

Faculté des bioingénieurs

Neural network-based detection of tropical moist forest disturbances using standardised Sentinel-1 time series

Regions of interest : Dekese (DRC) and Likati (DRC)

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List of Acronyms

ALOS	Advanced Land Observing Satellite
AVHRR	Advanced Very High Resolution Radiometer
BCELoss	Binary Cross Entropy Loss
BVOC	Biogenic Volatile Organic Compounds
CAM	Cameroon
CAR	Central African Republic
CNN	Convolutional Neural Networks
DEM	Digital Elevation Model
DRC	Democratic Republic of the Congo
EC	European Commission
EM	Electromagnetic
EO	Earth Observation
EQG	Equatorial Guinea
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus
EU	European Union
F	Forest
FN	False Negatives
FP	False Positives
FPR	False Positive Rate
GAB	Gabon
GEE	Google Earth Engine
GFC	Global Forest Change
GFW	Global Forest Watch
GLAD	Global Land Analysis and Discovery
GRD	Ground Range Detected
HH	Horizontal-Horizontal
HV	Horizontal-Vertical
INPE	National Institute for Space Research
IR	Infrared

IW	Interferometric Wide
JERS	Japanese Earth Resources Satellite
LUCA	Land Use Change Alert
MERIS	MEdium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MSELoss	Mean Squared Error Loss
NASA	National Aeronautics and Space Administration
NF	Non-Forest
NN	Neural Networks
NOAA	National Oceanic and Atmospheric Administration
NRT	Near Real-Time
OA	Overall Accuracy
OLI	Operational Land Imager
OPP	Optimal Operating Point
PAL	Pathfinder Land
PALSAR	Phased Arrayed L-band Synthetic Aperture Radar
PolSAR	Polarimetric SAR
RADAR	RAdio Detection And Ranging
RADD	Radar for Detecting Deforestation
RCR	Radar Change Ratio
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristics
RoC	Republic of the Congo
ROI	Region Of Interest
SAR	Synthetic Aperture Radar
SDG	Sustainable Developments Goals
SOA	Secondary Organic Aerosols
SPOT	Satellite Pour l’Observation de la Terre
SRTM	Shuttle Radar Topography Mission
TDF	Tropical Dry Forest
TMF	Tropical Moist Forest

TN	True Negatives
TP	True Positives
TPR	True Positive Rate
UAV	Unmanned Aerial Vehicles
UN	United Nations
USGS	United States Geological Survey
VH	Vertical-Horizontal
VV	Vertical-Vertical

Introduction

The transition from the 20th century to the 21st century has been defined by a growing awareness regarding the influence of human activities on the planet and its ecosystems. This deeper understanding of society's impacts has led to critical reflections on how resources and energy are produced and consumed, largely enabled by the technological advancements and revolutions that have shaped the past two centuries. Over the last three decades, environmental issues have received increased media and political attention. Amplified by climate summits and global activism efforts, this coverage has sustained public and political focus on climate-related concerns well beyond the immediate aftermath of such initiatives. This trend reflects a rising engagement with environmental issues, potentially fostering greater awareness of global environmental challenges and increased support for regulatory measures to address them (Lochner et al., 2024).

Concurrently, more ambitious national and international regulations aimed at combating climate change and promoting sustainable development have been introduced over the past decade. At the core of those efforts lie the 17 Sustainable Development Goals (SDG), adopted by all United Nations (UN) member states in 2015 as part of the 2030 Agenda for Sustainable Development. Building on initial actions undertaken by countries since the early 1990s, the SDGs provide a shared blueprint to address the most pressing global challenges and promote prosperity while protecting the planet. Designed to be universal, they apply to all countries and highlight the interconnected nature of social, economic, and environmental sustainability (United Nations, nd).

Among the global challenges associated with achieving a sustainable future is the conservation and systematic monitoring of tropical forests, as anthropogenic changes in forest cover profoundly affect the provision of numerous ecosystem services in these regions. To facilitate a methodic evaluation of the benefits derived from tropical forests and other ecosystems, the concept of ecosystem services has been introduced. Ecosystem services encompass all beneficial contributions of the natural environment to human well-being, including the supply of goods, resources, and ecological functions (Wallace, 2007). The usefulness of ecosystem services lies in its ability to raise awareness and inform decision-making processes by bridging ecological and economic systems (Norgaard, 2010).

Remote sensing has enabled a more systematic and comprehensive monitoring of tropical forest ecosystems. Over the past three decades, advancements in sensor technologies, data accessibility, and analytical methodologies have significantly enhanced the capacity to detect and characterise forest disturbances with greater temporal and spatial resolution. These developments are essential for understanding the dynamics of land cover change, particularly in tropical regions where forest disturbances remain major environmental concerns (Finer et al., 2018).

1 General context

1.1 Tropical forests : ecosystem services and impacts of tropical forest cover loss

Tropical forests provide a wide range of ecosystem services, contributing to environmental stability and supporting essential ecological functions necessary for life. Additionally, they offer direct benefits to humans through the provision of natural resources and non-material contributions that enhance human well-being. Forest cover change has significant consequences for the provision of these key ecosystem services. Intact tropical forest ecosystems maintain an exceptional capacity to sustain these services compared to deforested or degraded forests, where their functionality is substantially diminished (Watson et al., 2018).

Carbon sequestration and climate regulation

Through their vegetation and soil reservoirs, tropical forests store substantial amounts of carbon, playing a crucial role in the global carbon cycle. By sequestering carbon, they contribute to stabilising atmospheric CO₂ levels, thereby mitigating climate change. Historically, tropical forests were considered a net carbon sink, absorbing atmospheric CO₂ through photosynthesis and biomass accumulation. However, recent studies suggest that they have transitioned into a net carbon source, releasing more carbon into the atmosphere than they absorb. Between 2003 and 2014, annual changes in aboveground biomass resulted in an estimated mean net carbon release from tropical forests of 425.2 ± 92.0 Tg C per year (Baccini et al., 2017). This net carbon release into the atmosphere contributes to global atmospheric warming (Watson et al., 2018). The overall carbon imbalance results from carbon losses of 861.7 ± 80.2 Tg C yr⁻¹, primarily driven by land-use changes associated with deforestation and forest degradation, offset by carbon gains of 436.5 ± 31.0 Tg C yr⁻¹ due to forest regrowth and biomass accumulation. Carbon losses exceeded gains across all major tropical regions, with tropical America contributing 60% of the total net carbon loss, while Africa and Asia accounted for 24% and 16%, respectively. Within these regions, Brazil, the Democratic Republic of the Congo, and Indonesia had the greatest influence on continental carbon loss due to their extensive forest cover. Furthermore, carbon losses vary depending on the type of forest disturbance. Across the tropics, forest degradation accounts for up to 69% of total carbon losses. This proportion is even higher in Africa, where degradation contributes to up to 81% of carbon losses, compared to 70% in tropical America and 46% in Asia (Baccini et al., 2017). Other studies suggest that forest degradation contributes up to 40% of total emissions associated with aboveground vegetation (Houghton, 2012).

Tropical forests also influence the Earth’s radiation balance. Their dense canopies are characterised by low surface albedo, enhancing absorption of solar radiation. This reduces solar radiations reflected back to the atmosphere, potentially contributing to atmospheric warming. (Lawrence et al., 2022). In addition to their albedo effects, tropical forests release biogenic volatile organic compounds (BVOCs), which oxidize to form secondary organic aerosols (SOAs). These aerosols promote cloud formation and increase cloud albedo, providing a biophysical cooling effect (Topping et al., 2013). However, SOAs are also associated with the release of latent heat in deep convective cloud systems, which can contribute to atmospheric radiative warming (Fan et al., 2012). Disturbances to forest cover reduce both SOA production and canopy albedo, contributing to atmospheric warming (Lawrence et al., 2022; Topping et al., 2013). The biophysical warming effects linked to forest disturbances can account for 35–60% of the warming attributable to CO₂ emissions from these disturbances (Lawrence et al., 2022).

Hydrological regulation and watershed protection

Tropical forests regulate the hydrological cycle. They sustain regional rainfall through evapotranspiration, transferring water from vegetation and soil to the atmosphere and converting solar energy into latent heat (D’Almeida et al., 2007; Lawrence et al., 2022). This mechanism significantly contributes to atmospheric humidity, enhancing cloud formation and precipitation. In the Amazon Basin, evapotranspiration accounts for approximately 50–60% of total precipitation, with 25–35% being locally recycled. Tropical forests also influence both regional and global climate by modulating moisture transport and convective rainfall patterns. Additionally, their aboveground vegetation and root systems reduce surface run-off and enhance infiltration, thereby maintaining water balance within the ecosystem. By retaining and gradually releasing water, they regulate river discharge and groundwater recharge. This process controls the timing and intensity of water movement, mitigating soil erosion and preserving watershed integrity (D’Almeida et al., 2007).

Forest loss significantly impairs these functions. Reduced evapotranspiration diminishes atmospheric humidity and precipitation, limiting surface cooling by impacting associated latent heat flux (D’Almeida et al., 2007; Lawrence et al., 2022). Reduced cloud cover formation further decreases the cooling effect associated with its high albedo (Topping et al., 2013). Cleared areas also increase the risk of erosion and the transport of sediments into rivers, compromising watershed integrity. In fact, the removal of above- and belowground vegetation reduces water infiltration into soils and increases surface run-off. Consequently, cover loss significantly alters the seasonality of river discharge, leading to greater hydrological variability throughout the year. This disruption not only affects the equilibrium of river ecosystems but also increases the intensity and unpredictability of floods and droughts (D’Almeida et al., 2007).

Biodiversity and ecological stability

Tropical forests are the most biologically diverse terrestrial ecosystems, hosting at least two-thirds of global biodiversity. By providing unique habitats, tropical forests are essential for preserving a vast number of species, many of which are often endemic to these ecosystems. They support essential ecological processes such as seed dispersal, pollination, and nutrient cycling, which maintain forest structure and regeneration. Furthermore, the complexity of species interactions enhances ecosystem resilience, ensuring stability and adaptability to environmental changes (Gardner et al., 2009). Globally, 39% of tropical primary forests and 46% of intact forests are covered by protected areas (Crystal Davis, 2024). These protected regions provide a crucial role in conserving species that rely heavily on the presence of undisturbed habitats (Gardner et al., 2009).

Forest cover loss leads to habitat fragmentation and a decline in species that cannot adapt to altered environments. Key ecological processes previously mentioned deteriorate (Gibson et al., 2011). Species richness declines across most taxa. Birds, arthropods, and plants are particularly vulnerable, while mammals exhibit variable responses. Agricultural expansion is the most detrimental disturbance, followed by pasture conversion, plantations, and logging. Though selective logging retains higher biodiversity, it still results in substantial losses. While species richness, e.g., the total number of species, is the most sensitive metric to deforestation, species abundance, e.g., the total number of individuals, is less affected. Disturbed forests can experience an increase in generalist species but a decline in specialist species. Despite variations across taxonomic groups, ecological metrics, and disturbance types, biodiversity decline remains a consistent trend globally (Gibson et al., 2011).

Human livelihoods and cultural significance

Tropical forests hold profound significance for forest-dwelling indigenous communities, who have inhabited these ecosystems for millennia. Archaeological evidence reveals continuous human presence in regions such as Central Africa for over 250,000 years (Mercader, 2002). These forests provide a wide range of essential resources that support both subsistence and economic activities. Timber and non-timber forest products, such as fuelwood, resins, latex, palm fibers, rattans, and vines, are integral to daily life, used for construction, energy, crafting, and trade. Shifting cultivation and agroforestry practices, which reflect a deep understanding of ecological cycles, are commonly employed to ensure food security and maintain soil fertility. In addition, forested areas are often cleared to create small-scale agricultural plots, while industrial plantations devoted to export-oriented cash crops have introduced further land-use transformations (Wiersum, 1997).

However, the accelerating loss and degradation of tropical forests severely disrupt these long-standing relationships. Forest disturbances compromise food security by reducing access to wild foods, hunting grounds, and arable land for traditional agriculture. Loss of forest cover degrades ecological conditions that underpin sustainable cultivation systems, threatening both agricultural productivity and ecosystem resilience. Simultaneously, erosion of access to vital forest products undermines income-generating opportunities many communities rely on. Forest loss also profoundly affects the spiritual and cultural dimensions of indigenous life. Sacred sites and culturally significant landscapes are destroyed, weakening traditional belief systems and eroding intergenerational knowledge (Wiersum, 1997; Watson et al., 2018). As commercial logging, state policies, and agricultural expansion increasingly override collective land tenure, traditional governance structures and resource stewardship are compromised (Wiersum, 1997). This marginalisation forces many communities to adopt market-based livelihoods, which may offer less sustainability and accelerate the disintegration of cultural identities (Watson et al., 2018).

Public health and medicinal resources

Tropical forests are valuable repositories of medicinal plants, serving both traditional health systems and modern pharmaceutical research. Beyond compromising the availability of these resources, forest cover loss also increases the risk of infectious diseases. Human activities bring people into closer contact with wildlife that may carry infectious pathogens. Malaria outbreaks, for instance, have been linked to areas where logging and agriculture degrade tropical forests. These disturbed landscapes create ideal breeding sites for disease-carrying mosquitoes, further amplifying public health risks (Wiersum, 1997; Watson et al., 2018).

Global importance and the need for conservation

These essential ecosystem services must not be overlooked in efforts to achieve sustainable development. The conservation and active monitoring of tropical forest are therefore crucial in reaching key objectives, especially SDG 13 (Climate Action), SDG 15 (Life On Land), SDG 1 (No Poverty) and SDG 2 (Zero Hunger) (United Nations, nd). Safeguarding these ecosystems from forest cover loss not only favours carbon sequestration but also supports biodiversity and hydrological functions essential for maintaining local and global ecological balance. Furthermore, tropical forests are vital for the livelihoods, economic activities, and cultural practices of local communities. As a result, allocating efforts towards tropical forest conservation, and therefore monitoring, is a fundamental component of global climate and development strategies.

1.2 Global trends of tropical forest cover change

The accurate characterisation of tropical forest cover change dynamics at a global scale is essential for a better assessment of the impacts of forest disturbances on the various ecosystem services provided by undisturbed tropical forests. Forest cover disturbances generally encompass two main types of changes: deforestation and forest degradation. Deforestation is commonly defined as the stand-replacement or complete removal of tree cover (Hansen et al., 2013). In contrast, forest degradation refers to the thinning of forest cover and a loss of carbon stocks, leading to the deterioration of previously undisturbed forests (Hosonuma et al., 2012).

Tropical moist forests (TMF) are a subcategory of tropical forests characterized by high and consistent rainfall. In the context of this work, TMF refers specifically to the product developed by Vancutsem et al. (2021) for monitoring forest cover. The evolution of continental and global undisturbed TMF areas over the period 1990–2020 is presented in Figure 1.1 (Vancutsem et al., 2021).

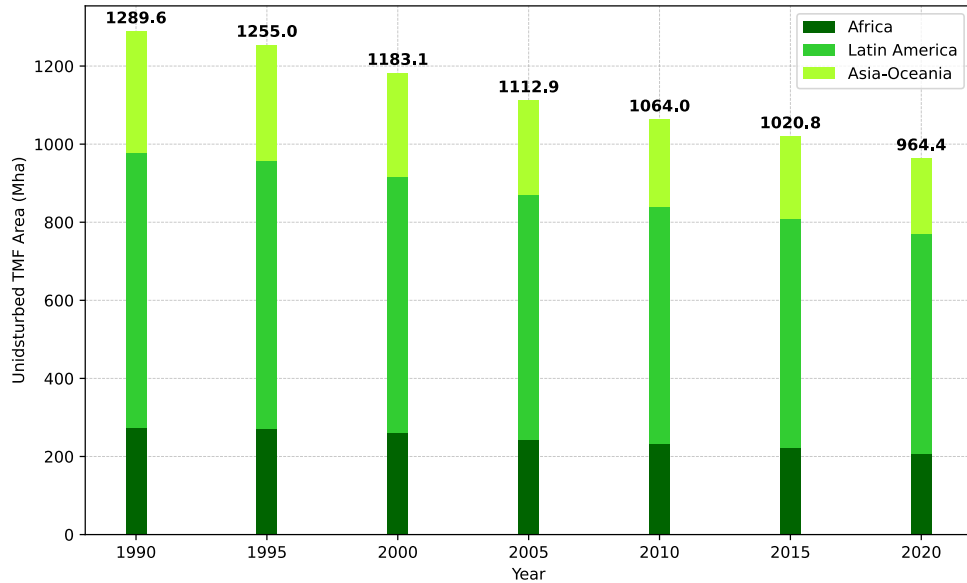


Figure 1.1: Evolution of continental and global undisturbed TMF areas over the period 1990–2020

Over a 30-year period, the pan-tropical undisturbed TMF area declined from 1,289.6 million ha to 964.4 million ha, resulting in a loss of 325.2 million ha of undisturbed forest cover. This 25.2% decrease in area was 67% driven by deforestation (218.7 Mha), while the remaining 33% was attributed to forest degradation (106.5 Mha). Furthermore, 45.4% of degraded forests eventually underwent deforestation, highlighting the progressive nature of forest loss (Vancutsem et al., 2021). The evolution of continental and global undisturbed + degraded TMF areas from 1990 to 2020, as well as a comparative analysis of undisturbed

TMF area and undisturbed + degraded TMF area, are presented in Appendix A, Figures 9.1 and 9.2. The decline in undisturbed TMF over the 30-year period is prominent in countries like Ivory Coast (-81.5%), Mexico (-73.7%) or Ghana (-70.8%). If current forest disturbances rates are maintained, 15 countries will have lost more than 50% of their undisturbed TMF area by 2050 (Vancutsem et al., 2021).

1.3 The Congo Basin tropical moist forest

1.3.1 Overview of the tropical moist forest ecosystem

As the second-largest tropical moist forest ecosystem in the world after Amazonia, the Congo Basin tropical moist forest plays a crucial role in providing many ecosystem services. Figure 1.2 illustrates that the forest spans, although to varying extents, mainly across six countries: Cameroon (CAM), the Central African Republic (CAR), the Democratic Republic of the Congo (DRC), Equatorial Guinea (EQG), Gabon (GAB), and the Republic of the Congo (RoC) (Somorin et al., 2012). Among these countries, the DRC is particularly significant, as it hosts 60% of the total extent of the Congo Basin tropical forest.

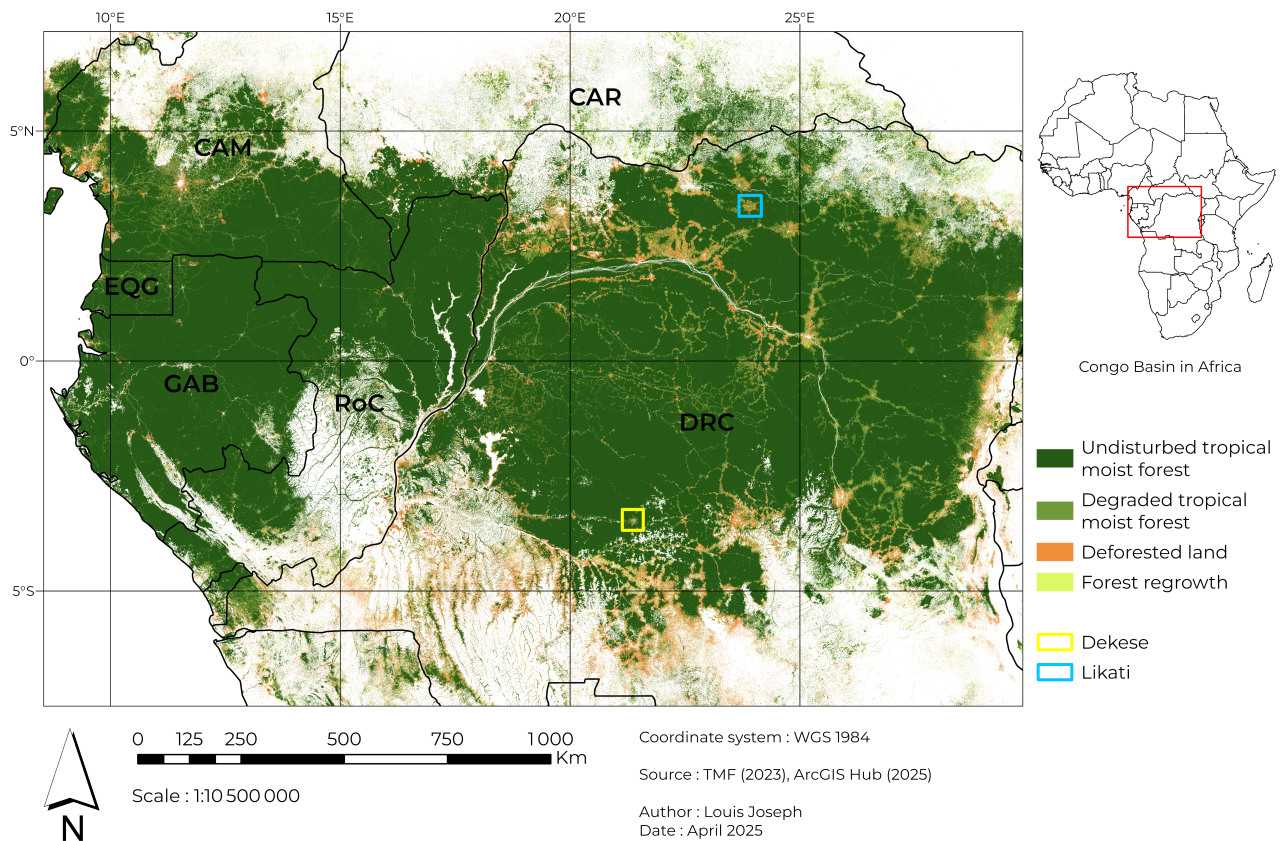


Figure 1.2: Geographical extent of TMFs in the Congo Basin region with highlighted calibration (Dekese) and transfer (Likati) region of interests (ROI), with detailed respective views in Sections 4.1.1 and 4.1.2

Although the Congo Basin is one of the most important tropical forest ecosystems globally, it remains insufficiently studied in relation to the Amazon and Southeast Asian tropical forests. The tropical forest exhibits structural variability, encompassing distinct categories such as primary and mature secondary dense cover, young secondary dense cover, primary woodlands and dry forests, secondary woodlands and sparse secondary cover, and plantations (Tyukavina et al., 2018).

1.3.2 Tropical forest dynamics in the Congo Basin

The Congo Basin experienced a notable shift in forest cover change dynamics between 1990 and 2005, with a marked increase in deforestation and forest degradation rates. Regional statistics indicate that the annual net deforestation rate nearly doubled, rising from 0.09% (1990-2000) to 0.17% (2000-2005). Similarly, the annual net degradation rate followed a comparable trend, increasing from 0.05% to 0.09% (Ernst et al., 2013).

Among the six countries making up the Congo Basin, DRC exhibited the highest deforestation rate increase, with net forest loss doubling from 0.11% to 0.22% between the two periods. RoC experienced a moderate increase, rising from 0.03% to 0.07%. In contrast, GAB maintained a stable net deforestation rate between the two periods, while both CAM and CAR showed a decline in their annual net deforestation rates. Finally, EQG recorded a 0.02% net deforestation rate for the period 1990–2000, but data for the period 2000–2005 was unavailable Ernst et al. (2013).

While the net degradation rate followed a similar increasing trend regionally as the net deforestation rate, national statistics revealed notable variations. In the DRC, the net degradation rate increased from 0.06% to 0.12%, the highest rate among all countries. CAM experienced a slight increase, rising from 0.06% to 0.07%, whereas RoC and CAR remained stable at 0.03% across both periods. GAB was an exception, with a net degradation rate of 0.04% for the period 1990–2000, which then shifted to a slight net recovery rate of -0.01% for 2000–2005, suggesting a localised positive impact of forest regeneration. Similarly, EQG lacked data for the 2000–2005 period (Ernst et al., 2013).

These findings provide critical insights into the evolving forest dynamics of the Congo Basin tropical moist forest, and underscore the need to further investigate the drivers, significance, and causes of deforestation and degradation.

1.3.3 Drivers of tropical forest disturbances in the Congo Basin

As the Congo Basin tropical forest extends across six countries, the direct drivers and underlying causes of forest disturbances vary depending on the geographic, demographic, and economic characteristics of each country. These variations were identified for the period 2000 to 2014, using a stratified sampling methodology designed to quantify forest disturbance drivers within each country, as illustrated in Figure 1.3 (Tyukavina et al., 2018). The significance and underlying causes of the various drivers during this period are detailed below.

