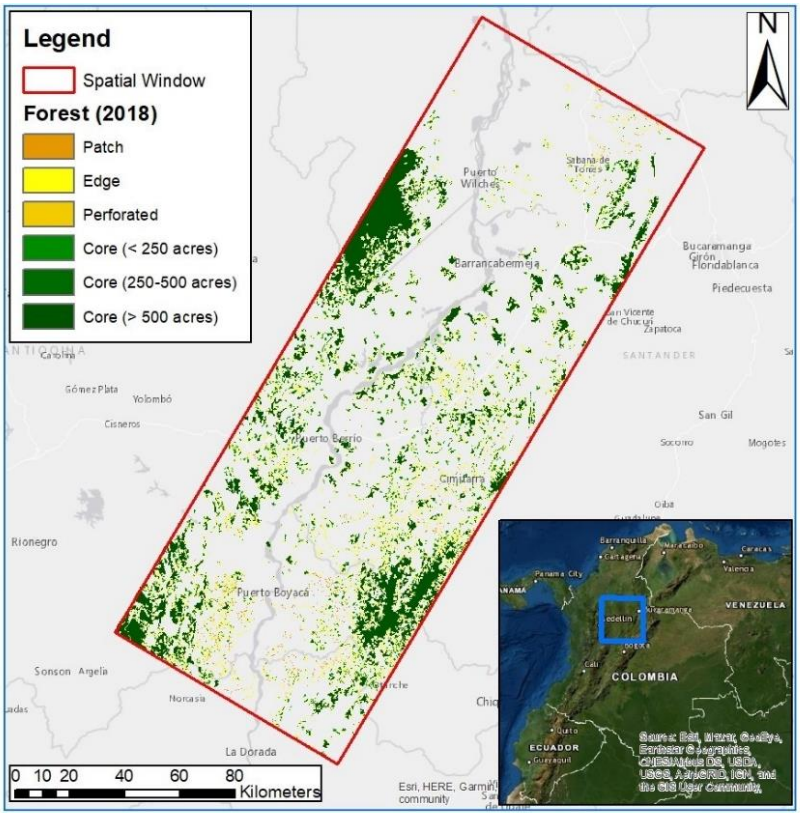
Investigating the Effect of Multitemporal Land Use Changes to the Middle Magdalena River Valley on the Abundance and Distribution of Important Plant Species



Submitted by Thomas Edward Bailey, to the University of Exeter as a thesis for the degree of MSc by Research in Geography, September 2022.

I certify that all material in this thesis which is not my own work has been identified and that any material that has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

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Abstract

This thesis investigates changes to the lowland rainforest of the Middle Magdalena River Valley, Colombia, a region high in species diversity that is under severe anthropogenic pressures. Geographic Information Systems are utilised to conduct forest change analysis and Human Footprint Index (HFI) calculations between 2000 and 2018. Seven plant species are selected for reasons of ecological and economic importance, and their abundances and distributions are calculated over the same time scale. A Generalised Linear Model is created to test for correlation between each species' abundance and distribution, and the measures of forest change and HFI, to identify which land use changes are having a statistically significant impact upon their abundance and distribution. The HFI of the study site consistently increased from 2000-2018, and the area of forest consistently decreased, indicating that the study site is being increasingly degraded by anthropogenic activities, particularly after the recent end of the Colombian armed conflict. The Serranía de Las Quinchas was found to be an important relic within the study site that has been better preserved, potentially owing to its status as a Regional Natural Park. Slope and Normalised Difference Vegetation Index (NDVI) are the two most correlated explanatory variables for species abundance and distribution, but the presence of clouds makes conclusions based on NDVI uncertain. Lack of accessibility is found to be a significant barrier to deforestation, with forests on steeper slopes being better preserved. The abundance and distribution of some species reduced, suggesting little resistance to landscape changes. Other species are more robust to changes, but this may be due to planting by roadside or in agroforestry systems. Regional conservation classifications for the species vary from their global IUCN classifications, highlighting the importance of regional assessments.

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Table of Abbreviations

Abbreviation	Meaning
AOO	Area of Occupancy
DEM	Digital Elevation Model
EOO	Extent of Occurrence
FDI	Fractal Dimension Index
GIS	Geographic Information System
GLM	Generalised Linear Model
HFI	Human Footprint Index
NDVI	Normalised Difference Vegetation Index

1. Introduction

1.1 Background on Colombian Ecosystems

Colombia is one of the most biodiverse countries in the world, with its varied ecosystems hosting 10% of the Earth's species, a figure which rises as high as 20% depending on taxonomic group (Murcia et al., 2013; Abud et al., 2017; Baptiste et al., 2017; González-González et al., 2021). Amongst this species diversity is an estimated 30,736 plant species (Noreña et al., 2018). Colombia's high biodiversity can be attributed to its location at the connection of the Americas, the bordering of two oceans, and the history of Andean uplift that collectively have created ecosystems with high levels of diversity and endemism (Murcia et al., 2013). It is clear, therefore, that Colombia is a unique and highly species-rich country, making its ecosystems globally important and imperative to protect.

Unfortunately, Colombia's ecosystems are at risk of deforestation and degradation from a variety of threats including the drug trade and civil conflict, with a major driver being the conversion of forest to pastures and crops (legal and illegal). The conversion of forest to arable land is often to an even greater extent in remote regions with an active agricultural frontier (Armenteras et al., 2013). Agricultural production in Colombia has reached such levels that the total cultivated land area was estimated to be in excess of 14 million hectares in 2012, compared to 60 million hectares of forest in the same year (Vargas et al., 2019; The World Bank, 2022). Crops vary depending on region and climate, with palm oil, conifers, fruit trees, and rice being predominant in the Caribbean, and coffee, peas, beans, cotton and cocoa being the predominant crops in the Andean region (Vargas et al., 2019). Throughout the country, the presence of cattle ranching is accompanied by management techniques such as the setting of fires to create pastures (Armenteras et al., 2013).

The cultivation of illicit crops accounted for approximately 50% of total land area deforested in 1998 and their area increased by 21% per year between 1997 and 2002 (Álvarez, 2002). Coca cultivation area increased by 17.1% between 2016 and 2017 (Rodríguez et al., 2020), demonstrating the ever-increasing ferocity of this threat. Furthermore, deforestation for coca does not only occur to clear land for planting, but also through the additional infrastructure needed for the entire production and distribution process. For example, coca deforestation also occurs to clear areas for future crops or subsistence crops and airfields, as well as fields that have been previously used and now abandoned, amplifying the area deforested by 2.5-3 times the area of the cultivated land itself (Álvarez, 2002).

The 52-year civil conflict that ended in 2016 is believed to have caused a loss of one million hectares of Colombian forest (Baptiste et al., 2017). The civil conflict in Colombia caused a vast array of impacts, both environmentally, and socio-economically, with up to 2.9 million people involuntarily displaced from their homes (Ibáñez and Vélez, 2008). Displacement has largely affected vulnerable demographics, such as women and children, who account for 77% of those displaced (Ibáñez and Vélez, 2008).

The unique topography of Colombia creates ecological distinctions between altitudinal levels that affect the severity of deforestation and degradation. Between 0-1200m, natural vegetation is largely replaced by semi-natural shrub and cropland (Etter and Villa, 2000). Differences in deforestation rates between altitudinal ranges are attributed to differences in accessibility and, consequently, economic activities (Armenteras et al., 2011). Due to their accessibility being the greatest of all habitats across altitudinal ranges, lowland rainforests are at the highest risk of deforestation and degradation. For example, Armenteras et al. (2011) found that deforestation hotspots generally occur in the lowlands. Therefore, this thesis will focus on this altitudinal level, investigating how deforestation and degradation has affected the lowland rainforests of the Middle Magdalena River Valley over time.

1.2 The Magdalena River Valley

The study site of this thesis is in the Magdalena River Valley, Colombia, a region of great importance to the surrounding ecosystems and communities alike (Galvis and Iván Mojica, 2007). Studies have shown that the lowland rainforest in the valley hosts a high number of endemic species of fauna and flora (Amador-Jiménez and Serrano, 2021), but is under high anthropogenic pressures. This thesis classifies lowland rainforest as falling below 800m in elevation, a range which has seen large amounts of degradation (Etter and Villa, 2000). Lowland rainforest is characterised by high rainfall of 1800mm or higher annually and mean monthly temperatures of ~18°C or greater (Burnham and Johnson, 2004).

For use in this thesis, several datasets in Serranía de Las Quinchas and the Magdalena Medio have been kindly provided by collaborators. Figure 1.1 shows the spatial window of the study site (red rectangle) and the ecosystems present, encompassing long-term monitoring plots (see section 3.2 for details). The spatial window was chosen using a digital elevation model and a shapefile of tropical dry forest (figure 1.2) to ensure the study site fell within the 0-800m elevation (as much as possible, some edges of the study site may be higher where the valley rises), and to ensure it contained as little tropical dry forest as possible so any conclusions on the region’s rainforests were accurate and not skewed by the presence of dry forest. This region has also been selected because findings from it may have a real-world impact on local ecosystems and communities, for example aiding the establishment of efficient conservation policies that provide a sustainable income alternative for local populations.

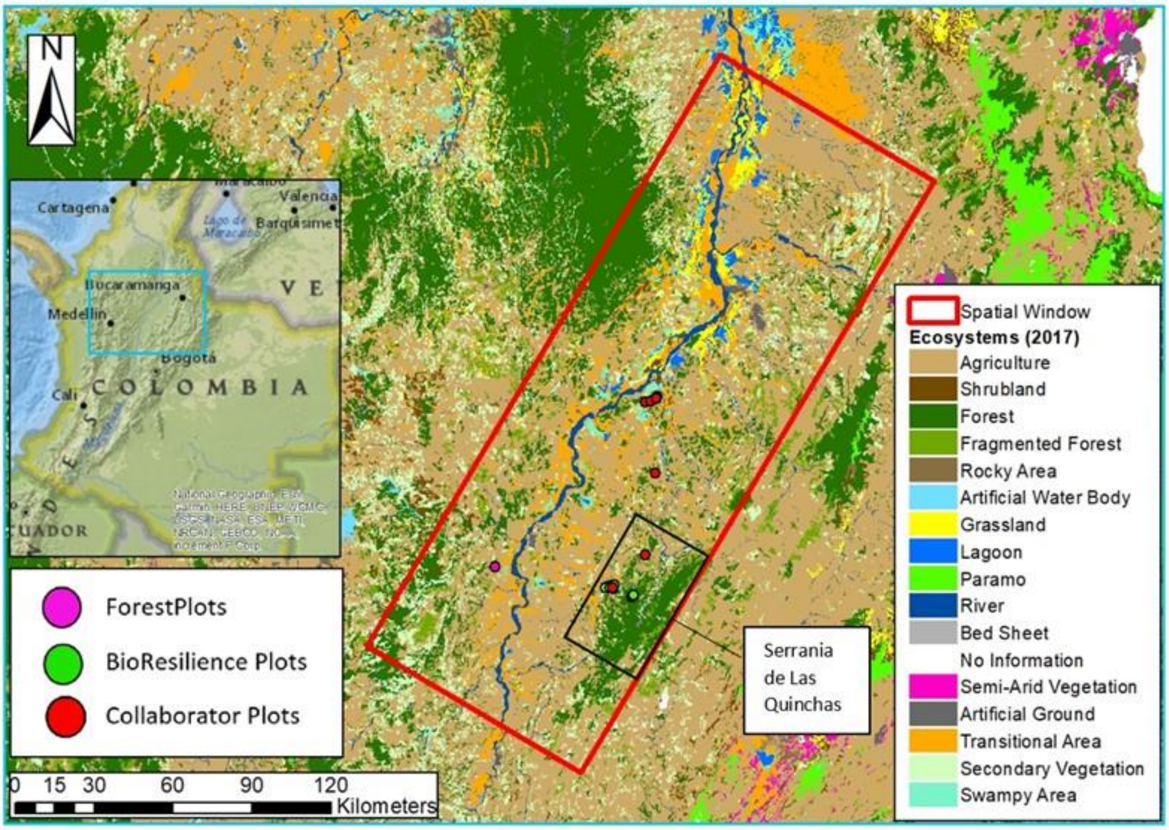


Figure 1.1: Map of study site, including ecosystems present, Serranía de Las Quinchas, and location of forest plots from the BioResilience project, the ForestPlots.net database, and from collaborators (see section 3.2).

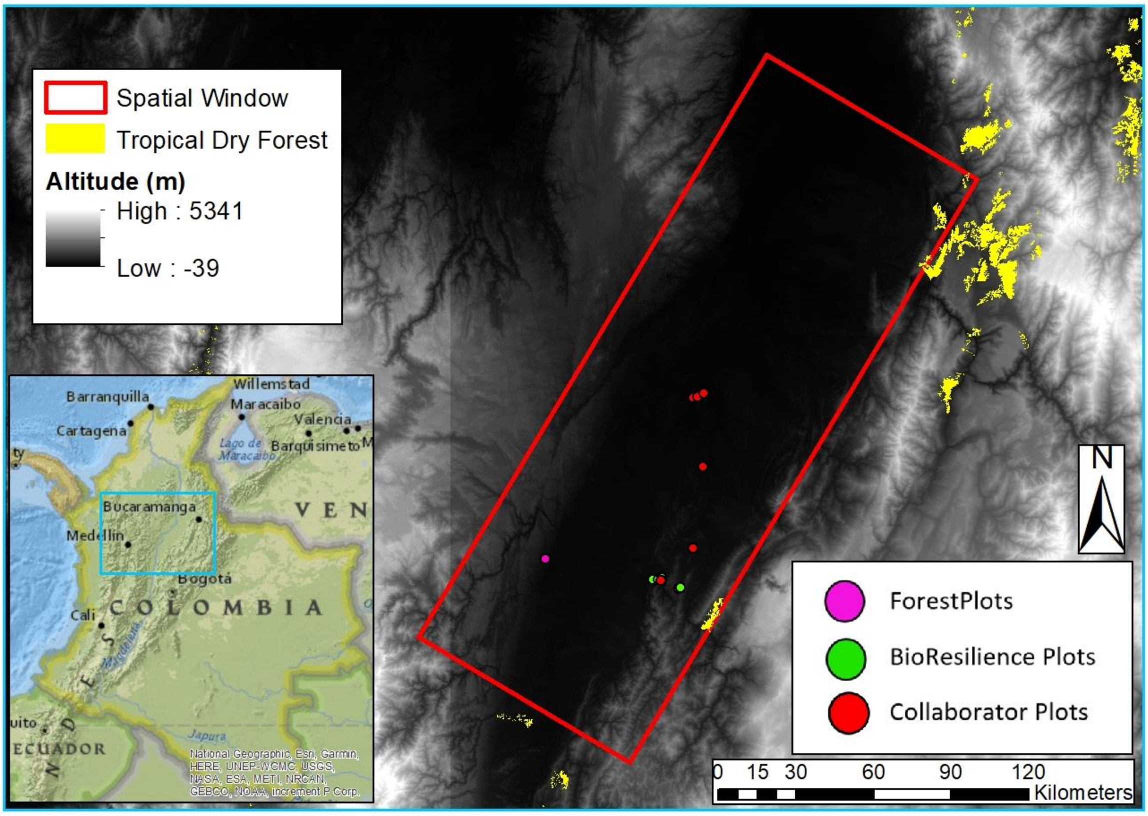


Figure 1.2: Map showing process of identifying study site. Contains digital elevation model and tropical dry forest to aid the identification of a lowland study site containing primarily rainforest. Also includes plot locations.

1.3 The Need for Species Conservation

Many studies analyse deforestation and degradation to Colombian ecosystems, but it is largely unclear how this affects particular plant species that may be in danger of being lost to Colombia (Armenteras et al., 2013; Baptiste et al., 2017). Conservation of Colombian taxa has drawn criticisms that efforts are largely focussed on bird species such as the blue-billed curassow (Rainforest Trust n.d.), and that plant species that often draw less attention, for example from ecotourism, are consequently less protected.

This project, therefore, has selected a variety of plant species to investigate, and will calculate their abundance and distribution over time and test their correlation with multitemporal changes to the landscape. This will demonstrate how efficiently these species are protected, and if this is reflected in their conservation status as measured by the criteria of the International Union for Conservation of Nature (IUCN) Red List.

1.4 The IUCN Red List Assessment

The IUCN is a global environmental union that has produced a system for assessing the global risk of extinction for species. This thesis will analyse data for species deemed important for reasons such as endemism and importance to the traditional economies in the study area of the Middle Magdalena River Valley. In addition, it will provide suggestions for potential adjustments to the conservation status of these species based upon findings and this thesis' measures of abundance and distribution. For species with a distribution larger than the study region, a status will be suggested on the regional scale, but for species to which are located solely within the region this will effectively be a “global” reassessment.

1.5 Aim

To identify correlations between multitemporal land use changes in the Middle Magdalena River Valley and the abundance and distribution of important plant species.

1.6 Objectives

The objectives of this study of the lowland rainforests of the Middle Magdalena River Valley are to:

1. Identify multitemporal land use changes.
2. Calculate the changes in abundance and distribution of important species.
3. Use multivariate statistical modelling to test for correlation between multitemporal changes in the landscape and changes in the abundance and distribution of important species.
4. Provide suggestions for the regional evaluation of the IUCN Red List status of important species.

2. Degradation in Colombia with a Focus on the Magdalena Valley and Studies utilising Geographic Information Systems (GIS): a Literature Review

2.1 The Importance of the Middle Magdalena River Valley and Serranía de Las Quinchas

2.1.1 The Magdalena River Valley's Importance Within Colombia

The Magdalena River is home to 80% of Colombia's population, and its waters provide drinking water for 38 million people (The Nature Conservancy, n.d.). The Magdalena River Valley also provides services associated with its rich flora and fauna (Bernal et al., 2019), that are essential under current scenarios of climate change where increases in the frequency of extreme events such as flooding pose risks to local communities (Romero, 2022; IPCC, 2022). Such ecosystem services include protection against flooding and regulation of sediment yields (Restrepo et al., 2006; Galvis and Iván Mojica, 2007; Moreno et al., 2020), regulation of the water cycle, and provision of food and building materials, among others (The Nature Conservancy, n.d.).

The Magdalena Valley originated 10 million years ago. At this time, the uplift of the Eastern Cordillera of the Andes separated it from the basin of the Orinoco and the Maracaibo (Galvis and Iván Mojica, 2007). The isolation of the valley from nearby basins has promoted speciation and influenced levels of endemism (Galvis and Iván Mojica, 2007). Studies have estimated a level of plant species endemism in the Magdalena Valley of 25-30% (Jørgensen et al., 2011; Rodríguez-Mahecha et al., 2004; Stiles Hurd and Bohórquez, 2000).

Despite mountain uplift, biotic migration to other rainforest areas in Colombia has occurred. Serrano et al. (2021) found that historical migration of lineages to the east and west Andean Cordilleras occurred before and after the uplift of the Andes, suggesting that the valley is and has been connected to other areas of Colombian rainforest such as in the Chocó and Catatumbo (Serrano et al., 2021). This further adds to the significance of the valley, as any negative impacts upon the lowland rainforest in the Magdalena may in the longer term affect other rainforests within Colombia, thus further adding to the need to investigate and conserve the region.

2.1.2 The Importance of the Middle Magdalena Valley

The Middle Magdalena Valley contains lowland rainforest, alluvial plains, and swamps (Pallares and Joya, 2018). This region has, since the 1960s, been among the main centres for pasture development in the valley (Van Ausdal, 2009). Much of this can be attributed to the turbulent mix of settlers, miners, cattle owners, and coca growers in the area (Galvis and Iván Mojica, 2007). How this will change in the coming years remains to be seen, but the onset of peace and the COVID-19 pandemic lockdown in Colombia has intensified the militarisation of coca plant removal, preventing voluntary crop substitutions and leaving rural communities with little income to rely on (Ortiz-Ayala, 2021), therefore contributing to the rural-urban migration pattern (Camargo et al., 2020).

The Middle Magdalena Valley is often neglected in research, with the majority of scientific attention being paid to the lower valley (Galvis and Iván Mojica, 2007). As ecosystems in the middle valley have been rapidly cleared by a variety of industries (Galvis and Iván Mojica, 2007; Ovalle-Pacheco et al., 2019; Van Ausdal, 2009), it is important that the area is researched and sufficiently conserved to prevent the absolute loss of ecosystems containing endangered, endemic, and otherwise important flora and fauna. Therefore, the Middle Magdalena Valley provides a study region that can be investigated, and original findings can be produced. In-turn, research may be used to influence conservation policies within this region, aiding the conservation and restoration of the natural rainforests (van Ausdal, 2009).

2.1.3 The Importance of Serranía de Las Quinchas

Within the Middle Magdalena Valley, Serranía de Las Quinchas is the largest remaining area of lowland rainforest (Link et al., 2012; Amador-Jiménez and Serrano, 2021). Serranía de Las Quinchas is located on the western flank of the Cordillera Oriental range, within the departments of Santander, and Boyacá (Balcázar-Vargas et al., 2000). This area has high species diversity, containing in excess of 1000 plant species and over 380 bird species (Balcázar-Vargas et al., 2000; García-Monroy et al., 2020). In addition to high species diversity, Serranía de Las Quinchas hosts a number of species that are endemic to the valley, including 276 vascular plants and seven bird species (Bernal et al., 2016; Amador-Jiménez and Serrano, 2021).

Currently the fauna and flora of the area understudied, and conservation efforts are largely focussed on birds, such as the blue-billed curassow (Rainforest Trust, n.d.). For instance *Magnolia cespedesii* is endemic to the Magdalena River Valley and insufficient information on changes in its distribution has been gathered to date (Gbif.org, n.d.; Govaerts, 2017). Without sufficient research and protection of its habitat, this species may become extinct due to its limited range. Several plant species in the valley also fall within the IUCN Red List imperilled categories, including *Cedrela odorata* (Mark and Rivers, 2017), *Swietenia macrophylla* (World Conservation Monitoring Centre, 1998b), and *Zamia incognita* (Lopez-Gallego, 2022).

Despite its importance for the survival of species of high ecological importance, Serranía de Las Quinchas now comprises a mixture of rainforest and new pastures (Link et al., 2012). Lowland rainforests throughout Colombia have been rapidly cleared, without legislative control, for several decades (Etter et al., 2006b; Van Ausdal, 2009; BirdLife International, 2018), for both industrial and domestic use (Moreno, 2020). Studies suggest that this has slowed in recent decades, and potentially reached its peak in the 1970s when deforestation and degradation caused by timber and agriculture were applying the most pressure (García-Monroy et al., 2020). The recent history of lowland rainforest deforestation and degradation in Colombia has undoubtably effected Las Quinchas similarly, and thus research and conservation are imperative to ensure the survival of ecosystems that are home to a high species diversity.

For decades, various stakeholders have called for the protection and conservation of the Quinchas ecosystems. In 2003 El Paujíl Bird Reserve was established to protect the habitat of the blue-billed curassow (Quevedo et al., 2005; Amador and Millner, 2019). Also, in 2008, 21,228 hectares of Serranía de Las Quinchas was declared a Regional Natural Park and protected area by the regional autonomous corporation; Corpoboyacá (Amador and Millner, 2019; Amador-Jiménez, 2020). This adds regulations to the region, limiting the use of natural resources and thus preserving the large numbers of endemic and threatened species that reside there such as the blue-billed curassow, and *Magnolia cespedesii*, among many others.

The establishment of protected areas has created problems for the local community in Serranía de Las Quinchas. The limitation of access to natural resources has meant that traditional industries such as agriculture are limited and no longer economically viable and a lack of support from authorities in finding sustainable alternatives has left the communities feeling neglected and pushed out (Ortiz-Ayala, 2021; Moreno, 2020; Amador-Jiménez, 2020; Amador and Millner, 2019). This creates a complex socio-political context, and one that has considerable impact upon communities local to Serranía de Las Quinchas. For conservation policies to be effective, all stakeholders must be considered. This socio-cultural setting influences changes in land use at the landscape level and draws attention towards the effectiveness of conservation measures on a range of important plant species. This may generate potential solutions to problems with conservation policies currently in place within Serranía de Las Quinchas.

2.2 Anthropogenic Activity within Colombia

2.2.1 Degradation Over Time and Factors

Anthropogenic activity and its impacts on biodiversity have increased in Colombia over the last century. In 2003, the Colombian deforestation rate was 600,000 hectares per year, demonstrating the pressure that Colombian ecosystems were under two decades ago (Armenteras et al., 2003). Ayram et al. (2020) used a Legacy-Adjusted Human Footprint Index (LHFI) to evaluate the spatiotemporal variation of this impact between 1970 and 2015. The Human Footprint Index (HFI) is a measure of anthropogenic impact, measured between 0 (no impact) and 100 (extreme impact). Ayram et al. (2020) found that the Human Footprint in Colombia had increased, meaning that, overall, Colombia has been increasingly affected and degraded by anthropogenic activity over this time. Etter et al. (2011; 2006a) quantified this impact, finding that approximately 45% of the terrestrial ecosystems of Colombia have now been cleared of their natural vegetation.

