHANG, LIANGPEI; ZHANG, LEFEI; DU, B. Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art. **IEEE Geoscience and Remote Sensing Magazine**, v. 4, n. 2, p. 22–40, 2016.

ZHANG, W.; TANG, P.; ZHAO, L. Remote Sensing Image Scene Classification Using CNN-CapsNet. **Remote Sensing**, v. 11, n. 5, 2019. Available at:<https://www.mdpi.com/2072-4292/11/5/494>.

ZHAO, J.; ZHANG, Z.; YAO, W.; et al. OpenSARUrban: A Sentinel-1 SAR Image Dataset for Urban Interpretation. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 13, p. 187–203, 2020.

ZHAO, Y; KARYPIS, G; FAYYAD, U. Hierarchical Clustering Algorithms for Document Datasets. **Data mining and knowledge discovery** 10, 141–168, 2005. Available at: < https://doi.org/10.1007/s10618-005-0361-3>.

ZHAO, Z.-Q.; ZHENG, P.; XU, S.-T.; WU, X. Object Detection With Deep Learning: A Review. **IEEE Transactions on Neural Networks and Learning Systems**, v. 30, n. 11, p. 3212–3232, 2019.

ZHENG, J.; LI, W.; XIA, M.; et al. Large-Scale Oil Palm Tree Detection from High-Resolution Remote Sensing Images Using Faster-RCNN. **IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium**. **Anais,** p.1422–1425, 2019.

ZHU, X. X.; TUIA, D.; MOU, L.; et al. Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. **IEEE Geoscience and Remote Sensing Magazine**, v. 5, n. 4, p. 8–36, 2017.