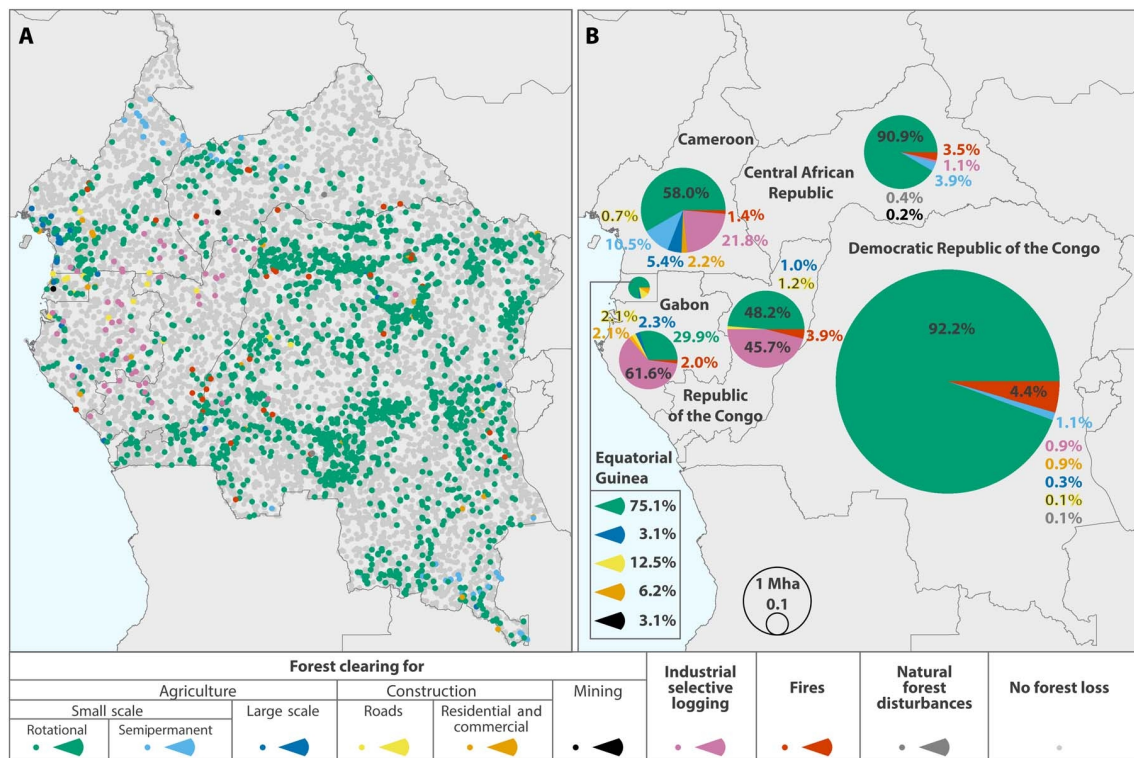


Figure 1.3: Forest disturbance driver. (A) Reference disturbance driver for each sampled pixel. (B) National estimates of 2000 to 2014 forest loss area by disturbance driver (Tyukavina et al., 2018).

Smallholder agriculture is the dominant driver of forest disturbances in the Congo Basin, accounting for an estimated 84% of forest disturbances due to small-scale, non-mechanized forest clearing (Houghton, 2012; Tyukavina et al., 2018). This estimate primarily includes both rotational agriculture and semi-permanent agriculture, practiced either for subsistence farming or commercial crop production (Moonen et al., 2016). Between 2000 and 2014, the annual rate of smallholder clearing for agriculture doubled across the Congo Basin, primarily due to population growth as shown on Figure 1.4. This trend is particularly pronounced in DRC, as nearly two-thirds of the total forest loss in the Congo Basin was associated solely with smallholder clearing in DRC. This is directly linked to high population pressure, as DRC's population in 2014 was more than twice that

of the other five Congo Basin countries combined (Tyukavina et al., 2018). Additionally, this pattern can be attributed to high poverty levels, as the majority of the population in both the DRC and CAR depends on smallholder farming as their primary livelihood (Fisher, 2010).

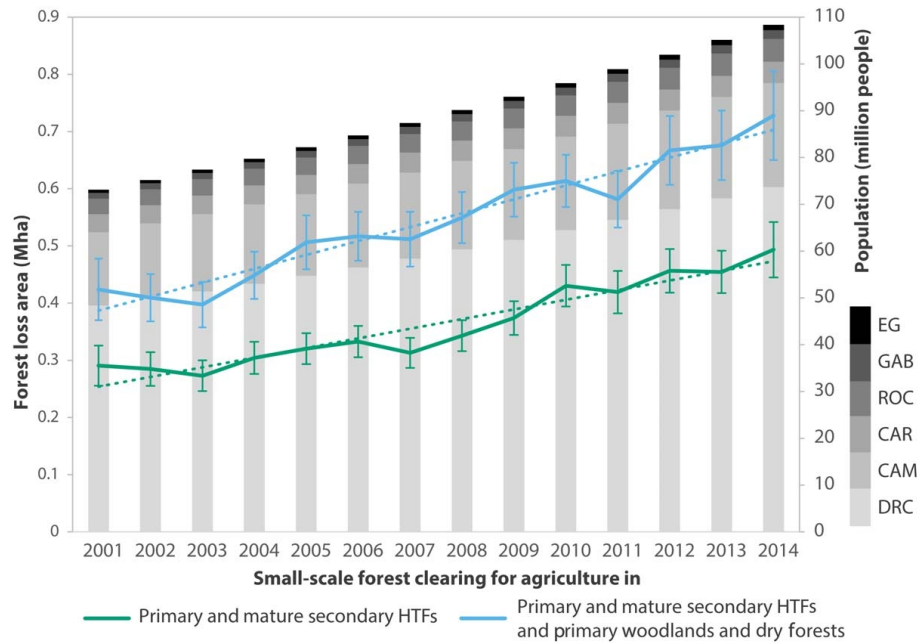


Figure 1.4: Expansion of small-scale agriculture into recently undisturbed forests and woodlands (lines) and population growth in the region by country (bar chart). Solid lines connect the annual forest loss area estimates and dashed lines represent the linear trend based on ordinary least squares regression (Tyukavina et al., 2018).

Industrial selective logging is the second-largest contributor to forest disturbances, accounting for approximately 10% of total disturbances. Unlike clear-cutting, selective logging does not necessarily results in the complete removal of the tree canopy. GAB is the leading contributor, responsible for over 60% of selective logging-related disturbances in the region.

Infrastructure development accounts for approximately 1.5% of forest disturbances in the Congo Basin. These are associated to road construction and residential and commercial developments. EQG exhibits the highest proportion of construction-related forest disturbances.

Fires, often linked to escaped agricultural fires or hunting practices contributes for around 4% of forest disturbances in the basin with DRC contributing the most to those fire related forest disturbances.

While small-scale clearing for agriculture is the predominant driver of forest disturbances across the basin, large-scale mechanised clearing for agriculture represents only around 1% of the total forest loss. These activities, primarily involving palm plantations and industrial pastures, are concentrated in the Gulf of Guinea countries (CAM, GAB, and EQG), where export opportunities are facilitated by access to port infrastructure (Hosonuma et al., 2012; Tyukavina et al., 2018). Unlike in the DRC, CAR, and RoC, where logistical constraints limit large-scale expansion, the Gulf of Guinea countries are experiencing a surge in agro-industrial investments, which are expected to further increase the contribution of this driver to deforestation (Feintrenie, 2014).

Other minor drivers of forest disturbances include natural forest disturbances and mining activities (Tyukavina et al., 2018).

These findings highlight how the geographic, demographic and economic contexts of each countries of the Congo Basin contributes to the different drivers of forest disturbances.

2 Literature review

2.1 Remote sensing for tropical forest monitoring

2.1.1 Optical remote sensing fundamentals

Remote sensing refers to the acquisition of information about objects or areas from a distance through sensors mounted on various platforms. In Earth Observation (EO), remote sensing is employed to monitor the planet's surface, atmosphere, and water bodies across multiple spatial scales, ranging from individual agricultural fields to entire continents. Depending on the required field of view, sensors are mounted on platforms such as unmanned aerial vehicles (UAVs), aircraft, or satellites (Defourny, 2022; Lambin, 2023). Among these, satellites provide the only platform capable of continuous, large-scale, and systematic monitoring of land cover dynamics, including disturbances in tropical forests cover (ESA, 2020).

Sensors aboard remote sensing platforms measure electromagnetic (EM) energy reflected or emitted by the Earth's surface. These sensors are designed to detect specific wavelengths or spectral bands of the EM spectrum, allowing for targeted observation of various environmental parameters (Defourny, 2022; Lambin, 2023). The energy detected by remote sensing instruments may originate locally, such as thermal radiation emitted by vegetation in the infrared (IR) spectrum, or from solar radiation reflected off the Earth's surface. In the latter case, the amount and spectral characteristics of reflected solar radiation depend on the reflective surface properties (ESA, 2020).

Moreover, the energy detected by remote sensing sensors can be affected by the chemical composition of the atmosphere. Specific wavelengths are absorbed by atmospheric constituents, like water vapor or CO₂, while others remain unaffected by atmospheric interactions. The spectral regions where atmospheric absorption is minimal, enabling effective space-based remote sensing, are referred to as atmospheric windows (Defourny, 2022; Lambin, 2023). Figure 2.1 displays the location of the different atmospheric windows along the EM spectrum (NOAA, 2025).

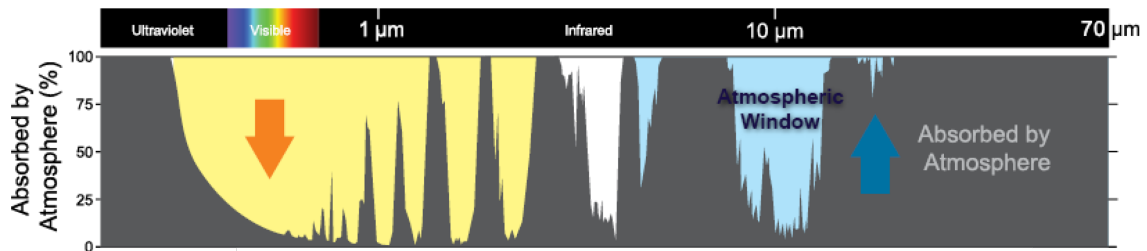


Figure 2.1: Atmospheric absorption of EM radiation: incoming solar (yellow) and outgoing terrestrial (blue) wavelengths (NOAA, 2025).

2.1.2 Optical remote sensing products for tropical forest monitoring

When monitoring forest dynamics, two main objectives are typically pursued. The first involves generating forest cover maps at specific time intervals, such as annually, to assess long-term changes in forest cover, or more frequently, to support disturbance alert systems capable of detecting new forest cover disturbances as rapidly as possible. The second objective focuses on classifications of forest cover types (Hirschmugl et al., 2020). Since remote sensing datasets first became accessible, various optical products have been developed to monitor forest cover change, including both tropical and non-tropical forests.

Legacy products

Endeavours to develop global forest cover change products using EO imagery are not recent, as the generation of global continuous fields representing the percentage of woody vegetation to assess vegetation cover change across multiple years was already feasible in the early 2000s. This was achieved using the Advanced Very High Resolution Radiometer (AVHRR) Pathfinder Land (PAL) dataset, which estimated the percentage of woody vegetation, herbaceous vegetation, and bare ground at an 8 km spatial resolution to monitor changes between 1982 and 1999 (Defries et al., 2000a; Hansen and DeFries, 2004).

The AVHRR sensor family, flown onboard satellites operated by the National Oceanic and Atmospheric Administration (NOAA) and EUMETSAT, has provided continuous data acquisition since 1981 (Brest and Rossow, 1992). Further advancements based on the AVHRR PAL dataset eventually led to prototype global forest cover percentage products with an improved spatial resolution of 1 km for the years 1992 and 1993 (Defries et al., 2000b).

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor represented the next significant advancement in land cover and forest cover change monitoring. Launched aboard the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites in the early 2000s, MODIS provides near-daily imagery at spatial resolutions of up to 250 m (MODIS, 2025). Compared to the 1 km AVHRR PAL dataset, MODIS data offered improved spatial and spectral details, enabling the production of the first global percent tree cover map at a spatial resolution of 500 m (Hansen et al., 2003).

As early as 2004, MODIS datasets with a spatial resolution of 250 m have been utilised for the development of an operational, near real-time NRT deforestation detection system in the Brazilian Amazon. This system, known as DETER, was developed by Brazil's National Institute for Space Research (INPE) to monitor deforestation in the Amazon tropical moist forest (Shimabukuro, 2006).

In contrast, MODIS datasets were employed to conduct a comprehensive assessment of the extent of Africa’s rainforests for the year 2005, offering a spatial resolution of 250 m (Mayaux et al., 2013). Complementary regional analyses utilised the Satellite Pour l’Observation de la Terre (SPOT) VEGETATION time series, with a spatial resolution of 1 km, to map and classify vegetation types across the DRC (Vancutsem et al., 2009). Subsequently, SPOT time series were integrated with MEdium Resolution Imaging Spectrometer (MERIS) data at 300 m spatial resolution to generate more detailed vegetation maps of the Congo Basin (Verhegghen et al., 2012).

Landsat-derived products

A major breakthrough in long-term forest cover change monitoring was made possible by the opening of the United States Geological Survey (USGS) Landsat data archive in 2008 (Wulder et al., 2012). Initiated in 1972 with the launch of Landsat-1, the Landsat program is the longest-running program dedicated to acquiring Earth imagery from space. Over the decades, successive Landsat satellites have been developed and deployed, with the most recent, Landsat-9, launched in 2021 (USGS, 2025). The program was originally designed for systematic land cover mapping at a spatial resolution of 30 m with a 16-day revisit cycle. The transition to a free and open data policy revolutionised EO initiatives aimed at monitoring land cover changes, including tropical forest dynamics. This continuity in data acquisition has provided invaluable resources for long-term environmental analysis and has significantly increased its use in scientific research, operational monitoring, and land management applications (Wulder et al., 2012).

One of the first applications of this newly available medium-resolution, long-term archive was the development of the Global Forest Change (GFC) product under the Global Forest Watch (GFW) initiative. This product enabled the quantification of global forest loss and gain for the period 2000–2012 at a spatial resolution of 30 m. This was achieved using data from the Enhanced Thematic Mapper Plus (ETM+) onboard Landsat 7. This approach facilitated the production of annual percent tree cover maps as well as annual forest loss and gain maps for the study period and became an operational product still accessible today (Hansen et al., 2013).

The opening of the Landsat archive also facilitated the development of products focusing on tropical forest cover dynamics. At the national scale, the Landsat ETM+ imagery archive was utilised to produce a tropical forest cover loss mapping for the period 2000–2010 in the DRC (Potapov et al., 2012). Additionally, this newly available data was integrated into the DETER system for monitoring deforestation in the Brazilian Amazon, which had previously relied solely on MODIS datasets like mentioned before (Wulder et al., 2012).

Globally, an enhanced assessment of tropical moist forest dynamics was made possible using data from the ETM+ and Operational Land Imager (OLI) onboard the various Landsat satellites. Spanning an unprecedented 30-year period from 1990 to 2019, this analysis was conducted at a spatial resolution of 30 meters. It enabled the first comprehensive mapping of tropical forest disturbances and the analysis of their temporal evolution at a pan-tropical scale over the past three decades (Vancutsem et al., 2021). The TMF annual change dataset produced by Vancutsem et al. (2021) is employed in the present study to delineate the extent of both undisturbed and disturbed TMF.

To support the annual GFC product updates, Landsat archives also facilitated the development of the Global Land Analysis and Discovery (GLAD) NRT disturbance alert system for monitoring tropical forests at a global scale. Utilising data from the Enhanced ETM+ and OLI sensors, this system is designed to provide frequent updates on forest loss to support law enforcement, conservation efforts, and land management (Hansen et al., 2016).

Sentinel-2-derived products

The Copernicus program was established in 2014 by the European Commission (EC) in partnership with the European Space Agency (ESA). Copernicus is designed to provide long-term monitoring of Earth’s ecosystems and contribute to a vast, coordinated environmental monitoring system. This initiative aligns with the European Union’s (EU) commitments toward sustainable development. To support the extent of its operational services, a family of satellites known as Sentinels has been developed by the ESA, with each satellite constellation assigned to specific objectives. As new Sentinel satellites are launched and planned, the program’s capabilities continue to extend, ensuring continuity and scalability for future observations requirements. Alongside the Sentinel satellites, current or upcoming contributing missions provide valuable data that contributes to the extent of Copernicus services (Copernicus, 2025; ESA, 2025b).

Although Landsat imagery was made freely available in 2008, the Copernicus program was designed with an open data policy at its core, enabling widespread use of its data for scientific, governmental and commercial applications. Furthermore, Sentinel satellites generally propose higher revisit frequency and spatial resolution than Landsat satellites. In particular, data from Sentinel-2 has enhanced the efforts of the GLAD NRT product by enabling the development of a disturbance alert system for the Brazilian Amazon with a spatial resolution of 10 m (Hansen et al., 2016).

NewSpace

Recent developments in EO programs are now also driven by the emergence of new actors inside the private space industry, a phenomenon known as NewSpace. This movement represents a transformative shift in the established space industry by reducing reliance on government support and initiatives. Instead, NewSpace focuses on commercially driven activities aimed at generating profit by providing services such as satellite launches, network infrastructures, and EO satellites constellations. The rise of the private space sector has been facilitated by technological advancements and cost-reduction strategies that enable an easier access to space (Defourny, 2022).

Moreover, private EO programs have transitioned from relying on a few massive, costly satellites to developing and deploying smaller, cheaper, mass-produced satellites in extensive constellations. This shift enables higher revisit frequencies and unprecedented high spatial resolutions ($<5\text{m}$), enhancing the ability to monitor Earth's surface with greater detail and frequency (Defourny, 2022). Among those new constellations, Planet Labs' PlanetScope constellation, stands out with around 130 satellites capable of capturing daily global land surface imagery at a spatial resolution of up to 3 m (Planet Labs, 2025).

Since the emergence of space-based remote sensing, technological advancements in both sensor design and platform capabilities have substantially improved the spatial, spectral, temporal, and radiometric resolution of EO imagery. In parallel, advancements in automated forest-loss detection have progressed alongside satellite developments (Finer et al., 2018). The evolution of remote sensing for monitoring land cover dynamics, including tropical deforestation, initially relied on mission-specific satellites and pioneering government-led programs. These early initiatives laid the foundation for contemporary EO systems, which are increasingly advanced, sustainable and driven by commercial as well as public-sector initiatives.

Limitations

While high-spatial-resolution sensors are becoming increasingly operational, products relying on medium-resolution sensors are less able to detect small-scale disturbances. This limitation results in a significant underestimation of tropical forest cover disturbances caused by smallholder agriculture or selective logging (Potapov et al., 2012).

Furthermore, tropical regions, such as the Congo Basin, are characterised by semi-permanent cloud cover (Reiche et al., 2018b). The limited availability of cloud-free data from optically-based sensors affects their ability to monitor forest cover loss. NRT dis-

turbance alert systems are particularly impacted by cloud cover, as dense time series are essential for effective near real-time monitoring. Short-duration events caused by small-holder agriculture or selective logging often remain undetected when temporal gaps occur in the time series (Hirschmugl et al., 2020).

2.1.3 SAR remote sensing fundamentals

The following Section 2.1.3 is primarily based on the online courses “Introduction to Radar Remote Sensing” and “Basic Principles of Radar Backscatter” available on the EO College learning platform (EO College, 2025b,a).

RADAR remote sensing refers to any systems that are actively emitting EM microwaves while controlling the wavelength, frequency and polarisation of the transmitted signal. These systems are equipped with antennas capable of receiving the echoes backscattered from the Earth’s surface. In contrast to passive optical sensors, which are highly sensitive to cloud cover and dependent on sunlight, radar remote sensing sensors can acquire day and night imagery and are largely unaffected by atmospheric conditions, including cloud cover.

Synthetic Aperture Radar (SAR) is an engineering method in radar remote sensing designed to overcome the spatial resolution limitations inherent to real aperture radars systems. Using the forward motion of the remote sensing platform, SAR systems emit and receive multiple radar pulses sequentially along the orbital trajectory of the satellite. The individual backscattered signals received from different positions are then combined to form a synthetic aperture, effectively simulating a much larger antenna. This approach enables the achievement of higher spatial resolutions than real aperture radars, while relying on small physical antennas and relatively long wavelengths.

A fundamental measurable variable of the returned signal is its intensity, which corresponds to the strength of the fraction of the radar signal reflected from a target on the Earth’s surface back to the sensor. The amount of reflected signal is referred to as the backscattering. The most commonly used expression of backscattering is sigma naught (σ^0), also known as the backscatter coefficient, and is typically expressed in decibels (dB) to simplify analysis and interpretation. Other forms of backscatter representation include beta naught (β^0) and gamma naught (γ^0). The primary distinction among these expressions lies in the reference area used to normalise the returned signal, as shown in Figure 2.2.

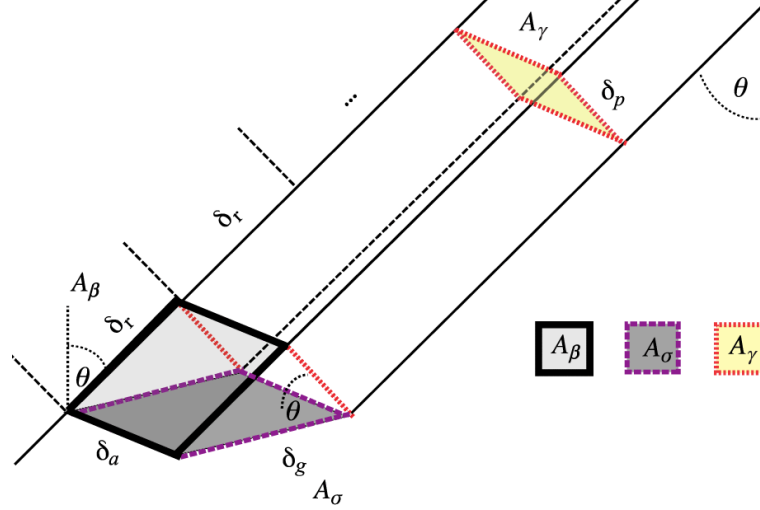


Figure 2.2: Backscatter variables and their reference areas (EO College, 2025a).

As the emitted SAR signal interacts with a target or scatterer on the ground, the strength of the backscattered signal is influenced by both sensor-related parameters and ground-related parameters. These parameters, summarized in Table 2.1, govern the type of backscattering mechanism that is encountered. The most relevant parameters for monitoring tropical forest cover are discussed in greater detail below.

Table 2.1: Sensor and ground parameters affecting the radar backscatter

Sensor parameters	Ground parameters
Wavelength and frequency	Topographic features
Polarisation	Surface roughness
Cell size	Geometric target properties
Viewing geometry (incidence angle, ...)	Dielectric constant (moisture content)

Surface, or single-bounce, scattering occurs when the emitted SAR signal interacts with a heterogeneous surface. In this case, a portion of the signal is scattered back toward the sensor, while the remainder is scattered in other directions. As surface roughness increases, diffusive scattering becomes more prominent. However, when the signal encounters a surface that is flat and smooth relative to the wavelength, most of the energy is reflected in a specular direction, away from the sensor, resulting in no backscatter returning to the sensor.

Double-bounce scattering takes place when the radar signal reflects between two relatively smooth surfaces positioned at near-perpendicular angles to one another. In such configurations, the reflected energy is redirected toward the sensor with minimal diffusive scattering, resulting in a strong return signal. In tropical forest, this scattering mechanism typically arises when the signal first interacts with the ground and then with a vertical

structure such as a tree trunk, or vice versa, for example, at the edge of a forest cover.

Volume scattering occurs when the emitted radar signal penetrates a medium with randomly oriented elements, like leaves or branches in a forest canopy. The signal bounces and scatters multiple times in different directions before a fraction of it is returned to the sensor.

In contrast to double-bounce scattering, SAR shadows refer to areas where no returned signal is received. These occur when the line of sight is obstructed by topographic features or tall vertical elements, such as tree trunks located at the edge of a forest cover.

As a result of these mechanisms, forest disturbances such as deforestation or forest degradation are typically associated with a decrease in backscatter intensity.

A visual representation of the different types of backscattering mechanisms encountered in tropical forests dynamics is illustrated in Figure 2.3.