The main driver of deforestation in Colombia is the expansion of agriculture, often directly or indirectly driven by a range of factors such as the five decades of conflict, the coca trade, over-extraction of resources, and socio-economic pressures. Civil conflict began after *La Violencia* between 1948 and 1958 (Felter and Renwick, 2017) when the armed groups FARC (Revolutionary Armed Forces of Colombia) and the ELN (National Liberation Army) were established, and conflict among them, local communities, paramilitary groups and governmental institutions increased. Baptiste et al. (2017) investigated the impacts of the conflict on Colombian ecosystems and found that one million hectares of forest had been lost over five decades. They found that "gun-point land grabbing" has created complex mosaics of land containing patches of natural forest and regenerating areas (Baptiste et al., 2017). Liévano-Latorre et al. (2021) found that 73.1% of FARC-occupied areas had a negative impact on forest cover by deforesting for resources. Contrastingly, armed occupation of forested regions in Colombia can also have a positive impact by preventing economic activity that would otherwise deforest and degrade the land (Prem et al., 2020). Coca cultivation is a significant contributor to degradation, as Colombia is the world's largest coca leaf producer (Moreno-Sanches et al., 2003). Coca leaf farmers can become displaced, often due to conflict, and be pushed into remote, forested areas, subsequently increasing deforestation (Baptiste et al., 2017; Negret et al., 2019).

Many factors have socio-economic roots. For example, the primary cause of degradation in Colombia is the extraction of materials, which is now at a level that exceeds the self-regenerative capacity of environments (Armenteras et al., 2018). This in itself is seen as a result of population pressure influencing the sustainability of natural resource use (Heath and Binswanger, 1996), particularly affecting regions of pervasive socio-economic inequality (Ayram et al., 2020). Extraction of resources is not only to supply local markets, but also for global export, with the greatest proportion of consumption belonging to high-income markets (Malerba, 2020).

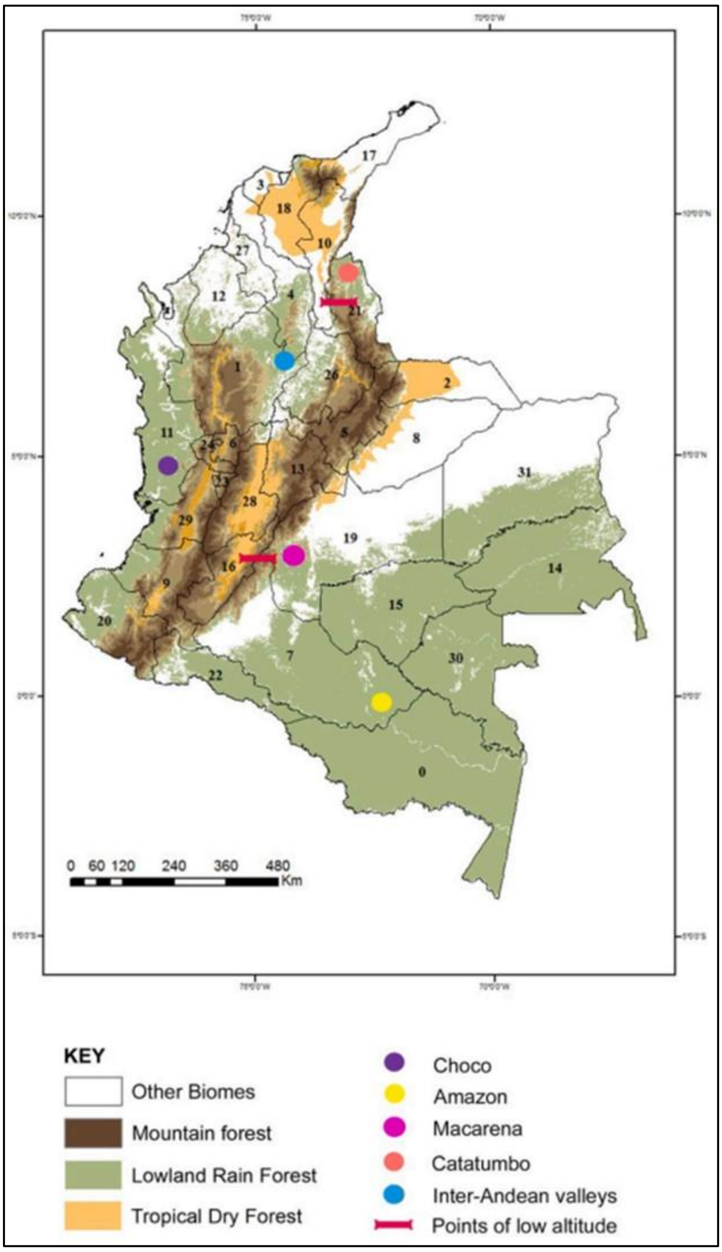


Figure 2.1 displays the main regions of lowland rainforest into the Choco, Amazon, Macarena, Catatumbo, and the Inter-Andean valleys. The Middle Magdalena River Valley contains a large area of lowland rainforest, including Serranía de Las Quinchas, the largest stronghold of lowland rainforest within the valley, as well as other biomes such as pasture that produce a complex ecosystem with conflicting economic interests.

Those national trends in deforestation are also evident in the lowland rainforest biome which has demonstrated a consistent decline (exhibiting an average annual deforestation rate of 1.5% between 1940 and 2000), with pastures being the primary replacement (Etter et al., 2006a; Sanchez-Cuervo and Aide, 2013).

Specifically within the lowland rainforests of the Magdalena River Valley, a significant proportion of intense deforestation and degradation occurred between 1950 and 1980, with nearly 40,000 km^2 of rainforest being removed (Galvis and Iván Mojica, 2007). The largest remaining area of lowland rainforest is located within Serranía de Las Quinchas (Amador- Jiménez and Serrano, 2021), but a significant cause of deforestation and degradation within the Serranía was the take-over of a Texaco oil enclave (formed in the 1940s) by paramilitary groups, increasing deforestation and degradation through illicit agricultural production, trafficking, logging, and the expansion of pastures (Amador- Jiménez and Serrano, 2021). Despite this, areas of well-preserved forest are still present, and natural regeneration by fast-growing plants has begun to naturally occur in some areas (García-Monroy et al., 2020).

2.2.3 Potential Future Deforestation Degradation

The potential future deforestation and degradation of Colombian ecosystems could be decided by the response of various stakeholders to the post-war landscape. Clerici et al. (2020) suggested that deforestation has generally increased post-conflict, with an increase of 177% in six years. This is attributed to the withdrawal of armed groups from remote, forested areas enabling commercial deforestation to recommence where it had previously been prevented (Clerici et al., 2020; Ayram et al., 2020). Subsequently, the establishment of infrastructure to access natural resources in these regions has increased, which has also greatly added to a post-war increase in deforestation (Baptiste et al., 2017).

However, a post-war increase in deforestation and degradation cannot be solely attributed to the withdrawal of armed groups. Negret et al. (2019) suggested that a lack of governance after the signing of the peace accords has increased armed conflict in some areas. The need for resources to fuel these areas of conflict, coupled with the process described by Baptise et al. (2017), Clerici et al. (2020), and Ayram et al. (2020) is undoubtably facilitating a post-war increase in deforestation.

Contrastingly, Amador and Millner (2019) found that Serranía de Las Quinchas has seen a recovery in native fauna and flora in recent years, a trend that had been identified by members of the local community. They attribute this to the demobilisation of paramilitaries and the recent occupation of the army, reducing coca cultivation and cocaine production and allowing for the relict forests to expand.

The full potential of future degradation in Colombia remains to be seen, but the studies examined here present an overall negative trend, with deforestation increasing post-war.

2.3 Conservation and Protection

2.3.1 Past and Present Conservation and Protection Plans

Lack of strong governance in certain administrative areas is exacerbating anthropogenic impacts. Poor governance in frontier regions is facilitating the expansion of agriculture, often driven by an export economy of coca in remote lowland rainforests, and the creation of pastures (Etter et al., 2011).

Governance was once more effective at mitigating anthropogenic damage to ecosystems in Colombia. Between the 1800s and the 1930s, the general location of land clearing was predictable, as land clearing rights were allocated on the basis of individual or collective rights (Etter et al., 2006a). Being able to predict the location of land clearing will in turn help the governance of Colombian ecosystems by ensuring clearance is confined to areas that are of lower biodiversity importance. Unfortunately clearing has been mostly uncontrolled since the 1950s (Etter et al., 2006a).

One form of protection that has seen some success is the establishment of protected areas. Protected areas have been the most common conservation strategy in Colombia (Sanchez-Cuevo and Aide, 2013). Protected areas have been effective with significantly lower deforestation and fires than unprotected areas (Rodriguez et al., 2013). However, this may be due to the majority of protected areas being situated in areas with low rates of economic activities and thus low levels of threat (Sanchez-Cuevo and Aide, 2013). Rodriguez et al. (2013) do suggest that Colombia's protected areas have flaws, finding that protected areas in lowland tropical regions have a higher deforestation rate than protected areas in Andean environments (1.47% and 0.3%, respectively). This may therefore suggest that, although Colombia's application of protected areas has been efficient (Rodriguez et al., 2013), they may be predominantly protecting areas that simply did not require the protection that areas with higher levels of economic activity did. However, the precautionary principle (which allows for the establishment of protected areas in advance of scientific evidence of degradation or deforestation) may mean that regions of lower economic activity are protected to maintain their high conservation values (concentration of endemic species etc., WWF, 2012).

A key aspect of conservation is the socio-economic effects on the local population. Moreno (2020) suggested that when a protected area is established, there is a clear and direct impact on the local population, as traditional means of earning a living must be transformed, and this process is often not supported by local governance. This impact has been felt in the Middle Magdalena River Valley, and specifically within Serranía de Las Quinchas, as outlined below.

2.3.2 Protection of the Middle Magdalena River Valley

There is a dominant theme within literature surrounding the protection of the Middle Magdalena River Valley; that it has, on the whole, not succeeded. Galvis and Iván Mojica (2007) found that most of the Magdalena Valley has not been adequately protected and is now predominantly covered in pastures. The valley is one of the most troubled areas of the country, with a mix of settlers, miners, coca growers, cattle owners, and fishermen (Galvis and Iván Mojica, 2007), each using the land to produce an income in different ways. In part, this was incentivised by the government and international institutions, with the expansion of cattle ranching actively promoted as a means to solve the agrarian problem that the country faced between the 1950s and 1980s (Galvis and Iván Mojica, 2007).

One region within the valley that has seen mixed success with its protection and conservation is the Regional Natural Park of Serranía de Las Quinchas. On the one hand, Serranía de Las Quinchas contains one of the largest inter-Andean lowland rainforests on the eastern bank of the Magdalena River, much of which is mature and well-preserved forest (Link et al., 2012, Bernal et al., 2019; García-Monroy et al. 2020). On the other hand, the situation has been far less favourable for the local community.

Corpoboyacá (the regional autonomous corporation) and the System of Regional National Parks became the two entities assigned as leading administration of the Regional Natural Park (Amador and Millner, 2019). Within Serranía de Las Quinchas, policies are not currently in place to support the transition that local communities must make to forge new, sustainable means of making a living (Moreno, 2020; Amador- Jiménez and Serrano, 2021). The confusing layers of bureaucracy and lack of opportunities has been noted to actively disempower local people, pushing rural communities out of the region, and excluding them from discussions on policy decisions (Amador- Jiménez and Millner, 2019; Amador- Jiménez and Serrano, 2021). It is clear that the institutions in charge of managing the Regional Natural Park in Serranía de Las Quinchas (and in Colombia in general) must put an increased emphasis on providing new, sustainable opportunities for the local populations that can no longer rely on traditional economic activities, and participatory mechanisms that ensure local views, practices and needs are represented during the definition and establishment of protected areas.

2.3.3 Potential Future Adaptations to Colombian Conservation Policy

Changes must be made to increase the protection of important ecosystems and place an increasing emphasis on dealing with socio-economic impacts of policies. In some cases, this is beginning to happen. Amador and Millner (2019), for example, noted that paramilitary demobilisation in Serranía de Las Quinchas is beginning to allow for areas to be occupied by the army, reducing illegal activities and hence going some way to reduce the lack of enforcement protecting conservation areas (see also Clerici et al. (2020)). Despite this, of 39 Colombian national parks, 31 have seen increased degradation post-war (Clerici et al., 2020), demonstrating the need for longer-term systematic changes to the conservation of Colombian ecosystems in addition to stronger enforcement.

Furthermore, there must also be an increase in emphasis on protecting certain ecosystems. For example, Rodriguez et al. (2013) found that deforestation rates inside lowland tropical protected areas are higher than in Andean protected areas (1.47% and 0.3% respectively). Thus, increases in enforcement should be initially focussed on lowland tropical protected areas in an attempt to lower the rate of deforestation. Within the Magdalena Valley, forests connect to rainforests in other regions (see figure 1), thus meaning that any deforestation or degradation there may have knock-on effects elsewhere (Serrano et al., 2021).

Other methods of conservation and protection could be utilised to reverse deforestation and degradation of Colombia’s ecosystems. One of the more intuitive of which is ecosystem restoration, for which Colombia has had a national plan since 2012 (Murcia et al., 2016). Ecosystem restoration involves restoring previously degraded and deforested environments to a more natural state. Ecosystem restoration in Colombia has been largely successful, and the Colombian government have supported the process, initiating 64% of projects and financing 78% in full (Murcia et al., 2016). Ecosystem restoration should not be a replacement for protecting ecosystems in Colombia, as it is notoriously difficult to design criteria for successful ecosystem restoration and equally hard to implement it (Meli et al., 2016). Furthermore, success must also consider if the ecosystem is self-supporting, resistant to future perturbations, and contains significant levels of original species diversity (Ruiz-Jaén and Aide, 2005). When ecosystem protection and ecosystem restoration are used in tandem the positive results are multiplied, reducing the amount of natural land being degraded, and increasing the health of already degraded land.

Additionally, the Colombian government could put emphasis on agroforestry systems (a land use system containing pastures, crops, and trees), providing economic incentives for farmers to maintain them (Jara-Rojas et al., 2020). Not only would this improve the health of ecosystems and encourage a maintenance of biodiversity, but it would also help solve a major criticism of protected areas as noted by Amador and Millner (2019), Moreno (2020), and Amador-Jiménez and Serrano (2021), potentially providing a new and more sustainable method of generating income for the local community. Furthermore, studies have shown that agroforestry systems often produce higher quality crops than monoculture systems, for example coffee (de Leijster et al., 2021).

2.4 IUCN Red List of Threatened Species

2.4.1 The IUCN and Red List Categories

The International Union for Conservation of Nature (IUCN, 2001) is a membership Union that is comprised of governments and civil society organisations (IUCN, 2021). Amongst the work of the IUCN is their Red List of Threatened Species, a list containing risk categorisation of more than 130,000 species (IUCN, 2021). It is widely accepted as the most objective and authoritative system available for making conservation assessments (Vié et al., 2009). Species can be categorised as Extinct, Extinct in the Wild, Critically Endangered, Endangered, Vulnerable, Near Threatened, Least Concern, or Data Deficient (Harris et al., 2012; IUCN, 2021). These categories can be grouped into four, larger umbrella terms: imperilled (Critically Endangered, Endangered, or Vulnerable), not imperilled (Near Threatened or Least Concern), extinct (Extinct, Extinct in the Wild), or Data Deficient (Harris et al., 2012).

IUCN Red List assessments have been used increasingly within national policy and conservation, now informing policy and action in over 100 countries (Rodríguez et al., 2011). In addition, an ever-increasing number of conservation funding bodies request IUCN Red List assessments in their application process (Betts et al., 2020). Red List assessments are seen as imperative for connecting stakeholders, providing vital data for conservation applications, and ensuring conservation actions are taken (Rodríguez et al., 2011; Betts et al., 2020).

However, as the IUCN Red List is a global assessment, national lists often produce differing results because species span national boundaries. For example, Brito et al. (2010) compared the national threatened species lists of Brazil, Colombia, China, and the Philippines to the global IUCN Red List, finding that 20% of the species pool considered in each country have been listed nationally as threatened but had not been globally assessed, and a further 14% of species are considered globally threatened by the IUCN, but not listed as threatened in the national lists.

It is clear that the IUCN Red List of Threatened Species is able to inform conservation actions at a national scale despite potential discrepancies with international lists, and studies have argued for the integration of a similar list for threatened ecosystems. Rodríguez et al. (2011) argued that an IUCN Red List of Ecosystems may more effectively represent biological diversity, and declines in an ecosystem's status may be more apparent than extirpations or extinctions of individual species. The IUCN Red List of Ecosystems has established the categories: Collapse, Critically Endangered, Endangered, Vulnerable, Near Threatened, Least Concern, or Data Deficient (IUCN, n.d.).

2.4.2 Parameters and Criteria for Categorisation

Categorisation of species is decided by parameter thresholds, including distributional range, population size, population size and history, and risk of extinction (Akçakaya et al., 2000; Harris et al., 2012). Within these parameters, certain criteria must be met in order for a species to be classified as Critically Endangered, Endangered, or Vulnerable. These are: a) population reduction (a reduction in a species' population), b) small distribution decline or fluctuation (a species with a small distribution that has seen a decline or fluctuation), c) small population size and decline (a species with a small population that has seen decline), d) very small or restricted (a species with a very small or restricted population), and e) quantitative analysis (where analysis has shown the species is vulnerable or endangered) (Gärdenfors et al., 2001).

The IUCN Red List of Threatened Species assessments can be carried out on regional populations, in which case the assessment process consists of two steps. Firstly, the criteria are applied to the regional population of the species to infer a preliminary categorisation, and secondly, the existence and state of any conspecific populations outside the region that might affect extinction risk within the region are investigated (Gärdenfors et al., 2001). Studies show that this is necessary, as often populations outside of a region may exert a “rescue effect” if their populations are connected, thus increasing chances of the species survival (Brown and Kodric-Brown, 1977; Gärdenfors et al., 2001). In most cases this leads to a downgrade of classification (Gärdenfors et al., 2001).

2.4.3 Uncertainties in the IUCN Red List

The IUCN Red List of Threatened Species has uncertainties of three types (Akçakaya et al., 2000): semantic uncertainty, measurement error, and natural variability. The lack of exact definitions within parameters, such as the use of words such as ‘extreme’, creates semantic uncertainty (Akçakaya et al., 2000). Measurement errors can be created due to a lack of precise information or data for variables, such as the exact number of mature individuals of a species (Akçakaya et al., 2000). Finally, parameters such as extinction risk depend on how a population may change or respond to environmental variation, something that can only be put into probabilistic terms (Akçakaya et al., 2000), thus creating natural variation uncertainty.

However, the IUCN have evolved the Red List to respond to criticisms. Over the past decade, data-driven and objective criteria have been implemented for estimating extinction risk, suggesting that the criteria are now clear and comprehensive, but yet flexible enough to handle uncertainty (Rodrigues et al., 2006). However, there is still taxonomical and geographic bias in the assessment process, largely towards terrestrial vertebrates and plants found in biologically well-studied parts of the world, species that are thought to be threatened, and species with readily available data (Vié et al., 2009).

Furthermore, it is imperative in regional assessments that the geographical context of the population is considered. Gärdenfors et al. (2001) explained that the global criteria need no modification when the extinction risk of an isolated population is assessed, but when a population defined by a geopolitical border or a regional population with occasionally interchanging individuals is assessed, a lack of modification will cause thresholds of the criteria and thus the estimate of extinction risk to be incorrect. To mitigate such issues, assessments are peer reviewed by at least two evaluators (assigned by the relevant Red List Authority) and checked for regional and taxonomical consistency by the Red List Programme Officer (Rodrigues et al., 2006).

The Red List of Threatened Species currently spans just <2% of all known species, and thus is far from complete (Rodrigues et al., 2006). A species' status must be reassessed every ten years, meaning a large increase in budget for IUCN Red List assessments is needed to ensure that the percentage of species assessments that are outdated does not increase, a figure which already stands at 17% (Rodrigues et al., 2006; Rondinini et al., 2014).

2.5 Application of GIS in Deforestation and Degradation Studies

2.5.1 Evolution of GIS in Deforestation and Degradation Studies

Geographical Information Systems (GIS) analyse geographical data, taking it from its rawest to produce outputs, often in the form of maps. GIS has been used within studies of forest degradation for the past 25-30 years (Brown et al., 1994; Reusing, 2000; Feoli et al., 2002), but the way it has been applied has evolved over time, as have the data it analyses, and the software it uses.

One of the earliest studies of forest degradation using GIS was Brown et al. (1994), published only one year after the World Wide Web launched in the public domain (HISTORY, 2020). This study used the software ARC/INFO (released by ESRI on mini-computer in 1982, originally as a command-based programme (Wheeler, 2018)) to calculate land use change and biomass of the forests of Peninsula Malaysia using forest inventories, aerial photographs, and ground measurements (Brown et al., 1994). ARC/INFO is often seen as the first GIS software, and thus was unsurprisingly the dominant software used in forest degradation studies at this time. For example, Reusing (2000) utilised ARC/INFO (in tandem with IDRISI) to calculate the forest cover change of a region of Ethiopia.

These early GIS studies differed in their data sources. For example, Reusing (2000) used Landsat-TM (Thematic Mapper, the sensor used on Landsat 4 and 5: Reusing, 2000) data, whereas Brown et al. (1994) relied on forest inventories and aerial photographs. Landsat is a series of satellites launched by NASA and the US Geological Survey, capturing satellite imagery of the Earth's surface (USGS, n.d.c). Utilising Landsat data allowed Reusing (2000) to digitise forest cover in the region, without relying on the availability of forest inventories.

The usage of satellite data became increasingly common through the early part of the 2000s. Both Feoli et al. (2002) and Riebau and Qu (2005) used satellite data, namely Landsat-TM and Spot, and the Advanced Very High-Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS), respectively. Both studies used images from these satellites to calculate the NDVI (Normalised Difference Vegetation Index) of their regions, a key indicator of vegetation cover and health, measured between 1 (perfectly healthy vegetation) and -1 (barren land). Feoli et al. (2002) investigated many explanatory factors to forest degradation, including slope, precipitation, potential erosion, and altitude. These maps were layered, and administrative boundaries were superimposed over different combinations to work out values within different administrative regions. Interestingly, the superimposing and combining of maps is much closer to the way GIS is applied to studies of forest degradation in the present. Although Riebau and Qu (2005) produced less GIS outputs from their study, satellite data were used more prominently to investigate fire risk and assess forest degradation.

Towards the late 2000s and early 2010s, studies continue to increase their usage of satellite data (most commonly Landsat data) with GIS studies of forest degradation. Within this period, GIS capabilities evolved significantly. Hadeel et al. (2011), for example, used ARC/INFO and Earth Resources Data Analysis System (ERDAS) software to produce land use-land cover (LULC) classifications, supervised classifications, NDVI, and Topsoil Grain Size Index (GSI). This highlights the development of GIS software, from command-based systems in the 1980s to having multiple capabilities towards the 2010s. These studies of 2000s to 2010s increasingly highlighted the potential of GIS to inform conservation and management actions (Panta et al. 2008).

2.5.2 Current GIS Usage in Deforestation and Degradation Studies

GIS-based forest degradation studies have drastically improved because of improvements to data quality and availability, an increase in GIS software capabilities, and an accessibility to software and GIS skills.

For example, Naing Tun et al. (2021) looked at similar patterns and drivers of deforestation to Feoli et al. (2002) but had access to improved satellite data using imagery from Landsat 7 ETM+ (Enhanced Thematic Mapper Plus), Landsat 8 OLI (Operational Land Imager), as well as LISS-3. The resolution of the Landsat ETM+ and OLI sensors is 30m, and LISS-3 sensors produce a resolution of 23.5m. In addition to increased resolution, Landsat ETM+ and OLI sensors capture more bands than earlier sensors (thus aiding land cover detection as different land covers reflect more significantly in different bands of light), with a panchromatic band being as sharp as 15m in resolution (USGS, n.d.b). It is for this reason that many recent studies have utilised this enhanced data source (Panchal et al., 2021; Subedi et al., 2022).

In addition to improvements in data quality, GIS software capabilities have drastically improved. Where early studies relied on pre-processed data and were only able to calculate a mere handful of metrics (e.g. Brown et al., 1994; Reusing, 2000), studies over recent years have conducted their entire analysis chain in GIS software programmes. For example, Pacheco-Angulo et al. (2021) used a 30-year Landsat time series to analyse forest degradation in the Venezuelan Amazon. The Landsat time series was used to map selective logging on the TerraAmazon GIS programme, and additionally validate results, construct forest degradation maps, and estimate aboveground biomass and carbon. Similarly, Subedi et al. (2022) used ArcMap 10.8 for the entirety of their analysis chain, producing thorough and varied measured of degradation over time in the Punarbas Municipality of Nepal.