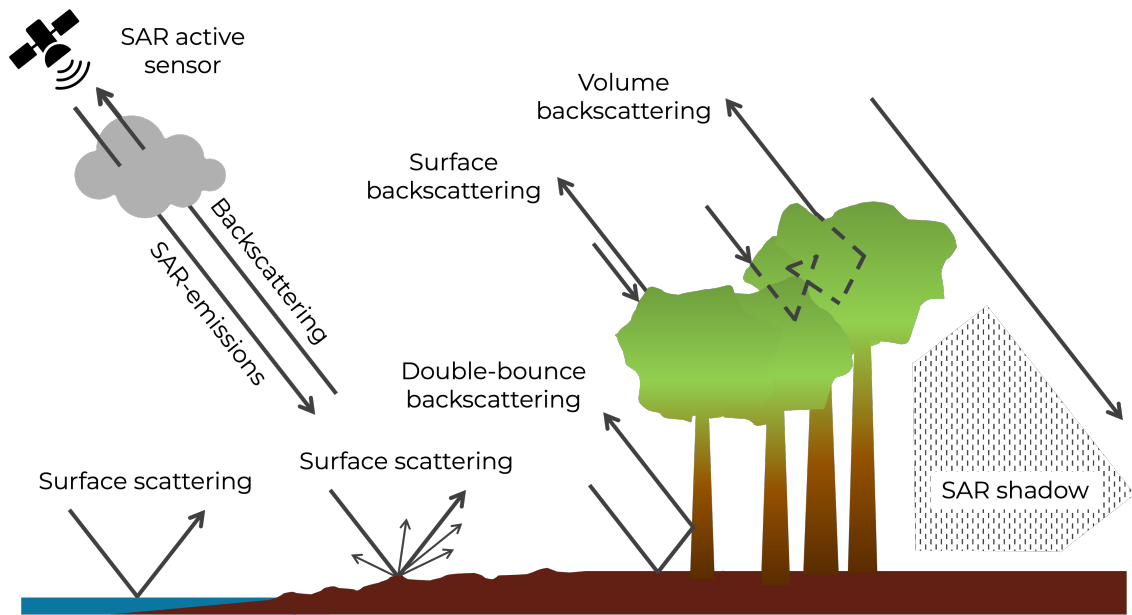


Figure 2.3: Overview of backscattering mechanisms in tropical forests environments (Delhez et al., 2024).

The interaction between the SAR pulse and a scatterer is also strongly influenced by the emitted wavelength (or frequency). For a given wavelength, certain objects will scatter the incoming pulse, while others may allow partial or complete penetration, resulting in weak or no detection by the sensor. Consequently, it is the relative size of the target in relation to the wavelength that determines whether significant interaction occurs. Table 2.2 presents some of the most commonly used radar bands in SAR remote sensing.

Table 2.2: Common radar frequency bands in remote sensing : frequency and wavelength ranges

Radar band	Frequency range (Ghz)	Wavelength range (cm)
X	8-12	2.5-3.75
C	4-8	3.75-7.5
S	2-4	7.5-15
L	0.5-2	15-60
P	0.25-0.5	60-120

As active instruments, SAR systems have the capability to control not only the polarisation of the received signal but also that of the transmitted signal. Polarisation describes the orientation of the signal wave’s electric field. In polarimetric SAR (PolSAR) systems, sensors typically employ linear polarisation, meaning that the electric field of the wave is constrained to a single plane aligned either vertically or horizontally with respect to the direction of propagation. These systems may operate in several configurations: transmitting and receiving in the same polarisation (e.g., HH for horizontal–horizontal or VV for vertical–vertical), transmitting in one polarisation and receiving in both (e.g., HH and HV), or transmitting and receiving in both polarisations (e.g., HH, HV, VH, VV).

2.1.4 SAR remote sensing products for tropical forest monitoring

The ability of SAR remote sensing instruments to operate independently of cloud cover and illumination conditions constitutes a major advantage over optical sensors for monitoring tropical forest disturbances. This capability is particularly important for NRT forest disturbance alert systems, which require dense time series to enable timely detection. Furthermore, it enables the identification of disturbances events even in cases of rapid vegetation regrowth, which may hide disturbance signals in less frequent optical observations (Hirschmugl et al., 2020).

L-band SAR for tropical forest monitoring

For tropical forest cover change detection, L-band SAR sensors are generally considered more suitable than C-band SAR sensors, as the longer wavelength of L-band SAR allows deeper penetration into the forest canopy. This facilitates improved observation of structural changes occurring beneath the canopy layer (Reiche et al., 2021). Additionally, L-band SAR provides a clearer backscatter distinction, resulting in greater contrast between forested and non-forested areas (Reiche et al., 2015). In contrast, C-band SAR is more susceptible to signal saturation over dense forest canopies and is more sensitive to surface moisture variations, which introduces noise and reduces the reliability of forest cover change assessments (Reiche et al., 2021).

The availability of globally covered L-band SAR imagery has significantly expanded the potential for tropical forest monitoring. In particular, the release of the archives from the global Japanese Earth Resources Satellite (JERS) (1992–1998), the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) (2006–2011), and ALOS-2 PALSAR-2 (2014–present) has enabled the use of L-band SAR for systematic monitoring of tropical forests (Hirschmugl et al., 2020; Shimada et al., 2014).

Annual ALOS-2 PALSAR-2 acquisitions between 2007 and 2010, using HH and HV polarisation modes at a spatial resolution of 25 meters, supported the production of global forest/non-forest maps. These maps were generated by applying region-specific thresholds to the HV backscatter to distinguish forested from non-forested areas. Due to higher classification errors observed in the HH channel, only HV polarisation data were utilised for this mapping process (Shimada et al., 2014). The potential of L-band SAR for early-stage deforestation detection was also demonstrated using ALOS-2 PALSAR-2 over deforestation hot-spots in Brazil and Peru (Watanabe et al., 2018).

Sentinel-1 C-band SAR for tropical forest monitoring

The Copernicus program includes a dedicated SAR-based Earth observation mission: the Sentinel-1 mission. Sentinel-1A was launched in April 2014, followed by Sentinel-1B in April 2016, forming a two-satellite constellation in a near-polar orbit with a revisit cycle of 6 to 12 days, depending on the location. The system provides C-band SAR imagery in VV and VH polarisations. Sentinel-1B experienced an anomaly in December 2021 and was replaced by Sentinel-1C in December 2024. Sentinel-1D is currently under development, with its launch planned for the second half of 2025 (SentiWiki, 2025a).

Sentinel-1 has become a key resource in tropical forest monitoring applications. Numerous recent studies have demonstrated that the high spatial resolution and frequent revisit cycle of Sentinel-1 imagery can compensate the weaknesses typically associated with C-band SAR when compared to L-band SAR (Reiche et al., 2021). Several of these key studies and their respective methodologies are presented below.

One of the most prominent products developed with Sentinel-1 C-band SAR imagery is the Radar for Detecting Deforestation (RADD) disturbance alert product, which provides frequent deforestation alerts across the pan-tropical region since 2020. In this product, an alert is triggered for each Sentinel-1 image, future observations are then used to improve confidence and validate or dismiss the alerts (Reiche et al., 2021).

To mitigate the effects of seasonal variability, particularly during the dry season, incoming Sentinel-1 imagery in both VV and VH polarisations is first normalised by aligning the median backscatter distribution of forest signals with the expected median distribution derived from historical time series metrics (Reiche et al., 2018a). Following this normalisation, forest (F) and non-forest (NF) backscatter distributions are modelled as Gaussian distributions N based on the depersonalised observations. The F distribution is represented as $N(\tilde{x}, 2\sigma)$, while the NF distribution is defined as $N(\tilde{x} - 4\sigma, 2\sigma)$, with the NF median positioned 4σ lower than the F median to ensure clear separability between the two classes (Reiche et al., 2018b).

Each newly acquired VV and VH observation is appended to the time series (s) of observations. By applying Bayes' theorem and utilising the previously defined F and NF distributions, a corresponding time series of conditional NF probabilities (s^{NF}) is generated (Reiche et al., 2015). An alert is then triggered when the conditional probability at time t , s_t^{NF} , exceeds a threshold of 0.75 (Reiche et al., 2021).

As new imagery becomes available, the conditional probability of disturbance for previously triggered alerts is iteratively updated using Bayesian updating, by taking into account previous $(t - 1)$ and upcoming $(t + 1)$ s^{NF} data using the following equation:

$$P(D_t | s_{t+i}^{NF}) = \frac{P(s_{t+i}^{NF} | D)P(D_t | s_{t+i-1}^{NF})}{P(s_{t+i}^{NF})} \quad (1)$$

where $P(D_t | s_{t+i}^{NF})$ denotes the conditional probability of disturbance at time t , given the new observation s_{t+i}^{NF} . The term $P(s_{t+i}^{NF})$ represents the total probability of observing the signal s_{t+i}^{NF} , with i indicating the i -th future observation in the time series (Reiche et al., 2015).

Ultimately, alerts with a $P(D_t | s_{t+i}^{NF}) > 0.85$ are initially categorized as unconfirmed, low-confidence alerts. These alerts are upgraded to confirmed, high-confidence alerts if $P(D_t | s_{t+i}^{NF}) > 0.975$ within a 90-day period following the initial detection. If the $P(D_t | s_{t+i}^{NF})$ does not reach this threshold within the 90-day window, the alert is considered discarded (Reiche et al., 2021).

Most of the previously mentioned L-band or C-band SAR approaches assume that forest disturbances are only characterised by a sudden decrease in backscatter intensity within the time series. However, this relationship does not always hold true, as SAR backscatter is influenced by numerous ground parameters, such as those illustrated in Table 2.1. To address this limitation, other studies performed over Peru and French Guiana have focused on exploiting the SAR shadowing effect associated with tall vertical structures, such as tree trunks, for tropical forest monitoring like explained in Section 2.1.3 and illustrated in Figure 2.3. Their methodology consists of two main steps (Bouvet et al., 2018; Ballère et al., 2021).

The first step involves detecting shadows associated with forest disturbances. For this purpose, the shadows must be sufficiently large, limiting the applicability of the method to dense forests with tall canopies. Additionally, due to the near-polar orbit of the Sentinel-1 satellites, only shadows cast by forest edges oriented in a near North–South direction can be effectively detected. In the event of a disturbance, the resulting shadow corresponds to a drop in backscatter intensity within the time series. Disturbance detection is then performed using the Radar Change Ratio (RCR), which represents the ratio between the post-disturbance and pre-disturbance averaged backscatter. A new shadow is identified when the minimum RCR over a given period falls below a predefined threshold, set at -4.5 dB (Bouvet et al., 2018; Ballère et al., 2021).

The second step consists of reconstructing the disturbance patches. When both ascending and descending orbit data are available, the detected shadows are paired, and a boundary operator is applied to delineate the disturbance patches. In cases where only one orbit direction is available, the detection is refined by relaxing the threshold to -3 dB. Segments containing fewer than 10 pixels are discarded, and only those intersecting with a previously detected shadow are retained. The final deforestation patch is then extracted by applying a boundary function (Bouvet et al., 2018; Ballère et al., 2021).

This detection method, which relies on the presence of geometric artifacts such as SAR shadows, is constrained by the requirement for tall vertical structures. Its effectiveness significantly decreases in forests with canopy heights below 15 meters (Ballère et al., 2021).

Other applications of Sentinel-1 C-band SAR imagery have integrated it with Sentinel-

2 and Landsat data to address gaps in optical time series resulting from persistent cloud cover. These approaches employed either the previously described SAR shadowing methodology or the use of empirical thresholds for forest disturbances detection (Hirschmugl et al., 2017, 2020).

Regardless of whether they rely entirely or partially on L-band or C-band imagery, the aforementioned SAR-based approaches for tropical forest monitoring share a common dependence on identifying forest disturbances through changes in backscatter intensity within time series. These methods typically apply empirical thresholds, often based on abrupt decreases in backscatter, to differentiate forested from non-forested areas or to trigger forest disturbances alerts. However, the reliance on empirically defined thresholds can hinder transferability across regions. Developing methods that adaptively learn from data could reduce this dependence and enhance generalization.

2.2 Deep learning and tropical forest monitoring

The following Section 2.2.1 is primarily based on the online courses “Introduction to deep learning with PyTorch” and available on the DataCamp learning platform (Ludolf and Hossier, 2025).

2.2.1 Deep learning fundamentals

Deep learning is a subset of machine learning that relies on feature learning directly from raw data, rather than depending on manually engineered features. Deep learning models are inspired by the connections established by neurons in the human brain, that is why they are often called Neural Networks (NN). NN are designed to learn complex patterns in data and generate outputs suited to specific tasks, such as classification or regression. The basic structure of a NN is shown in Figure 2.4 and is explained below.

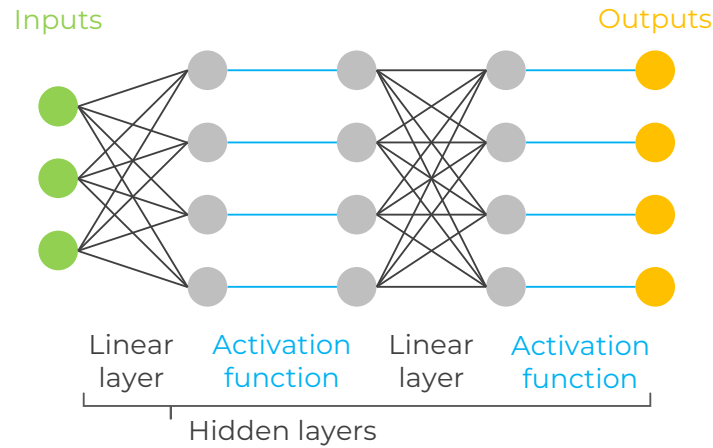


Figure 2.4: Basic structure of a NN

- **Input layer:** receives the input features (x_i) (e.g., pixel value) and passes them to the first processing layer. The number of neurons in the input layer matches the dimensionality of the input data.
- **Linear layers:** apply linear functions as defined in Equation 2, and are responsible for learning linear combinations of input features through trainable weights (w_i) and biases (b), collectively referred to as the model’s parameters. The output of a linear function is denoted by y .

$$y = \sum w_i x_i + b \quad (2)$$

- **Activation layers:** introduce non-linearity into the NN, enabling the model to learn complex, non-linear relationships. Common activation functions include sigmoid, softmax, and ReLU.

- **Hidden layers:** regroup the linear and activation layers situated between the input and output layers. The number of hidden layers (depth) and the number of neurons within each layer (width) directly influence the model’s capacity.
- **Output layers:** produce the final predictions of the model (e.g., class label or continuous value). Here, the number of neurons and the type of activation function depend on the task to be accomplished by the NN.

The process of passing input data through a NN to generate a prediction is referred to as a forward pass. Initially, the model’s parameters, the weights and biases are randomly initialised, resulting in outputs that lack meaningful interpretation. To enable a network to produce accurate predictions, it must be trained by providing input features along with their corresponding expected outputs. This allows the NN to iteratively adjust its weights and biases using a process called backpropagation or backward pass, which is detailed here below.

During model training, the objective is to minimize the difference between the model’s predictions ($\hat{y}$) and the expected outputs (y). In practice, this is achieved using loss functions, which quantify the error between $\hat{y}$ and y . The training process aims to minimise the value of the selected loss function. Common loss functions include Mean Squared Error Loss (MSELoss), Binary Cross Entropy Loss (BCELoss), and Cross Entropy Loss. The appropriate loss function is selected based on the type of task performed by the NN.

To minimise the value of the loss function, the partial derivatives of the loss with respect to each weight and bias, referred to as gradients, are computed. These gradients are used to update the network’s parameters by subtracting them, scaled by the learning rate (lr), from the current parameter values. The lr is a hyperparameter that determines the magnitude of each update. Since most loss functions are non-convex, an iterative optimisation algorithm known as gradient descent is employed to progressively adjust the parameters and converge toward a minimum of the loss function.

This backpropagation process is applied iteratively within a training loop of a NN model. In each iteration, a subset of the training data, referred to as the batch size, is passed through the network, and the model parameters are updated accordingly. A single pass through the entire training dataset is defined as an epoch. The training process is typically terminated after a predefined number of epochs, or when the loss function reaches satisfactory values. A visual representation of a basic training loop is provided in Figure 2.5.

After training of a NN model is completed, the model can be used to generate predictions by feeding it previously unseen input data.

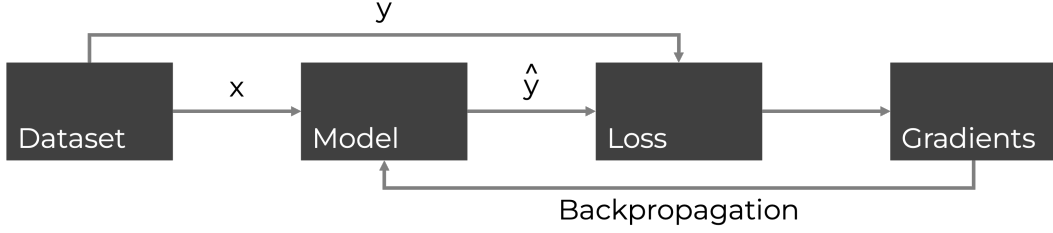


Figure 2.5: Schematic representation of a NN model training loop

2.2.2 Leveraging Neural Networks for tropical forest monitoring with C-SAR imagery

In recent years, the integration of NN models with temporally dense Sentinel-1 C-band SAR time series has been explored for NRT detection of forest disturbances in tropical dry forests (TDFs) regions such as Mozambique and Paraguay. Due to the pronounced seasonal variability of TDFs phenology, this approach was investigated as standard C-SAR-based NRT disturbance products are often influenced by seasonal fluctuations, which can hinder the ability to distinguish natural changes from actual disturbances (Mullissa et al., 2023).

To train the NN, historical stable TDFs metrics were first computed for 2018 and 2019 using both VV and VH Sentinel-1 polarisations. From this analysis, the median and the minimum 2% values of the backscatter time series in both polarisations were selected to characterise stable TDFs dynamics. Forest disturbance labels for December 2020 were identified by detecting significant drops in Sentinel-1 backscatter and were refined using an initial NN, with final labels derived from the intersection of the model predictions and observed disturbances in the 2020 forest cover loss map from Hansen et al. (2016). A weekly supervised learning approach was then adopted to iteratively refine this initial selection. Stable forest labels were extracted by subtracting the 2020 forest cover loss map from the 2019 forest cover map from Hansen et al. (2016), followed by the application of an inverse 50 m buffer (Mullissa et al., 2023).

For each polarisation, the input features consisted of the median and 2% minimum backscatter values from the 2018–2019 period, along with the December 2020 Sentinel-1 imagery. These three values formed a 1×3 input feature vector. Subsequently, a stratified random sampling approach was employed to select representative samples for both the TDF and disturbance classes.

Separate NN models were trained for each polarisation and study area. The selected NN architecture comprised three hidden layers, each followed by a batch normalisation layer, a ReLU activation function, and a dropout layer, as illustrated in Appendix B, Figure 9.3 (Mullissa et al., 2023).

To further refine disturbance detection, a Bayesian updating approach based on the method developed in Reiche et al. (2018b, 2015) was applied. Additionally, a minimum mapping unit of 0.05 ha was applied.

The developed NRT TDF disturbance detection methodology demonstrated improved detection speed and accuracy compared to GLAD alerts. This approach was subsequently expanded for global application in detecting forest cover changes, leading to the development of the Land Use Change Alert (LUCA) system, which also relies on Sentinel-1 C-SAR imagery (Mullissa et al., 2024).

2.3 Synthesis

Tropical forests provide critical ecosystem services, but despite their ecological and socio-economic value, they continue to experience significant rates of deforestation and forest degradation. In particular, the Congo Basin’s tropical moist forest is facing increasing forest cover loss, primarily driven by smallholder agriculture.

The advent of remote sensing has revolutionised tropical forest monitoring by enabling global-scale observation of forest cover dynamics. Over time, advances in remote sensing technologies have paralleled the development of forest disturbance detection products. The introduction of SAR remote sensing, with its cloud-penetrating capabilities, has allowed for more frequent and reliable near-real-time (NRT) disturbance alert systems in tropical regions that experience persistent cloud cover.

In addition, deep learning models have shown strong potential for enhancing traditional SAR-based NRT disturbance alert systems in tropical dry forests by learning complex temporal patterns directly from SAR time series data. These models help reduce reliance on empirically defined thresholds, supporting the development of more robust and transferable detection approaches, and encouraging further exploration of their applicability in other tropical forest regions.

3 Objectives

The detection of tropical forest disturbances induced by smallholder agriculture using remote sensing remains hindered by two major limitations: the limited availability of cloud-free optical data in tropical regions and the need for high temporal resolution. Sentinel-1 C-SAR imagery offers a promising solution to both constraints due to its cloud-penetrating capabilities and frequent revisit cycle.

The main objective of this research is to develop Neural Networks (NN) for the near-real time (NRT) detection (and monitoring) of tropical forest disturbances caused by smallholder agriculture in the Congo Basin, based on dense standardised Sentinel-1 C-SAR time series. Performances of NN models are quantified using mainly two different accuracy metrics: the True Positive Rate (TPR) and the False Positive Rate (FPR). This approach is designed to avoid reliance on a fixed detection threshold and to reduce dependence on empirically applied spatial filters.

The research is performed over two regions of interest (ROI) within the Congo Basin:

- An initial calibration phase is conducted over a calibration ROI, Dekese in the Democratic Republic of the Congo (DRC) ($3^{\circ}27'$ South, $21^{\circ}21'$ East), involving both training and spatial validation of the NN models.
- Then, a transferability evaluation phase is performed. Selected trained NN models are applied and spatially validated over a transfer ROI, Likati in the DRC ($3^{\circ}22'$ North, $23^{\circ}55'$ East), to assess the model's transferability between two distinct areas with similar observation characteristics. The temporal accuracy of disturbances detection is also evaluated within this transfer ROI.

4 Material and methods

4.1 Regions of interest

Two ROIs have been defined: one calibration ROI and one transfer ROI. Both are situated within the tropical forest of the Congo Basin. It is important to recall that, in the context of this study, the annual change collection of the TMF product developed by Vancutsem et al. (2021) is employed to differentiate between undisturbed, deforested, and degraded tropical forest cover. Hereafter, the term TMF refers specifically to this product; otherwise, the more general term tropical forest is used.

The calibration ROI is used to develop and train the NN models. The second ROI, referred to as the transfer ROI, is subsequently employed to evaluate the model’s transferability across both time and space. The methodology for the use of both the calibration and transfer ROIs is schematically illustrated in Section 4.2.

Both selected ROIs are situated within the DRC, which hosts approximately 60% of the total area of the Congo Basin TMF, as indicated in Section 1.3.1. Furthermore, among the six countries spanning over the Congo Basin, the DRC has experienced the most significant increase in forest disturbance rates, as detailed in Section 1.3.2. Notably, small-scale subsistence agriculture is the predominant driver of forest disturbances in the DRC, accounting for 92.2% of forest disturbance events recorded between 2000 and 2014 (Tyukavina et al., 2018), as discussed in Section 1.3.3.

The selection of the ROIs is also guided by specific geographical criteria. Both the calibration and validation ROIs are centered around a town that is predominantly surrounded by undisturbed TMF. Transitional zones between the urban centers and the undisturbed TMF are primarily composed of degraded TMF, deforested areas, and zones of forest regrowth. New occurrences of forest disturbances associated with smallholder agriculture are primarily observed along the inner periphery of the undisturbed TMF, where subsistence agriculture progressively expand into previously intact forest areas each year. These agricultural activities are principally aimed at meeting the subsistence needs of the nearby urban populations. As demographic pressure increases, forest disturbances driven by smallholder activities are expected to intensify (Tyukavina et al., 2018).

Additionally, the ROIs were selected to exclude areas affected by large-scale commercial logging activities, as the focus is placed on detecting more challenging, small-scale disturbances associated with subsistence agriculture.

4.1.1 Calibration ROI - Dekese (Kasaï province, DRC)

Situated in the Southern Hemisphere, the calibration ROI is centered on the urban area of Dekese (3°27' South, 21°21' East), located in the northern part of the Kasaï province of DRC and illustrated by Figure 4.1. Covering a total area of just over 2,500 km², the Dekese ROI extends approximately 50 km across in width and height. The region is referenced using the WGS 1984 / UTM zone 34S coordinate system. The Lukenie River crosses the region from east to west, with a portion of the Dekese urban area bordering the river. This calibration ROI is positioned along the southern boundary of the Congo Basin TMF, a position visually depicted in Figure 1.2.

In terms of climate, the Kasaï province recorded an average mean surface air temperature of about 25.4°C and an annual mean precipitation of 1,637 mm in 2021 (Climate Change Knowledge Portal, 2025).

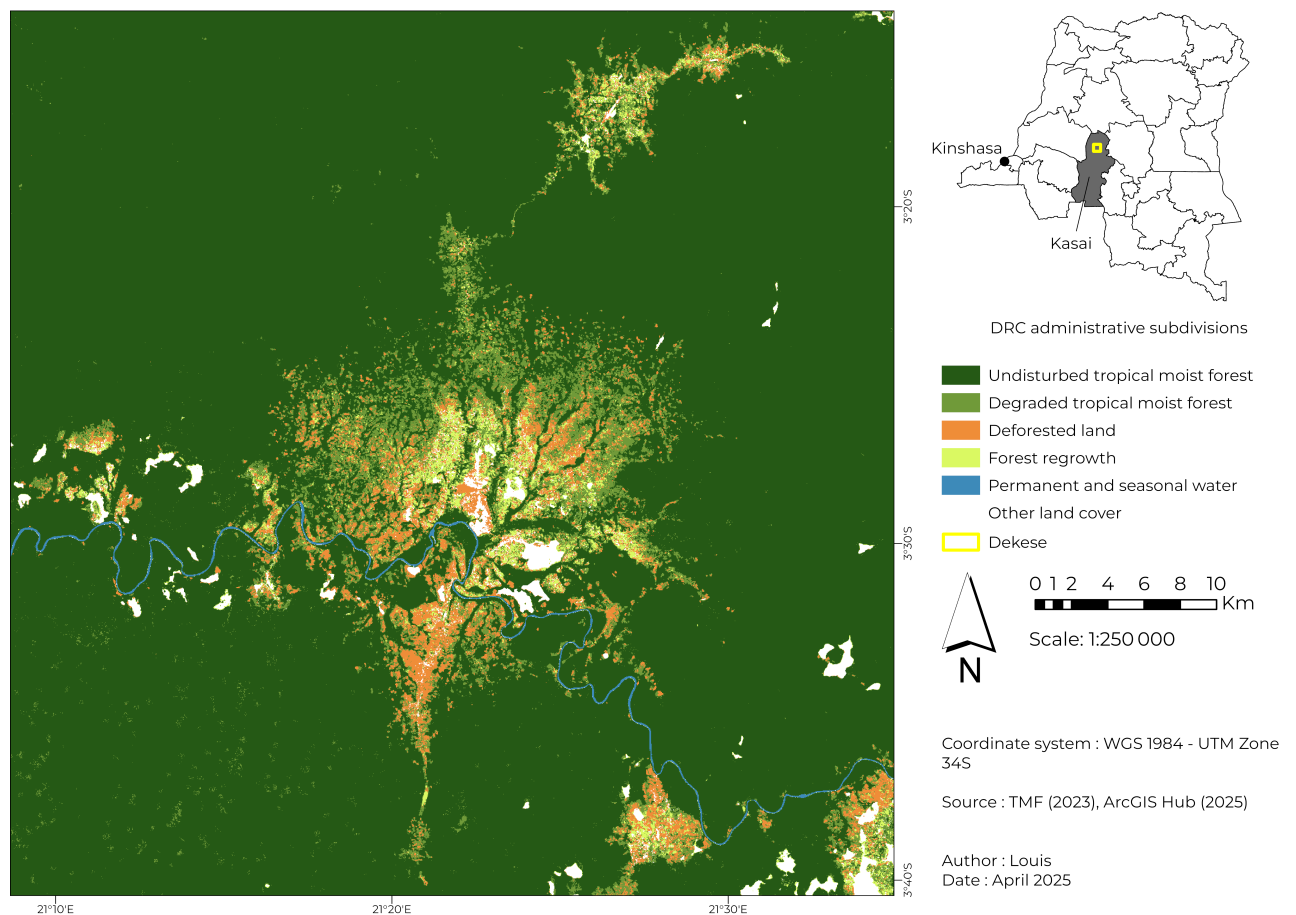


Figure 4.1: Dekese 2023 TMF annual cover change product (Vancutsem et al., 2021).

4.1.2 Transfer ROI - Likati (Bas-Uele province, DRC)

Situated in the Northern Hemisphere, the transfer ROI is centered on the urban area of Likati (3°22' North, 23°55' East), located in the western part of the Bas-Uele province of DRC and illustrated by Figure 4.1. Covering a total area of around 2690.9 km², the Likati ROI extends approximately 53.84 km across in width and 49.98 km in height. The region is referenced using the WGS 1984 / UTM zone 34N coordinate system. The Likati River crosses the region in a northwest-southeast direction, with a portion of the Likati urban area bordering the river. This calibration ROI is positioned along the northern boundary of the Congo Basin TMF, a position visually depicted in Figure 1.2.

In terms of climate, the Bas-Uele province recorded an average mean surface air temperature of about 25.1°C and an annual mean precipitation of 1,638 mm in 2021 (Climate Change Knowledge Portal, 2025).

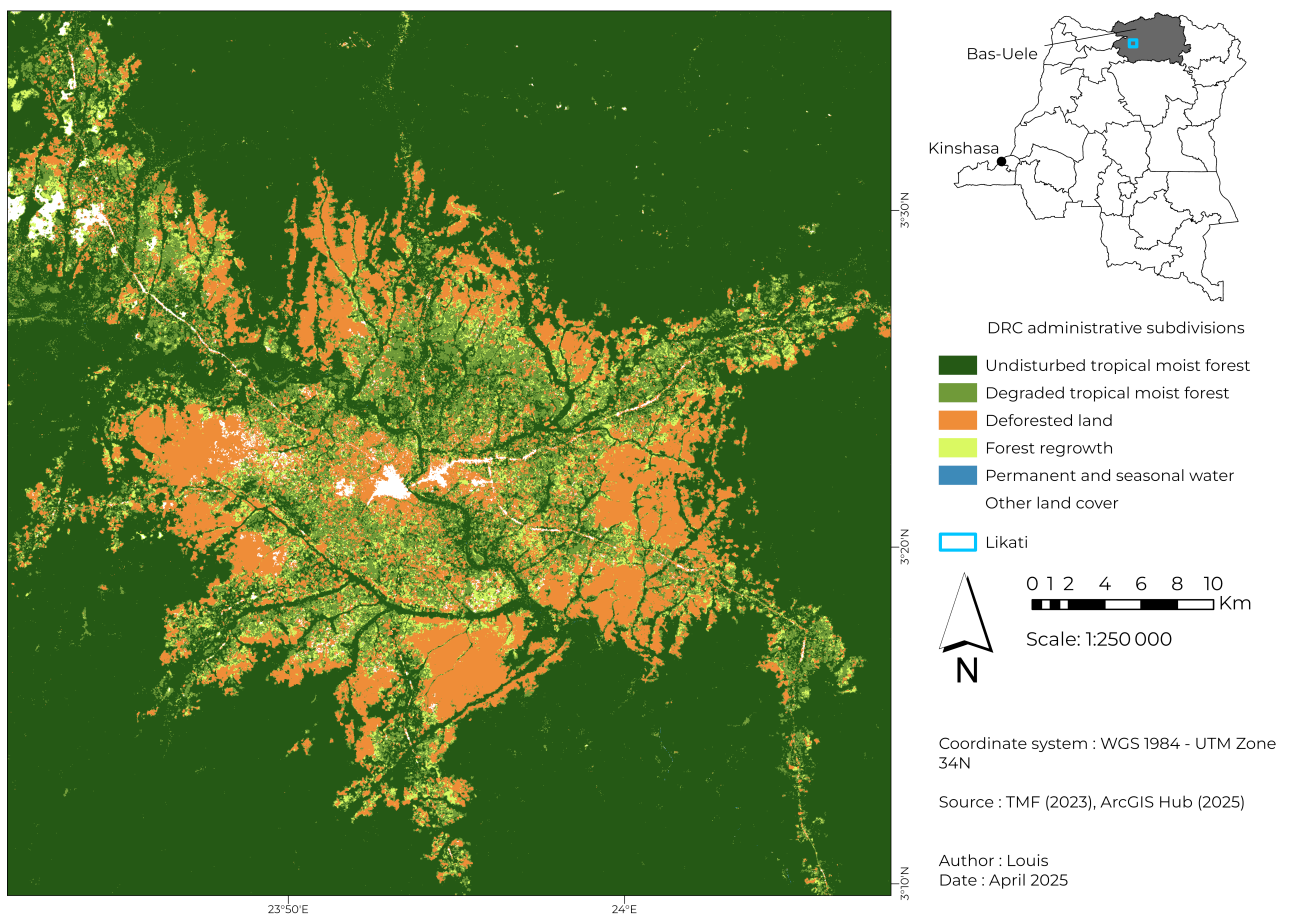


Figure 4.2: Likati 2023 TMF annual cover change product (Vancutsem et al., 2021).

4.2 Methodology summary

A summary of the methodology is presented in Figure 4.3, which outlines all the main steps described in the following sections.

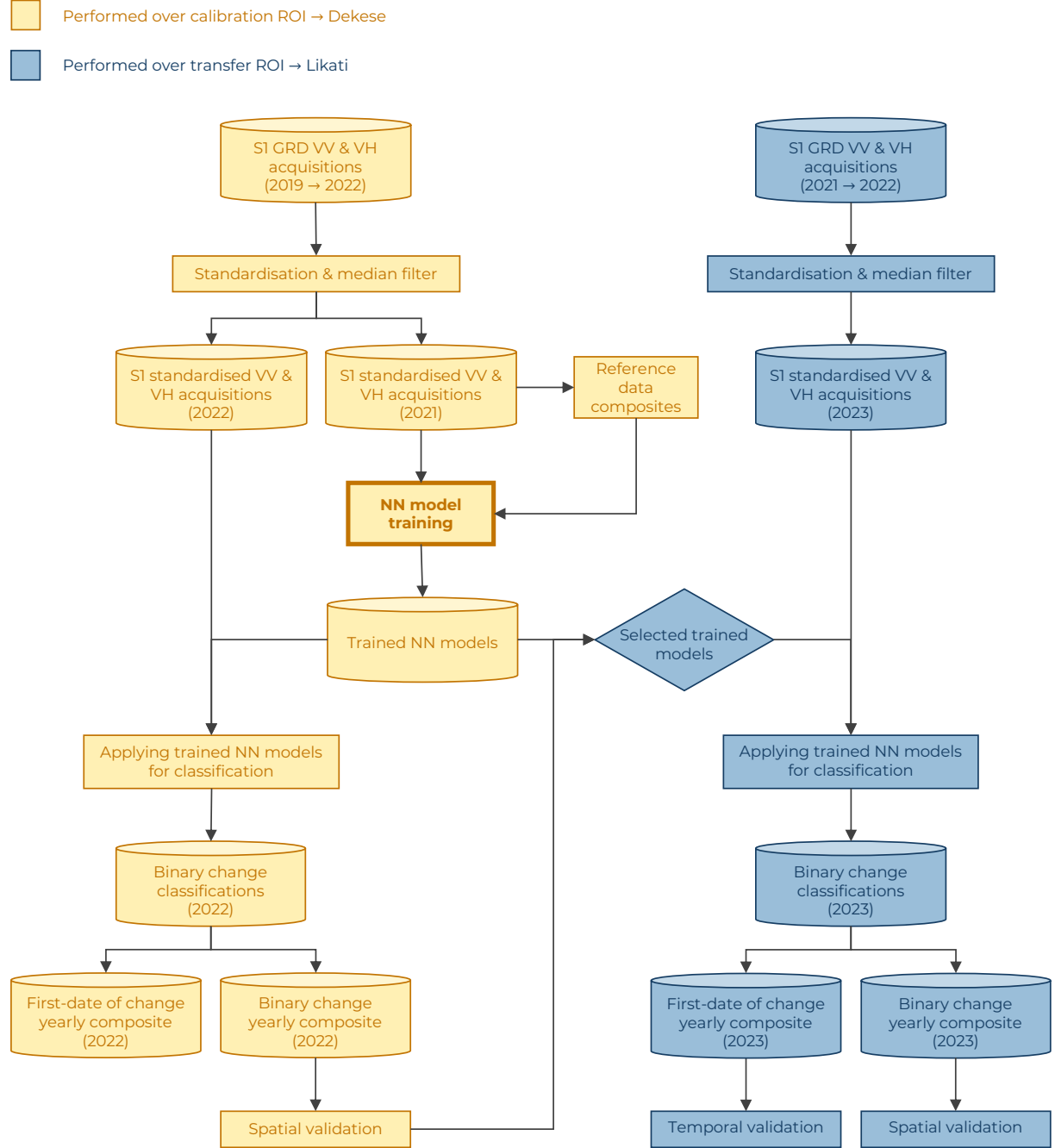


Figure 4.3: Summary of the primary methodology performed over the calibration and transfer ROIs.

4.3 Data sources

4.3.1 Sentinel-1 C-SAR imagery

Sentinel-1 C-SAR imagery is employed for the purposes of this research. The Sentinel-1 SAR sensor operates in the C-band, with a central frequency of 5.405 GHz, corresponding to a wavelength of approximately 5.55 cm. Each Sentinel-1 satellite follows a near-polar, sun-synchronous orbit with a nominal revisit time of 12 days. The mission is designed as a constellation composed of two satellites operating in the same orbital plane but offset by a 180° orbital phasing, thereby enabling a 6-day revisit frequency when both satellites are functional. This was the case between April 2016 and December 2021, during which Sentinel-1A and Sentinel-1B were both operational. However, following an anomaly affecting Sentinel-1B in December 2021, only a 12-day revisit cycle remained possible until December 2024, when Sentinel-1C became operational (SentiWiki, 2025a).

Using the Google Earth Engine (GEE) cloud computing platform, Level-1 Ground Range Detected (GRD) acquisitions were retrieved in Interferometric Wide (IW) swath mode, with both VV and VH polarisations and a descending orbit configuration. The spatial resolution of the imagery is 10 m. Those Sentinel-1 GRD acquisitions were subjected to a series of preprocessing steps, following instructions from the The Sentinel-1 Toolbox, in order to derive the backscattering coefficient σ° expressed in decibels (dB) (GEE, 2024; SentiWiki, 2025b):

- **Apply orbit file:** updates orbit metadata using restituted orbit files.
- **GRD border noise removal:** eliminates low-intensity noise and invalid data typically found at the edges of the scene.
- **Thermal noise removal:** reduces additive noise present in sub-swaths to minimize discontinuities between them in multi-swath acquisition mode.
- **Radiometric calibration:** computes the backscatter coefficient σ° using sensor-specific calibration parameters contained in the GRD metadata.
- **Terrain correction / orthorectification:** compensates for topographic distortions by projecting radiometrically calibrated σ° values onto a terrain-corrected geometry using the Shuttle Radar Topography Mission (SRTM) 30 m Digital Elevation Model (DEM).
- **Logarithmic scaling:** converts the backscatter coefficient σ° to decibel (dB) scale.

As a 6-day revisit cycle is not available over the selected ROIs, only Sentinel-1A GRD acquisitions, collected at 12-day intervals, are utilised for both the calibration and transfer ROIs during the years specified in Table 4.1.

Table 4.1: Sentinel-1 GRD acquisitions years for the calibration and transfer ROIs

Sentinel-1 satellite	Calibration ROI - Dekese	Transfer ROI - Likati
Sentinel-1A	2019	
	2020	
	2021	
	2022	
		2023

Compiled as time series, the aforementioned acquisitions are standardised according to Equation 3. This standardisation facilitates the visualisation of changes in backscatter intensity, which are indicative of alterations in backscattering mechanisms associated with land cover changes, such as forest disturbances.

$$S1_{standardised}^{GRD} = \frac{S1^{GRD} - \overline{X}_{2years}}{\sigma_{2years}} \quad (3)$$

where $S1_{standardised}^{GRD}$ denotes the standardised acquisition, $S1^{GRD}$ represents the original acquisition, $\overline{X}_{2years}$ is the mean backscatter intensity over the two years preceding the acquisition, and σ_{2years} is the corresponding standard deviation.

A median filter of 5×5 is then applied to smooth the signal by removing highly localised outliers and enhancing broader spatial patterns. Following this spatial smoothing, the acquisitions are re-standardised, resulting in standardised, spatially filtered, VV and VH Sentinel-1 GRD time series at 12-day intervals for both the calibration and transfer ROIs, corresponding to the years listed in Table 4.2. As a result, the initial pixel values in each raster are converted into z-values, a statistical measure describing how many standard deviation a pixel value is from the mean of the distribution. Hereafter, these data will be referred to as Sentinel-1 standardised acquisitions or time series.

Table 4.2: Sentinel-1 GRD standardised and spatially filtered acquisitions years for the calibration and transfer ROIs

Sentinel-1 satellite	Calibration ROI - Dekese	Transfer ROI - Likati
Sentinel-1A	2021	
	2022	
		2023

4.3.2 Reference samples

Reference data are required to calibrate a forest disturbance detection NN model. They allow the network to perform backpropagation by comparing its outputs to the reference labels, thereby enabling the model to learn and produce meaningful classifications.

In the context of this research, reference data are generated using the same Sentinel-1 standardised acquisitions that serve as inputs features to the NN models. This process is fully automated and conducted without any visual inspection or manual intervention. The generation procedure follows the steps detailed below.

A temporal floating window of three consecutive acquisitions is applied to both VV and VH standardised time series, and is considered as one detection period. VV and VH mean composites have been computed at each detection period from the standardised Sentinel-1 time series and constitute the raw material of a two feature change detection model. The two features are then cross-thresholded considering their z-values every 0.1σ , from 0 to -3σ . This produces a reference raster data for each period, ranging values from 0.0 to -3.0, corresponding to a confidence index for forest disturbance detection occurring during a 3-acquisitions time step.

This method is based on the expectation that forest disturbances occurring within the period covered by the Sentinel-1 standardised time series are associated with an decrease in the z-value in both VV and VH polarisations. The procedure for selecting a standard deviation threshold value to distinguish reference data representing undisturbed forest, or no-change, from forest disturbance, or change, during model training is further detailed in Section 4.4.

4.3.3 Other data

In addition to Sentinel-1 C-SAR imagery and reference data, the annual change collection of the TMF product developed by Vancutsem et al. (2021) is employed. Planet imagery is also acquired to support the temporal validation process (Planet Labs, 2025). Monthly climatological precipitation data for the period 1991–2020 are obtained for both the Kasai and Bas-Uele provinces of the DRC (Climate Change Knowledge Portal, 2025). Moreover, administrative boundary data for the countries of the African continent, as well as for the provinces of the DRC, are utilised (ArcGIS Hub, 2025).

4.4 NN model calibration

Calibration of the NN model is carried out over Dekese, the designated calibration ROI. The NN model is trained using data from the year 2021 and is spatially validated using data from the year 2022.

4.4.1 Data management

Since the reference data for each date are constructed using a temporal floating window of three consecutive acquisitions, both VV and VH Sentinel-1 standardised acquisitions covering these three dates are used as input features for model training. For each date and for every pixel within the calibration ROI, the input feature is a 1×6 vector. It consists of z-values from both VV and VH acquisitions across the three consecutive dates. The reference data for the same pixel and date consist of a 1×1 vector with values ranging from 0.0 to -3.0 , representing the confidence index for forest disturbance detection as described in Section 4.3.2. For each pixel, these two vectors are then merged into a 1×7 vector for each one of the 30 acquisitions dates selected for the year 2021.

To ensure that detected changes are limited to areas previously classified as undisturbed TMF, only pixels located within the spatial extent of the stable TMF mask from the preceding year (2020 in this case) are considered (Vancutsem et al., 2021). This restriction prevents the inclusion of non-forest dynamics in the training data.

For each pixel, the reference data is then converted into a reference label, 0 representing "no-change" and 1 representing "change". To do so, two threshold values are defined, which can be chosen in increments of -0.1 :

- **"No-change" threshold:** threshold value below which a pixel is labelled as "no-change".
- **"Change" threshold:** threshold value above which a pixel is labelled as "change"

Defining two distinct threshold values instead of a single one to separate change and no-change pixels during training allows the exclusion of pixels with reference values that are too ambiguous to be reliably labelled.

As change pixels represent a minority compared to no-change pixels within the calibration ROI, a target ratio parameter is implemented. This parameter reduces the number of no-change pixels included in the dataset to match a specified multiple of the change pixels. For this study, a target ratio of 1:1 was selected to ensure equal representation of both classes during training, as recommended for imbalanced datasets (Olofsson et al., 2014).

Hereafter, the no-change threshold, change threshold, and target ratio parameters are referred to as reference data parameters.

Finally, the 30-acquisition dataset is randomly split into two sub-datasets: a training dataset including 70% of the acquisition dates and a verification dataset including the remaining 30%. The specific use of the training and verification datasets is explained in Section 4.4.2.

4.4.2 NN model definition and training

The definition and training of the NN model are implemented using the TensorFlow Python library. Figure 4.4 represents the simplified structure of the NN model developed. An explanation of each layer of the NN model is provided below (Ludolf and Hossier, 2025).

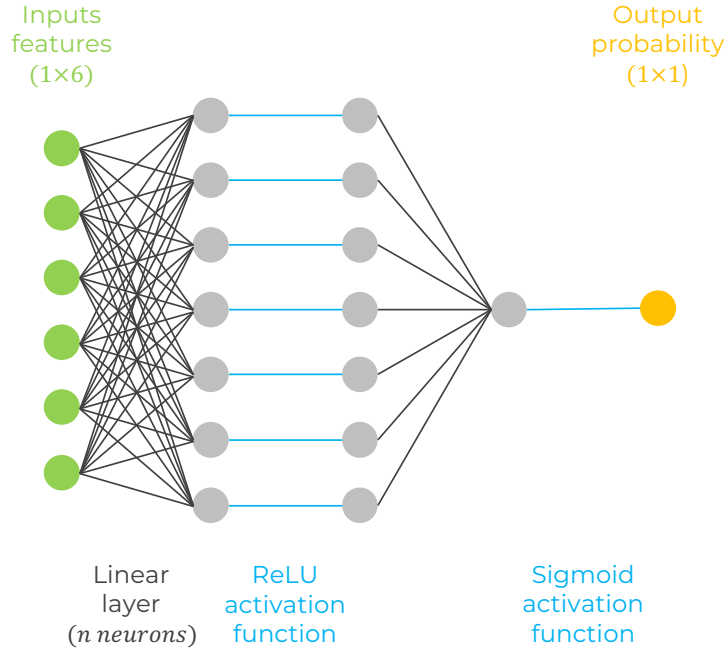


Figure 4.4: NN model architecture.

- **Inputs features:** consist of 1x6 vectors containing the z-values from three consecutive acquisitions in VV and VH polarisations, as described in Section 4.4.1.
- **Linear layer:** performs linear operations on the input features. The number of neurons (n) forming this layer is a hyperparameter that will be evaluated.
- **Rectified Linear Unit (ReLU) activation function** (Equation 4): introduces non-linearity and enables the model to learn more complex relationships. The ReLU function returns the input value for positive inputs and 0 for negative inputs, as illustrated in Figure 4.5.

$$\text{ReLU}(x) = \max(x, 0) \quad (4)$$

- **Sigmoid activation function** (Equation 5): transforms inputs into an output classification probability value between 0 and 1. This function is commonly used in binary classification tasks and is characterized by an S-shaped logistic curve, as shown in Figure 4.6.

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (5)$$

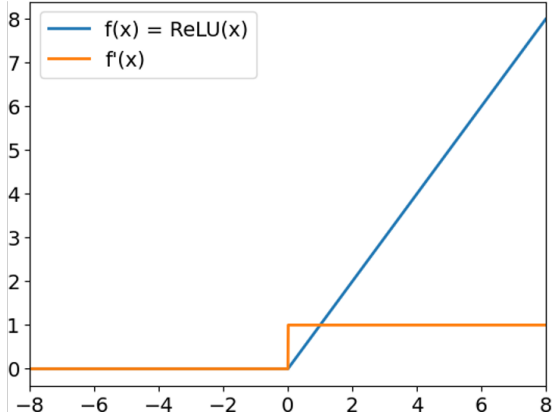


Figure 4.5: ReLU activation function (Ludolf and Hossier, 2025).