ArcMap is the descendant of ARC/INFO, a desktop software that contains a myriad of analysis options, and is easy to use, making it more accessible to researchers that may not have a background in GIS. Presently, there are far more software options for GIS analysis. For example, Panchal et al. (2021) utilised ERDAS-Imagine's remote sensing capabilities to perform a supervised land cover classification on the Jaisamand Wildlife Sanctuary in Rajhastan. ERDAS-Imagine provides an intuitive interface for dealing with satellite data, particularly the ability to stack individual Landsat bands, and subsequently perform a supervised classification of land covers on high-resolution data (e.g. Panchal et al., 2021).

2.5.3 Future Applications of GIS in Degradation Studies

One key recent development is the potential for “digital twins” to be used within forest degradation studies. A digital twin is a set of virtual information constructs that fully describes a real or potential environment from the micro-atomic to macro-geometrical level (Jiang et al., 2022a). In other words, a digital twin is an exact virtual copy of a real-world environment. A digital twin consists of five parts: the physical part, the virtual part (of which the physical part is the basis of), connection, data, services (Jiang et al., 2022a). Although largely used at present for city planning and infrastructure modelling, many suggest the concept has applications for forest degradation studies (Wallgrün et al., 2021; Sanchez-Guzman et al., 2022; Jiang et al., 2022a; Jiang et al., 2022b).

A handful of studies have begun to explore digital twins in ecosystems. Wallgrün et al. (2021) used 360° images of forest from drones, and although highly realistic, this was found not to be fully immersive. Building upon the drone footage, a full 3D model of a forest environment was produced, allowing for free movement and providing the capability to adapt the model to realise simulations (Wallgrün et al., 2021). Finally, LiDAR data was used to produce point-cloud models that allowed for the derivation of individual tree models. When this was combined with 360° imagery, Wallgrün et al. (2021) noted that the digital twin had excellent functionality due to the potential to break the forest into individual tree models, but also provides a photorealistic impression of particular points of interest. Finally, the study added an embodied interface within the VR experience, enabling interactive visualisation and quantitative measuring, thus creating a digital twin of a forest environment that can be used by researchers to study a forest without needing to travel (Wallgrün et al., 2021).

In addition to creating digital twins of current environments, the same approach can recreate past environments or simulate future conditions. Jiang et al. (2022b) used Landsat data to create a digital twin of a forest, and then used historical remote sensing data and a model to predict the future state of the ecosystem. Building on this concept, Sanchez-Guzman et al. (2022) created a digital twin of the Cerro Blanco forest in Ecuador, and used it to run fire simulations to predict and prevent future ignition points. It is clear, therefore, that digital twins have the potential to drive GIS application in forest degradation studies, both for research of current environments, and for modelling potential future states of forest environments. However, as noted by Wallgrün et al. (2021), the complexity of the natural world poses additional challenges to built environments, something that must be acknowledged when building digital twins of forest.

3. Methods

3.1 Introduction to Methods

This thesis utilises a variety of remote sensing and GIS methods, as well as calculations of species' abundance and distribution in order to identify correlations between multitemporal land use changes in the Middle Magdalena River Valley and the abundance and distribution of important plant species.

The first step was to choose plant species on the basis of their conservation, economic or social importance. Fragmentation analysis, fractal dimension index mean calculation, and Euclidean distance to nearest neighbour mean calculation were then used to calculate metrics of forest change. These methods were all conducted using remote sensing and GIS and were chosen to investigate the land use change that has occurred in the study site. They are standard methods for measuring changes in forests and have been used in many studies (Imre and Bogaert, 2004; Gasparri and Grau, 2009; Singh et al., 2014; Lamine et al., 2018).

Next, the Human Footprint Index value of the site in each study period was calculated by first conducting normalised difference vegetation index analysis, distance to roads and settlements mean measurements, and mean value of slope calculations. These methods were selected to uncover the anthropogenic impact upon the land and the subsequent changes to land cover and vegetation. When used in tandem with the forest change analyses, they can build a thorough interpretation of multitemporal land use change. The Human Footprint Index is commonly used in similar studies to analyse the extent of anthropogenic impact on the landscape (Etter et al., 2011; Ayram et al., 2020).

Species abundance and distribution was then calculated within each study period to enable correlation tests with the forest change and HFI analyses. Distribution was measured using two methods employed in IUCN conservation assessments (IUCN, 2022), the extent of occurrence (the range of the species in the study site) and the area of occupancy (the area within this currently occupied by the species). Abundance was calculated for each study period as a sum of all the individuals of a species present in that time.

Finally, a generalised linear model was used to identify potential correlations between the multitemporal land use changes and changes in each species' abundance and distribution. This is crucial to provide a statistical conclusion to the aim and objectives of this study.

3.2 Species Rationale

3.2.1 Introduction

Seven plant species have been selected for this thesis. The overarching aim of this is to bring attention to other important species, as conservation in the Middle Magdalena Valley primarily focuses on the bird *Crax alberti* (Rainforest Trust, n.d.), and promote conservation actions that target threats to important plant species. Other reasons why these species have been selected include vulnerability due to distributional range, or value to local communities.

3.2.2 *Cariniana pyriformis*

Cariniana pyriformis is a member of the Lecythidoideae (Brazil nut) family and is native to Colombia and Venezuela, but also occurs in humid tropical forests as far north as Panama (Pelaez et al., 2018). Its IUCN status is Near Threatened (World Conservation Monitoring Centre, 1998a). It is important for its value to local communities as a timber resource.

It is prized for its high-quality wood, used in furniture production, and its bark is also used in the production of rope (World Land Trust, n.d.b). It is also used as a component of agroforestry systems (Pelaez et al., 2018). *Cariniana pyriformis* is known as Colombian mahogany, or abarco.

3.2.3 *Cedrela odorata*

Cedrela odorata is a member of the Meliaceae family and is present throughout northern South America. Its IUCN status is Vulnerable (Mark and Rivers, 2017). It is important for its value to local communities as a timber resource, and its Vulnerable IUCN Red List status.

Cedrela odorata is known as Spanish-Cedar and is the most commercially important species in the genus *Cedrela* (Cintron, 1990). Its importance as a timber resource is global, and it is commonly used in furniture and construction (Cavers et al., 2003). It makes an excellent resource for these purposes, as its aromatic wood is naturally rot- and termite-resistant and thus less susceptible to ailments that effect other timber species (Cintron, 1990; Cavers et al., 2003).

Due to these qualities, *C. odorata* has been severely exploited in Latin America over the past 200 years (Cavers et al., 2003) numbers have continuously declined (Cintron, 1990).

Despite this, *C. odorata* is still widely distributed and considered a ‘climatic generalist’ (Cintron, 1990), growing in both dry and moist soils, most abundantly in lowland regions (Cavers et al., 2003).

3.2.4 *Isidodendron tripterocarpum*

Isidodendron tripterocarpum is a member of the Trigoniaceae and is endemic to Colombia. Its IUCN status is Least Concern (Lopez-Gallego and Morales, 2020). It is important as it is endemic to Colombia and has value to communities as a timber resource.

Isidodendron tripterocarpum was scientifically described in the 1990s. It is thought that this species had been tentatively placed under different names and families, withal under the vernacular name of “Marfil” (Fernández-Alonso et al., 2000). Samples taken from plots in the valley confirmed the new genus and species, *Isidodendron tripterocarpum*, a member of the Trigoniaceae family (Fernández-Alonso et al., 2000).

3.2.5 *Magnolia cespedesii*

Magnolia cespedesii is a member of the Magnoliaceae family and is endemic to the Magdalena River Valley. Its IUCN status is Critically Endangered (Calderon et al., 2016). It’s status as a local endemic gives it an economic importance because it helps to attract ecotourism, and it’s IUCN Red List status of Critically Endangered demonstrates that it is considered highly vulnerable.

Magnolia cespedesii has large, spherical fruit; making it similar to many of the *Magnoliaceae* family (Aguilar-Cano et al., 2018).

3.2.6 *Microdesmia arborea*

Microdesmia arborea is a member of the Chrysobalanaceae family and is distributed from Mexico to Southern Tropical America. Its IUCN status is Least Concern (Condit, 2021). It is important as a timber and oil resource for local communities.

M. arborea can grow up to 25m in height and 60cm in diameter (Ríos-García et al., 2014). It is a multi-use species, often being used as timber, and its fast-drying oil being used in paints (Prance, 2021; Ríos-García et al., 2014).

The species was once known as *Licania arborea*, leading to potential issues when collating the full occurrence record of *Microdesmia arborea*.

3.2.7 *Swietenia macrophylla*

Swietenia macrophylla is a member of the Meliaceae (mahogany) family and naturally occurs in Amazonia, Colombia and northern Venezuela. Whilst it is cultivated in plantations across Central America and southeast Asia (World Land Trust, n.d.a), its IUCN status is Vulnerable (World Conservation Monitoring Centre, 1998b). It is important for the value of its rich timber as a resource for local communities.

Swietenia macrophylla is commonly known as “big-leaf mahogany”, due to its large leaves which can grow up to 50cm in length (Global Trees Campaign, 2020). It is a highly sought-after species due to its rich, red timber – true mahogany – which is used for furniture, panelling, and musical instruments (Global Trees Campaign, 2020). *Swietenia macrophylla* regenerate by shedding seeds into clearings, which makes it vulnerable because logging operations will selectively remove all seed sources (i.e., the largest trees) and allow competing vegetation to prosper (Snook, 1996; Global Trees Campaign, 2020).

Due to the ‘rush for red gold’ and subsequent over-exploitation by logging operations, global populations of *S. macrophylla* have declined by up to 70% since the 1950s (Global Trees Campaign, 2020). A change to current harvesting practices, such as a switch to a silvicultural management practice, will allow for increased regeneration (Snook, 1996).

3.2.8 *Zamia incognita*

Zamia incognita is a member of the Zamiaceae family and is endemic to the Magdalena River Valley. It is a cycad (a non-flowering plant). Its IUCN status is Endangered (Lopez-Gallego, 2022) and was given its first classification in 2020. It is important as a regional endemic and endangered species, which lends importance to the ecotourism industry.

Zamia incognita was scientifically described in 2009 after taxonomic and nomenclatural clarifications provided additional knowledge on the South American *Zamia* (Lindström and Idárraga, 2009). Knowledge of *Zamia* is incomplete; few specimens have been collected due to the inaccessibility of many habitats, and some species have been described from a single cultivated individual (Lindström and Idárraga, 2009).

Zamia incognita is found in shaded areas on well-drained hills surrounded by moist tropical forest of an elevation of between 200m and 500m (Lindström and Idárraga, 2009). Several populations of *Z. incognita* are known (historic and current), however, most are not included in protected areas and deforestation is a significant threat, meaning that once dense populations are now often severely disturbed (Lindström and Idárraga, 2009). Studies published before *Z. incognita* was first classified in 2020 suggested an IUCN Red List status of 'Vulnerable' (Lindström and Idárraga, 2009), suggesting that the species is in decline.

3.2.9 Summary

Species	Family	Distribution	IUCN Status	Importance
Cariniana pyriformis	Lecythidoideae	Colombia and Venezuela (up to Panama in humid areas).	Near Threatened	Economic value as a timber resource.
Cedrela odorata	Meliaceae	Northern South America	Vulnerable	Vulnerable and has value as a timber resource.
Isidodendron tripterocarpum	Trigoniaceae	Colombia	Least Concern	Colombian endemic and has economic value for timber.
Magnolia cespedesii	Magnoliaceae	Magdalena River Valley	Critically Endangered	Critically Endangered, endemic, economic value for ecotourism due.
Microdesmia arborea	Chrysobalanaceae	Mexico to Southern Tropical America	Least Concern	Economic value as a timber and oil resource.
Swietenia macrophylla	Meliaceae	Amazonia, Colombia and Northern Venezuela (plantations in Central America and South-East Asia).	Vulnerable	Vulnerable and rich timber has economic value.
Zamia incognita	Zamiaceae	Magdalena River Valley	Endangered	Endemic, endangered and value for ecotourism.

Table 3.1: Table showing a summary of key deciders of importance for this thesis, including distribution, IUCN Red List of Threatened Species status, and how they are important for local communities.

Species	Photograph	Reference
Cariniana pyriformis		World Land Trust. n.d.b. Colombian Mahogany - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/colombian-mahogany/> [Accessed 6 October 2021].
Cedrela odorata		World Land Trust. n.d.c. Spanish Cedar - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/spanish-cedar/> [Accessed 6 October 2021].
Isidodendron tripterocarpum		iNaturalist.ca. n.d. *Isidodendron tripterocarpum*. [online] Available at: <https://inaturalist.ca/taxa/887361-Isidodendron-tripterocarpum> [Accessed 6 October 2021].

Magnolia cespedesii		Gbif.org. n.d. Occurrence Detail 436999488. [online] Available at: <https://www.gbif.org/occurrence/436999488> [Accessed 6 October 2021].
Microdesmia arborea		Wikispecies. n.d. *Microdesmia arborea* - Wikispecies. [online] Available at: <https://species.wikimedia.org/wiki/Microdesmia_arborea> [Accessed 6 October 2021].
Swietenia macrophylla		World Land Trust. n.d.a. Big-Leaf Mahogany - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/big-leaf-mahogany/> [Accessed 6 October 2021].
Zamia incognita		World Land Trust. n.d.d. *Zamia incognita* - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/zamia-incognita/> [Accessed 6 October 2021].

Table 3.2: Table showing a photograph of each plant species, and the associated reference.

3.3 Data

3.3.1 Plot Data

Nine 0.5 Ha plot inventories were provided by the BioResilience project (Serrano et al. 2021), eight 1 Ha plot inventories were provided by collaborators in Colombia (Stevenson, 2011; 2012), and a 1 Ha plot inventory were downloaded from ForestPlots.net (Lopez-Gonzalez et al., 2009; Lopez-Gonzalez et al., 2011). Additional data from botanical collections was provided by Álvaro Idárraga. All open-access ForestPlots plot coordinates for Colombia were checked using Google Earth to ensure only plots within the spatial window of this project were used. One suitable plot was identified: Puerto Nare (PTN-01) from Esteban Álvarez Dávila and collaborators. Plot locations can be seen within figure 1.1. These plot inventories were measured and recorded using the RAINFOR fieldsheet template (RAINFOR, 2021). Trees were given preliminary identifications in the field by the plot teams. Voucher specimens were subsequently identified by comparison with collections in regional and national herbaria in Colombia. Table 3.3 presents an overview of plot information.

Plot Code	Principal Investigator	Area (ha)	Minimum DBH (mm)	Year of Establishment	Recensus Year	Vegetation Classification	Altitude (m)	Latitude	Longitude
BR_QUIN_T1.1	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2006	2019	Terrafirme	441	6.0223	-74.1988
BR_QUIN_T1.2	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2006	2019	Terrafirme	351	6.0184	-74.2047
BR_QUIN_T1.3	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	222	6.0468	-74.2671
BR_QUIN_T2.1	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	219	6.0473	-74.2673
BR_QUIN_T2.2	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	216	6.0463	-74.2659
BR_QUIN_T2.3	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	289	6.0484	-74.2950
BR_QUIN_T3.1	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	195	6.0536	-74.2736
BR_QUIN_T3.2	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	220	6.0485	-74.2777
BR_QUIN_T3.3	Julieth Serrano, Toby Pennington, Ted Feldpausch	0.5	50	2019		Terrafirme	218	6.0565	-74.2644
PS Lusitania	Pablo Stevenson	1	100	2019		Terrafirme	166	6.4404	-74.1227
PS Flooded, El Paujil	Pablo Stevenson	1	100	2021		Flooded	206	6.1595	-74.1570
QUIN_TF_1	Pablo Stevenson	1	50	2006		Terrafirme	200	6.0468	-74.2683
QUIN_TF_5	Pablo Stevenson	1	50	2006		Terrafirme	200	6.0470	-74.2660
LEA-14	Pablo Stevenson	1	100	2010		Flooded	100	6.6827	-74.1570
LEA-15	Pablo Stevenson	1	100	2010		Flooded	100	6.6858	-74.1393
LEA-16	Pablo Stevenson	1	100	2010		Terrafirme	100	6.7020	-74.1165
LEA-18	Pablo Stevenson	1	100	2010		Terrafirme	100	6.6970	-74.1200
PTN-01 (ForestPlots)	Esteban Álvarez Dávila	1	100	2010		Terrafirme, mixed	230	6.1200	-74.6700

Table 3.3: Table showing plot information and locations. Minimum DBH refers to the minimum diameter measured at breast height.

3.3.2 Land Cover Data

Land cover data was downloaded from the SIAC (the Environmental Information System of Colombia) data catalogue (SIAC, 2022) for the whole of Colombia for the years; 2000-2002, 2005-2009, 2010-2012, 2018. These data were created and provided by the Institute of Hydrology, Meteorology and Environmental Studies, which is based in Colombia's capital, Bogotá (IDEAM, n.d.). Imagery was captured by Landsat 8, meaning that they have a high resolution of 30m (USGS, n.d.b). SIAC publish the data in time slices such as 2000-2002, instead of having one dataset that is updated when new data is available. This meant that comparable data was unavailable for 2003-2004, and 2013-2017.

3.3.3 GBIF Data

To calculate metrics of species distribution and abundance, a comprehensive dataset of species occurrences, including location and date of record, was downloaded for each species from GBIF (Global Biodiversity Information Facility). GBIF is an international network and data infrastructure that is funded by national governments around the world (GBIF.org., 2022). GBIF contains an open-source occurrences catalogue, in which a species can be searched, and a complete list of occurrences can be downloaded.

RStudio (RStudio Team, 2021) code was used to handle GBIF data to extract: species name, species key, latitude, longitude, type of record, scientific name, taxon rank, continent, geodetic datum, country, nomenclatural status, record number, dataset name, collection code, name of data recorder, date the occurrence was identified, and who it was identified by. CSV files were produced that contained the occurrence information for each species and saved to the working directory and named after the species in which their occurrences were based.

CSV files were added into the ArcMap document, and a basemap from ArcMap's basemap library was added to help visualise occurrence location. This process was repeated for all species, and the symbology of the point data (described by ArcMap as "Event" data of the CSVs) were changed and a legend produced to identify which points belonged to each species. This allowed preliminary analysis of species distribution.

As this project investigates changes to the Middle Magdalena River Valley on the abundance and distribution of the species, datasets had to be clipped to the study site to prevent inaccurate conclusions being reached. This was done for all species by using the 'Clip' tool on the points in ArcMap, and then by exporting them as a new CSV file containing just occurrences within the region.

It is possible that any identified increases in a species' distribution may be the result of increased botanical collection and publishing on GBIF as existing, but previously unidentified individuals appear to be new. This is a caveat that will be noted in the conclusion of this thesis.

3.4 Forest Change

3.4.1 Fragmentation Analysis

Fragmentation analysis using GIS techniques aids the identification of landscape degradation and fragmentation patterns. When examined over time, fragmentation analysis can provide a clear picture of land cover change and any patterns of forest loss or conversion. This thesis uses fragmentation analysis and the FRAGSTATS software (McGarigal, 1995; Singh et al., 2014; Lamine et al., 2018) to study the effect of multitemporal changes to the Magdalena River Valley on a range of important plant species.

IDEAM land cover data (IDEAM, n.d.; SIAC, 2022) was added to an ArcMap document for the study periods of 2000-2002, 2005-2009, 2010-2012, and 2018. The land cover data was clipped to the size of the study site to speed up subsequent analysis. The projection (the coordinate system) of the land cover shapefile was changed from WGS_1984 (a degree-based projection) to Bogota_UTM_Zone_18N (a metre-based projection) for subsequent analysis. Land cover data was then converted to raster form with a cell size of 50m to maintain the data's high resolution without compromising the software's efficiency and loading times.

The final step before fragmentation analysis was to reclassify the new raster data as either forest or non-forest. This project looks at multitemporal changes to the landscape of the Middle Magdalena Valley and therefore it was decided that conducting fragmentation analysis on forest in the study site and comparing this over time was the most suitable approach to allow fragmentation analysis to be carried out on any land class. Classes that were deemed as "forest" were *bosque denso* (dense forest), *bosque fragmentado* (fragmented forest), *bosque abierto* (open forest), and *bosque de galería y ripario* (gallery and riparian forest) and given the value of 2. All other classes were designated as non-forest and given the value of 1, including *plantación forestal* (forest plantation) as this was deemed as unnatural and changes to this class may skew results. Once this analysis was run, a new raster file was produced, with forest given one colour and non-forest given another. This was signified in the Table of Contents with a legend showing which value (1 or 2, and thus non-forest and forest respectively) belonged to each colour.

When the raw IDEAM land cover data had been processed and converted into the exact format and specifications needed to conduct the fragmentation analysis, FRAGSTATS (McGarigal, 1995) was used to produce an outputted file that categorised land classes as core forest of <250 acres, 250-500 acres, and >500 acres, patch forest, edge forest, or perforated forest. The reclassified file was inputted to ArcMap and the edge width was set to 50m (the cell size of the file). Edge width (the width from the perimeter of the forest inwards that cells are classed as in the edge of the forest) is a user-assigned variable. 50m was assigned as the edge width as any smaller would not compute (due to it being lesser than the cell size) and any larger was deemed unsuitable as it may disguise small patches of core forest.

The process was repeated for all study periods (2000-2002, 2005-2009, 2010-2012, 2018). By multiplying cell count by the cell size, the area of each forest category for each study period was calculated.

3.4.2 Fractal Dimension Index

The fractal dimension index is an index of the complexity of shapes within a landscape (O'Neill et al., 1988). Fractal dimension index (FDI) is estimated by regressing polygon area against perimeter for a given shape. It is related to the slope of the regression (S) by the relationship: FDI = 2S (O'Neill et al., 1988). An ecosystem's fractal dimension index value has been found to be correlated to anthropogenic disturbance and habitat fragmentation and it has been used for various habitat types (O'Neill et al., 1988; Imre and Bogaert, 2004). The fractal dimension index can vary from 1 to 2, with 1 representing a perfect square (and hence a very regular shape) and 2 representing an extremely complex shape with zero autocorrelation (O'Neill et al., 1988; Turner and Ruscher, 1988). Simpler shapes possess a lower fractal dimension index value and are often found in anthropogenic landscapes where patterns are defined and natural landscapes are diminished, where-as more irregular and random shapes with a higher fractal dimension value are likely to be the result of natural (and hence random) processes, characteristics of a less disturbed landscape (O'Neill et al., 1988).

The fractal dimension index of forest within the Middle Magdalena River Valley (see figures 1.1 and 1.2) of each study period (2000-2002, 2005-2009, 2010-2012, 2018) was calculated and compared to investigate levels of anthropogenic disturbance and fragmentation, and thus aid the discovery of multitemporal changes to the landscape. It is a given as a mean value for the whole landscape.

Values were calculated for each fragmentation analysis output, providing the fractal dimension index value for only the forest of each year. Furthermore, the fragmentation analysis output separates the forest in the region into different classes of core, edge, patch, and perforated forest, and thus calculating the fractal dimension index values of each class enabled a more detailed investigation into how the forest in the region has changed over time. The tool catalogue on ArcGIS Hub (ESRI, n.d.a) was used to identify an external toolbox utilised for this calculation. The most appropriate toolbox was the Vector-based Landscape Analysis Tools Extension (V-LATE 2.0, Lang and Tiede, 2003) due to the provision of many landscape metrics that are divided into seven categories: area, form, interior, edge, proximity, diversity, and subdivision analysis (Tiede, n.d.). Within the ‘form’ category of the V-LATE extension, the fractal dimension index can be calculated.

Each fragmentation analysis raster output was converted into a polygon. Data in raster format consists of a grid of cells; contrastingly, the polygon format is used to represent areas and perimeters, the focus of this analysis (Dempsey, 2021). The V-LATE extension then calculated the area and perimeter of each polygon, from which the mean fractal dimension index value of the forest, as well as separate values for each forest class, were calculated.

Outputs for the fractal dimension index calculations using the V-LATE 2.0 extension for ArcMap were provided in numerical form. The outputs were extracted to an Excel table for further analysis. This process was then replicated for 2005-2009, 2010-2012, and 2018, and again tabulated for comparison.

3.4.3 Euclidean Distance to Nearest Neighbour

The final section of the fragmentation analysis was the Euclidean distance to nearest neighbour calculation, a form of spatial analysis that calculates an average distance between neighbouring areas of a given land classification. The average distance between neighbouring forest cells was calculated as it is an effective method of identifying deforestation patterns. For example, Gasparri and Grau (2009), found a clear correlation between an increase in Euclidean distance to nearest neighbour of forest patches and increasing deforestation. This measure is rather intuitive because, if deforestation is occurring and forest is being removed, the average distance between two neighbouring forest cells is likely to increase.