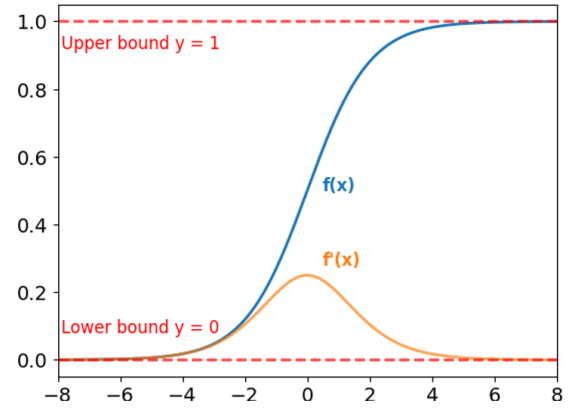


Figure 4.6: Sigmoid activation function (Ludolf and Hossier, 2025).

- **Output probability:** represents the model’s estimated probability that an input pixel corresponds to a change event.

Once the model architecture is defined, a training loop is implemented to perform forward propagation and improve model performance by updating its parameters (weights and biases) through backpropagation, as described in Section 2.2.1. The training process relies on a defined set of hyperparameters and a loss function, which are summarised in Table 4.3.

The learning rate is set to 0.005, a value that falls within the commonly recommended range for neural network models. A batch size of 32 is selected, as this setting has demonstrated good performance in practice. Although relatively small, such a batch size may increase the number of iterations required to complete training, but it often results in better generalisation. The binary cross-entropy loss function is chosen, as it is well-suited for binary classification tasks (Ludolf and Hossier, 2025). This function is defined in Equation 6:

$$\text{BCE Loss} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (6)$$

where N is the number of samples, y_i is the reference label, and $\hat{y}_i$ is the predicted probability. Lastly, data is shuffled before each epoch to prevent the model from learning patterns based on data order.

Table 4.3: Summary of the hyperparameters and loss function selected for the NN model.

Hyperparameters / loss function	Selected value / function
Learning rate	0.005
Batch Size	32
Loss function	Binary cross-entropy
Patience	10

During training, the training sub-dataset is employed to iteratively update the NN model parameters through backpropagation. The network progressively learns the relationship between input features and their associated change or no-change labels. After each epoch, the training loss is computed to monitor the evolution of the model’s performance. In parallel, the verification sub-dataset is used to calculate the verification loss at each epoch, without modifying the model parameters. This step allows for the assessment of the network’s generalisation ability and facilitates the detection of overfitting by comparing training and verification losses. Overfitting occurs when the verification performance degrades while the training performance continues to improve. This is prevented by triggering an early stopping based on a predefined patience parameter. Once the training loop is finished or stopped, the model with the lowest verification loss observed during training is saved.

4.4.3 NN model validation

NN models trained on the 2021 data from the Dekese calibration ROI are subsequently used to generate binary classifications for a different time period. Specifically, the models are applied to all 30 acquisition dates from the year 2022 over the same geographic area. Regardless of the classification year, the resulting outputs consist of binary rasters corresponding to each acquisition date. These individual rasters can then be compiled over the classification year to produce a cumulative raster representing all detections across the full annual period. The Sentinel-1 standardised acquisitions are processed as described in Section 4.4.1 to generate the input features for each pixel, which are then passed through the different trained networks. Spatial validation of each model, parametrised differently, is then performed following the methodology described in Section 4.6.

4.5 NN model transfer learning

To further test the generalisation capability of the trained NN models, transfer learning is performed over the transfer ROI, Likati, for the year 2023. Transfer learning is a machine learning approach where a model developed and trained for a specific task is reused to perform a second, similar task Ludolf and Hossier (2025). It is important to note that the transferability assessment is conducted on a transfer ROI that exhibits similar characteristics to the calibration ROI and is observed under comparable conditions.

Selected networks trained over Dekese are used to perform classifications over Likati for the 31 acquisition dates of 2023. The standardised Sentinel-1 acquisitions are processed as described in Section 4.4.1 to generate the input features for each pixel, which are subsequently passed through the trained networks. Classification performance is then evaluated following the methodology described in Section 4.6. This enables a direct comparison of accuracy metrics across both ROIs for a given network.

4.6 Spatial validation

In the context of this research, the spatial validation methodology required to correctly evaluate the model’s performance and resulting classifications outputs is primarily constrained by two factors.

As a range of hyperparameters and reference data parameters are used to train multiple models, several classifications are produced. The spatial accuracy assessment of those multiple classifications must be computed. Since the objective is to identify the NN model that generates the best classification output for different use cases, commonly used sampling methodologies designed for a single classification output cannot be directly applied.

Secondly, forest disturbance occurrences and their extent are relatively small compared to the vast areas of undisturbed TMF within the calibration and transfer ROIs. This results in increased difficulty when targeting small-scale land cover changes, such as those associated with small-scale agriculture clearing. Consequently, this imbalance in land cover classes must be carefully considered both when designing the sampling methodology and when selecting appropriate accuracy metrics.

4.6.1 Sampling design and labelling protocol

The spatial validation methodology is first applied to the calibration ROI, Dekese, for the year 2022 to evaluate the performance of the different models. It is then applied to the transfer ROI, Likati, for the year 2023 to assess the transferability of the selected model or models. For both ROIs, validation is conducted on the compiled binary classification raster representing one full year of detections. The methodology is described below in the

context of the Dekese calibration ROI.

The aim is not only to assess whether the model accurately detects forest disturbance patches but also to ensure the minimisation of commission errors both in their vicinity and within large undisturbed TMF areas. To this end, two strata are constructed using the 2021 and 2022 annual change products of the TMF, originally provided at a 30 m spatial resolution and resampled to a 10 m spatial resolution (Vancutsem et al., 2021).

The first stratum is designed to assess True Positives (TP) and False Negatives (FN). It is defined by selecting pixels that transitioned from the undisturbed TMF class in 2021 to either the degraded or deforested classes in 2022. A 3×3 kernel is then applied to each pixel within this stratum, retaining only those with at least three neighbouring pixels that also underwent change during the same period. Given the coarser resolution of the TMF product, this filtering step is applied to increase the likelihood that spatial validation points are placed over actual forest disturbances. A simple random sampling methodology is subsequently used to generate spatial validation points within this stratum. Each validation point label is manually confirmed as forest disturbance using high spatial resolution (<5 m) Planet monthly basemaps if a disturbance occurred during the year. Following this process, 250 spatial validation points are retained (Olofsson et al., 2014).

The second stratum is designed to assess False Positives (FP) and True Negatives (TN). In this case, a traditional random sampling approach cannot be used, as the undisturbed TMF class is extensive and represents the majority class in both ROIs. Even if a large number of points were sampled, many FP detections could be missed, leading to an overestimation of the model’s performance. Therefore, a pixel-based approach is employed to construct this stratum by using the undisturbed TMF layer of the classification year, here 2022, and applying an inverse 100 m buffer. The resulting mask is then considered to represent undisturbed forest, and any detections from the models occurring within the extent of this mask are classified as FP detections.

4.6.2 Accuracy metrics

Once acquired, the sample data is compared to the classification outputs. When a common strategy is used to acquire the sample data, TP, TN, FP, and FN values can be organized into a confusion matrix, which summarises the raw performance outcomes. From this matrix, several additional accuracy metrics can be derived, including Overall Accuracy (OA) and F1-score (Luque et al., 2019).

However, since two different sampling strategies are employed across two distinct strata, this approach is not applicable in the context of this research. OA and F1-score,

being aggregate measures computed using TP, TN, FP, and FN values simultaneously, would not accurately represent model performance. This is due to the imbalance between the strata. While a few hundred points are used for the change stratum, the no-change stratum relies on a mask composed of millions of pixels.

To overcome this limitation, two alternative accuracy metrics can be employed and attributed separately to each stratum: the True Positive Rate (TPR) and the False Positive Rate (FPR). The TPR (Equation 7) measures the proportion of actual positives that are correctly identified, whereas the FPR (Equation 8) represents the proportion of actual negatives incorrectly identified as positive.

$$TPR = \frac{TP}{TP + FN} \quad (7)$$

$$FPR = \frac{FP}{FP + TN} \quad (8)$$

TPR and FPR metrics can be organized as Receiver Operating Characteristic (ROC) curves or scatter plots, which are graphical representations used to assess the performance of binary classification models. In these visualisations, the TPR is plotted against the FPR, allowing assessment of the trade-off between the two metrics. This trade-off reflects the influence of different combinations of model hyperparameters and reference data parameters used during training. ROC representations are therefore useful when dealing with unbalanced classes. A diagonal line defined by $TPR = FPR$ indicates the performance of a random classifier. Models that perform better than a random classifier are represented by points located above this line (Hoo et al., 2017). A theoretical example of an ROC is illustrated in Figure 4.7 (Evidently AI, 2025).

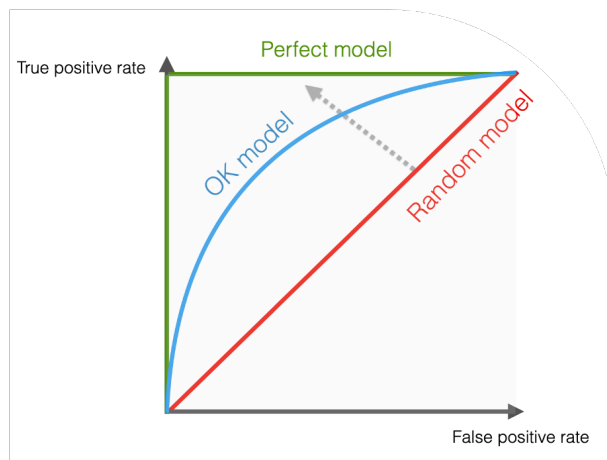


Figure 4.7: Theoretical representation of ROCs curves (Evidently AI, 2025).

4.7 Temporal validation

In addition to the spatial accuracy of classifications, the timeliness of change detection is also assessed. As SAR imagery overcomes the limitations of optical imagery in regions with persistent cloud cover, it facilitates the earlier identification of forest disturbances and supports the implementation of NRT disturbance alert systems. SAR-based NRT systems can therefore provide disturbance alerts earlier than optical-based NRT systems or annual change products derived from optical data. This advantage is particularly important for detecting short-duration disturbance events linked to smallholder agriculture or selective logging. Therefore, it is essential to evaluate the temporal delay associated with the detection of forest disturbances (Hirschmugl et al., 2020).

Temporal validation and comparison are conducted over the transfer ROI, Likati. This validation was not performed over the calibration ROI, Dekese, due to the lack of sufficiently frequent cloud-free optical imagery during the peak period of forest disturbances. For a selected year and a specific model, a first-date-of-change composite is generated from a series of individual binary classifications. RADD disturbance alerts covering the transfer ROI are acquired, with only alerts corresponding to the selected year retained (Reiche et al., 2021). A mask is then generated within the previous-year undisturbed TMF mask by identifying the intersection between the first-date-of-change composite and the RADD disturbance alerts (Vancutsem et al., 2021). Within this mask, 70 temporal validation points are randomly sampled. Each point is visually interpreted using near-daily Planet imagery within a 15 m radius buffer to assign three key dates:

- **Undisturbed date:** the last date on which the entire buffer area is visually confirmed to be undisturbed.
- **Degraded date:** the first date on which less than 50% of the buffer area is visually identified as degraded.
- **Loss date:** the first date on which more than 50% of the buffer area is visually identified as degraded.

5 Results

The results are structured into four main sections. First, the calibration of the NN models is presented, based on the calibration ROI, Dekese, using data from 2021 to 2022. The transferability of the selected models is assessed over the transfer ROI, Likati, for the year 2023. A temporal validation is also conducted over Likati using the 2023 classifications results. This is followed by a presentation of tropical forest disturbances trends and statistics for both ROIs. Finally, a forest disturbance product covering the entirety of both ROIs is introduced.

5.1 NN model calibration

5.1.1 Selected (hyper-)parameters

For the training of each model, both reference data parameters and NN model hyperparameters are defined. As outlined in Section 4.4.1, reference data parameters include the "no-change" threshold, the "change" threshold, and the target ratio. The NN model hyperparameters encompass the loss function, the number of neurons (n) in the linear layer, and other training-specific settings, as described in Section 4.4.2. Several of these values were fixed according to general recommendations or set hypothesis, as discussed in Section 4.4.

For this research, three key parameters and hyperparameters are primarily evaluated: the no-change threshold, the change threshold, and the number of neurons (n) in the linear layer. The ranges of values considered for the calibration of the NN models are presented in Table 5.1.

Table 5.1: Ranges of values considered for the reference data parameters and NN model hyperparameters.

(Hyper-)parameter	Values
"no-change" threshold	[-1.0, -1.5, -2.0, -2.5]
"change" threshold	[-1.5, -1.7, -1.9, -2.1, -2.3, -2.5, -2.9]
number of neurons (n)	[10, 25, 50, 100]

Both threshold values are subject to the constrain that the no-change threshold must be higher or equal to the change threshold value. Therefore, only specific combinations of the (hyper-)parameters listed in Table 5.1 are eligible for use during NN model training.

5.1.2 NN model performances

The NN models are trained in the calibration ROI, Dekese, using the combinations of (hyper-)parameters listed in Table 5.1. The TPR and FPR performance metrics are computed according to the methodology described in Section 4.6. The resulting values are then organized into matrices to identify performance patterns related to the different (hyper-)parameter combinations.

For the Dekese 2022 classifications, the variation in TPR values for a linear layer size of $n = 10$ neurons is presented in Figure 5.1. Distinct trends can be observed in the matrix, illustrating the influence of threshold combinations on model performance.

TPR values increase as the change threshold takes on higher numerical values, that is, as it becomes less negative. An increase in the change threshold value implies that a larger number of pixels are labelled as change in the reference data during training. As a result, NN models trained with higher change threshold values exhibit a more permissive approach to change detection. Corresponding classifications thus encompass a broader range of spatial validation points, which leads to increased TPR values.

On the other hand, TPR values decrease as the no-change threshold takes on lower numerical values, that is, as it becomes more negative. A decrease in the no-change threshold value implies that a larger number of pixels are labelled as no-change in the reference data during training. As a result, NN models trained with lower no-change threshold values exhibit a less permissive approach to change detection. Corresponding classifications thus encompass a narrower number of spatial validation points, which leads to decreased TPR values.

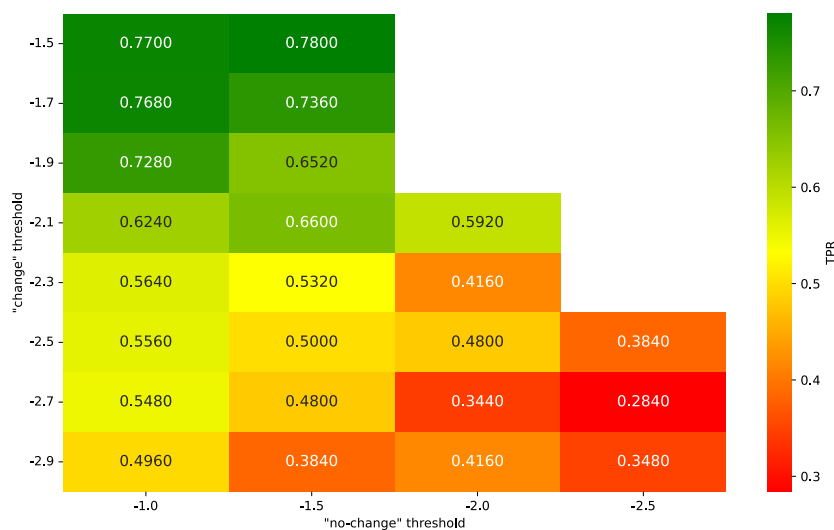


Figure 5.1: Evolution of TPR values across selected no-change and change thresholds for a linear layer size of $n = 10$ neurons.

For the Dekese 2022 classifications, the variation in FPR values for a linear layer size of $n = 10$ neurons is presented in Figure 5.2. Distinct trends can be observed in the matrix, illustrating the influence of threshold combinations on model performance.

FPR values increase as the change threshold takes on higher numerical values, that is, as it becomes less negative. As previously mentioned, a larger number of pixels is therefore labelled as change in the reference data during training. As a result, NN models trained with higher change threshold values exhibit a more permissive approach to change detection. Corresponding classifications contain more FP detections within the undisturbed TMF layer of the classification year, which leads to increased FPR values.

On the other hand, FPR values decrease as the no-change threshold takes on lower numerical values, that is, as it becomes more negative. As previously mentioned, a larger number of pixels is therefore labelled as no-change in the reference data during training. As a result, NN models trained with lower no-change threshold values exhibit a less permissive approach to change detection. Corresponding classifications contain less FP detections within the undisturbed TMF layer of the classification year, which leads to decreased FPR values.

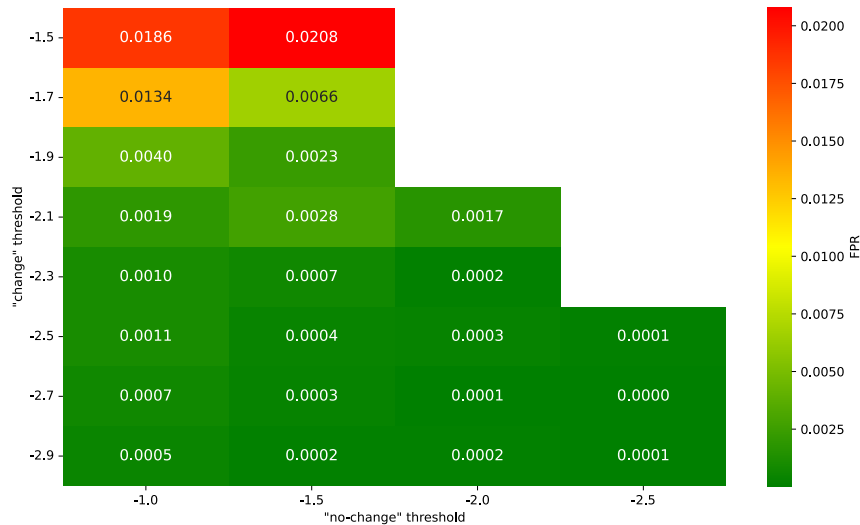


Figure 5.2: Evolution of FPR values across selected no-change and change thresholds for linear layer size of $n = 10$ neurons

TPR and FPR matrices for $n = 25, 50, 100$ are shown in Appendix C, Figures 9.4, 9.5 and 9.6 and Figures 9.7, 9.8 and 9.9, respectively. These matrices yield observations consistent with those discussed for a linear layer size of $n = 10$ neurons. For specific combinations of TPR and FPR values, no clear trend or significant performance difference can be identified across the different layer sizes. TPR and FPR matrices for a linear layer size of $n = 10$ were therefore presented, as they correspond to the same layer size used in the Optimal Operating Point (OPP) configuration described later in this section.

To better visualise the relationship between TPR and FPR values for varying combinations of thresholds and linear layer size (n), those can be represented using ROC scatter plots. Figures 5.3 and 5.4 display all (hyper-)parameter combinations from Table 5.1, with points coloured according to the change threshold and the no-change threshold values, respectively. The grey diagonal striped line represent the performance of a random classifier.

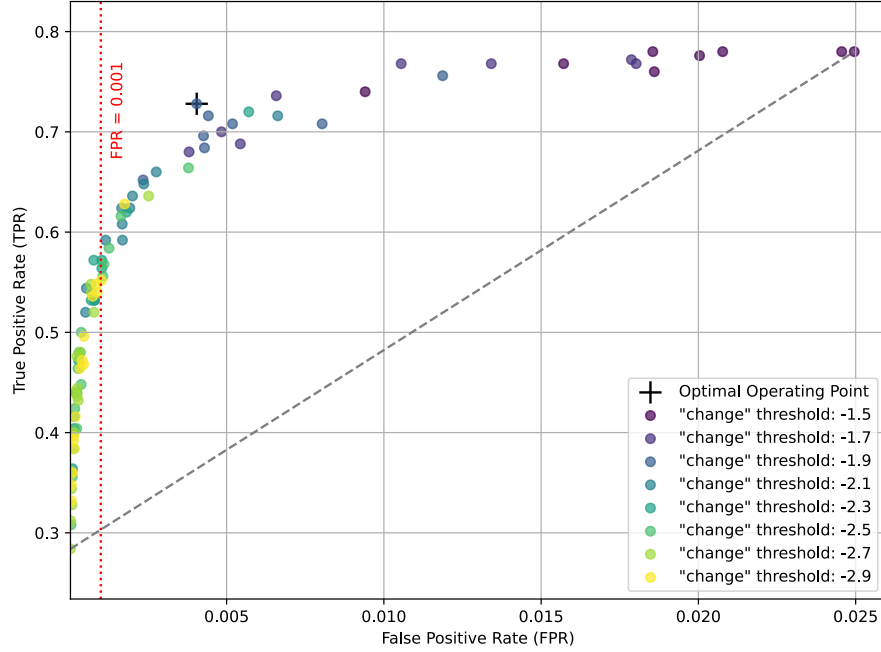


Figure 5.3: ROC scatter plot of TPR and FPR values coloured by the change threshold.

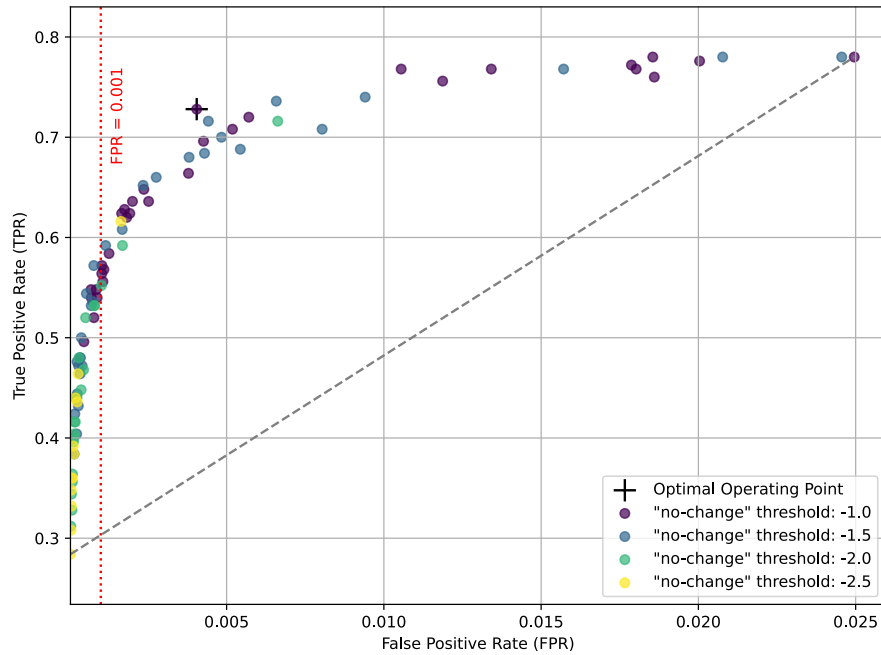


Figure 5.4: ROC scatter plot of TPR and FPR values coloured by the no-change threshold.

TPR and FPR trends relative to the no-change and change thresholds values, as highlighted in Figure 5.1 and 5.2, are also depicted onto the ROC scatter plot shown in Figures 5.3 and 5.4. However, no clear patterns can be observed in the ROC scatter plots where points are coloured according to linear layer size, as presented on Figure 9.10, available in Appendix C.

As illustrated by both the matrices and the RoC scatter plots, variations in FPR values remain markedly smaller than those observed for TPR. This difference is due to the distinct sampling strategies used for spatial validation, as detailed in Section 4.6. Specifically, FP detections are counted within the undisturbed TMF mask, which is generated with an inverse buffer of 100 m and comprises just under 18 million pixels. As a result, even a seemingly low FPR (e.g., 0.005) corresponds to a substantial absolute number of FP detections, potentially tens of thousands.

ROC scatter plots highlight the trade-off that must be considered between maximizing TPR and minimising FPR values. Selection of an appropriate balance depends on the specific use case and can be guided by an application-driven decision-making framework. Three distinct NN model training parametrisations, and their three separate disturbance classification outputs, are further examined.

The first classification yields the highest TPR value, and consequently, the highest FPR value.. The second represents the best trade-off between TPR and FPR, referred to as the Optimal Operating Point (OPP), and is indicated by a cross marker in Figures 5.3 and 5.4. The third achieves the highest TPR under the constraint that the $FPR < 0.001$. This selection is justified by the sharp decline in TPR observed for FPR values below 0.001, as shown by the points situated left of the red dotted line in the same Figures 5.3 and 5.4.

The (hyper-)parameter values of the three selected classifications, along with their corresponding TPR and FPR values, are presented in Table 5.2.