This analysis was conducted on ArcMap and built upon the fragmentation analysis, using its output as the input of this calculation. The 2000-2002 fragmentation analysis raster was first transformed into a polygon because the tool calculates distance, thus data in polygon format is more suitable than the grid-based raster format (Dempsey, 2021). The polygon layer was inputted to the 'Average Nearest Neighbour' tool to calculate Euclidean Distance, the straight-line distance between two points, enabling a straight-line average of distance between nearest neighbours of forest (Danielsson, 1980). This tool was selected as it calculates the nearest neighbour distance between closest features of a class. Given the nature of the data, this was between closest cells of forest. Outputs were produced in the form of mean distance, z-scores, and p-values, and repeated for all time periods (2000-2002, 2005-2009, 2010-2012, 2018). The z-score and p-value are a measure of statistical significance, showing if the average distance between cells of forest is not randomly distributed. This value is given as a mean across the whole landscape.

The same analysis was run for core and patch forest classes to allow for a more thorough investigation into landscape patterns in the forest and for the simplified identification of any processes of degradation or regeneration that might be occurring. If core forest reduced, for example, there would be an increase in forest patches, thus potentially reducing the mean distance between neighbouring forest cells as what were a few large gaps between clumps of forest would be transformed into numerous smaller gaps between smaller patches of forest.

After analysis was run on all years for whole forest, core forest, and forest patches; values were extracted and tabulated in Excel. Values were then standardised in order to produce a graph comparing the trajectory of values for the whole forest, core forest, and forest patches over time.

3.5 Human Footprint Index

3.5.1 Normalised Difference Vegetation Index

Normalised Difference Vegetation Index (NDVI) is a key indicator of the cover and health of vegetation and is derived from the ratio of near-red light reflection to near-infrared reflection, measured by satellite (Myeni et al., 1997). The NIR-red ratio relates to vegetation as chlorophyll absorbs red light, and the mesophyll leaf structure scatters NIR (Pettorelli et al., 2005). NDVI is expressed on a scale of -1 to 1, from barren land to a cover of healthy vegetation (Myeni et al., 1997). Thus, if more red light is being absorbed by chlorophyll, and more NIR is being scattered by the mesophyll leaf structure, the NDVI will increase towards 1 and indicate that vegetation is present and photosynthesising, an indication of good health (Myeni et al., 1997; Pettorelli et al., 2005).

The NDVI methodology relied on raw satellite imagery. USGS Earth Explorer (USGS, 2022) was used to download Landsat 7 imagery with a spatial resolution of only 15m (NASA, n.d.). The recent Landsat 8 and, as of 2021, Landsat 9 have overtaken Landsat 7, but were not launched by the start of this project's period of study - and thus Landsat 7 is an appropriate choice for this thesis. Data was downloaded in its raw multispectral form, a zip-file (GeoTIFF) containing images of the study region in all spectral bands (in .TIFF format), for each time period (2000-2002, 2005-2009, 2010-2012, 2018). Data was extracted from the GeoTIFF file using the 7-Zip application (Pavlov, 2022) as the GeoTIFF downloads as a .TAR file, a type of archive file that 7-Zip is capable of opening.

All images in all spectral bands were uploaded into ERDAS-Imagine and merged into one composite, multispectral image using the 'Stack' feature. Every band (1-8) was stacked except band 6, due to it having a lower resolution than the other bands.

NDVI analysis was run on ERDAS-Imagine, using the NDVI tool and the multispectral image with bands assigned to NIR (Near-Infrared) and Red electromagnetic bandwidths. To ensure that NDVI outputs were accurate and reliable, Landsat 7 bandwidths were researched and the appropriate band to assign to NIR and Red was confirmed. Landsat 7's ETM+ instrument contains eight spectral bands, with the Red band being categorised as band 3, and the NIR band being designated band 4 (USGS, n.d.a). Therefore, NIR was set to band 4, and Red was set to band 3.

The output of the analysis was provided by ERDAS-Imagine as an NDVI shapefile, a map of the region in a monochrome variable colour scheme, with 1 being white, -1 being black, and anything in between from light to dark as values get lower and more negative. The outputted shapefiles were added to an ArcMap document. The mean

NDVI value was extracted to be able to use in subsequent analysis, such as the GLM model. Steps were repeated for all time periods of this study (2000-2002, 2005-2009, 2010-2012, 2018).

3.5.2 Distance to Settlements and Roads

The distance to settlements and roads was chosen as part of the Human Footprint Index calculation, based on previous work where a positive correlation between road proximity and deforestation was found, due to road development increasing the accessibility of previously unreachable areas (e.g., Sader and Joyce, 1988). This correlation was further confirmed by Mas et al. (2004) who used GIS to map deforestation and road development and found that deforestation rapidly decreased when further from roads. In addition to roads, distance to settlements was also calculated. In Colombia specifically, proximity to settlements is a proxy to identify areas likely to be deforested (Forman, 1995; Geist and Lambin, 2001; Etter et al., 2006b) because increasing accessibility to remote forest regions allows increased deforestation and degradation. Thus, both distance to roads and settlements (from forest regions) was calculated, to ensure that the HFI value was calculated with the greatest number of relevant variables.

This analysis took place on ArcMap and used the land cover map shapefile from IDEAM that was also used for the forest change analysis (SIAC, 2022), because it has accurate land cover data of a high resolution, thus providing an excellent data source to identify and isolate roads and settlements. The first step identified which land cover classes were “roads” and “settlements”, which meant translating land cover classes from Spanish to English. The following classes were designated “road”: *red vial* (road system), and *aeropuerto* (airports). The following classes were designated as “settlement”: *instalaciones recreacionales* (recreational facilities), *zonas industriales* (industrial zones), *tejido urbano continuo* (continuous urban region), and *tejido urbano discontinuo* (discontinuous urban region). These classes represented those that best fit “road” and “settlement”, without containing other sub-classes that would produce misleading results.

The land cover shapefiles for each study period were clipped to the study site converted from a shapefile into a raster dataset. The newly rasterised data were reclassified (first for 2000-2002, then for each of the remaining study periods), setting each “road” class to 2, each forest class (with the same defined classes for forest as in the fragmentation analysis methodology) to 1, and the remaining classes to “NoData”. The reclassified file was added into the ArcMap document. This was repeated for 2005-2009, 2010-2012, and 2018. The reclassification was repeated on the clipped raster for settlements, setting each “settlement” class to 2, forest class to 1, and the remaining classes to “NoData” as before. The result was eight reclassified raster datasets representing for each study period a road and forest reclassification, and a settlement and forest reclassification.

The ‘Near’ tool on ArcMap was used to calculate proximity information between input features and the closest features in another layer (ESRI. n.d.b). This tool was chosen as it provided an output outlining distance between pixels of road (or settlement, depending on which reclassified raster was being analysed), and of forest. The output provided by the tool was a long list of distances between every cell of road/settlement and every cell of forest that was added to the attribute table of the reclassified raster. The ‘Summarise’ feature within the attribute table was used to simplify this into an output that could be used for the Human Footprint Index and Generalised Linear Model. Within the Summarise menu, data was summarised by Gridcode to simplify outputs into an average distance based on class and set to including NIVEL3 (the class name) and the Near output. This produced a new summary table outlining the average distance from a cell of forest to a cell of road/settlement depending on which reclassified raster was inputted, which was extracted into an Excel table. This analysis was repeated for each of the eight reclassified raster datasets.

3.5.3 Mean Values for Slope

The degree of slope on which forest patches are present plays an important role in deciding their fate. For example, in Sumatra, Kinnaird et al. (2003) found that lowland forests on gentle slopes were removed sixteen times as swiftly as forests on steep slopes largely due to accessibility, as conversion of forest on steep slope to agriculture is far more difficult than converting forest on a gentle slope (Kinnaird et al., 2003). Bavaghar (2015) used a logistic regression model to test this relationship and found that the probability of deforestation was “significantly” determined by slope and followed a negative correlation.

To calculate average slope, data must include altitude as well as longitudes and latitudes. A Digital Elevation Model (DEM) was used here which is a dataset that reflects topography and includes information on longitude and latitude, and crucially, altitude. A DEM for Colombia was identified within the Colombian data library, IGAC (The Agustín Codazzi Geographic Institute), with a 30m resolution and topographic coverage of the entire country (IGAC, 2011). Data were downloaded using STRM (2022) in 5x5 degree tiles in .TIFF format, to reduce file size, and added into ArcMap.

DEM data were stitched into one DEM of the study site using ArcMap’s ‘Merge’ tool. Next, the IDEAM land cover data for each time period was added to the ArcMap document, clipped and converted to raster. Land cover raster files were reclassified using the ‘Reclassify’ tool as either forest (the classes that were assigned to this were kept consistent with the fragmentation analysis and distance to roads and settlements analyses) and given the new value of 1, or non-forest and classified as "NoData". This process, although identical to that adopted in the fragmentation analysis, was repeated as the data projection had not been changed from the standard degree-based WGS_1984 (unlike the fragmentation analysis where it was converted into a localised, linear-unit-based projection). The projection was kept as default for two reasons, firstly because the subsequent analysis did not require data to be of a linear format, and secondly because slope would be given in degrees and thus matched the default projection.

The 'Extract by Mask' function was used to clip the DEM to the extent of the 2000-2002 reclassified raster. As the raster was reclassified as either 1 (forest) or NoData (anything else), the outputted DEM was clipped to the forest extent of the study region. This process was repeated for each study period, thus producing four DEM's, clipped precisely to the extent of forest in each time period.

The 'Slope' tool was used to produce a map of slope (in degrees) of forest topography for all study periods. The four outputs (slope maps for 2000-2002, 2005-2009, 2010-2012, and 2018) were added to ArcMap and in turn their symbology was changed to a "Classified" scale, producing a scale of colour corresponding to a different level of slope (e.g. <5 degrees, 5-10 degrees, etc.). As well as visual representations of slope, the minimum, maximum, mean, and standard deviation of slope (in degrees) of each study period were extracted and added to an Excel table.

3.5.4 Human Footprint Index Value

The Human Footprint Index (HFI) is measured between 0 and 100, with 0 signifying that the landscape is not impacted by anthropogenic activities, and 100 indicating extreme impact upon the landscape (Ayram et al., 2020). The formula is: HFI = (sum of standardised variables values/number of variables)*100. As measures of human impact, NDVI, distance to roads, distance to settlements, and mean values for slope were included in the HFI calculation following evaluation of Etter et al.'s (2011) and Ayram et al.'s (2020) HFI equations and extracting the factors most suited to the specific geographic and spatial context of the Middle Magdalena River Valley. This decision also depended on the availability of data, with factors such as soil fertility being unattainable for the study site.

NDVI, distance to roads, distance to settlements, and mean values for slope were standardised using the min-max standardisation method:

estd = (x-min)/(max-min)

esti = 1-abs((x-min)/(max-min))

Variables were standardised according to their effect on the HFI, with "direct" variables (those that have a positive correlation with the HFI) being inputted into the direct min-max equation (*estd*), and those that are "indirect" variables being added to the indirect min-max equation (*esti*). Next, the standardised values were summed, and an average was calculated by dividing the sum of variables by the number of variables (in this case, four). The output was multiplied by 100 to give a HFI score. This method was repeated for all study periods.

3.6 Species Metrics

3.6.1 Abundance

Species abundance is a fundamental ecological parameter for conservation and biodiversity studies, but it is notoriously difficult to determine unless at a very fine and localised scale (He and Gaston, 2000). Current species abundance methods can be split into two groups: occupancy-area relationship methods and occupancy-abundance relationship methods, where occupancy-area relationship methods scale occurrences to the scale of the map, and occupancy-abundance relationship methods model abundance in terms of direct occupancy (Yin and He, 2014).

The occupancy-abundance relationship method was used, and abundances were calculated by summing the number of occurrences of each species within the study site (as a total number from GBIF and plots), in each study period. Species occurrence data was filtered to produce a separate occurrence file for each study period of the project. This was done by filtering by date and habitat constraints, examining when occurrences were recorded and using the IDEAM land cover data to deduce whether the individual was likely to still be present, or whether it had been removed by deforestation. This produced four occurrence datasets (2000-2002, 2005-2009, 2010-2012, 2018) for each of the seven species.

3.6.2 Extent of Occurrence

The extent of occurrence (EOO) is a variable used by the IUCN to determine changes in species distribution and classify taxa within the Red List of Threatened Species (IUCN Standards and Petitions Committee, 2022). The EOO can be calculated using the convex hull method. This method envelopes the occupied environment of a species by creating a convex shape surrounding all distribution points (Capinha and Pateiro-López, 2014). This is the method that the IUCN uses (IUCN Standards and Petitions Committee, 2022). However, the convex hull method has been found to overestimate species ranges (Meyer et al., 2017), particularly when they do not follow a convex shape. Given the localised nature of this project, the convex hull method (which the IUCN uses on global populations), was deemed inappropriate because it is likely to over-estimate distribution sizes in a forest habitat matrix that the remote-sensed data presented in this thesis show to be patchy.

To account for this bias, the convex hull method has been adapted to allow for concave angles (Meyer at al., 2017), a method known as the alpha hull that relaxes the assumption of concavity to produce a shape that encloses disjunct areas of range (Capinha and Pateiro-López, 2014).

The value of the alpha hull required to accurately represent the distribution of a species will vary, because it depends on how continuous or disjunct the distribution of the species is. As alpha tends to infinity, the alpha hull tends to the convex hull of the sample, as it tends to zero, the alpha hull shrinks and cavities appear amongst the distribution (Capinha and Pateiro-López, 2014).

The alpha hull method was used because a number of the species have disjunct distributions, either as single distribution points, or clumps of points separated by large spaces. This means that the convex hull method is likely to produce an overestimate of the species range. Using the alpha hull method in this scenario will produce cavities where there is no distribution data, thus producing a more realistic extent of occurrences of the species.

Alpha hull methods followed Lee-Grant (2021). Latitude and longitude were added to the occurrence datasets and the ‘EOO computing’ function in the ‘ConR’ R package (Dauby et al., 2017) was used to calculate the EOO. The shapefile produced was visualised in ArcMap. Due to the local scale, a small alpha hull value (0.2) was used as this ensured that ranges were not overestimated by overtly convex shapes.

Analyses were carried out for all seven species in each of the four study periods. The EOO sizes were exported to an Excel workbook, and the EOO shapefiles were saved for usage in ArcMap. Results were displayed as the shape of each species’ EOO, symbolised by coloured boundaries (with colours indicating the time period).

3.6.3 Area of Occupancy

The area of occupancy (AOO) is also used to measure species distribution and used by the IUCN to decide upon species categorisation within the Red List (Jiménez-Alfaro et al., 2012). The AOO is the result of exclusion of all non-suitable habitats and areas unoccupied by a species within the EOO (Gaston, 1994). The IUCN calculates the AOO as the localities in which the species currently exists, but the AOO can also include the potential AOO, defined as all areas suitable for a given species including those where the species has not yet been registered (Jiménez-Alfaro et al., 2012).

The AOO, in principle, has similarities with the alpha hull EOO method. They are both measures of species distribution and are less general than standard EOO (convex hull methods). However, their definition is different, because the AOO is the localities in which the species currently exists, whereas the alpha hull is the range of the species with either a concave or convex shape. Moreover, the AOO is measured by imposing a grid on top of the localities (IUCN Standards and Petitions Committee, 2022), and the AOO is the sum of the grid squares multiplied by the area of a single grid square (Hernández et al., 2007).

To calculate the AOO, the EOO was added to an ArcMap document. Next, the 'Grid Index Features' tool was used to create a grid with 2x2 km^2 squares (Hernández et al., 2007). By inputting the EOO shape as the grid boundary, the outputting grid is created just over the EOO shape and not the entire study site. Furthermore, given the size of the study region, a grid of 2x2 km^2 squares was able to be created and visually examined without significantly slowing downloading times on ArcMap, something that would not have been possible if this was done globally.

Next, the corresponding occurrence file was added to ArcMap and 'Add X&Y Data' was used to overlay the occurrence data over the grid. Then, the number of grid squares containing an occurrence was counted and multiplied by the area of a grid square (4 km^2) to calculate the AOO. This process was then repeated for each species in each study period.

3.7 Generalised Linear Model

A generalised linear model (GLM) was created to determine the relationship among temporal changes in species abundance and distribution, and changes in the fragmentation and human footprint index. The choice of model was based on findings from literature. For example, the Canonical Correspondence Analysis (CCA) was found to perform better for a wider spatial scale and for a broader range of species (Guisan et al., 1999), whereas the Random Forest algorithm was found to not perform well when using data with a non-symmetric error distribution (Lopatin et al., 2016). In comparison, the GLM performed better and demonstrated less bias for these distributions (Lopatin et al., 2016). However, GLMs contain assumptions such as the statistical independence of observations, and the correct scale for measurement of the explanatory variables (Breslow, 1996). To account for this, collinearity was tested for, and variables standardised. Overall, GLMs are said to be a relatively intuitive and highly flexible tool (Monti, 2011).

The generalised linear model used was created in RStudio v1.4.1103 (RStudio Team, 2021), using a database per species that included years, species metrics, fragmentation measures, and HFI measures.

Measures of fragmentation and HFI that were produced as maps were transformed into numerical values, with fragmentation analysis being taken as the forest area of each year, and the NDVI values taken as the average of the year. To calculate total forest area, the sum of all cell counts, multiplied by the cell size in metres was used, derived from the attribute table of the layer (in ArcMap). NDVI averages were extracted from the properties of each NDVI layer in ArcMap. The Human Footprint Index value itself was omitted from the database as this index is the function of variables already included within the file.

A data-frame was produced for each of the seven species. Basic plots were created to test the data including histograms of the log of the species abundance and distribution metrics (EOO, AOO, and abundance). Transforming the species metrics to a logarithmic scale was chosen to reduce skew towards larger values (Robbins, 2012).

Variables were standardised for comparison using the z-score, and to test for correlation between variables, using the ‘corr’ function (RStudio Team, 2021). Standardisation enabled simplified comparison between variables and their effect on the species metrics. Testing the variables for correlation was important to understand the effect they exert on each other and avoid collinearity in the analyses.

A GLM was run for each of the variables against each of the metrics for every species, producing a coefficient estimate, standard error, t-value, and p-value for each. The coefficient estimate indicates how a one unit increase in the variable changes the log odds of the species metric, a positive value means that higher values of the variable are associated with a higher likelihood of the metric having a value of 1, the standard error then demonstrates the variability associated with this value (Statology, 2021). The t-value is the coefficient estimate divided by the standard error, the probability of which is provided by the p-value (Statology, 2021).

The GLM was produced using the ‘glm’ function in the ‘stats’ RStudio package (RStudio Team, 2021). Results were visualised using the ‘summary’ function (appendices A to G).

4. Results

4.1 Forest Change

4.1.1 Fragmentation Analysis

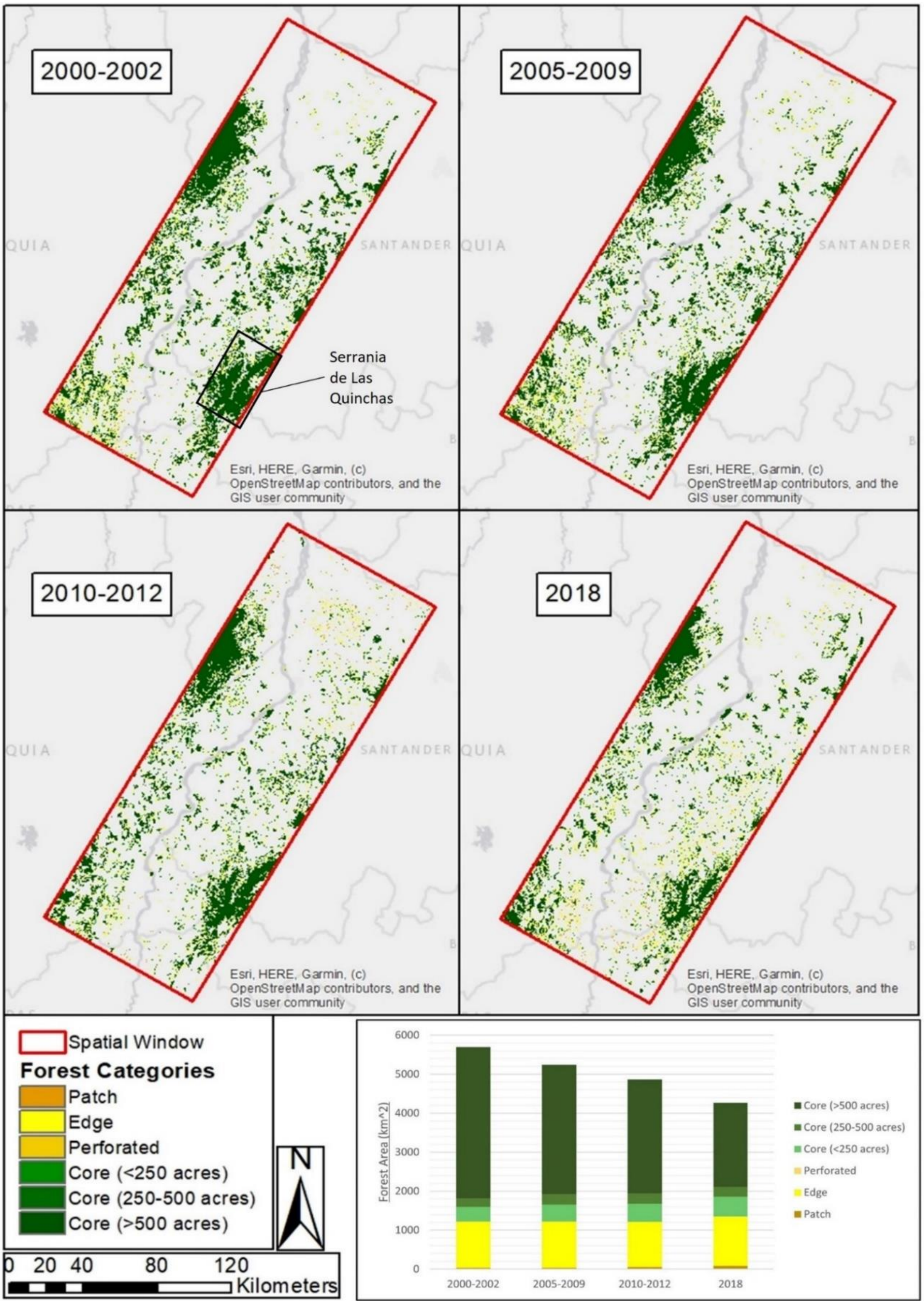


Figure 4.1: Maps of the fragmentation analysis within the study site for each time period. Embedded is a graph showing forest area, also broken down into individual classes.

Figure 4.1 displays the change in forest density over time. The graph shows a clear trend of forest steadily declining over time, reducing in overall area from 5696.7 km^2 in 2000-2002 to 4270.8 km^2 in 2018 (a decline of 25.03%).

Core forest of >500 acres shows the largest decline, losing 1720.1 km^2 (44.29%) in area over the study period. The greatest proportion of this decline is situated within the stronghold of core forest in the northwest of the study site. 2018 also demonstrates a large decline in the forest in the southeast, a region encompassing the Serranía de Las Quinchas Regional Natural Park. Furthermore, patch forest increased by 50.8 km^2 over the study period (increasing by 159.38%), with the greatest proportion of that increase occurring between 2010-2012 and 2018. The time series of maps show that patch growth occurred mainly in the centre, east, and south of the study site, largely where small clumps of core forest were present. Core forest of <250 acres consistently increased over the study period as evident by the light green bar steadily increasing in size over time on the graph. This increase is evident over a large proportion of the maps, occupying spaces previously belonging to core forest of >500 acres that is yet to be reduced to the size of patch forest.

Edge forest has fluctuated over time, initially decreasing between 2000-2002 and 2005-2009, and 2005-2009 and 2010-2012, then increasing between 2010-2012 and 2018. Overall, the area of edge forest in the study site has increase by 75 km^2 (6.32%). The time series demonstrates that this change is evident throughout the study site and not confined to any particular region.

In the southwest of the site, approximately 60 km northeast of the southwest corner of the study site, an unforested area has reduced in size from approximately 20 km in length in 2000-2002 to approximately 2km (a 90% reduction in size) in 2018, almost entirely covered in forest.

4.1.2 Fractal Dimension Index

Forest Type	2000-2002	2005-2009	2010-2012	2018
Mean	1.366	1.364	1.365	1.365
Patch	1.369	1.368	1.364	1.364
Edge	1.444	1.443	1.435	1.432
Perforated	1.367	1.367	1.362	1.367
Core (<250 acres)	1.348	1.345	1.348	1.353
Core (250-500 acres)	1.308	1.308	1.302	1.302
Core (>500 acres)	1.336	1.334	1.334	1.333

Table 4.1: Fractal dimension index value for forest in the study site, then divided into individual categories.