Table 5.2: (Hyper-)parameters, TPR and FPR values for the three selected classifications.

Classification name	Highest TPR	OPP	Highest TPR for $FPR < 0.001$
Linear layer size (n)	100	10	50
"no-change" threshold	-1.0	-1.0	-1.5
"change" threshold	-1.5	-1.9	-2.3
TPR	0.780	0.728	0.572
FPR	0.024955	0.004050	0.000778

The selected classifications are visually represented over a subset of the calibration ROI in Dekese for the year 2022, as shown in Figure 5.5. Frame (a) presents Planet imagery from May 2022 to illustrate areas of undisturbed tropical forest, while Frame (b) displays Planet imagery from August 2022 to depict forest disturbances. The subsequent frames also utilise August 2022 imagery as a basemap to enable visual comparison between detected disturbance classifications and actual disturbance patches. In all frames, a grey mask indicates pixels previously classified as disturbed or as belonging to other TMF annual change classes in 2021, according to Vancutsem et al. (2021).

Frame (c) presents the classification with the highest TPR, and therefore highest FPR value. While disturbance patches located near previously disturbed areas are largely captured, a substantial number of detections also appear within undisturbed TMF regions, likely corresponding to FP detections. Frame (d) displays the OPP classification, which shows fewer FP detections within undisturbed areas, but with reduced coverage of disturbance patches emerging from previously disturbed zones. Frame (e) illustrates the classification achieving the highest TPR under the constraint $FPR < 0.001$. This configuration exhibits the lowest detection of emerging disturbance patches, while minimizing or eliminating detections within the undisturbed TMF.

Using the OPP disturbances detection classification, representing the best trade-off between TPR and FPR, a post-processing step is applied in an attempt to further improve classification performance. In this post-processing step, a minimum of two or three detections is required for a disturbances to be considered. This approach aims to reduce potential FP detections within extensive areas of undisturbed TMF. The outcome of this post-processing, for the case requiring a minimum of three detections, is illustrated in Frame (f) of Figure 5.5. TPR and FPR values of this post-processing step are presented in Table 5.3. It is important to note that while this post-processing step significantly reduces the FPR, it does so at the expense of TPR.

Table 5.3: Comparison of TPR and FPR for OPP-based classifications with varying minimum detection thresholds.

Classification name	OPP	OPP (min. 2 detections)	OPP (min. 3 detections)
TPR	0.728	0.588	0.5
FPR	0.004050	0.000614	0.000179

Finally, RADD disturbance alerts isolated for the year 2022 are presented in frame (g) of Figure 5.5 (Reiche et al., 2021).

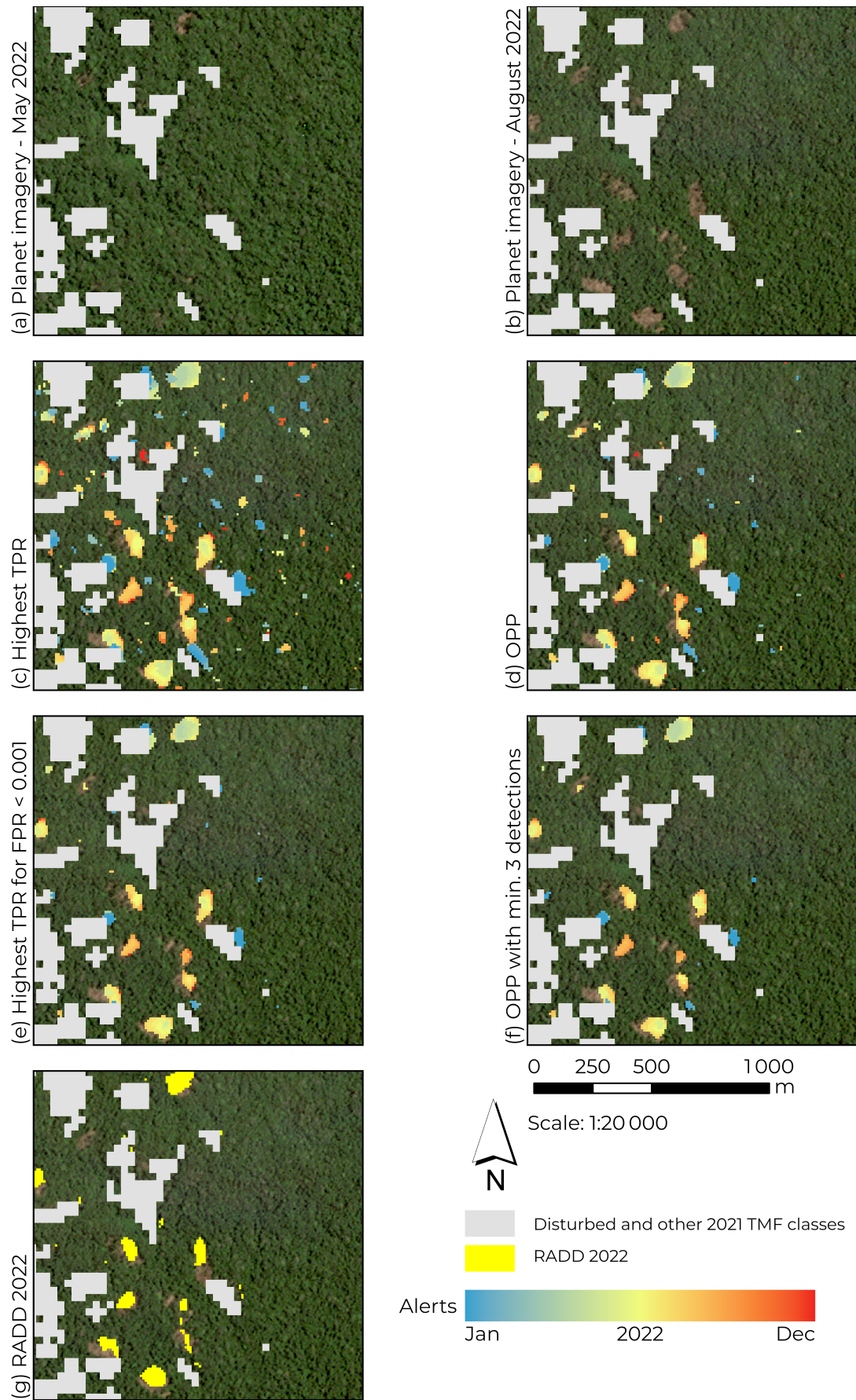


Figure 5.5: Comparison of selected classification results within a subset of the calibration ROI in Dekese, using Planet imagery and RADD disturbances alerts for 2022 (Reiche et al., 2021).

5.2 NN model transferability

In addition to calibrating the NN models over the calibration ROI, Dekese, using 2021 data for training and 2022 data for validation, selected NN models are also used to evaluate their transferability to a different ROI. For this purpose, the selected NN models are applied to the transfer ROI in Likati, for the year 2023.

Classifications produced over Likati using the selected NN models trained on Dekese, as described in Section 5.1.2, are visually represented over a subset of the transfer ROI for the year 2023 in Figure 5.6. Frame (a) presents Planet imagery from January 2023 to illustrate areas of undisturbed tropical forest, while Frame (b) displays Planet imagery from April 2023 to depict forest disturbances. The subsequent frames also use April 2023 imagery as a basemap to facilitate visual comparison between detected disturbance classifications and actual disturbance patches. These scenarios correspond to those previously described and illustrated for Dekese in Figure 5.5, Section 5.1.2. In all frames, a grey mask indicates pixels previously classified as disturbed or as belonging to other TMF classes in 2022, according to Vancutsem et al. (2021).

Similar qualitative observations to those described in Section 5.1.2 for Figure 5.5 can be made for the selected NN models applied to classify disturbances over Likati, as shown in Figure 5.6. This initially confirms the transferability of selected NN models to another ROI. Quantitatively, the TPR and FPR values obtained over Likati, reported in Table 5.4, are higher than those obtained when applying the same models to Dekese, as shown in Table 5.2.

Table 5.4: TPR and FPR values for classifications performed over Likati using NN models trained over Dekese.

Classification name	Highest TPR, FPR	OPP	Highest TPR, FPR < 0.001
TPR	0.82	0.74	0.74
FPR	0.031331	0.006095	0.001385

Finally, RADD disturbance alerts isolated for the year 2023 are presented in frame (g) of Figure 5.6 (Reiche et al., 2021).

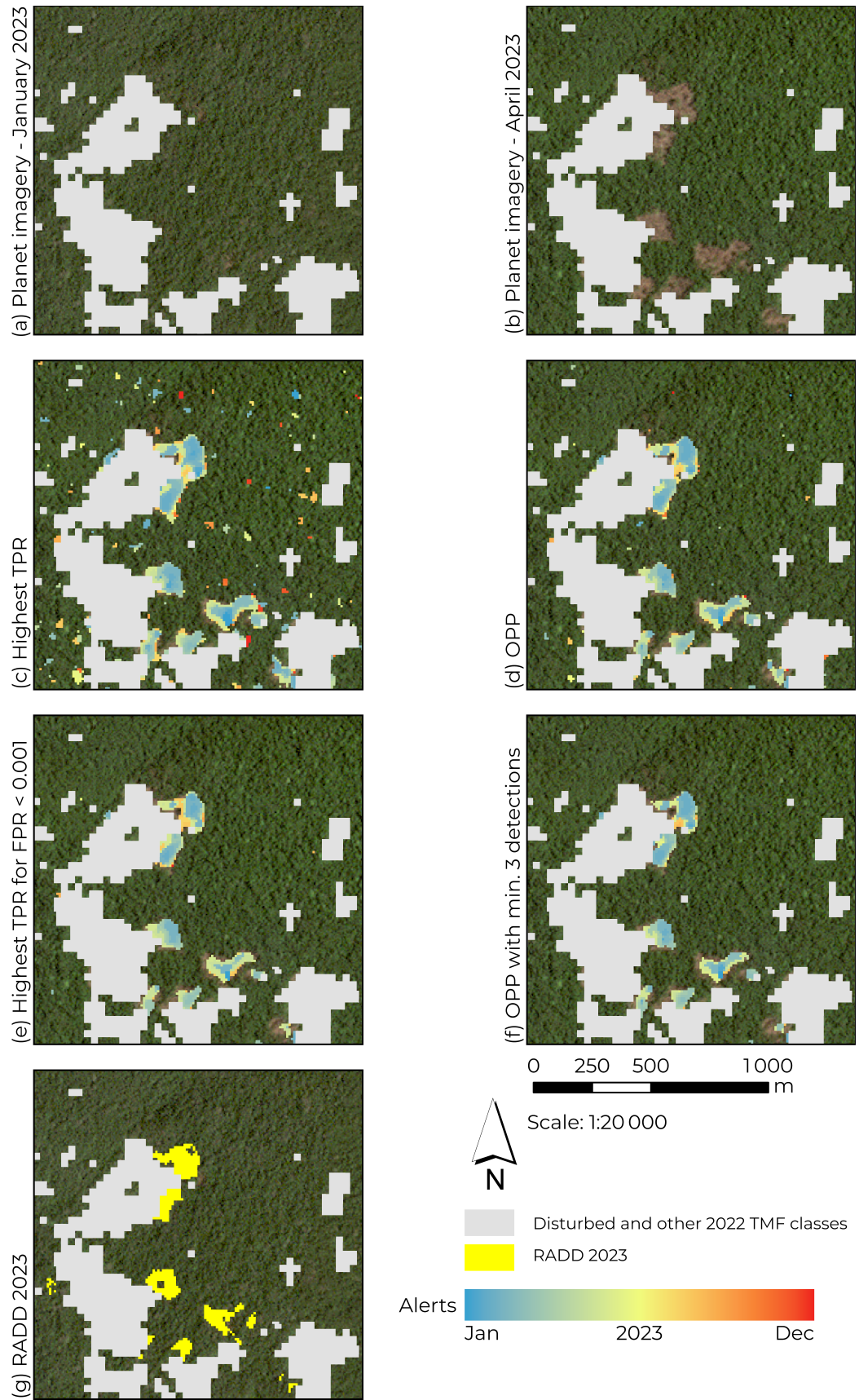


Figure 5.6: Comparison of selected classification results within a subset of the transfer ROI in Likati, using Planet imagery and RADD disturbances alerts for 2023 (Reiche et al., 2021).

5.3 NN model temporal validation

Temporal validation is conducted over the transfer ROI, Likati, for the year 2023. For this purpose, the first-date-of-change composite generated using the OPP configuration with a minimum of three detections is employed. RADD disturbance alerts for the year 2023 are also acquired (Reiche et al., 2021). Sample points are drawn from the intersection of these two layers and confined to areas classified as undisturbed TMF in the preceding year (2022) (Vancutsem et al., 2021). These points are labelled according to the procedure described in Section 4.7.

Firstly, the delay between the labelled degradation and loss dates are assessed. Figure 5.7 illustrates the distribution of delays between the assigned degradation and loss dates for the 70 temporal validation points. A median delay of 12 days is observed between the onset of degradation and the occurrence of forest loss.

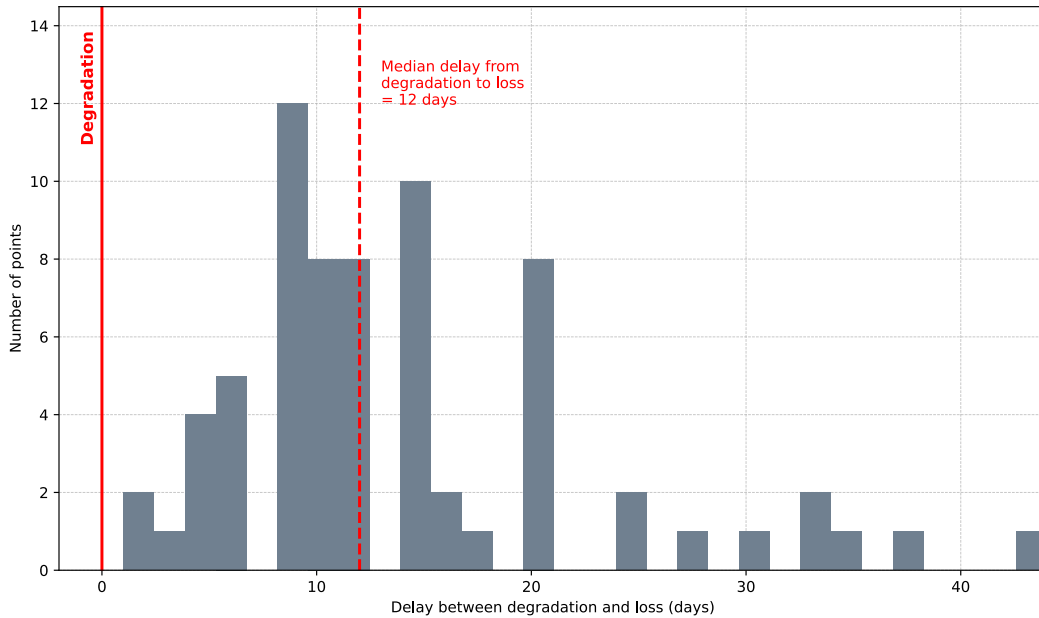


Figure 5.7: Delay in days between the labelled degradation dates and loss dates.

Secondly, the delay between the labelled degradation / loss dates and the disturbance classification dates derived from the OPP scenario with a minimum of three detections are computed. The distribution of these delays is illustrated in Figure 5.8. A median delay of -2 days relative to the loss date and 8 days relative to the degradation date is observed for the classified disturbances.

Thirdly, the delay between the labelled degradation / loss dates and RADD disturbances are computed (Reiche et al., 2021). The distribution of these delays is illustrated in Figure 5.9. A median delay of -1 days relative to the loss date and 15 days relative to the degradation date is observed for the classified disturbances.

Similar median delays following the loss date are observed for both the OPP with a minimum of three detections disturbances and the RADD disturbances. However, the median delay following the degradation date is shorter for the OPP disturbances compared to the RADD disturbances.

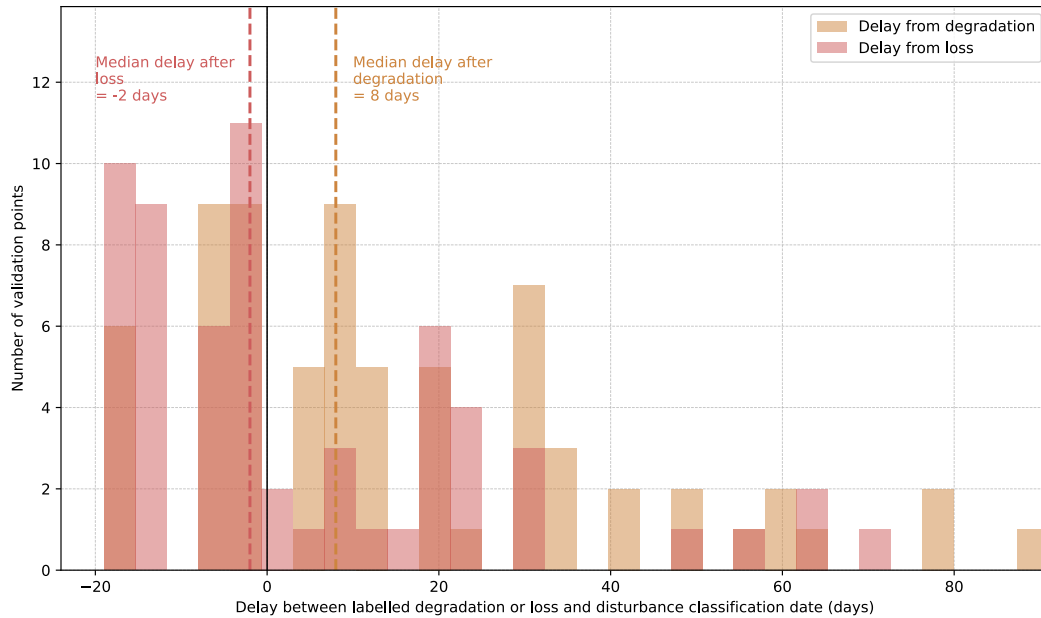


Figure 5.8: Delay in days between the labelled degradation dates, loss dates and disturbance classification dates.

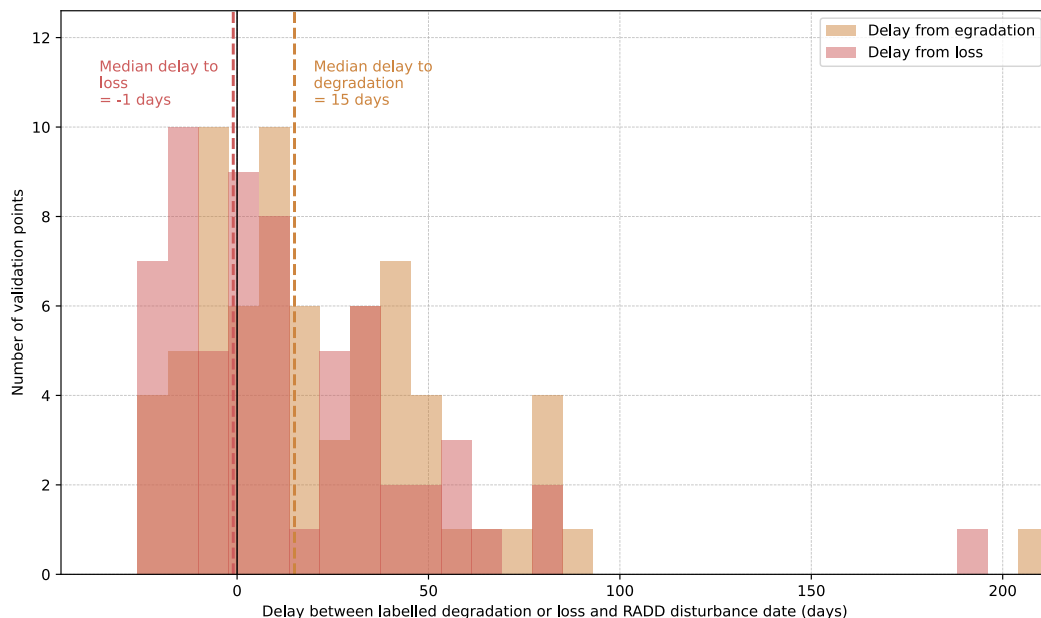


Figure 5.9: Delay in days between the labelled degradation dates, loss dates and RADD disturbance dates (Reiche et al., 2021).

5.4 Trends and statistics of tropical forest disturbances in Dekese and Likati

Classifications generated using the OPP NN model parametrisation combined with the minimum three detections constraint are used to derive disturbance trends and statistics across both ROIs. Despite a lower TPR, as indicated in Table 5.3, the substantially reduced FPR allows for a more reliable evaluation of emerging disturbance patches, particularly those associated with smallholder agriculture at the edges of undisturbed tropical forest.

When a NN model classifies standardised Sentinel-1 acquisitions, the entire spatial extent of the ROI is processed, and disturbances are detected independently of the underlying land cover. For the following section, only detections falling within the undisturbed TMF mask from the year preceding each classification are included, ensuring that only newly detected disturbances are considered.

5.4.1 Intra-annual distribution of tropical forest disturbance detections

First, the distribution of tropical forest disturbance detections for Dekese in 2022 is shown in Figure 5.10, alongside average monthly precipitations in the Kasai province for 1991 to 2020. A distinct maximum in disturbance detections is observed between July and August. This maximum occurs prior to the start of the rainy season in the southern part of the DRC, which roughly extends from October to April, as also illustrated in Figure 5.10 (Climate Change Knowledge Portal, 2025).

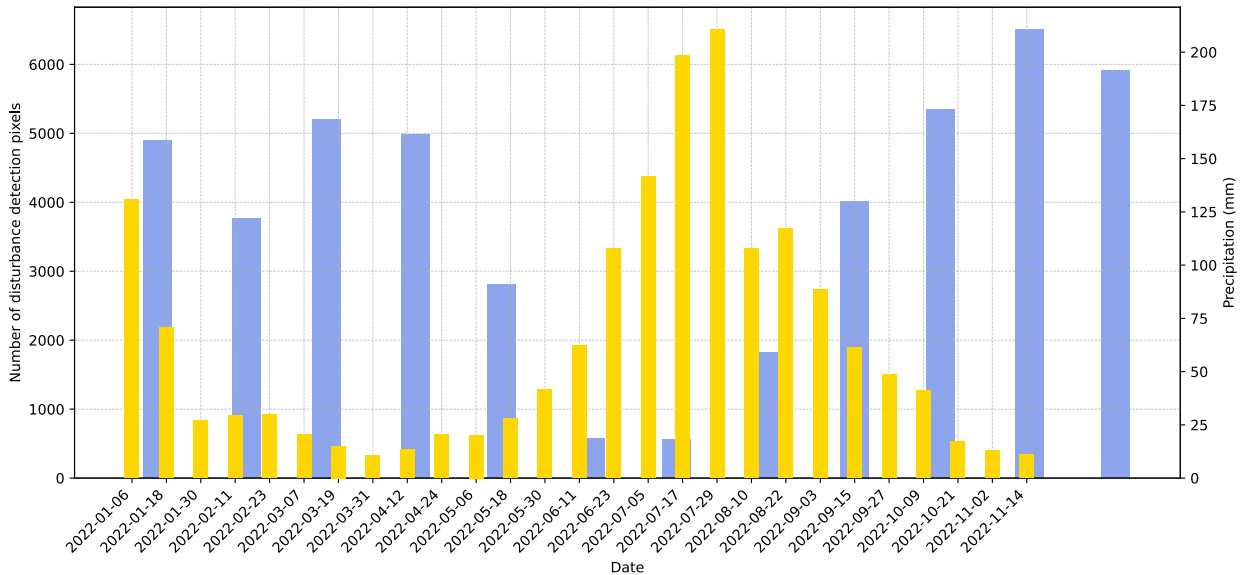


Figure 5.10: Intra-annual distribution of tropical forest disturbance detections (yellow) in Dekese (2022) and monthly climatological precipitation data (1991-2020) for the Kasai province (blue).

Secondly, the distribution of tropical forest disturbance detections for Likati in 2023 is shown in Figure 5.11, alongside average monthly precipitations in the Bas-Uele province for 1991 to 2020. In contrast to Dekese, peaks in disturbance detections are observed between mid-February and the end of May. These maxima occurs during the start of the rainy season in the northern part of the DRC, which roughly extends from April to October, as also illustrated in Figure 5.11 (Climate Change Knowledge Portal, 2025).

It is worth noting that Dekese and Likati are respectively located south and north of the equator, which explains the inversion of their seasonal precipitation patterns.

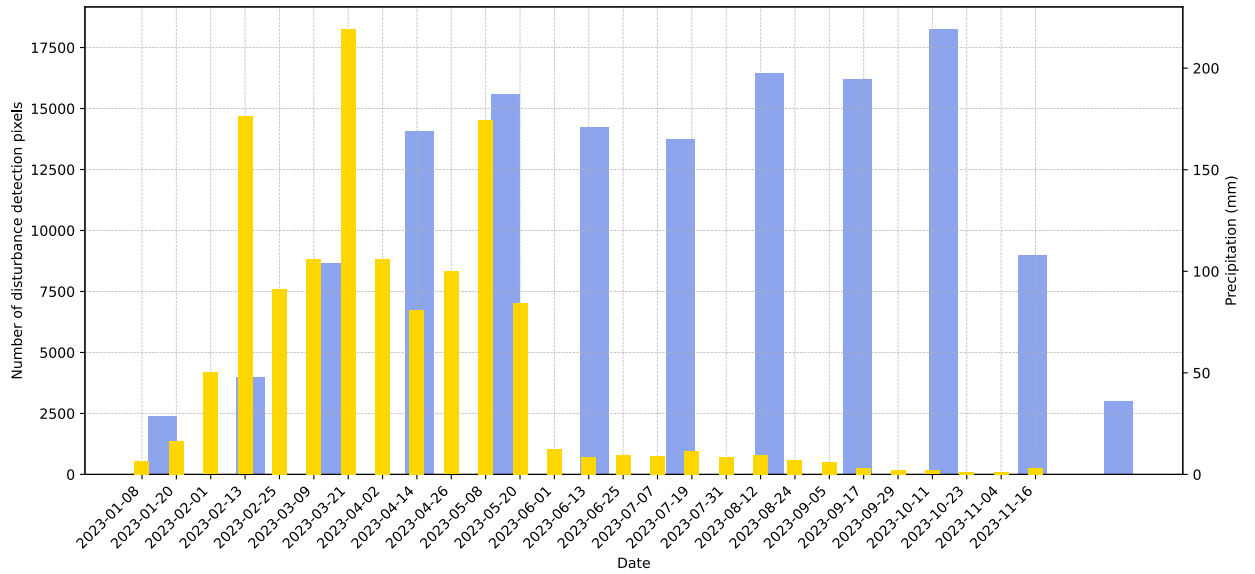


Figure 5.11: Intra-annual distribution of tropical forest disturbance detections (yellow) in Likati (2023) and monthly climatological precipitation data (1991-2020) for the Bas-Uele province (blue).

5.4.2 Inter-annual comparison of cumulative tropical forest disturbance detections

An inter-annual comparison of cumulative tropical forest disturbance detections is conducted over both ROIs to assess potential differences in the timing and intensity of disturbance peaks across years and illustrated in Figure 5.12 and Figure 5.13.

For Dekese, inter-annual variations are observed, with higher cumulative disturbance detections recorded by the end of 2021 and 2020 compared to 2023 and 2022. An acceleration in disturbance detections is seen during the local dry season, approximately from May to August, although the timing and intensity of this increase vary across years.

For Likati, inter-annual variations are also observed, with higher cumulative disturbance detections recorded by the end of 2022, 2020 and 2023 compared to 2021. An

acceleration in disturbance detections is seen during the local dry season, approximately from November to March. The timing and intensity of this increase is more consistent across years than for Dekese.

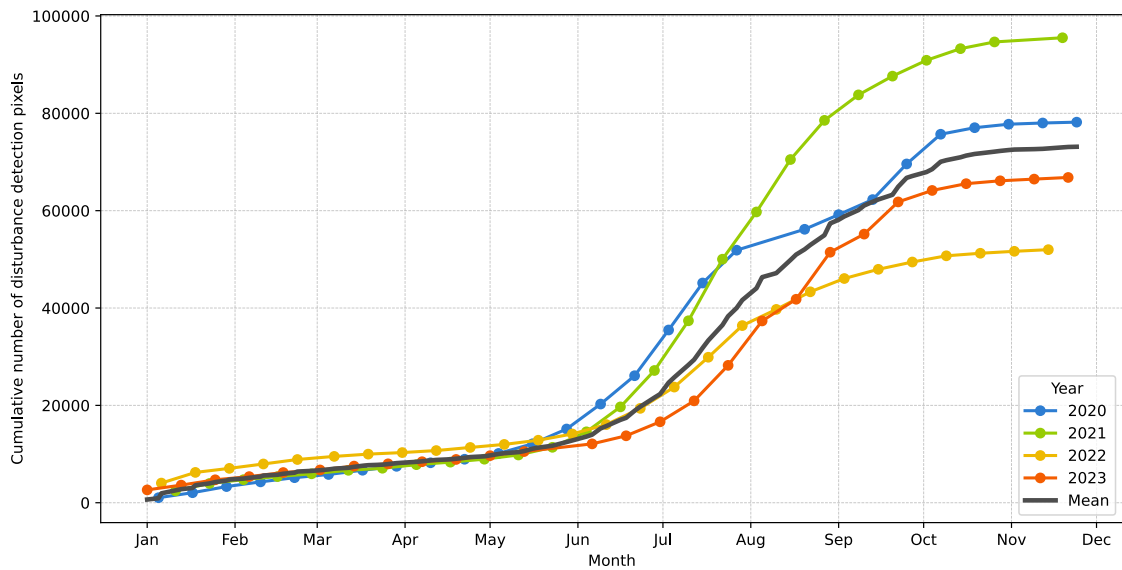


Figure 5.12: Monthly cumulative tropical forest disturbance detections in Dekese (2020-2023).

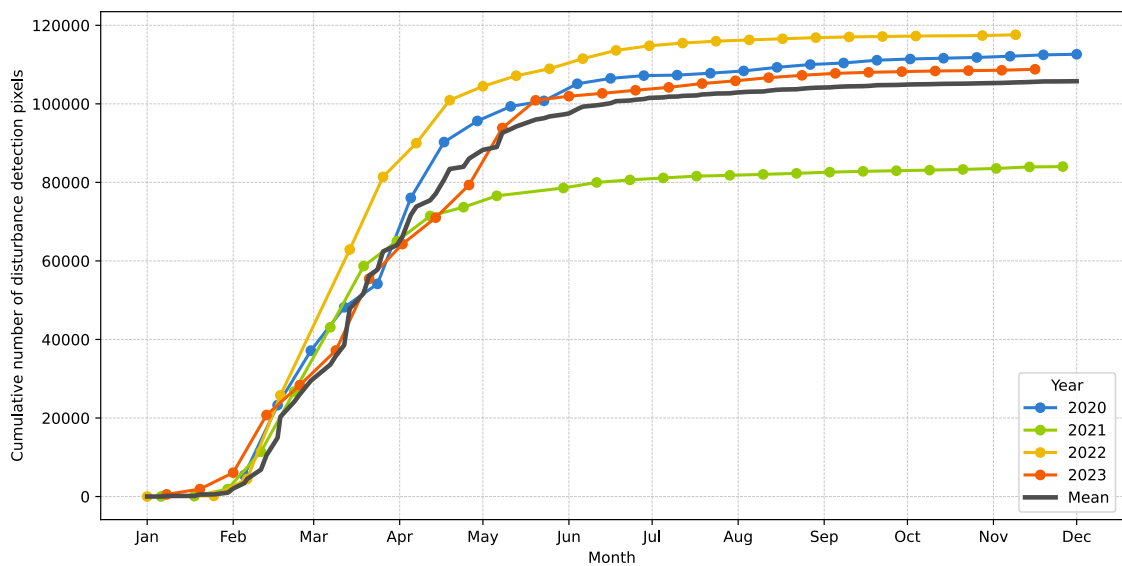


Figure 5.13: Monthly cumulative tropical forest disturbances detections in Likati (2020-2023).

5.4.3 Disturbance patch size distribution in terms of count and area.

In Dekese, for the year 2022, the vast majority of disturbance patches are smaller than 1 ha, with 54.3% of the detected patches covering less than 0.05 ha, as shown in Figure 5.14. When considering the contribution of each patch size class to the total disturbed

area, patches between 0.1 and 1 ha account for 71.4% of the total disturbed area, as illustrated in Figure 5.15. This is followed by patches between 0.05 and 0.1 ha and those smaller than 0.05 ha, with 11% and 9.8% respectively. Patches larger than 1 ha represent 7.9% of the total disturbance area. The largest disturbance patch detected in 2022 covers 2.39 ha.

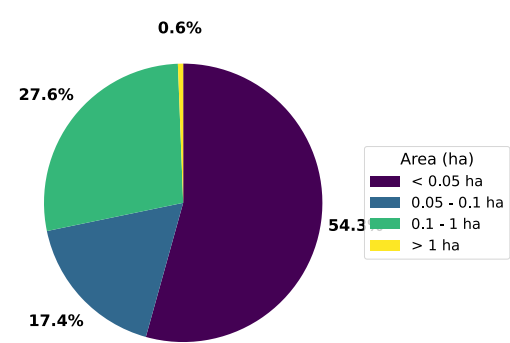


Figure 5.14: Distribution of disturbance patch sizes as a percentage of the total number of disturbance patches in Dekese (2022).

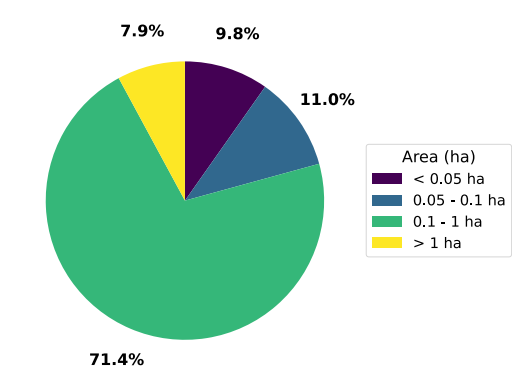


Figure 5.15: Distribution of disturbance patch sizes as a percentage of the total disturbed area in Dekese (2022).

In Likati, for the year 2023, the vast majority of disturbance patches are smaller than 1 ha, with 58.2% of the detected patches covering less than 0.05 ha, as shown in Figure ???. When considering the contribution of each patch size class to the total disturbed area, patches between 0.1 and 1 ha account for 48% of the total disturbed area, as illustrated in Figure ??. This is followed by patches greater than 1 ha and those between 0.05 and 0.1 ha, with 36.2% and 8% respectively. Patches smaller than 0.05 ha represent 7% of the total disturbance area. Disturbances patches larger than 1 ha are more prevalent in Likati than in Dekese. The largest disturbance patch detected in 2023 covers 12.28 ha.

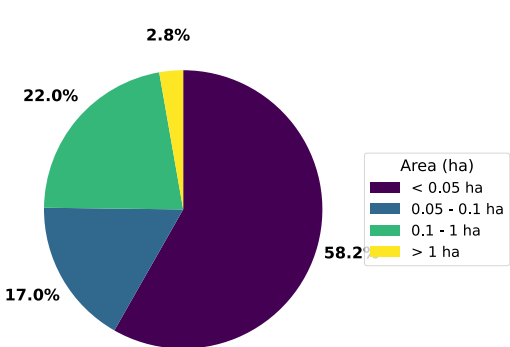


Figure 5.16: Distribution of disturbance patch sizes as a percentage of the total number of disturbance patches in Likati (2023).

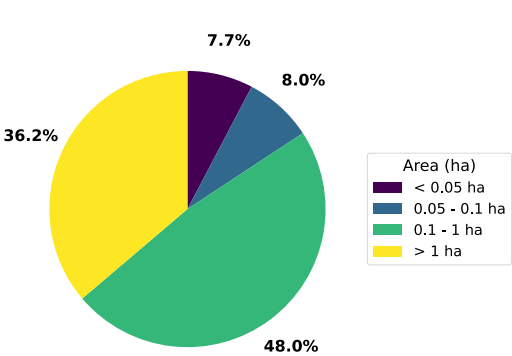


Figure 5.17: Distribution of disturbance patch sizes as a percentage of the total disturbed area in Likati (2023).

5.5 Disturbances alerts mapping over both ROIs

Disturbance detections obtained using the OPP NN model parametrisation with the minimum three detections constraint are mapped over representative areas within both ROIs in Figures 5.18 and 5.19. This mapping serves to demonstrate the model's ability to detect tropical forest disturbances associated with smallholder agriculture.

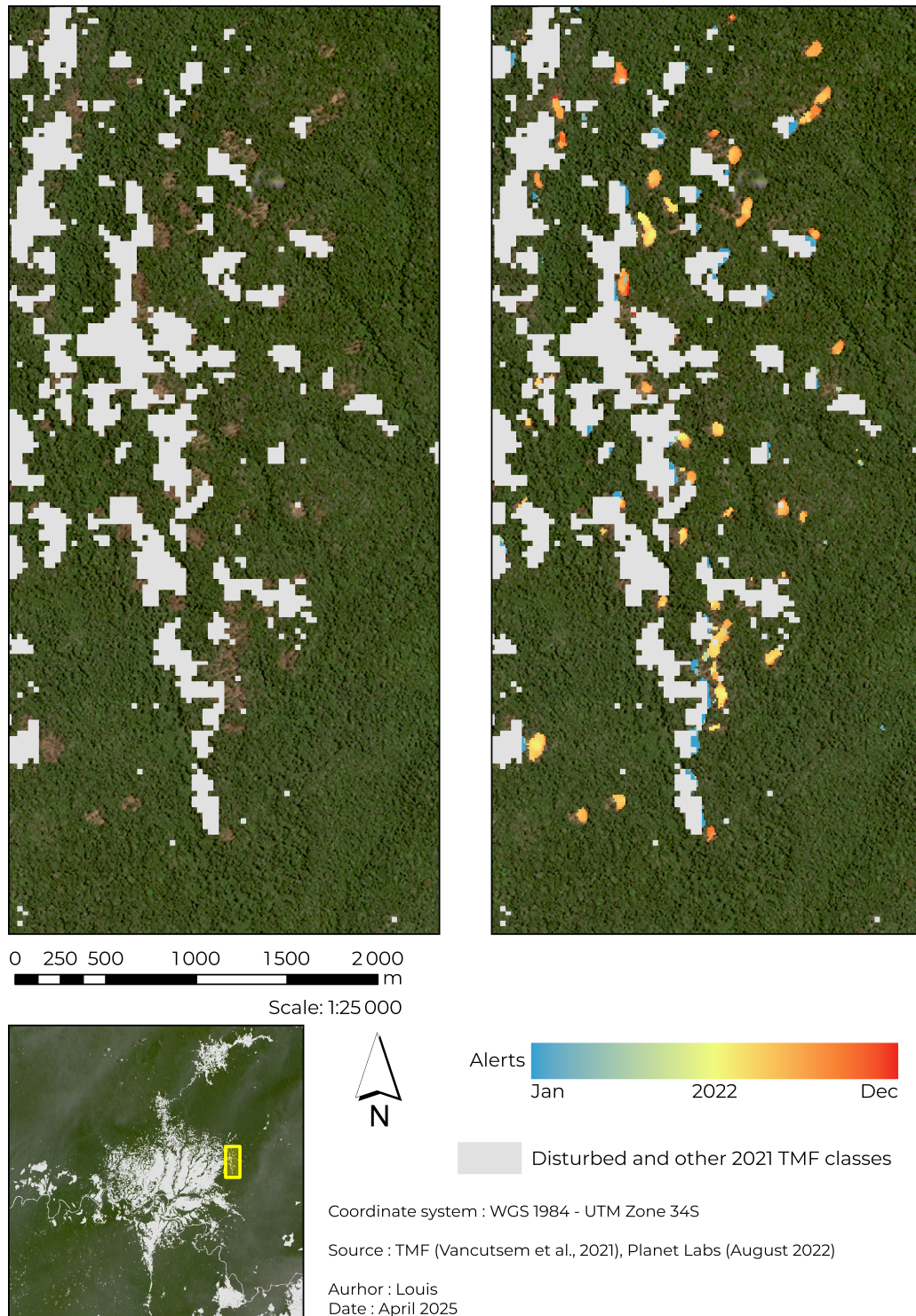


Figure 5.18: Tropical forest disturbances detections caused by smallholder agriculture over a selected extent within the Dekese ROI (2022).

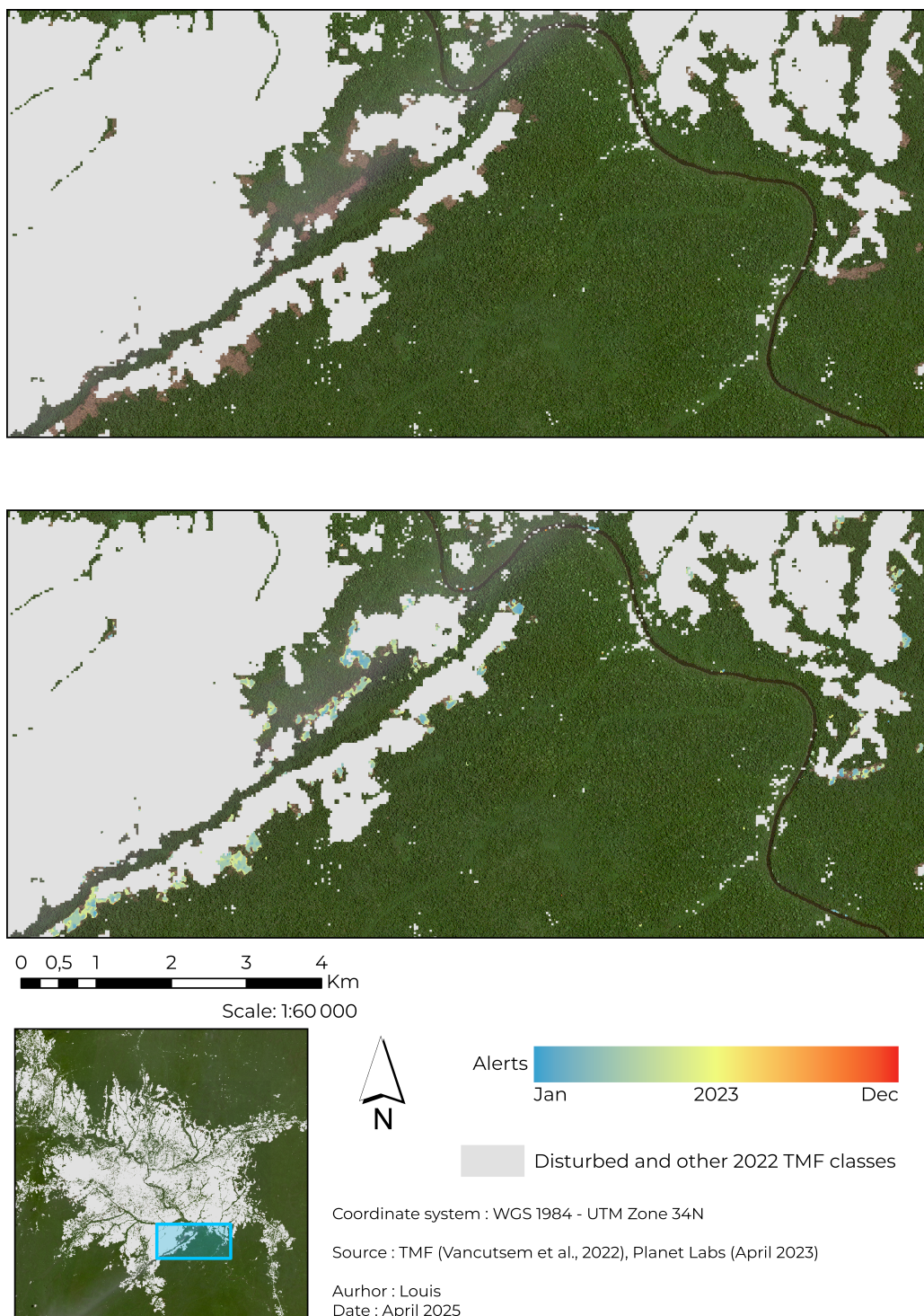


Figure 5.19: Tropical forest disturbances detections caused by smallholder agriculture over a selected extent within the Likati ROI (2023).

6 Discussion

The NN models developed in this study are designed to detect tropical forest disturbances using Sentinel-1 C-SAR data in a timely manner, thereby supporting forest disturbance monitoring and addressing the limitations associated with optically based sensors. The disturbance classifications obtained from these NNs are discussed in details in this section, along with an examination of their limitation and potential perspectives regarding future research.

6.1 NN model calibration

The calibration phase conducted over the calibration ROI, Dekese, for the year 2021 (training) and 2022 (spatial validation) demonstrated that the developed NN architecture is suitable for detecting tropical forest disturbances.

By standardising VV and VH polarisation acquisitions using a two-year time series preceding each observation, it becomes possible to differentiate changes in backscatter intensity from more stable signals over an extended period. This standardisation approach facilitates the attribution of significant drops in backscatter intensity to actual changes, and more specifically to tropical forest disturbances, when such changes occur in previously undisturbed forest areas.

In addition to the standardisation of input features, the strategy used to construct both input features and reference samples plays a crucial role in the calibration of NN models. Each detection period is defined using a temporal floating window of three consecutive acquisitions for both VV and VH polarisations. This temporal aggregation reinforces the interpretation of consistent drops in backscatter intensity as indicators of actual change, specifically tropical forest disturbances. It reduces the likelihood of incorporating anomalies, such as drops observed in only one acquisition or limited to a single polarisation, the two standardised features (VV and VH) of a detection period are cross-threshold considering their z-values every 0.1σ , from 0 to -3σ . This procedure yields a confidence index for change, and thus for forest disturbance, occurring within the three-acquisition time window. It enables an automated, scalable, and adjustable construction of reference samples, suitable for model training with the aim of avoiding reliance on empirically set thresholds.

Given the strong class imbalance between tropical forest disturbances and undisturbed forest areas, two distinct sampling strategies were employed. One was designed to assess TPR performance, while the other targeted the evaluation of FPR performance. These complementary spatial validation strategies were instrumental in evaluating the ability of differently configured NN models to accurately delineate disturbance patches while minimising FP detections. Their effectiveness is particularly evident when comparing the

selected model from Table 5.2, their performances illustrated in the ROC scatter plots of Figures 5.3 and 5.4, alongside the visual representations of their corresponding disturbance classifications shown in Figure 5.5.

For a given set of (hyper-)parameter configurations, the selected NN architectures demonstrated strong performance in terms of both TPR and FPR, indicating that the model design is well-suited for tropical forest disturbance detection. During the calibration phase, and in all classification scenarios without post-processing, the highest observed TPR reached 0.78, while the lowest recorded FPR was 0.000778. These results confirm that the architecture, in combination with the chosen (hyper-)parameters, is capable of achieving both high sensitivity and high specificity in disturbance detection.

The final selected NN model configuration corresponds to the OPP scenario, which provides the best trade-off between TPR and FPR performance, with a TPR of 0.728 and an FPR of 0.004050. To further reduce FP detections within large areas of undisturbed tropical forest, a post-processing step was applied in which only disturbances detected with a minimum of three occurrences were retained. This step reduced the TPR to 0.500 but also significantly lowered the FPR to 0.000179. While this post-processing reduced the spatial extent of some disturbance patches along forest edges, it also substantially decreased the number of FP detections deep within undisturbed forest areas, as illustrated in Frame (d) and Frame (f) of Figure 5.5.

Despite the decrease in TPR, visual inspection of the resulting disturbance maps revealed that the number of disturbance patches detected along the forest edge remained comparable, although their spatial extent was reduced. At the same time, fewer FP detections were observed in core areas of undisturbed forest. For these reasons, the OPP configuration with a minimum of three detections was retained for generating the final disturbance detection maps presented in Figures 5.18 and 5.19. This configuration achieves the primary goal of NRT detection of tropical forest disturbances using NN and standardised Sentinel-1 C-SAR time series and avoid relying on empirically applied change threshold.

6.2 NN model transferability

NN model transferability was evaluated over the transfer ROI, Likati, for the year 2023. For this purpose, the three selected NN models from Table 5.2, all trained over Dekese, were applied to detect forest disturbances in Likati. Similar trends in TPR and FPR values were observed across the three selected configurations. However, slightly higher TPR and FPR values were recorded in comparison to results obtained in Dekese. While the higher TPR indicates that a greater number of disturbance patches were detected, the increase in FPR may suggest limited generalisation capacity, resulting in more

FP detections within large areas of undisturbed tropical forest.