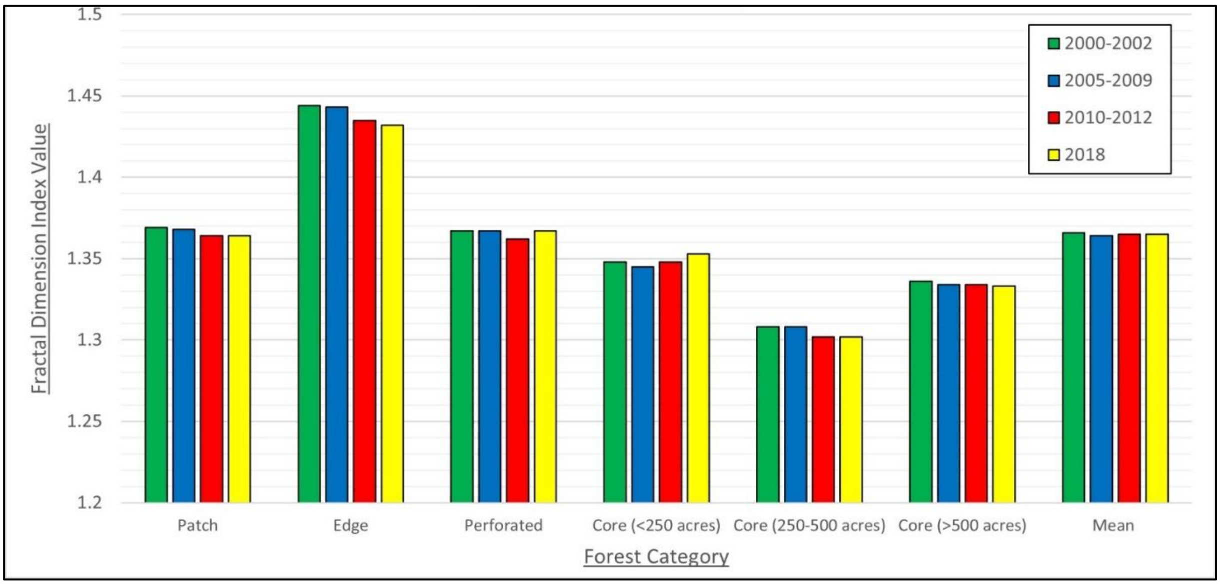


Figure 4.2: Change in FDI over time for each forest category.

The mean fractal dimension index value of all forest in the study site has not shown any consistent or significant change, overall reducing by 0.001 between 2000-2002 and 2018 (table 4.1 and figure 4.2).

Edge forest demonstrated the largest change, with the FDI value lowing by 0.012 from 1.444 to 1.432 (declining 0.83%) over the course of the study period. This value consistently declined over time as evident by the constant shrinking of the yellow bar on figure 5. The direction and rate of change varied between forest categories, with core forest of <250 acres showing an overall increase (the only category to do so) of 0.005 from 1.348 to 1.353 (increasing 0.37%).

The greatest changes generally occurred between 2005-2009 and 2010-2012, with patch, edge, perforated and core of 250-500 acres all exhibiting their largest changes between these intervals (table 4.1). As changes to FDI values were small in magnitude, this trend is not visible on figure 4.2.

4.1.3 Euclidean Distance

	Eudlicean Distance to Nearest Neighbour (m)		
Year	Overall	Core	Patch
2000-2002	340.74	1985.92	515.16
2005-2009	337.02	1957.59	588.74
2010-2012	306.04	2295.11	447.61
2018	293.28	2018.35	415.52

Table 4.2: Table containing Euclidean distance to nearest neighbour values for overall forest, core forest (over 250 acres in density), and patch (under 250 acres in density) forest for each study period.

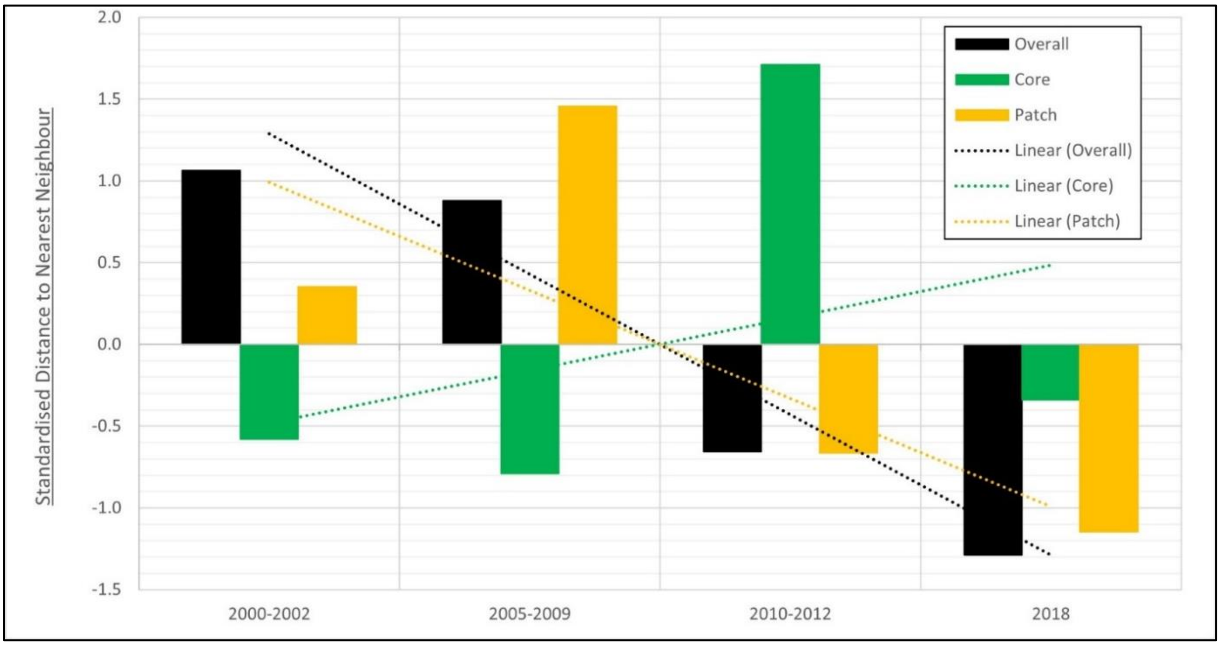


Figure 4.3: Standardised Euclidean distance to nearest neighbour values for overall, core, and patch forest over time and their associated trend lines.

Table 4.2 and figure 4.3 demonstrate that, overall, the Euclidean distance to the nearest neighbour of forest has decreased over time, reducing from 340.7m in 2000-2002 to 293.3m in 2018 (decreasing 13.91%) with a consistent decrease over that period.

When broken down into categories, this trend is less clear. Table 4.2 shows the nearest neighbour distance for core forest (forest of density over 250 acres) has increased between 2000-2002 and 2018 by 32.4m (1.61%). Figure 4.3 demonstrates that core forest has not exhibited a consistent increase in nearest neighbour distance but has fluctuated considerably. Distance initially decreases between 2000-2002 and 2005-2009 before increasing by 337.5m by the 2010-2012 and then subsequently decreasing by 2018. The trendline on figure 4.3 confirms an overall trend of increasing distance between core forest nearest neighbours, contrasting the negative trend of distance between overall forest nearest neighbours.

Patch forest (forest of density under 250 acres, table 4.2) also exhibits an inconsistent change over time, but an overall decrease from 515.2m in 2000-2002 to 415.5m in 2018 (a reduction of 19.33%).

4.2 Human Footprint Index

4.2.1 Human Footprint Index Value

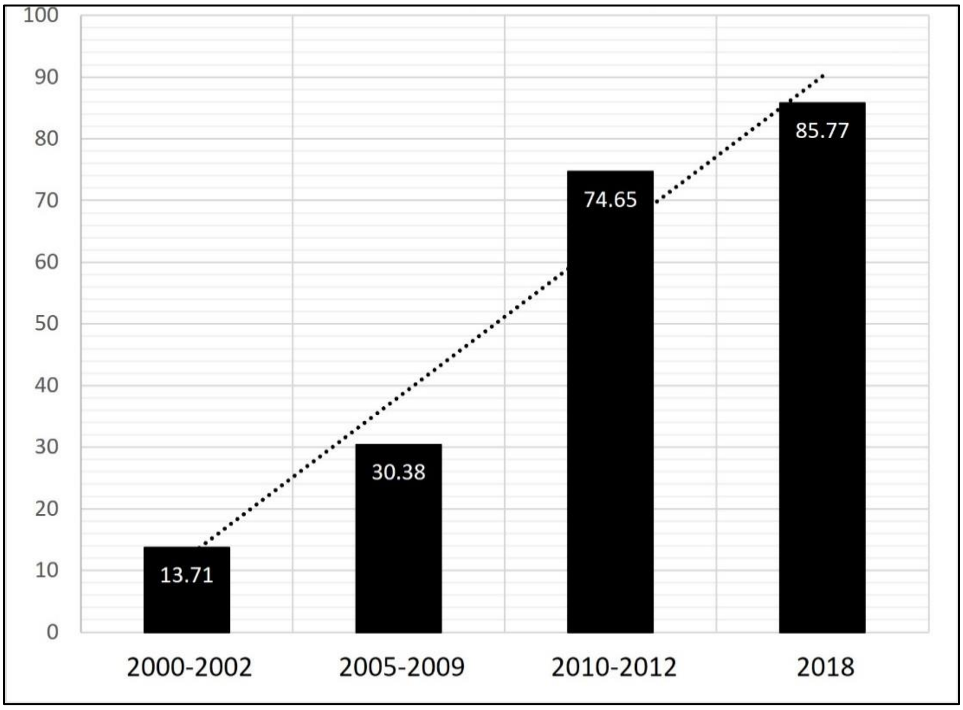


Figure 4.4: Graph showing the change in Human Footprint Index for the study site over the study period. Black dotted line signifies trendline.

Year	Slope (degrees)	NDVI	DTR (m)	DTS (m)
2000-2002	10.39	0.45	94.99	92.42
2005-2009	11.04	0.37	114.48	110.23
2010-2012	11.24	0.28	79.39	78.26
2018	11.14	0.35	44.87	43.87

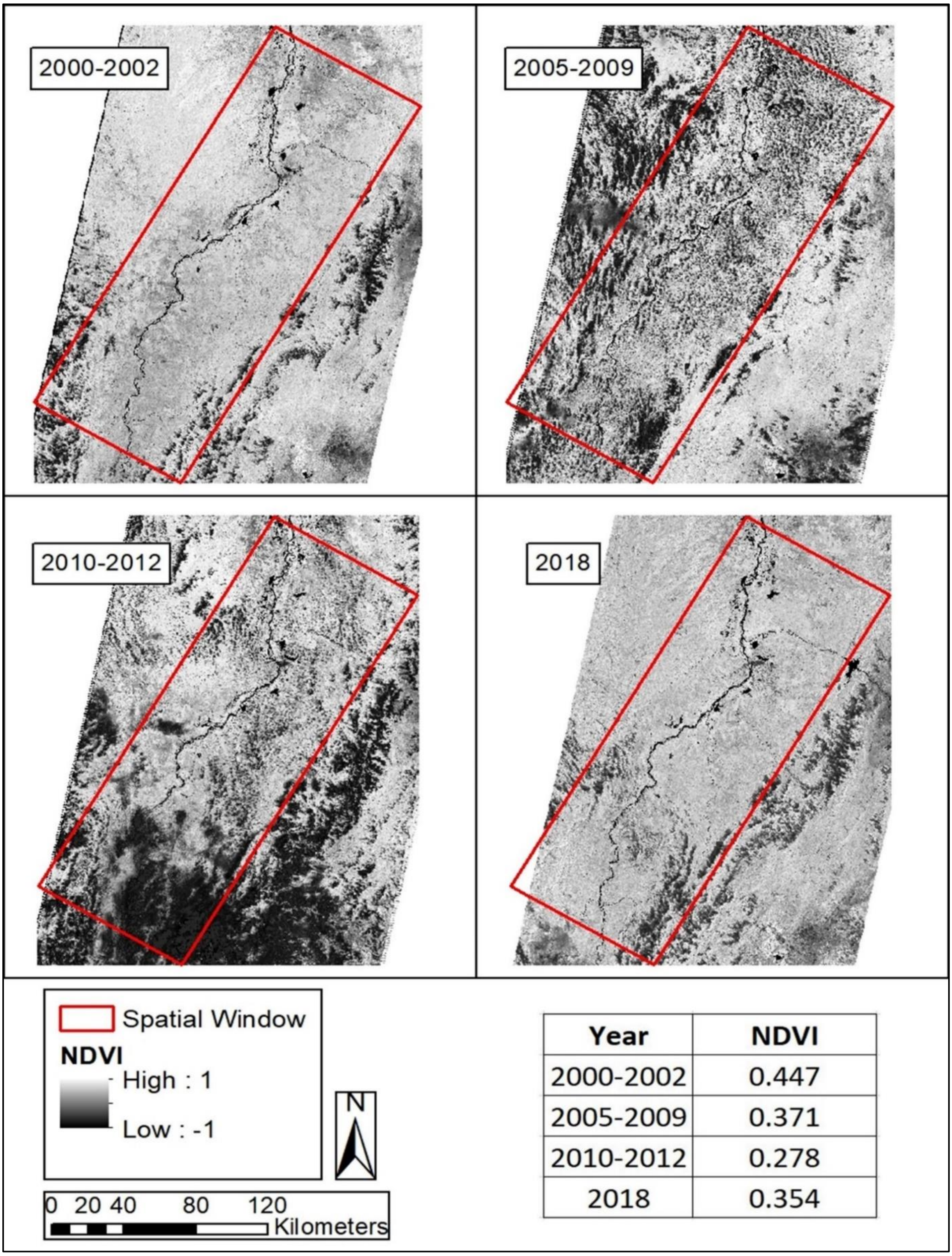
Table 4.3: Table displaying the numerical values over time of each explanatory variable that was inputted into the HFI equation.

The HFI value of the study site has continuously increased over the study period (table 4.3 and figure 4.4). Increasing from 13.71 in 2000-2002, the HFI rose to 30.38 in 2005-2009, 74.65 in 2010-2012, and 85.77 in 2018, a rise of 72.06 over the course of the study period (an overall increase of 525.6%). Figure 4.4 shows the clear positive relationship between HFI and time in the study site. The largest increase in

HFI came between 2005-2009 and 2010-2012 when the HFI value increased by 145.7%.

Table 4.3 displays the numerical values of the factors that produced the HFI values. 2000-2002 contained the lowest average slope on which forest is located of 10.39 degrees and the greatest value of NDVI (0.45). Values of distance to roads and settlements were the second smallest in 2000-2002 with distances of 94.99m and 92.42m, respectively. 2005-2009 exhibited the greatest distances to roads and settlements (114.48m and 110.23m, respectively), and the second smallest average slope and NDVI value (11.04 degrees and 0.37, respectively). In comparison, 2010-2012 exhibited the largest average slope of 11.24 degrees, the lowest NDVI value of 0.28, the second smallest distance to roads of 79.39m, and the second smallest distance to settlements of 78.26m. Finally, 2018 displayed the second steepest average slope of 11.14 degrees, the second lowest NDVI value of 0.35, and the smallest distance to roads and settlements of 44.87m and 43.87m respectively.

4.2.2 NDVI



Year	NDVI
2000-2002	0.447
2005-2009	0.371
2010-2012	0.278
2018	0.354

Figure 4.5: NDVI maps over time and the average value for the study site in the embedded table.

NDVI has lowered in some areas such as the northwest of the study site where large areas of dense forest (see figure 4.1) have lowered in their NDVI value between 2000-2002 and 2018. Contrastingly, areas in the southwest, bordering the river, showed increases in NDVI values. It is important to note that due to the nature of satellite imagery, cloud cover will and has undoubtably impacted NDVI results.

The table within figure 4.5 shows an initial decrease in NDVI between 2000-2002 and 2005-2009 (of 0.076), and subsequently a further decrease to 2010-2012 (0.093). An increase of 0.076 to 2018 is displayed, resulting in an overall decrease in NDVI between 2000-2002 and 2018 of 0.093 (20.81%). There is a clear trend of NDVI decreasing over time, but the strong presence of cloud (particularly in the southeast) in 2010-2012 is likely to have overestimated the magnitude of the decrease from the previous year (see section 5).

4.2.3 Distance to Roads and Settlements

Years	Average Nearest Distance to Roads (m)
2000-2002	94.99
2005-2009	114.48
2010-2012	79.39
2018	44.87

Years	Average Nearest Distance to Settlements (m)
2000-2002	92.42
2005-2009	110.23
2010-2012	78.26
2018	43.87

Table 4.4: Tables displaying the average distance to roads from forest over time, and the average distance to settlements from forest over time.

Between 2000-2002 and 2018, both the distance to roads and settlements has decreased (table 4.4). The average nearest distance of forest to road decreased by

50.1m to 44.9m by 2018 (a decline of 52.76%) and the average distance of forest to settlements decreased by 48.6m to 43.87m by 2018 (decreasing 52.53%).

Both distance to roads and distance to settlements have followed a similar pattern, both initially increasing between 2000-2002 and 2005-2009, then decreasing to 2010-2012 and further to 2018 (table 4.4).

4.2.4 Slope

	2000-2002	2005-2009	2010-2012	2018
Mean Slope (Degrees)	10.39	11.04	11.24	11.14
Max Slope (Degrees)	64.99	64.99	67.78	64.99
Min Slope (Degrees)	0	0	0	0
Standard Deviation	8.83	9.11	9.21	9.36

Figure 4.6: Maps showing the forest in the study site, divided into categories based on the slope of the land they are situated on. Embedded is a table of statistics regarding the slope of land upon which forest is located.

The mean slope on which forest is present (figure 4.6) fluctuates over time, producing an overall, but not consistent increase. Between the start and end of the study period, the mean slope on which forest is present within the study site increased by 0.75 degrees to 11.14 degrees (increasing by 6.73%). The mean slope initially rose between 2000-2002 and 2005-2009 (by 0.65 degrees), and between 2005-2009 and 2010-2012 (by 0.2 degrees), before falling by 0.1 degrees to 11.14 in 2018. The maximum slope remained consistent between 2000-2002 and 2005-2009 at 64.99 degrees, before rising to 67.78 degrees in 2010-2012, and subsequently lowering once more to 64.99 degrees in 2018. The standard deviation continuously increased over time rising by an overall 0.53 degrees over the study period.

Figure 4.6 displays the slope of the forest. One key region of change is in the large region of forest in the northwest, with the region of gentle slope (represented by dark and medium green) visibly and consistently reducing over every time period as the forest in these areas has been removed. Furthermore, throughout the centre of the study area along the river, the density of forest on a gentle gradient reduces from significant clumps in 2000-2002 to smaller patches in 2018. Finally, within Serranía de Las Quinchas, the area of forest on a gentle slope reduces over time, leaving primarily areas on steeper slopes by 2010-2012. By 2018, even the area of forest on steepest slopes declines. However, by 2018, a region of gentle slope in the northeast corner of the study site displays signs of recovery from previous reductions in 2005-2009 and 2010-2012.

4.3 Species Metrics

4.3.1 Abundance

	2000-2002	2005-2009	2010-2012	2018
Cariniana pyriformis	92	89	84	89
Cedrela odorata	31	34	32	38
Isidodendron tripterocarpum	74	72	68	69
Magnolia cespedesii	4	4	4	4
Microdesmia arborea	14	16	18	16
Swietenia macrophylla	2	2	3	3
Zamia incognita	22	15	13	17

Table 4.5: Table detailing the abundance of each species within the study site over time.

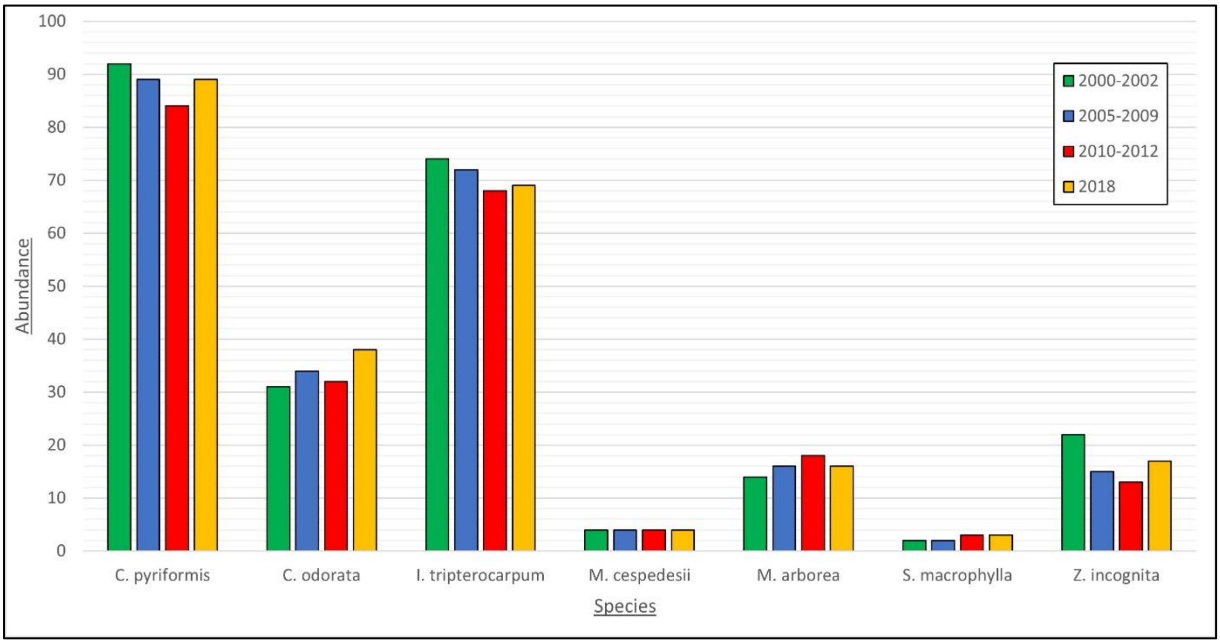
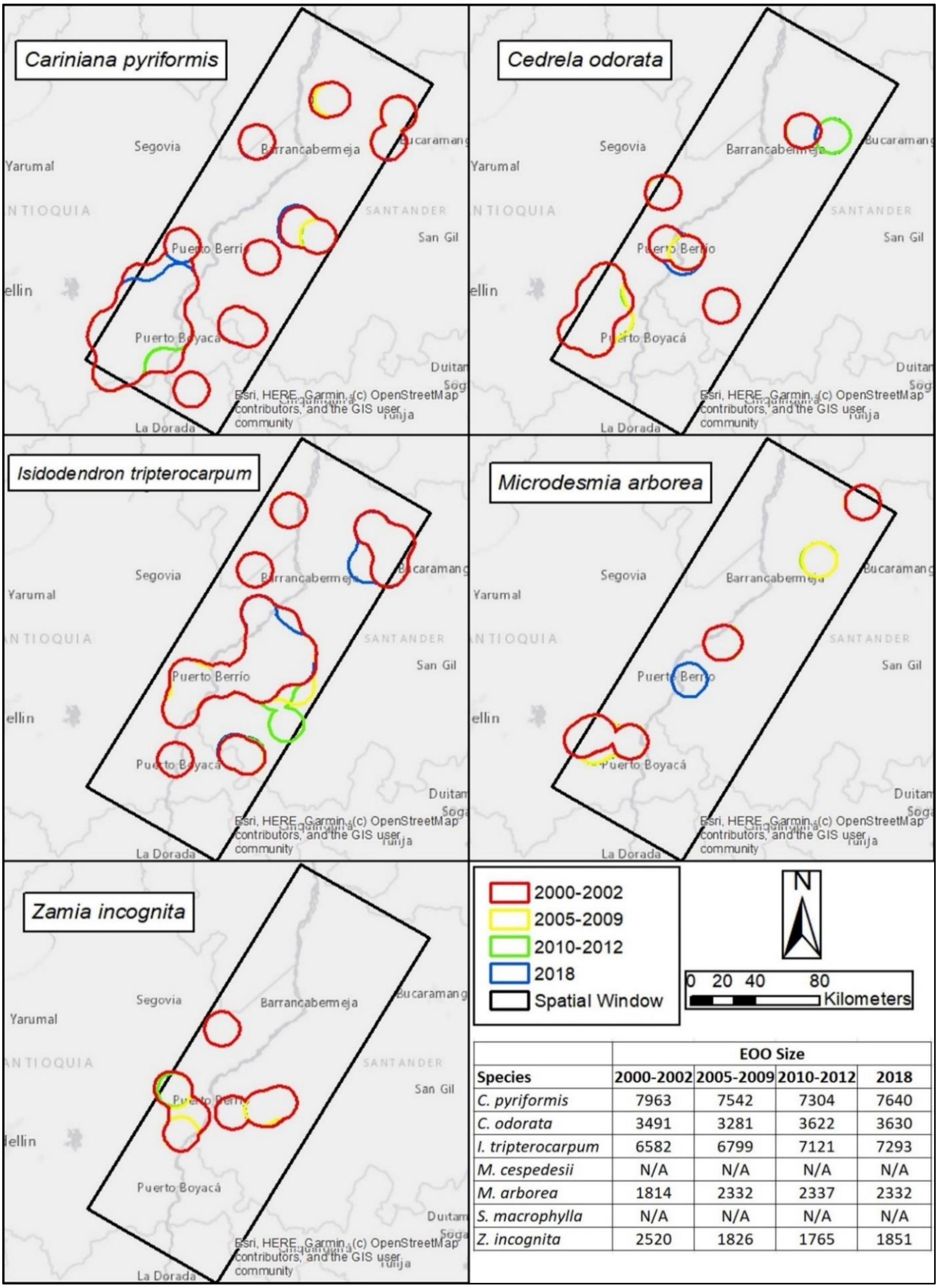


Figure 4.7: Graph showing the abundance of each species over time, with four bars corresponding to each species, each representing a different time period.

Table 4.5 shows that *C. pyriformis* had the consistently largest abundance over time, with figure 4.7 showing that its abundance fluctuated, initially decreasing between 2000-2002 and 2010-2012 (from 92 to 84) before recovering to 89 in 2018. The smallest abundance was *S. macrophylla*, with 2000-2002 and 2005-2009 containing two individuals, and 2010-2012 and 2018 containing three. Figure 4.7 demonstrates that the temporal trend of abundance varies by species. *Cariniana pyriformis*, *I. tripterocarpum*, and *Z. incognita* all exhibit an overall negative trend, all reaching their smallest abundance in 2010-2012, and subsequently displaying a recovery in 2018.

Despite this late recovery, the overall trend remains a decline for these species (-3.26%, -6.76%, -22.73%, respectively). Contrastingly, *C. odorata*, *M. arborea*, and *S. macrophylla* display an overall positive abundance trend (+18.42%, +12.5%, +50%, respectively). Both *C. odorata* and *M. arborea* experienced an inconsistent increase in known abundance, declining in 2010-2012 and 2018, respectively. *Magnolia cespedesii* remained stable with four known individuals across the study period.

4.3.2 Extent of Occurrence



	EOO Size			
Species	**2000-2002**	**2005-2009**	**2010-2012**	**2018**
C. pyriformis	7963	7542	7304	7640
C. odorata	3491	3281	3622	3630
I. tripterocarpum	6582	6799	7121	7293
M. cespedesii	N/A	N/A	N/A	N/A
M. arborea	1814	2332	2337	2332
S. macrophylla	N/A	N/A	N/A	N/A
Z. incognita	2520	1826	1765	1851

Figure 4.8: EOO calculation, showing the extent of occurrence for each species. Different colour distributions correspond to different time periods, see legend in the centre. The embedded table shows the size of each species' EOO over time.

Figure 4.8 shows the change in each species' EOO over-time and includes a table of EOO size over-time. *Cariniana pyriformis* sees fluctuation over-time, initially decreasing from 2000-2002 to 2010-2012 (7963 to 7304), and then recovering by 2018 (to 7640, an overall decrease of 4.01%). As evident from the EOO map for *C. pyriformis*, decreases in EOO were distributed across the spatial window, with notable recovery by 2018 in the east of the study site.

Cedrela odorata exhibits initial decline from 2000-2002 to 2005-2009 (3491 to 3281) and then recovers to 2010-2012 (3622) and again to 2018 (3630, an overall increase of 3.83%). Change in EOO is spread across the study site. The north of the study site sees both decline and recovery over the study period.

Isidodendron tripterocarpum displays a continuous increase in the size of its EOO, increasing from 6582 in 2000-2002 to 7293 in 2018 (an increase of 9.75%). An increase is evident in southeast of the study site in 2005-2009 and 2010-2012, which then recedes back to the 2000-2002 extent in that area by 2018. This is partially offset by an increase in the northeast in 2018.

Microdesmia arborea initially increases from in extent from 1814 in 2000-2002 to 2332 in 2005-2009 where it fluctuates in extent by only 5 for the remainder of the study period (producing an overall increase of 22.21%). Despite this, change is spread, with reductions in the North and centre being counteracted by increases to the south of both reductions in 2005-2009 and 2018 respectively.

Zamia incognita declines between 2000-2002 to 2010-2012, reducing in size from 2520 to 1765 before increasing to 1851 in 2018 (an overall decrease of 26.55%). To the south of the centre of the study site, initial reductions in extent occurred in 2005-2009, with smaller losses to the west of the area in 2010-2012. Recovery occurred to the west in 2018.

Calculations for *M. cespedesii* and *S. macrophylla* were not possible due to the limited number of known occurrences.

4.3.3 Area of Occupancy

	Area (km^2)			
Species	**2000-2002**	**2005-2009**	**2010-2012**	**2018**
C. pyriformis	152	168	164	172
C. odorata	44	52	48	64
I. tripterocarpum	96	88	80	88
M. cespedesii	8	8	8	8
M. arborea	40	48	48	48
S. macrophylla	4	4	8	8
Z. incognita	40	28	24	32

Table 4.6: Size of each species' area of occupancy over time, in km^2.

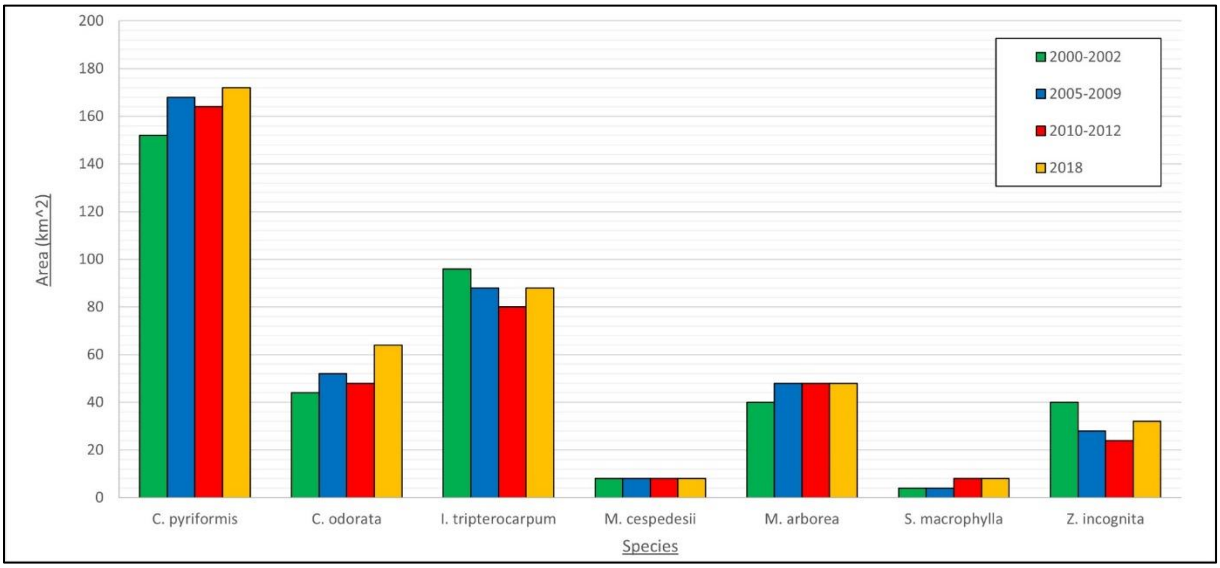


Figure 4.9: Graph displaying the area of occupancy for each species over time, with each bar corresponding to a study period.

Figure 4.9 and table 4.6 show (both graphically and numerically) the change in each species' area of occupancy over time. Figure 4.9 shows that four species have increased in area, two have declined, and one has remained constant. *Cariniana pyriformis*, *C. odorata*, *M. arborea*, and *S. macrophylla* have exhibited an overall increase in area of occupancy (increasing from 152-172 km^2 (+11.63%), 44-64 km^2

(+31.25%), 40-48 km^2 (+16.67%), and 4-8 km^2 (+100%) respectively). Both *C. pyriformis* and *C. odorata* experienced declines in 2010-2012 before increasing in area again in 2018. *Isidodendron tripterocarpum* and *Z. incognita* decreased in area, from 96-88 km^2 (-8.33%) and 40-32 km^2 (-20%), respectively. Both species exhibited their smallest area in 2010-2012 of 80 km^2 and 24 km^2 respectively. *Magnolia cespedesii* remained constant at 8 km^2.

4.4 Generalised Linear Model

Cariniana pyriformis (EOO)		
	Slope	NDVI
t-value	-3.051	5.383
pr	0.0927	0.0328

Cariniana (Known Abundance)	
	NDVI
t-value	6.465
pr	0.0231

Isidodendron tripterocarpum (EOO)		
	Frag An	Euclidean
t-value	-6.768	-6.123
pr	0.0211	0.0257

Isidodendron (AOO)	
	NDVI
t-value	13.42
pr	0.0055

Isidodendron tripterocarpum (K Abund)		
	Euclidean	NDVI
t-value	2.996	3.547
pr	0.0957	0.0711

Microdesmia arborea (EOO)	
	Slope
t-value	6.56
pr	0.0225

Microdesmia (AOO)	
	Slope
t-value	6.276
pr	0.0245

Microdesmia arborea (K Abund)		
	Slope	NDVI
t-value	3.363	-12.22
pr	0.0782	0.00663

Swietenia macrophylla (AOO)	
	Euclidean Distance
t-value	-4.884
pr	0.03945

Swietenia (Known Abundance)	
	Euclidean
t-value	-4.74
pr	0.0417

Zamia incognita (EOO)	
	Slope
t-value	-9.243
pr	0.0115

Zamia (AOO)	
	NDVI
t-value	3.77
pr	0.063718

Zamia incognita (K Abund)		
	Slope	NDVI
t-value	-3.092	3.881
pr	0.090626	0.060427

Table 4.7: All significant correlations identified by the GLM, broken down by species and the abundance/distribution measure that the explanatory factor(s) is(are) correlated to.

Appendix A to G present the results of the Generalised Linear Model that tested for correlation between multitemporal changes to the Middle Magdalena River Valley and the abundance and distribution of the seven species of interest in the study site. Table 4.7 then summarises the statistically significant correlations, presenting the t-value (the coefficient estimate divided by the standard error) and the associated pr-value (probability of this being by chance).

The EOO of *C. pyriformis* is positively correlated to NDVI, a statistically significant relationship at the 95% confidence interval with a t-value of 5.383 and a pr-value of 0.0328 (table 4.7). The abundance of *C. pyriformis* is similarly positively correlated to NDVI, with a t-value of 6.465 and a pr-value of 0.0231 showing significance at the 95% confidence interval (table 4.7). The negative correlation between slope and *C. pyriformis* is statistically significant for EOO (t-value of -3.051 and pr-value of 0.0927, significant at the 90% confidence interval, table 4.7), but not statistically significant for abundance (t-value of -1.951 and pr-value of 0.19, appendix A).

A large t-value (-2.717) suggests a negative correlation between fragmentation analysis and the AOO of *C. odorata*, but this is not statistically significant with a pr-value of 0.113 (appendix B).

Isidodendron tripterocarpum produced results with larger t-values on average than *C. pyriformis* and *C. odorata* (appendix C). The largest t-value was associated with the GLM results for NDVI against AOO of 13.42, a statistically significant relationship with a pr-value of 0.0055 (statistically significant at the 99% confidence interval, table 4.7). Two negative correlations are found between EOO and fragmentation analysis and EOO and Euclidean distance to nearest neighbour (t-values of -6.768 and -6.123, and pr-values of 0.0211 and 0.0257, respectively, table 4.7). Two positive correlations are found between known abundance and Euclidean distance to nearest neighbour and known abundance to NDVI (t-values of 2.996 and 3.547, and pr-values of 0.0957 and 0.0711, respectively, table 4.7).

Magnolia cespedesii had insufficient data to model EOO and known abundance against the factors. The AOO model produces t-values no greater than 1 (or -1). Appendix D confirms that there are no statistically significant correlations between changes to *M. cespedesii*'s AOO and the degradation factors.

The abundance of *M. arborea* and NDVI have a strong negative correlation (t-value of -12.22) that is statistically significant at the 99% confidence interval (pr-value of 0.00663). The correlations between EOO and slope, and AOO and slope are statistically significant at the 95% confidence interval (t-values of 6.56 and 6.276, respectively, pr-values of 0.0225 and 0.0245, respectively), and the correlation between known abundance and slope is statistically significant at the 90% confidence interval (t-value of 3.363, pr-value of 0.0782, table 4.7).

Swietenia macrophylla had insufficient data to model EOO and estimated abundance against factors. Appendix F shows that remaining correlations were largely negative, with only models of AOO and known abundance against slope presenting a positive correlation (neither statistically significant). The largest negative t-values suggest a negative correlation between Euclidean distance to nearest neighbour and AOO and Euclidean distance to nearest neighbour and known abundance (t-values of -4.884 and -4.74 respectively). These are statistically significant negative correlations at the 95% confidence interval (pr-values of 0.0395 and 0.0417, respectively, table 4.7).

Zamia incognita (appendix G) exhibits negative correlations between slope and EOO, and slope and known abundance (t-values of -9.243 and -3.092, respectively), and positive correlations between NDVI and AOO, and NDVI and known abundance (t-values of 3.77 and 3.881, respectively). These correlations are all statistically significant (table 4.7). The correlation between EOO and slope is significant at the 95% confidence interval (pr-value of 0.0115) and the correlations between slope and known abundance, NDVI and AOO, and NDVI and known abundance are significant at the 90% confidence interval (pr-values of 0.0906, 0.0637, and 0.0604, respectively, table 4.7).

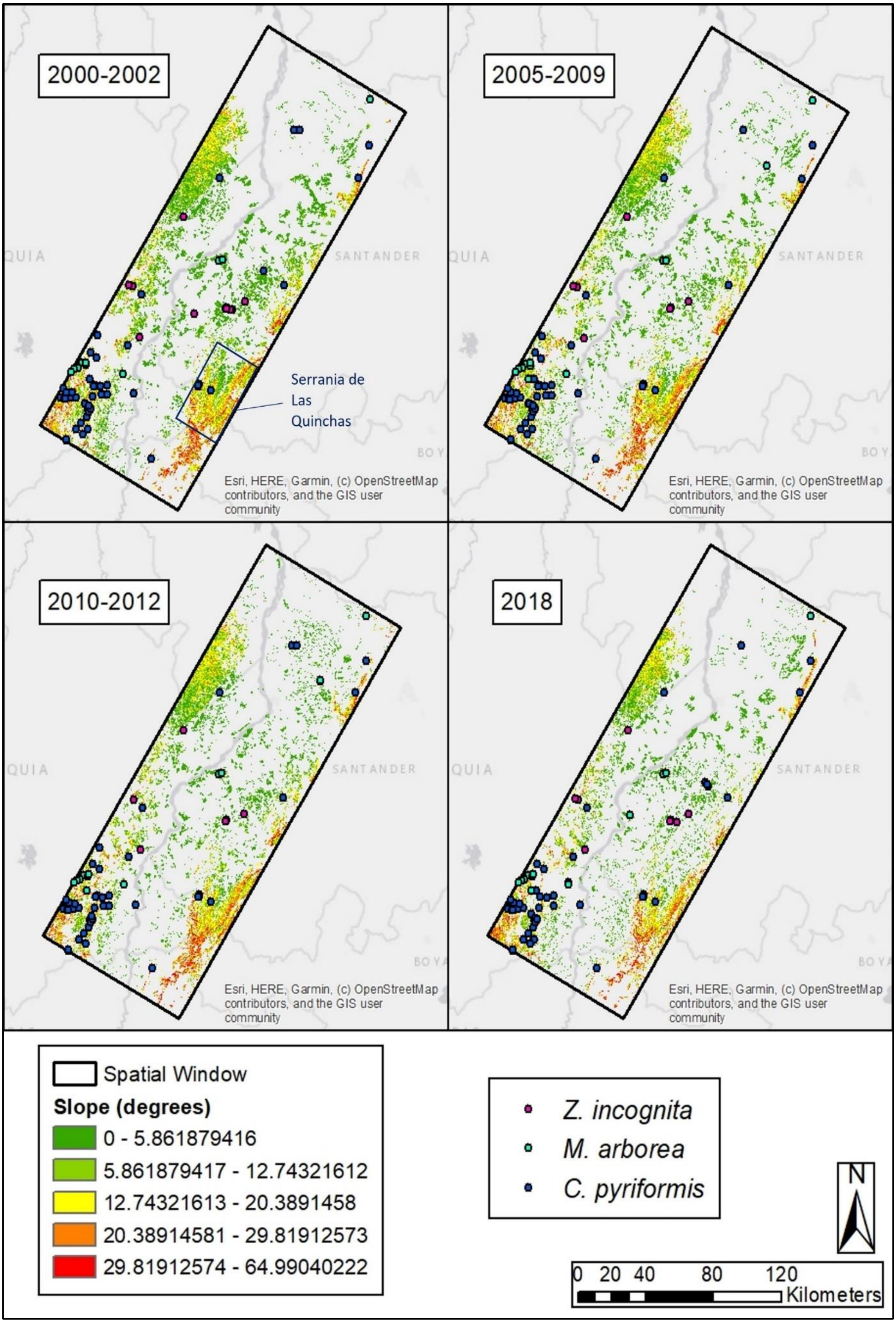


Figure 4.10: Slope maps (from figure 4.6), overlayed with the occurrence data of each correlated species in each of the study periods.

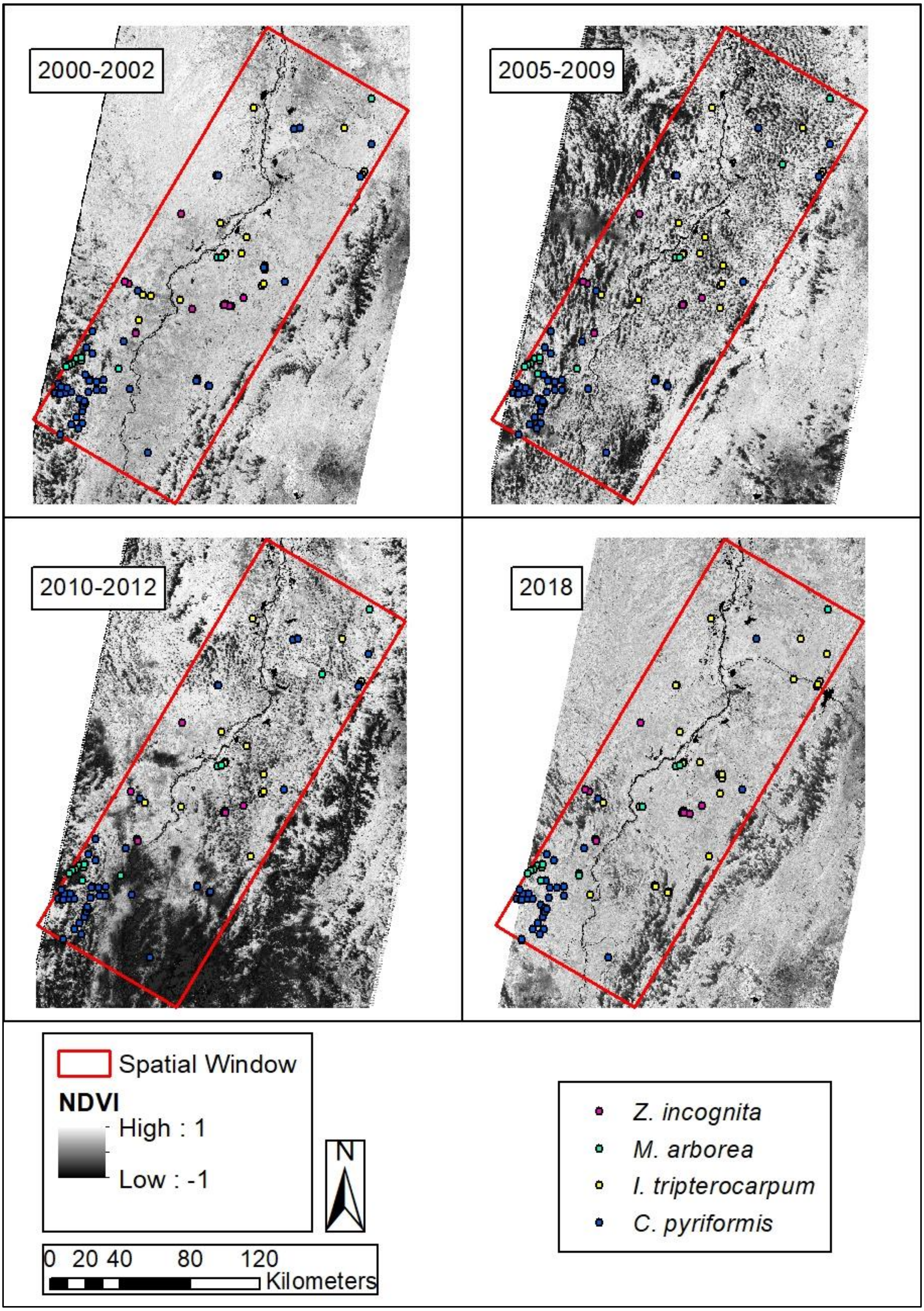


Figure 4.11: NDVI maps (from figure 4.5), overlayed with the occurrence data of each correlated species in each of the study periods.

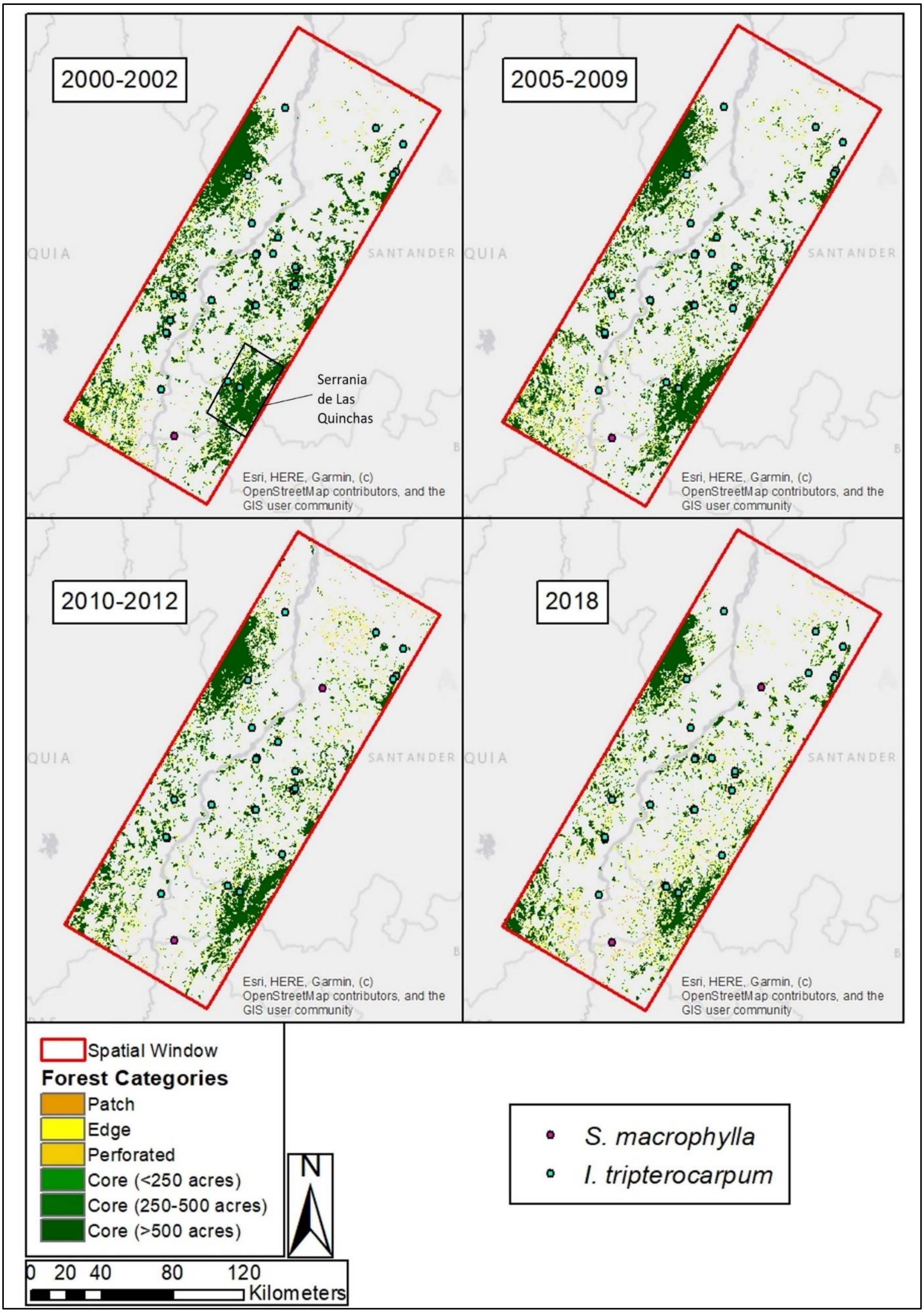


Figure 4.12: Fragmentation analysis results (from figure 4.1), overlayed with the correlated species in each study period.