However, it is important to emphasise that, although the results demonstrate the potential for transferability of NN models over a distinct geographic area, this assessment was conducted between two similar ROIs. Both ROIs are located within the Congo Basin, share comparable geographical characteristics, are predominantly affected by forest disturbances linked to small-scale agriculture at the forest edge, and are observed under similar environmental and sensor acquisition conditions.

6.3 Disturbances temporal delay

Due to the unavailability of frequent cloud-free Planet imagery over the calibration ROI, Dekese, during the study period, temporal validation was conducted over Likati for the year 2023. While the ability of C-SAR imagery to penetrate cloud cover enables more frequent observations compared to optical sensors, it is equally important that the proposed NN models generate disturbance detections in a timely manner to fulfill the near-real-time (NRT) component of the research objective.

In the OPP configuration with a minimum of three detections, a median delay of 8 days after degradation and -2 days after loss was observed, as shown in Figure 5.8. This indicates that the proposed disturbance detection approach is capable of identifying forest loss slightly before it can be visually confirmed, and degradation with a minor delay. These findings suggest that the disturbance detection product is able to operate in (NRT) for the majority of cases. It is also important to acknowledge that detection delays of up to 12 days may occur, primarily due to the Sentinel-1 revisit cycle over the transfer ROI. These delays are comparable to those observed for RADD, as illustrated in Figure 5.9 (Reiche et al., 2021).

6.4 Trends and statistics of tropical forest disturbances

Section 5.4.1 shows that disturbance detections exhibit distinct temporal peaks occurring at different periods of the year for Dekese and Likati. These peaks take place just before and during the onset of the respective rainy seasons, reinforcing the interpretation that the detected disturbance patches are associated with land clearing for smallholder agriculture, activities that are typically carried out in preparation for the rainy season.

Furthermore, Section 5.4.3 demonstrates that, in both ROIs, the majority of disturbance patches are smaller than 1 ha, with more than half measuring less than 0.05 ha. These patch size characteristics further support the link between the detected disturbances and small-scale agricultural practices.

6.5 Limitations and perspectives

Despite the promising results produced by the proposed NN models, several shortcomings could be addressed to improve this research and broaden its scope.

First, the input features require the standardisation of Sentinel-1 imagery using a two-year historical time series. This methodology assumes a regular revisit cycle and no significant downtime from any satellite in the Sentinel-1 mission. While this could represent a limitation, it is mitigated by the design of the Sentinel-1 mission, which normally includes two satellites. Moreover, long-term continuity of Sentinel-1 coverage is ensured, as confirmed by the ESA (ESA, 2025a).

The results from the spatial validation of the differently configured NN models highlight a clear trade-off between TPR and FPR: increased detection sensitivity often comes at the cost of reduced precision. The selection of an appropriate balance between these two metrics should be guided by the intended application, ideally through an application-driven decision-making framework. In the case of this research, priority was given to precision, resulting in a reduction of FP but also in the omission of certain disturbance areas, particularly around the peripheries of disturbance patches. Ideally, a model should be capable of capturing the full extent of disturbance patches while maintaining minimal or no FP detections in large areas of undisturbed tropical forest without the need of post-processing steps. Furthermore, transferability of the NN models should also be assessed over ROIs presenting more diverse geographical features.

With regard to temporal validation, only 70 validation points could be labelled. This limitation was due to the restricted monthly access provided by Planet’s Education and Research Program to their near-daily imagery. Additionally, challenges were encountered when assigning undisturbed, degradation, and loss dates, as cloud cover occasionally introduced delays of several days. This temporal uncertainty may result in an overestimation of the temporal performance of the proposed disturbance detection product.

The NN architectures developed in this study remain relatively simple. Exploring more diverse and complex architectures, such as those incorporating additional layers or alternative activation functions, could help achieve a better trade-off between TPR and FPR. Other types of deep learning models could also be considered. In particular, architectures that integrate spatial contextual information, such as Convolutional Neural Networks (CNN)s, may offer improvements. For instance, U-Net models, as explored by Mullissa and Saatchi (2024), are particularly promising given that tropical forest disturbance patterns associated with small-scale agriculture are highly spatially contextualised. New disturbance occurrences are more likely to emerge at the edges of existing patches rather than in isolation.

7 Conclusion

The main objective of this research was to develop Neural Networks (NN) for the near-real time (NRT) detection (and monitoring) of tropical forest disturbances caused by smallholder agriculture in the Congo Basin, based on dense standardised Sentinel-1 C-SAR time series. To this end, two separate regions of interest (ROI)s were selected: Dekese for calibration of the NN models, and Likati, employed to assess transferability of select NN models, Likati.

The results obtained from both ROIs demonstrate the potential of NN-based approaches to detect forest disturbances linked to small-scale agriculture. The proposed NN architecture, in conjunction with the applied feature and sample engineering strategy, effectively captured disturbance patterns. The spatial performance of the disturbance detections produced by differently configured models highlights the existence of a trade-off between precision and detection sensitivity. The transferability of the selected NN models yielded encouraging results when applied to a ROI with similar geographical and characteristics. However, further investigation across more diverse ecological settings is necessary to confirm these findings.

Detecting tropical forest disturbances induced by small-scale agriculture remains particularly challenging due to their subtle and short-lived nature. Leveraging the cloud-penetrating capability of C-SAR imagery, the proposed NN model is able to detect such disturbances in a timely manner. This is especially critical for the development of a NRT disturbance alert product, which could support relevant authorities in monitoring and regulating forest disturbances more effectively and promptly.

Building on the foundation established in this study, future research should focus on refining the current NN architecture or exploring more spatially contextualised deep learning models, such as Convolutional Neural Networks (CNN) or U-Net architectures. These approaches could offer improved accuracy and robustness in heterogeneous landscapes.

Ultimately, the precise, frequent, and large-scale monitoring of tropical forest disturbances is essential for the conservation and restoration of tropical forest ecosystems worldwide. Progress in remote sensing technology has made such monitoring increasingly better, and further enhancements in detection systems remain essential to achieving global sustainability objectives. Continued development of operational NRT disturbance alert systems will play a key role in promoting more effective forest governance and long-term tropical forest ecosystem resilience.

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9 Appendices

A General Context

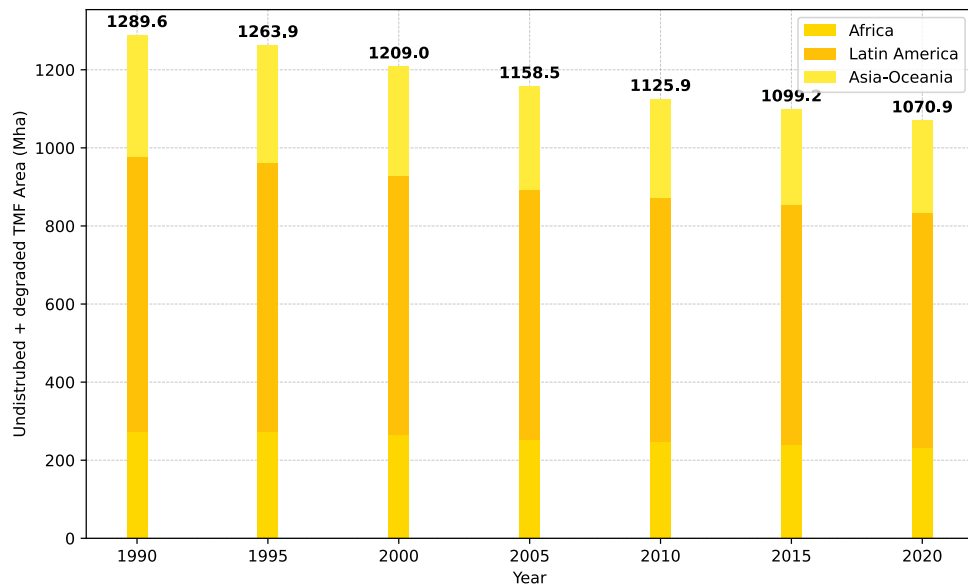


Figure 9.1: Evolution of continental and global undisturbed + degraded TFM areas over the period 1990–2020 (Vancutsem et al., 2021)

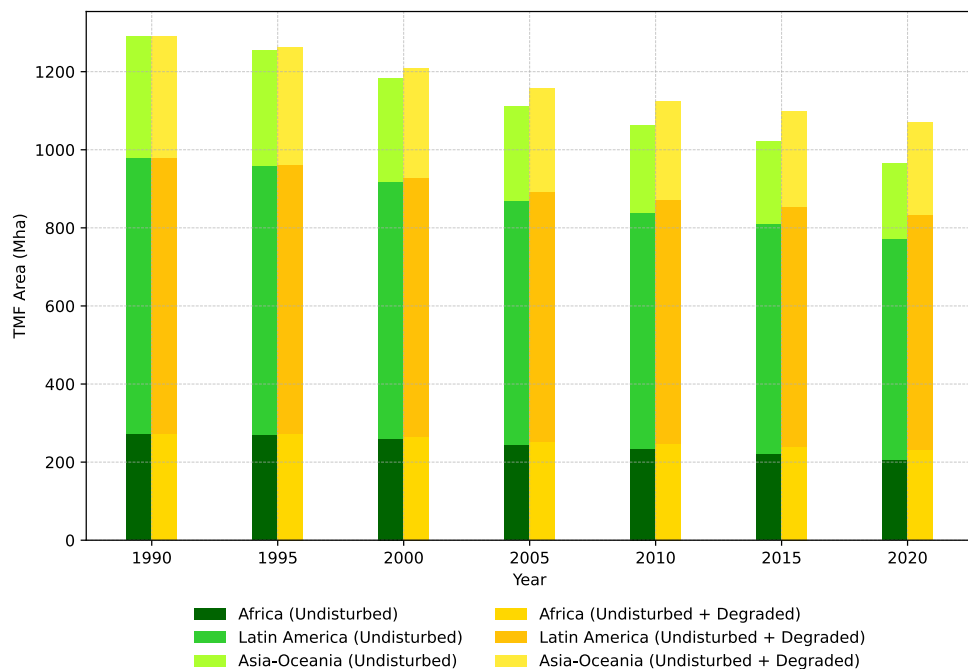


Figure 9.2: Comparative representation of undisturbed TFM are and undisturbed + degraded TFM over the period 1990–2020 (Vancutsem et al., 2021).

B Literature review

○ Dense + BatchNorm + ReLU + Dropout

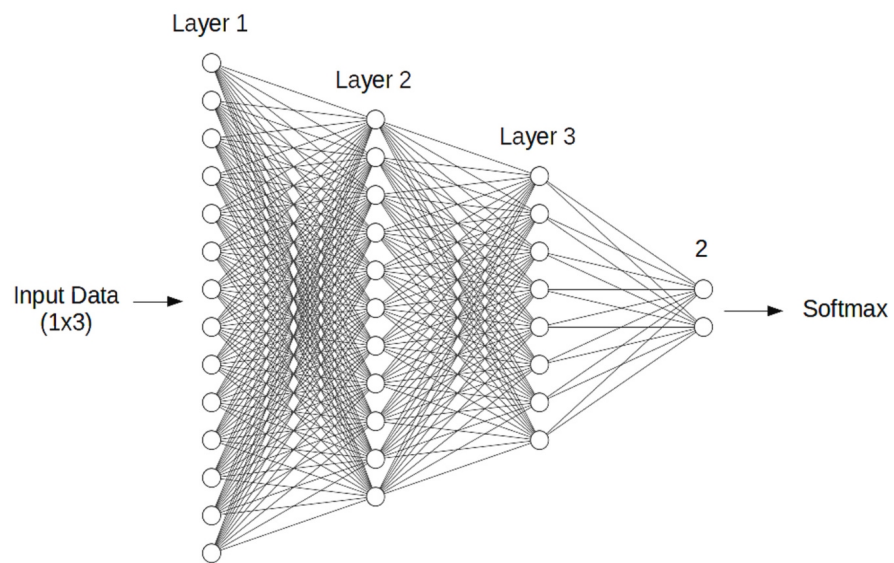


Figure 9.3: Deep NN architecture used for the methodology proposed by (Mullissa et al., 2023).

C Results

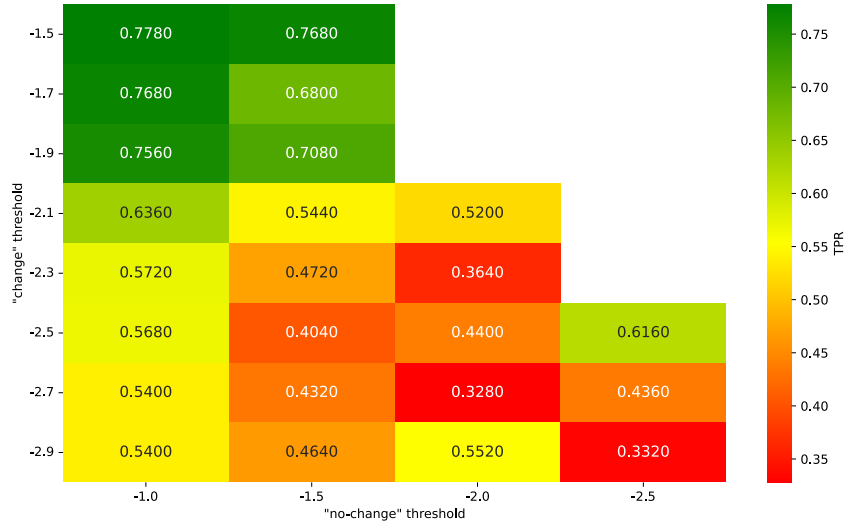


Figure 9.4: Evolution of TPR values across selected no-change and change thresholds for linear layer size of $n = 25$ neurons.

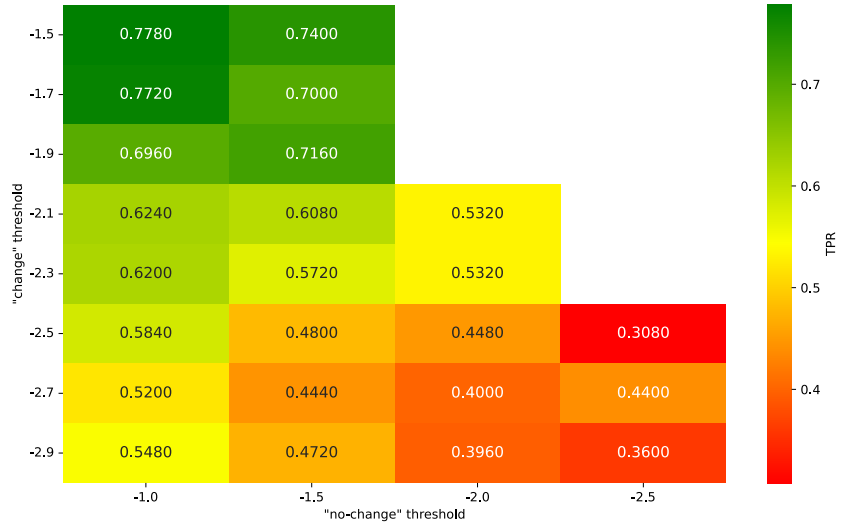


Figure 9.5: Evolution of TPR values across selected no-change and change thresholds for linear layer size of $n = 50$ neurons.

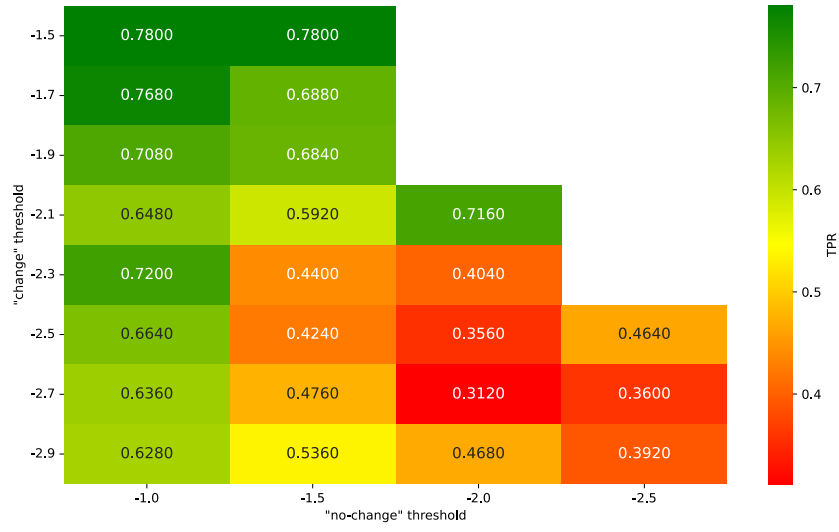


Figure 9.6: Evolution of TPR values across selected no-change and change thresholds for linear layer size of $n = 100$ neurons

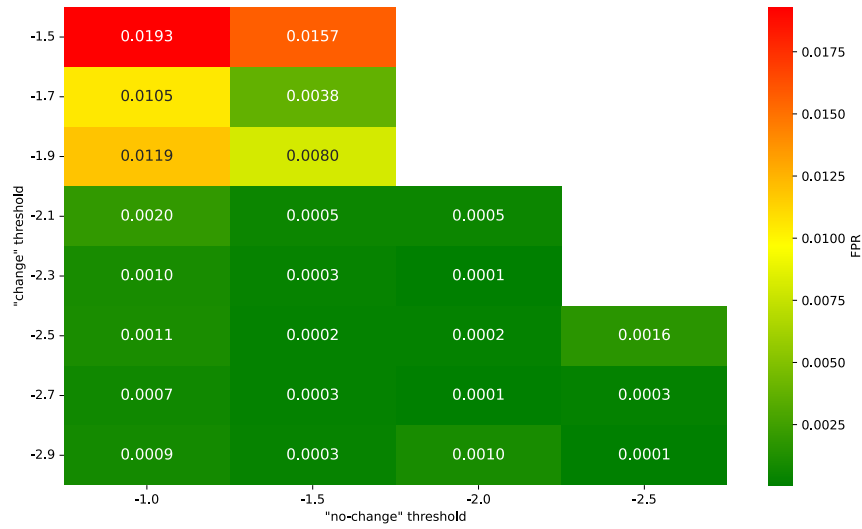


Figure 9.7: Evolution of FPR values across selected no-change and change thresholds for linear layer size of $n = 25$ neurons.

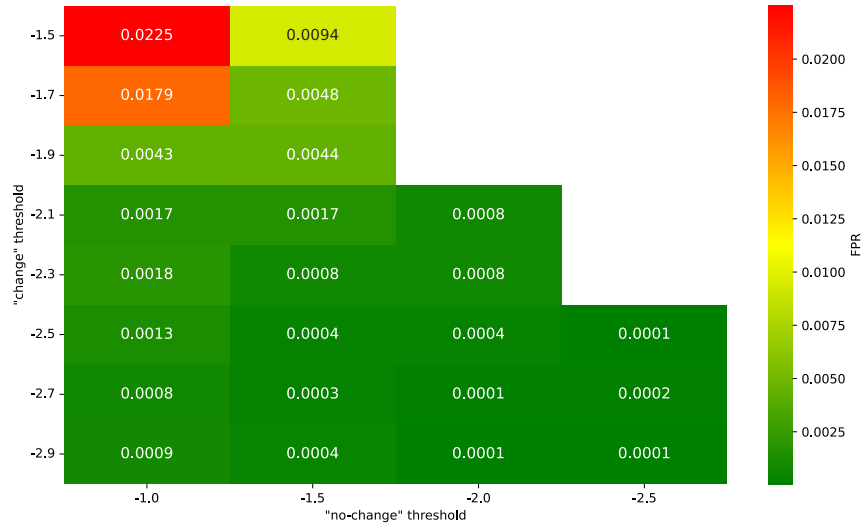


Figure 9.8: Evolution of FPR values across selected no-change and change thresholds for linear layer size of $n = 50$ neurons.

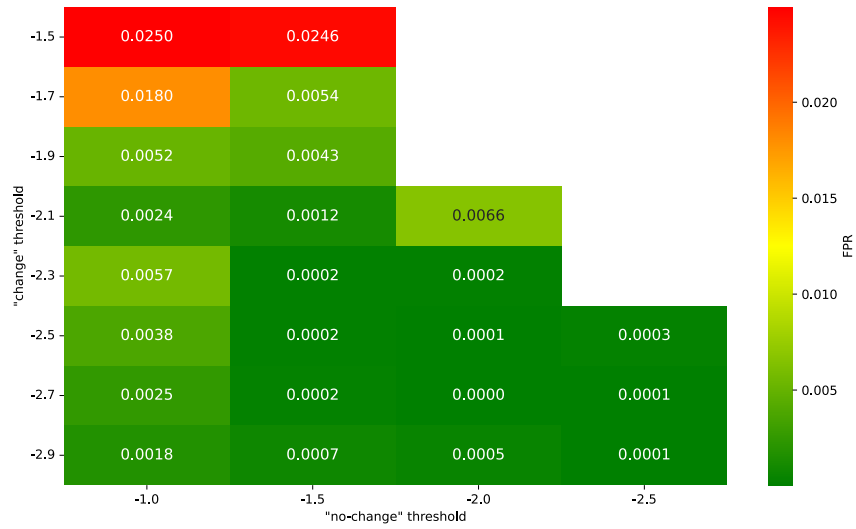


Figure 9.9: Evolution of FPR values across selected no-change and change thresholds for linear layer size of $n = 100$ neurons.

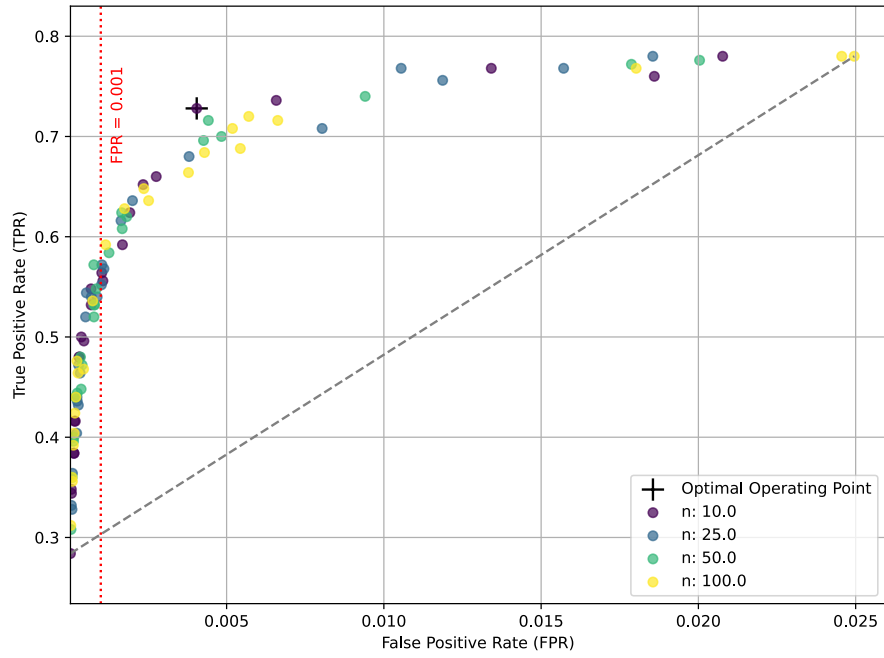


Figure 9.10: ROC scatter plot of TPR and FPR values coloured by linear layer sizes (n).

Neural network-based detection of tropical moist forest disturbances using standardised Sentinel-1 time series

Regions of interest : Dekese (DRC) and Likati (DRC)

Joseph Louis

The transition from the 20th to the 21st century has been marked by an increasing recognition of the impact of human activities on the planet and its ecosystems. Among the global challenges related to the achievement of sustainable development goals, the conservation and systematic monitoring of tropical forests remain critical. Anthropogenic changes in forest cover significantly compromise the provision of essential ecosystem services in these regions. This research focuses on the development of Neural Networks for the near-real time detection (and monitoring) of tropical forest disturbances caused by smallholder agriculture in the Congo Basin, based on dense standardised Sentinel-1 C-SAR time series. Two regions of interest are defined for this study : Dekese serves as the calibration region of interest for the developed neural networks, while Likati is used to assess model transferability and to perform temporal validation. The results highlight a clear trade-off between spatial precision and detection sensitivity, underscoring the difficulty in simultaneously achieving accurate localisation and comprehensive disturbance identification. The approach enabled timely detection of disturbances, allowing the generation of near-real-time forest disturbance alerts that are crucial for effectively monitoring short-duration events, such as those associated with smallholder agriculture. Such alert products can serve as valuable tools to promote more effective forest governance and long-term tropical forest ecosystem monitoring, ultimately contributing to the achievement of related sustainable development goals.

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