Figures 4.10, 4.11, and 4.12 overlay species occurrences onto the maps of factors with which they were found to be statistically significantly correlated to. For example, figure 4.10 overlays the occurrences of *C. pyriformis*, *M. arborea*, and *Z. incognita* onto the map of forest slope, pairing the slope map for each time period against the corresponding occurrence dataset. Figure 4.10 shows that all species are largely present on lower gradient slopes, with only *C. pyriformis* appearing on higher gradient slopes in the northeast and southwest. The loss of low gradient forest in the north and centre of the study site corresponds to a reduction of occurrences for all species in these regions. The more intact forests on steeper ground surrounding Serranía de las Quinchas (indicated by the region of red) has seen no occurrences of any correlated species over the study period.

Figure 4.11 overlays the occurrences of *C. pyriformis*, *I. tripterocarpum*, *M. arborea*, and *Z. incognita* onto the NDVI maps for the corresponding periods. Similarly to figure 4.10, a reduction in occurrences of all species except *I. tripterocarpum* has been evident in the north, where a reduction in NDVI has occurred over-time. This pattern is also demonstrated in the centre of the spatial window where NDVI has lowered over-time, with again *I. tripterocarpum* being the most resistant to the loss of individuals. The presence of clouds to the south of the study site in 2010-2012 makes the identification of patterns in the south more challenging.

Finally, figure 4.12 overlays the occurrences of *S. macrophylla* and *I. tripterocarpum* onto fragmentation analyses maps from corresponding periods. As Euclidean distance to nearest neighbour is a factor produced from fragmentation analysis, this was deemed a suitable choice to overlay *S. macrophylla* onto. Figure 4.12 shows that new occurrences (not present at the start of the study period) of *S. macrophylla* are associated with the regrowth of clusters of patch forest in the north of the study site. It is also evident that all occurrences of *S. macrophylla* occur in clusters of patch forest, and not in dense core forest. Furthermore, *I. tripterocarpum* has exhibited some regrowth to the northeast of the study site, primarily on larger clumps of new core forest. Reductions in *I. tripterocarpum* occurrences in the centre of the study site have often corresponded with the reduction of core forest to either patch forest or non-forest.

5. Discussion

5.1 Land Use Change in the Middle Magdalena Valley

5.1.1 Anthropogenic Impacts upon the Middle Magdalena Valley Landscape

Within the study site, forest declined by 25.03% from 2000-2002 to 2018 (figure 4.1). This result supports previous work indicating that in the lowland rainforest of the Middle Magdalena Valley, levels of deforestation have been high (Mendoza-Cifuentes et al., 2000; Villa and García, 2017). This more recent destruction adds to the intense deforestation that occurred in the Magdalena Valley between 1950 and 1980 (Galvis and Mojica, 2007), and makes clear that forests there are still not adequately protected. It is clear that the Middle Magdalena River Valley has suffered the same processes as Colombia more widely where lowland rainforests have been rapidly cleared for several decades (Etter et al., 2006a; Van Ausdal, 2009; BirdLife International, 2018), with pastures being the primary replacement (Etter et al., 2006a).

In particular, core forest in the study area declined by 44.29% over the study period, corresponding to a 159.38% increase in patch forest, and a 6.32% increase in edge forest (figure 4.1). The largest reduction of core forest came between 2010-2012 and 2018, declining by 19.6% of the 2000-2002 area in that time (figure 4.1). Furthermore, forest overall also displayed the largest decline between 2010-2012 and 2018, reducing by 10.43% of the 2000-2002 area (figure 4.1). This decline coincides with the signing of the peace accords in 2016 and deforestation in Colombia overall has increased by 177% post-conflict (Clerici et al., 2020), attributed to the withdrawal of armed groups from remote forests enabling an increase in commercial activities that degrade the ecosystem (Ayram et al., 2020; Prem et al., 2020). In addition, this acceleration of deforestation in recent years may be explained by a lack of governance facilitating an increase in resource consumption to fuel small-scale conflicts that have existed beyond the peace accords (Negret et al., 2019).

The overall decline in forest over the study period may reflect several factors including the drug trade, civil conflict, the timber industry, and the conversion of forest to arable land (see section 2.2). The cultivation and production of coca is a significant contributor to deforestation within Colombia (Moreno-Sanches et al., 2003), as was the civil conflict, with 73.1% of FARC-occupied areas showing reduced forest cover, and one million hectares of forest being lost (Baptiste et al., 2017; Liévano-Latorre et al., 2021). It is likely that the Middle Magdalena Valley is no exception and due to the remote nature of the study site, there may be a link between coca cultivation there and the indirect effect of the civil conflict, which often displaces coca farmers, pushing them into remote forested areas (Baptiste et al., 2017; Villa and Garcia, 2017; Negret et al., 2019). An increase in the number of coca farmers within the study site could therefore have contributed to deforestation and the reduction of core forest.

The worrying trend of forest destruction demonstrated here is consistent with the Human Footprint Index which has increased overall by 525.6% (table 4.3). This matches Colombia-wide HFI trends, which have been found to increase between 1970 and 2015 (Ayram et al., 2020). A consistent HFI increase confirms that the impact of anthropogenic activities upon the landscape has become more severe over time (Etter et al., 2006b; Van Ausdal, 2009; BirdLife International, 2018). The anthropogenic deforestation and degradation of forest within the study site is exceeding its recovery capacity (Armenteras et al., 2018), as an increasing HFI is reflecting an overall decline in forest and minimal regeneration (figure 4.1).

Contrastingly, there are areas of forest on gentle slopes that were naturally regenerating by 2018 after prior reductions (figure 4.6). In the northeast of the study site, patches of forest on gentle slopes are present in 2018, after being previously removed between 2000-2002 and 2010-2012. This suggests that contrary to much of the remainder of the study site, the deforestation rate has fallen within the recovery capacity of the forest (Armenteras et al., 2018), and natural regeneration has begun (García-Monroy et al., 2020). Secondary forest growth has also occurred in the southwest of the study site as an unforested region reduced in size by 90% over the study period (figure 4.1). Secondary forest growth is important because when it occurs adjacent to primary forest, the mean size and core area increases (Etter et al., 2005).

5.1.2 Trends in Serrania de Las Quinchas

Although fragmentation has been generally high in the Middle Magdalena Valley, Serranía de Las Quinchas seems to be an important relic of forest that has been better preserved over the study period potentially owing to its status as a Regional Natural Park (Amador and Millner, 2019; Amador-Jiménez, 2020), the establishment of private reserves and its steep terrain that is hard to access. However, degradation has been occurring in Las Quinchas, potentially due to the expansion of pastures and illicit agricultural production that has affected the area since the 1950s when there was an increase in the influence of oil enclaves, and in the impact of the conflict among political parties which resulted in civil unrest (Amador- Jiménez and Serrano, 2021).

Declines of core forest in the Las Quinchas area also occurred later, especially in 2018 (figure 4.1). Therefore, the trend evident in Las Quinchas largely echoes that of the study site more generally, but at a lower intensity (figure 4.1). Earlier studies have described Serranía de Las Quinchas as containing a mixture of well-preserved rainforest and new pasture (Link et al., 2012; García-Monroy et al., 2020), a description that concurs with the results of this fragmentation analysis, that suggest more new pasture as forest cover reduces over time. However, the overall pattern of better preservation is seen more widely in Colombia where deforestation rates within protected areas have been found to be significantly lower (Rodriguez et al., 2013).

Forest degradation and deforestation in the region are currently also driven by the lack of new, more sustainable means of earning a living. Such alternative livelihoods have not been provided to the local community as the Regional Natural Park prevents access to the area and strictly prohibits the use of forest resources even banning sustainable practices. e.g., agroforestry (Hoffman et al., 2018; Moreno, 2020). However, the recent increase in deforestation suggests a more likely driver in recent years is the withdrawal of armed groups after the peace accords, enabling an increase in economic activity in the form of resource extraction and conversion of forest to agricultural land (Ayram et al., 2020; Prem et al., 2020). However, areas of forest in Serranía de Las Quinchas have shown natural regeneration, attributed to the demobilisation of paramilitaries and the recent occupation of the army reducing illicit crop cultivation and production (Amador and Millner, 2019; García-Monroy et al., 2020).

5.1.3 Barriers to Anthropogenic Activity

Deforestation has particularly occurred on land with a gentle gradient, leading to an overall increase of 6.73% of the average gradient of remaining forested land (figure 4.6). It is likely that deforestation is driven by the difference in accessibility of land on different gradients because accessibility is a key correlate of deforestation in Colombian rainforests (Bautista-Cespedes et al., 2021), and forests on gentle slopes are more easily reached by the machinery and personnel required for commercial deforestation (Sader and Joyce, 1988; Etter et al., 2005). The correlation of deforestation with lesser slope is evident particularly in the northwest of the study site where a consistent decrease in forest on a gentle slope is visible, and the adjacent areas of forest on a medium-gradient slope are less affected (figure 4.6). Furthermore, due to the topography of the Magdalena Valley, areas of ground with a gentle gradient are present along the course of the river which is an effective route for the extraction of timber. These areas show a loss of forest over time, reducing from significant clumps to smaller patches (figure 4.6), likely due to their accessibility (Sader and Joyce, 1988; Etter et al., 2005; Bautista-Cepsedes et al., 2021).

Serranía de Las Quinchas contains the greatest variety of slope gradients across the study site (figure 4.6). In 2000-2002, Las Quinchas contained significant amounts of forest across all gradients, but by 2018 minimal amounts of forest remained on gentle gradients, and declining amounts on medium and steep gradients. A study investigating the relationship between slope and forest in Colombia between 1940 and 1983 found that it began to approach linearity towards the end of the study period (Sader and Joyce, 1988), as improvements in transportation have enabled even forests on steep gradients to be reached and removed. Therefore, a reduction of forest on steeper gradient slopes in Las Quinchas in 2018 may be due to improvements in transportation, likely in addition to the need for timber pushing commercial activities uphill as forest on lower gradient slopes is removed. Furthermore, socio-political drivers are also likely driving this process, such as the withdrawal of armed groups after the peace accords enabling increased commercial degradation of forested regions (Prem et al., 2020). When compared to figure 4.1, the core forest located on medium and steep gradients was noticeably reduced by 2018. As previously stated, it cannot be confirmed whether this deforestation is primarily driven by the conversion to agriculture including illicit crops, commercial logging, or by the civil conflict (Etter et al., 2006a; 2011; Baptiste et al., 2017), but all these drivers are likely to have had an effect.

5.1.4 Time Lag between Changes and Effects

The largest increase in HFI occurred between 2005-2009 and 2010-2012, increasing by 145.7% (figure 4.4). The largest increase in both the fragmentation analysis and the Euclidean distance to nearest neighbour occurred between 2010-2012 and 2018 (figure 4.1 and table 4.2), suggesting that there are other anthropogenic impacts not covered within this HFI calculation that are a driver of change. However, the trends in both the fragmentation analyses and the HFI calculations are comparable, which may suggest that a difference in the timings of peaks is due to a lag between a change in HFI metrics and their effect on the landscape. For example, the average distance between forest and roads, and forest and settlements both decreased most between 2005-2009 and 2010-2012 (table 4.4). The development of roads and settlements is an important proxy for forest loss (Sader and Joyce, 1988; Hoffman et al., 2018; Bautista-Cespedes et al., 2021), but there will be a time lag between their establishment and the removal of forest in the surrounding area. This will have a subsequent effect on the HFI calculations and thus may explain the difference in timings of peak severity between the fragmentation analyses and HFI values.

5.1.5 Forest Fragments Have Become Smaller and Less Healthy

The average distance between one area of forest to another has decreased over time, evidenced by a reduction of 13.91% in Euclidean distance to nearest neighbour (table 4.2). However, the mean distance between core forest increased over time (by 1.61%, table 4.2), once again showing that deforestation and degradation has occurred, and core forest has been removed. Contrastingly, the distance between patch forest decreased by 19.33% (table 4.2), a similar trend to that of the overall forest nearest neighbour distance (evident in figure 4.3). This suggests that it is the 159.38% increase in patch forest that is driving the overall decrease in Euclidean distance to nearest neighbour, as core forest is fragmented into smaller patches. Therefore, although a decrease in distance between forest nearest neighbours might imply forest growth and a reduction in unforested areas, in reality increased fragmentation of forest is leading to more numerous but smaller forested areas. This reinforces that the lowland rainforests of the Magdalena River Valley have been deforested and degraded over time (Mendoza-Cifuentes et al., 2000; Galvis and Iván Mojica, 2007; Villa and García, 2017), and highlights the need to contextualise such results, and to analyse patterns beyond forest cover to avoid presenting general conclusions that miss hidden trends.

In addition to land use change, vegetation within the study site has worsened in health as measured by the average NDVI value that decreased by 20.81% over time (figure 4.5). Spatially, regions of most change are located in the northwest, where the NDVI of large areas of forest has lowered, and in the southwest, where areas bordering the river have increased in NDVI (figure 4.5). However, the presence of significant clouds makes these findings inconclusive (Borgogno-Mondino et al., 2016).

In comparison to changes in forest cover and NDVI, there has been little change to the complexity of forest shapes (O’Neill et al., 1988) as the fractal dimension index showed little variation (table 4.1 and figure 4.2). When divided into categories of forest, edge forest exhibited a small decline in FDI over time (0.83%, table 4.1). Insignificant changes in FDI, suggesting a random pattern of deforestation, may be due to the nature of anthropogenic activities within the landscape, as deforestation in Colombia has been largely uncontrolled since the 1950s (Etter et al., 2006a). The deforestation evident in figure 4.1 may lack the organisation and subsequent pattern produced by more controlled clearing, and thus the FDI values may not reflect the loss of forest but show that clearing is still uncontrolled and follows a somewhat random pattern, subsequently maintaining the complex nature of forest shape (O’Neill et al., 1988; Etter et al., 2006b).

5.2 Species Conservation in the Middle Magdalena Valley

Endemic plant species are present within the lowland forests of the Magdalena, including *Z. incognita* and *M. cespedesii* (Mendoza-Cifuentes et al., 2000; Amador-Jiménez and Serrano, 2021), meaning significant deforestation could result in an increase in the risk of extinction of species of high ecological value.

This study represents the first attempt to gather all available occurrence data on these plant species within the Middle Magdalena Valley. Current conservation efforts in the region largely focus on the blue-billed curassow (Rainforest Trust, n.d.), and so the results here can be used to broaden the basis of conservation work that is currently taking place. There is clearly a pressing need to protect and conserve ecologically and economically important plant species in the study area because they have been impacted by multitemporal land use change. Even where the available data on certain species (*M. cespedesii*, *S. macrophylla*) was insufficient to calculate quantitative measures of distribution and how it has been affected by land use, it is clear that these ecologically and economically important species are threatened and need to be a focus of local conservation actions. In addition, IUCN Red List statuses are often required by conservation bodies as a basis for funding decisions (Betts et al., 2020).

As outlined previously, a caveat to all the analyses is that it is possible that botanical exploration might reveal new records demonstrating that species' have wider distribution and higher abundance.

5.2.1 Habitat Preferences

Species conservation in the Middle Magdalena Valley must consider the ecological preference of species to slope. Several correlations between species' abundance and distribution and slope were identified, suggesting that different species have different ecological preferences. Information such as this can help conservation actions be efficiently targeted, ensuring that species are conserved in regions they are most suited and likely to survive.

For instance, the EOO of *C. pyriformis*, and the EOO and abundance of *Z. incognita* were negatively correlated to slope (table 4.7), indicating that deforestation on gently sloping land is causing a decline in the distribution of *C. pyriformis*, and the abundance and distribution of *Z. incognita*. *Cariniana pyriformis*, and *Z. incognita* were all more prevalent in forest located on gentle slopes (figure 4.10), with only *C. pyriformis* appearing in forest on steep slopes in the northeast and southwest (figure 4.10). The presence of *C. pyriformis* on steeper slopes may indicate an ecological ability to survive on steep slopes that is lacking in *Z. incognita* meaning it is less limited in its potential AOO. Furthermore, it is possible that individuals of *C. pyriformis* on steeper slopes are being planted for timber, for example within agroforestry systems (Pelaez et al., 2018).

Spatially, centres of forest and loss of *C. pyriformis* and *Z. incognita* are located in the north and centre of the study site (figure 4.10) that is the bottom of the valley and contains almost entirely forest on gentle slopes. *Cariniana pyriformis* and *Z. incognita*'s abundance declined in these regions, likely due to commercial logging of

C. pyriformis and the conversion of forest to arable land, exploiting the accessibility of the gentle sloped land (Bautista-Cespedes et al., 2021). *Cariniana pyriformis* is classified by the IUCN as Near Threatened (World Conservation Monitoring Centre, 1998a), but given the reduction in distribution correlated to a loss of forest on a gentle gradient, revising this classification is suggested. Contrastingly, *Z. incognita* is classified as Endangered (Lopez-Gallego, 2020), a classification that, given its limited and declining abundance and distribution, is appropriate. However, both species exhibited some recovery of abundance and distribution in 2018 (table 4.5, figure 4.8, and table 4.6), so how this classification may change in the future remains to be seen. As the endemic *Z. incognita* is both less abundant and widely distributed, and appears to have an ecological preference for flatter, more accessible land; this species should be specifically targeted with conservation actions, particularly by protecting it from anthropogenic disturbances on the valley floor.

5.2.2 Commercial Deforestation and Plantation

The abundance and distributional range of *M. arborea* increased in the centre of the study site and showed both increases and subsequent decreases in the north (figure 4.10). This may suggest that the dominant driver of forest loss in these regions is commercial deforestation, and other species of timber are being favoured. *Microdesmia arborea* is often used as timber (Prance, 2021; Ríos-García et al., 2014), but the region is home to many timber species, including *C. pyriformis*, *S. macrophylla*, and *C. odorata*, and so *M. arborea* may be ignored by commercial logging which favours these other timber species. In turn, this may also explain why *M. arborea* seems to be unaffected by the reduction of gently sloped forest which affected *C. pyriformis* and *Z. incognita* (table 4.7 and figure 4.10). Furthermore, *M. arborea* is valued for the oil from its fruits, meaning that fruit may be being harvested without individual trees being removed (Universidad Nacional de Colombia, 2017).

The negative relationship of *M. arborea* with NDVI also suggests that *M. arborea* may either persist well in disturbed forest or in the understorey where satellites cannot detect. However, significant uncertainties surrounding NDVI arise from atmospheric disturbances, and further analysis and additional data are required to calculate the NDVI of understory vegetation (Pisek et al., 2015). *Microdesmia arborea* is classified as a Least Concern species by the IUCN (Condit, 2021) and the overall trend displayed within the study site of increased abundance and distribution (figures 4.7, 4.8, and 4.9) supports this classification. Furthermore, *M. arborea* should not be a conservation priority at this point in time, with other species under greater anthropogenic pressures and having smaller populations. However, hotspots of removal of *M. arborea* in the north (figure 4.10) show that the population in the study site is not without any anthropogenic pressures.

It appears that *S. macrophylla*'s population in the valley is also not dwindling due to commercial deforestation and the timber industry. *Swietenia macrophylla* is a large tree, prized for its timber (mahogany) in the furniture industry (Cavers et al., 2003; Global Trees Campaign, 2020). Whilst individuals may be removed from mature forest they are also, however, planted alongside roads and within farms, and thus any visible effects of commercial deforestation may be mitigated (Orwa et al., 2009; Paul and Weber, 2013; Tenorio and Moya, 2019). The negative correlation between the AOO and abundance of *S. macrophylla* and Euclidean distance to nearest neighbour (table 9) suggests that *S. macrophylla* can survive in smaller patches of forest and is more resistant to a reduction of core forest into patch forest. *Swietenia macrophylla* has been found to be more resistant to landscape disturbances than many common tree species (Gullison et al., 1996), and often benefits from disturbances as an open canopy can facilitate regeneration (Orwa et al., 2009; Paul and Weber, 2013; Tenorio and Moya, 2019). However, due to *S. macrophylla* being the least abundant species within the study site, and thus having a small and restricted population (Gärdenfors et al., 2001), its IUCN Red List classification of Vulnerable is appropriate. Due to the species' apparent resistance to disturbance, and not being overly exploited by the timber industry, *S. macrophylla* does not appear to be reducing in population and so is not a critical priority for conservation actions. Its limited abundance and distribution mean the population within the valley should be monitored, and conservation actions should be enacted if this begins to decline.

It is evident that *I. tripterocarpum* is being removed from dense core forest such as in the southwest of the study site but is spreading in the east and northwest within small patches of forest (figure 4.12). *Isidodendron tripterocarpum* is therefore becoming more widely distributed, but less abundant (figure 4.8 and table 4.5). The EOO of *I. tripterocarpum* was found to be negatively correlated to Euclidean distance to nearest neighbour and total forest area, suggesting that as deforestation occurs in the study site, *I. tripterocarpum* is becoming more widespread and thus does not require significant conservation actions. However, the positive correlation between Euclidean distance to nearest neighbour and its abundance shows that the population is in fact reducing as core forest is removed and patch forest becomes more prevalent (table 9). This suggests that *I. tripterocarpum* may be more able to survive in smaller patches of forest than some of the other timber species in the region, and thus may be more adept at surviving commercial deforestation. *Isidodendron tripterocarpum* is classified by the IUCN as a Least Concern species (Lopez-Gallego and Morales, 2020). Within the study site, a classification of Near Threatened would be suggested, due to a decrease in its abundance – despite the increase in distribution – demonstrating that *I. tripterocarpum* is threatened in the study site. Due to this, further conservation actions should be considered for the species, but its ability to survive in smaller patches of forest suggest other, less-resistant species should be prioritised.

5.2.3 Species Needing Further Research

Two species chosen for this study were found to have no correlations with any of the explanatory factors. These species should be researched further, as fluctuations in their abundance and distributions are showing that they are being influenced by changes to the landscape, whether these are the factors investigated here, or others not included. This means that any conclusions on potential conservation actions are made harder, as it is not currently clear what is driving changes in these species' abundances and distributions. However, by looking at how these have changed over time, suggestions on which species require attention are possible.

Magnolia cespedesii was found to have no significant correlations with any of the explanatory factors (Appendix D). This was largely due to the lack of data preventing the calculation of the EOO. *Magnolia cespedesii* is classified by the IUCN as Critically Endangered (Calderon et al., 2016), and is endemic to the Magdalena River Valley, meaning that any fluctuations to its abundance and distribution within the study site could be catastrophic. Due to the small population size evidenced here, *M. cespedesii* should be classed as an imperilled species (Gärdenfors et al., 2001; Harris et al., 2012), and the classification given by the IUCN of Critically Endangered thus seems appropriate (Calderon et al., 2016). It is imperative that this species is continuously monitored, as its limited abundance and distribution puts it at risk of becoming Extinct in the Wild (Harris et al., 2012; IUCN, 2021).

Cedrela odorata was also not correlated to any fragmentation or HFI factors (appendix B). The species has seen an increase in abundance of 18.42% (table 4.5) and EOO of 3.83% (figure 4.8), and AOO of 31.25% (table 4.6). This is likely to be predominantly driven by the planting of *C. odorata* in farms and alongside roads (Orwa et al., 2009; Paul and Weber, 2013; Tenorio and Moya, 2019). Furthermore, the IUCN classify *C. odorata* as Vulnerable (Mark and Rivers, 2017), and it is CITES listed (CITES, n.d.), meaning that international trade is prevented. Although the species, a close relative of mahogany (*S. macrophylla*), has been used as a timber resource for furniture and construction (Cavers et al., 2003), a ban on international trade likely means that this has slowed. *Cedrela odorata* has been subject to increased conservation actions since the 1990s due to high deforestation rates (Gillies et al., 1997), likely also preventing the negative trends evident in the study site's forest from being mirrored by the abundance and distribution of the species. This suggests that changes to the Middle Magdalena River Valley are not having a major effect on *C. odorata*, and the species classified globally as Vulnerable is, in this region, not overtly threatened. Therefore, a classification of Near Threatened, seems more appropriate for this region.

There can be a significant lag between a change in a landscape and the loss of biodiversity and ecosystem services (Lira et al., 2019), meaning that the associated decline of abundance and distribution is delayed, and thus correlations will not be evident. For example, deforestation of lowland rainforests in Colombia and the use of fires to clear has caused severe erosion and a subsequent reduction in soil fertility, converting some areas to savanna-like vegetation and reducing the ability of rainforest plant species to survive (Cavelier et al., 1999). Future work should investigate correlations between multitemporal landscape changes and changes to the abundance and distribution of plant species over a longer time period, in order to understand the potential effects of any time lag.

5.3 GIS, Remote Sensing and Conservation Assessments

The research presented here shows that GIS and remote sensing are versatile tools that can be used in tandem with ground-based data (e.g., specimen records) to accurately inform conservation assessments. Furthermore, the methodology used here has both investigated the geographical changes in the abundance and distribution of plant species and investigated the changes to vegetation in the study site as a whole. When combined, each of these aspects provide context to the other, thus enabling a full picture of the health of environments to be produced.

Multitemporal spatial analyses using individual metrics (e.g., nearest neighbour distance) alongside indices that aggregate such metrics (e.g., HFI) have demonstrated the ability of GIS to investigate the complexity of the effects of human activity on different spatial attributes in forest fragments. For example, the average nearest neighbour distance amongst fragments has decreased, which implies a positive message for forest cover, and the fractal dimension index of forest fragments has shown little change. However, overall forest cover has decreased, and critically, the average nearest neighbour distance between the key remaining areas of core forest has increased, showing in detail how the study area has suffered the same detrimental effects of human activity as forests elsewhere in the Magdalena Valley. Detailed understanding of how this landscape has been affected will aid the effective implementation of targeted conservation and protection measures more efficiently than other commonly used metrics such as change in forest area. Studies elsewhere, and in other vegetation types, carried out at similar, small, local scales that utilise these techniques can uncover other patterns of human influence, and in turn highlight areas in need of further protection and conservation.

However, remote sensing is often at the mercy of the data it utilises. One example of this is the satellite data used to produce the NDVI maps in this study. Due to a large presence of cloud, no conclusions were based upon the NDVI analyses. Atmospheric conditions are a major contributor to NDVI uncertainty and can make interpretations unreliable (Borgogno-Mondino et al., 2016), which must always be considered to avoid forming unreliable conclusions that feed into ineffective conservation assessments.

Future work should, using similar methods, determine if forest in the study site has been replaced by agricultural land over this time period. This could be conducted by following the same methodology on the same remotely sensed dataset as the forest change analysis, but on agricultural land, and comparing trends over time between changes to forest and changes to agricultural land. Depending on the scale of the study site, a ground-based habitat survey would be the most efficient method of classifying land, as it does not rely on atmospheric conditions and could be judged more efficiently by experts in the region. However, for a study site of this scale, remotely sensed data is the more practical option. The post-conflict acceleration of degradation evident in figure 4.1 suggests that there have been drivers of deforestation additional to the illicit cultivation of coca in the study site after the civil conflict had concluded. This is something that future analyses could help identify, as it may uncover if an increase in cropland or grazing pasture is a driving factor. The conversion of lowland rainforest to pastures and crops, often facilitated by a lack of strong governance, is widely cited as the dominant driver of deforestation in Colombia (Etter et al., 2006a; 2011).

The GIS and remote sensing methodology conducted on the important plant species relied on the availability and quality of occurrence data. Forest inventory data is not typically used in making IUCN conservation assessments of species but was invaluable to this project because it gives additional location information plus abundance data compared to occurrence records (e.g., herbarium specimens) that give location alone. Future conservation assessments of tropical forest tree species might usefully include plot-based inventory data, given the number of plots now available (Blundo et al., 2021). However, only 18 inventory plots were available with a combined area of 13.5 Ha for this local study, and so this detailed data was not distributed across the whole study site, with the greatest proportion being serviced by only occurrence records, demonstrating that ideally more inventory plots are needed.

GIS and remote sensing may be useful as a way of identifying regions that would benefit from additional forest plots, in the way this study has for the Middle Magdalena Valley. Furthermore, integrating remote sensing methodologies within conservation assessments could be used to validate abundance and distribution calculations. For example, this thesis used remote sensing to eliminate occurrences from regions where forest had been removed, therefore ensuring only valid occurrences remained (where native vegetation was still present). A similar approach could be integrated into IUCN methodologies as a way of validating occurrence locations and ensuring a species’ abundance and distribution are not miscalculated.

6. Conclusion

6.1 Land Use Change in the Middle Magdalena Valley

Forest within the study site has declined by 25.03% over the study period (figure 4.1), and the Human Footprint Index has increased by 525.6% (table 4.3), supporting previous studies showing deforestation has been high in the lowland rainforest of the Middle Magdalena Valley (Mendoza-Cifuentes et al., 2000; Villa and García, 2017). Declines may be due to the drug trade, civil conflict, the timber industry, and the conversion of forest to arable land. Serranía de Las Quinchas seems to be an important relic of forest that has been better preserved but has still seen degradation, potentially due to the expansion of pastures and illicit agricultural production that has affected the area since the 1950s (Amador- Jiménez and Serrano, 2021).

Slope, which determines accessibility, was found to be a significant barrier to anthropogenic activity, with the average gradient of forest increasing by 6.73% overall (figure 4.6) as anthropogenic activity was focussed on flatter and more accessible land (Sader and Joyce, 1988; Etter et al., 2005).

6.2 Species Conservation in the Middle Magdalena Valley

Species conservation in the valley must consider the ecological preference of species to slope. Species such as *Z. incognita* that prefer flatter land (figure 4.10) are more at risk and thus, also given its more restricted range, should be a conservation priority over species such as *C. pyriformis* that are able to survive on steeper slopes, though it is possible that individuals are being planted on slopes for timber (Pelaez et al., 2018), and so this must be investigated before decisions are made. Other species such as *S. macrophylla* and *C. odorata* may also be planted along roads and within farms and so may mask the effects of deforestation (Orwa et al., 2009; Paul and Weber, 2013; Tenorio and Moya, 2019). The preference of the timber industry for these species may explain why *M. arborea*, which is less favoured for its timber, is increasing in abundance and distribution (figures 4.7, 4.8, 4.9).

Future conservation actions must also consider the different resilience of species to disturbance, for example *S. macrophylla* and *I. tripterocarpum* appear more resistant to disturbances potentially because they rely on them to facilitate regeneration (Orwa et al., 2009; Paul and Weber, 2013; Tenorio and Moya, 2019).

This thesis suggested a regional classification of IUCN Red List status that differed from the global classification for three out of the seven study species. This highlights the importance of regional analysis in deciding regional conservation actions.

6.3 Implications of Results

The decline of forest and increase in HFI within the study site has wider implications for the future of Colombian forests as a whole. The trend shown here reflects the reduction of lowland rainforest nationally, which has been rapidly cleared in Colombia for a number of decades (Etter et al., 2006a; Van Ausdal, 2009; BirdLife International, 2018; Ayram et al., 2018). Whilst the local and national trend for deforestation needs to be halted, there is some hope shown in the study area by the observation of regeneration in areas such as the northeast, and the effectiveness of Las Quinchas as a protected area.

The difference in responses to anthropogenic activity of the focus species in the study area underline that conservation efforts must also focus on specific species, with threats, endemism, ecological preferences, resistance to disturbance, and population size and range being evaluated.

6.4 Global Suitability of Methodology

This thesis used a novel integration of remotely sensed and ground-based occurrence data from herbarium specimens and monitoring plots in a multifaceted methodology that enables a thorough investigation of changing land use in a Colombian study site.

The GIS and remote sensing methods are by nature global and could therefore be applied to a range of threatened areas around the world, across ecosystems. Ever-improving resolution of satellite imagery will improve our ability to distinguish different types of vegetation, allowing more nuanced GIS analyses.

Perhaps surprisingly, what will hinder this methodology's global application most will be the availability of simple, ground-based occurrence data, from individual collections of plants represented in global herbaria, and in particular the lack of forest inventory data from monitoring plots in many tropical countries. For example, such long-term monitoring efforts have currently focused mostly on tropical rain forests and there is a critical need to expand them to other biomes such as tropical dry forests and savannas (Pennington et al., 2018; Moonlight et al., 2021). If this was readily available for the threatened area of interest, this methodology could be quickly and effectively conducted.

7. Appendices

		Factor						
	C. pyriformis	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates	0.001992	0.002486	0.002013	-0.003623	0.0038704	0.0003289	0.0002946
	std.error	0.002456	0.002218	0.002446	0.001187	0.000719	0.0028201	0.002822
	t value	0.811	1.121	0.823	-3.051	5.383	0.117	0.104
	pr	0.502	0.379	0.497	0.0927	0.0328	0.918	0.926
AOO	estimates	-0.008839	-0.007974	-0.006852	0.009182	-0.006187	-0.004385	-0.004508
	std.error	0.004	0.004827	0.005631	0.003685	0.005998	0.006748	0.006705
	t value	-2.21	-1.652	-1.217	2.492	-1.032	-0.65	-0.672
	pr	0.158	0.24	0.348	0.13	0.411	0.582	0.571
Known Abundance	estimates	0.003886	0.003035	0.00473	-0.006803	0.008236	0.001562	0.001437
	std.error	0.005302	0.005568	0.004946	0.003483	0.001274	0.005866	0.005882
	t value	0.733	0.545	0.956	-1.953	6.465	0.266	0.244
	pr	0.54	0.64	0.44	0.19	0.0231	0.815	0.83
Estimated Abund.	estimates	0.0007868	0.001004	0.00143	-0.002662	0.003782	-0.0001313	-0.0002138
	std.error	0.003025	0.002992	0.002905	0.002424	0.001514	0.0030737	0.0030712
	t value	0.26	0.336	0.492	-1.099	2.498	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix A: Table of GLM results for C. pyriformis, detailing all results and coefficients.

		Factor						
	C. odorata	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates	-0.003293	0.00309	-0.004565	0.001332	-0.002333	-0.004952	-0.00488
	std.error	0.00336	0.003453	0.002508	0.003984	0.003742	0.002097	0.002183
	t value	-0.98	0.895	-1.821	0.334	-0.623	-2.361	-2.234
	pr	0.43	0.465	0.21	0.77	0.597	0.142	0.155
AOO	estimates	-0.03604	-0.01698	-0.02894	0.02431	-0.01073	-0.02806	-0.02866
	std.error	0.01326	0.02607	0.02018	0.02364	0.0277	0.02072	0.02026
	t value	-2.717	-0.651	-1.434	1.028	-0.387	-1.354	-1.414
	pr	0.113	0.581603	0.288074	0.411901	0.735741	0.30836	0.292872
Known Abundance	estimates	-0.021516	-0.01062	-0.01665	0.0137	-0.004821	-0.01664	-0.01707
	std.error	0.009685	0.01639	0.01367	0.01543	0.017711	0.01364	0.01336
	t value	-2.222	-0.648	-1.218	0.888	-0.272	-1.22	-1.278
	pr	0.156	0.583515	0.347	0.46828	0.811003	0.347	0.33
Estimated Abund.	estimates	0.0007318	0.000934	0.00133	-0.002477	0.003519	-0.0001222	-0.0002
	std.error	0.0028139	0.002784	0.002702	0.002255	0.001408	0.0028593	0.002857
	t value	0.26	0.336	0.492	-1.099	2.499	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix B: Table of GLM results for C. odorata, detailing all results and coefficients.

		Factor						
	I. tripterocarpum	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates	-0.005088	-0.001491	-0.0050659	0.004399	-0.003923	-0.00418	-0.004178
	std.error	0.0007517	0.003523	0.0008273	0.00198	0.002412	0.002184	0.002185
	t value	-6.768	-0.423	-6.123	2.222	-1.627	-1.914	-1.913
	pr	0.0211	0.713	0.0257	0.156	0.245	0.196	0.196
AOO	estimates	0.00919	0.008019	0.010064	-0.014688	0.016545	0.00353	0.00334
	std.error	0.009847	0.010326	0.009399	0.005314	0.001233	0.011514	0.011543
	t value	0.933	0.777	1.071	-2.764	13.42	0.307	0.289
	pr	0.449	0.519	0.396	0.11	0.0055	0.788	0.8
Known Abundance	estimates	0.007702	0.002646	0.008254	-0.008082	0.008471	0.005829	0.005758
	std.error	0.00347	0.006171	0.002755	0.002915	0.002388	0.004971	0.005014
	t value	2.22	0.429	2.996	-2.772	3.547	1.173	1.148
	pr	0.157	0.71	0.0957	0.109	0.0711	0.362	0.37
Estimated Abund.	estimates	0.0007875	0.001005	0.001431	-0.002665	0.003786	-0.0001315	-0.000214
	std.error	0.0030276	0.002995	0.002908	0.002426	0.001516	0.0030764	0.003074
	t value	0.26	0.336	0.492	-1.098	2.498	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix C: Table of GLM results for I. tripterocarpum, detailing all results and coefficients.

		Factor						
	M. cespedesii	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates							
	std.error							
	t value							
	pr							
AOO	estimates	-8.01E-17	-8.72E-17	-6.56E-17	1.04E-16	-8.67E-17	-2.79E-17	-2.84E-17
	std.error	1.51E-16	1.51E-16	1.51E-16	1.51E-16	1.51E-16	1.74E-16	1.74E-16
	t value	-0.53	-0.577	-0.435	0.691	-0.574	-0.16	-0.163
	pr	0.649	0.622	0.706	0.561	0.624	0.887	0.885
Known Abundance	estimates							
	std.error							
	t value							
	pr							
Estimated Abund.	estimates	0.0009966	0.001272	0.001811	-0.003367	0.004785	-0.0001661	-0.000271
	std.error	0.0038283	0.003787	0.003676	0.003066	0.001917	0.0038899	0.003887
	t value	0.26	0.336	0.492	-1.098	2.495	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix D: Table of GLM results for M. cespedesii, detailing all results and coefficients.

		Factor						
	M. arborea	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates	-0.012168	-0.013222	-0.010061	0.016114	-0.013267	-0.004304	-0.004373
	std.error	0.007691	0.006777	0.009116	0.002457	0.006735	0.011157	0.01114
	t value	-1.582	-1.951	-1.104	6.56	-1.97	-0.386	-0.393
	pr	0.254	0.19	0.385	0.0225	0.188	0.737	0.733
AOO	estimates	-0.017658	-0.019225	-0.01459	0.023474	-0.019126	-0.006275	-0.006379
	std.error	0.011194	0.009844	0.01328	0.00374	0.009943	0.016224	0.016197
	t value	-1.578	-1.953	-1.098	6.276	-1.923	-0.387	-0.394
	pr	0.255	0.19	0.387	0.0245	0.194	0.73621	0.73173
Known Abundance	estimates	-0.02121	-0.01925	-0.02262	0.034873	-0.036814	-0.008216	-0.007855
	std.error	0.02133	0.02233	0.02067	0.010369	0.003012	0.025503	0.025552
	t value	-0.994	-0.862	-1.095	3.363	-12.22	-0.322	-0.307
	pr	0.424858	0.479466	0.38796	0.0782	0.00663	0.777892	0.787576
Estimated Abund.	estimates	0.0008431	0.001076	0.001532	-0.002852	0.004052	-0.0001407	-0.0002291
	std.error	0.0032408	0.003206	0.003112	0.002596	0.001622	0.0032929	0.0032903
	t value	0.26	0.336	0.492	-1.098	2.497	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix E: Table of GLM results for M. arborea, detailing all results and coefficients.

		Factor						
	S. macrophylla	Frag Analysis	FDI	Euclid Neigbour	Slope	NDVI	DTR	DTS
EOO	estimates							
	std.error							
	t value							
	pr							
AOO	estimates	-0.19176	-1.51E-14	-0.21925	0.1915	-0.17677	-0.18033	-0.17724
	std.error	0.08487	0.1633	0.04489	0.1348	0.10545	0.08981	0.09118
	t value	-2.259	0	-4.884	1.421	-1.676	-2.008	-1.944
	pr	0.152	1	0.03945	0.2913	0.2357	0.1824	0.1913
Known Abundance	estimates	-0.21573	-1.66E-14	-0.24745	0.2223	-0.1995	-0.20224	-0.19865
	std.error	0.09673	0.1848	0.05221	0.1574	0.1199	0.10196	0.10341
	t value	-2.23	0	-4.74	1.412	-1.664	-1.983	-1.921
	pr	0.155	1	0.0417	0.293	0.238	0.186	0.195
Estimated Abund.	estimates							
	std.error							
	t value							
	pr							

Appendix F: Table of GLM results for S. macrophylla, detailing all results and coefficients.

		Factor						
	Z. incognita	**Frag Analysis**	**FDI**	**Euclid Neigbour**	**Slope**	**NDVI**	**DTR**	**DTS**
EOO	estimates	0.015759	0.017534	0.0133	-0.021399	0.01916	0.00496	0.005
	std.error	0.010798	0.009303	0.01229	0.002315	0.00752	0.01507	0.01506
	t value	1.459	1.885	1.082	-9.243	2.548	0.329	0.332
	pr	0.282	0.2	0.393	0.0115	0.126	0.773	0.772
AOO	estimates	0.02809	0.0438	0.02665	-0.05444	0.05945	-0.00134	-0.00184
	std.error	0.04058	0.03279	0.0409	0.0203	0.01577	0.04478	0.04476
	t value	0.692	1.336	0.652	-2.682	3.77	-0.03	-0.041
	pr	0.560357	0.313258	0.581531	0.115435	0.06372	0.97882	0.97098
Known Abundance	estimates	0.03935	0.0579	0.03602	-0.07	0.07525	0.00072	0.0002
	std.error	0.04984	0.03959	0.05077	0.02264	0.01939	0.0564	0.0564
	t value	0.79	1.462	0.709	-3.092	3.881	0.013	0.004
	pr	0.51247	0.28123	0.55161	0.090626	0.06043	0.99096	0.99748
Estimated Abund.	estimates	0.0008477	0.001082	0.00154	-0.002867	0.00407	-0.00014	-0.00023
	std.error	0.0032583	0.003223	0.003129	0.00261	0.00163	0.00331	0.00331
	t value	0.26	0.336	0.492	-1.098	2.497	-0.043	-0.07
	pr	0.819	0.769	0.671	0.387	0.13	0.97	0.951

Appendix G: Table of GLM results for Z. incognita detailing all results and coefficients.

8. Reference List

1. Abud, M., Agudelo, C., Aguilar-Cano, J. R., Aguilar-Garavito, M., Aguirre, J., Aldana, A., Álvarez, E., Alviz, Á., Amaya-Espinel, J. D., Arias-Alzate, A., Avella, A., Vallejo, M., Torres, A. M., Urbina, N., Valderrama, C., Valderrama Rincón, N., Valderrama, S., Valencia-Mazo, D., Vela, M., ... Torres, S., 2017. Biodiversidad 2016. Estado y Tendencias de la Biodiversidad Continental de Colombia. *Instituto de Investigaciónde Recursos Biológicos Alexander von Humboldt.* http://repository.humboldt.org.co/handle/20.500.11761/32962.

2. Aguilar-Cano, J., Mendoza-Cifuentes, H. and Ayala-Joya, M., 2018. Two new species of “molinillo” tree (Magnolia: Magnoliaceae) from Serranía de los Yariguíes, Santander, Colombia. *Biota colombiana*, *19*, pp.29-44.

3. Akçakaya, H.R., Ferson, S., Burgman, M.A., Keith, D.A., Mace, G.M. and Todd, C.R., 2000. Making consistent IUCN classifications under uncertainty. *Conservation biology*, *14*(4), pp.1001-1013.

4. Álvarez, M.D., 2002. Illicit crops and bird conservation priorities in Colombia. *Conservation Biology*, *16*(4), pp.1086-1096.

5. Amador, M. and Millner, N., 2019. *Serranía de las Quinchas: Introducing our fieldsites* | *BioResilience - Colombia*. [online] BioResilience. Available at: <https://blogs.exeter.ac.uk/bioresilience/blog/2019/10/02/introducing-our-fieldsites-from-the-socio-cultural-component-2-Serranía-de-las-quinchas-boyaca/> [Accessed 21 January 2022].

6. Amador-Jiménez, M., Millner, N., Palmer, C., Pennington, R.T. and Sileci, L., 2020. The unintended impact of Colombia’s COVID-19 lockdown on forest fires. *Environmental and resource economics*, *76*, pp.1081-1105.

7. Amador-Jiménez, M. and Serrano, J., 2021. *BioResilience in the Public Hearing about Socio-Environmental Conflicts in Serranía de las Quinchas at the Senate of Colombia | BioResilience - Colombia*. [online] BioResilience. Available at: <https://blogs.exeter.ac.uk/bioresilience/blog/2021/05/28/bioresilience-in-the-public-hearing-about-socio-environmental-conflicts-in-Serranía-de-las-quinchas-at-the-senate-of-colombia/> [Accessed 3 January 2022].

8. Armenteras, D., Gast, F., Villareal, H., 2003. Andean forest fragmentation and the representativeness of protected natural areas in the eastern Andes, Colombia. Biological Conservation 113, 245–256. https://doi.org/10.1016/S0006-3207(02)00359-2.

9. Armenteras, D., Gonzalez, T., Ramírez-Delgado, J.P., Meza Elizalde, M.C., Montenegro, E., García, G., Yepes, A., 2018. CAUSAS DE DEGRADACIÓN FORESTAL EN COLOMBIA: una primera aproximación.

10. Armenteras, D., Rodríguez, N., Retana, J., Morales, M., 2011. Understanding deforestation in montane and lowland forests of the Colombian Andes. Regional Environmental Change 11, 693–705. https://doi.org/10.1007/s10113-010-0200-y.

11. Ayram, C.A.C., Etter, A., Díaz-Timoté, J., Buriticá, S.R., Ramírez, W. and Corzo, G., 2020. Spatiotemporal evaluation of the human footprint in Colombia: Four decades of anthropic impact in highly biodiverse ecosystems. *Ecological Indicators*, *117*, p.106630.

12. Baptiste, B., Pinedo-Vasquez, M., Gutierrez-Velez, V.H., Andrade, G.I., Vieira, P., Estupiñán-Suárez, L.M., Londoño, M.C., Laurance, W. and Lee, T.M., 2017. Greening peace in Colombia. *Nature Ecology & Evolution*, *1*(4), pp.1-3.

13. Bautista-Cespedes, O.V., Willemen, L., Castro-Nunez, A. and Groen, T.A., 2021. The effects of armed conflict on forest cover changes across temporal and spatial scales in the Colombian Amazon. *Regional environmental change*, *21*(3), pp.1-16.

14. Bavaghar, M.P., 2015. Deforestation modelling using logistic regression and GIS. *Journal of Forest Science*, 61(5), pp.193-199.

15. Bernal, R., S.R. Gradstein & M. Celis (eds.). 2019. Catálogo de plantas y líquenes de Colombia. Instituto de Ciencias Naturales, Universidad Nacional de Colombia, Bogotá. [Online]. Available at: http://catalogoplantasdecolombia.unal.edu.com. [Accessed 26/01/2021].

16. Betts, J., Young, R.P., Hilton-Taylor, C., Hoffmann, M., Rodríguez, J.P., Stuart, S.N. and Milner-Gulland, E.J., 2020. A framework for evaluating the impact of the IUCN Red List of threatened species. *Conservation Biology*, *34*(3), pp.632-643.

17. BioResilience. n.d. *The project* | *BioResilience - Colombia*. [online] Available at: <https://blogs.exeter.ac.uk/bioresilience/bioresilience/> [Accessed 10 June 2022].

18. Blundo, C., Carilla, J., Grau, R., Malizia, A., Malizia, L., Osinaga-Acosta, O., Bird, M., Bradford, M., Catchpole, D., Ford, A. and Graham, A., 2021. Taking the pulse of Earth's tropical forests using networks of highly distributed plots. *Biological Conservation*, *260*, p.108849.

19. Borgogno-Mondino, E., Lessio, A. and Gomarasca, M.A., 2016. A fast operative method for NDVI uncertainty estimation and its role in vegetation analysis. *European Journal of Remote Sensing*, *49*(1), pp.137-156.

20. Breslow, N.E., 1996. Generalized linear models: checking assumptions and strengthening conclusions. *Statistica applicata*, *8*(1), pp.23-41.

21. Brito, D., Ambal, R.G., Brooks, T., De Silva, N., Foster, M., Hao, W., Hilton-Taylor, C., Paglia, A., Rodríguez, J.P. and Rodríguez, J.V., 2010. How similar are national red lists and the IUCN Red List?. *Biological Conservation*, *143*(5), pp.1154-1158.

22. Brown, J.H. and Kodric-Brown, A., 1977. Turnover rates in insular biogeography: effect of immigration on extinction. *Ecology*, *58*(2), pp.445-449.

23. Brown, S., Iverson, L.R. and Lugo, A.E., 1994. Land-use and biomass changes of forests in Peninsular Malaysia from 1972 to 1982: a GIS approach. In *Effects of Land-Use Change on Atmospheric CO2 Concentrations* (pp. 117-143). Springer, New York, NY.

24. Burnham, R.J. and Johnson, K.R., 2004. South American palaeobotany and the origins of neotropical rainforests. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *359*(1450), pp.1595-1610.

25. Calderon, E., Cogollo, A., Velasquez-Rua, C., Serna-Gonzalez, M. & Garcia, N. 2016. *Magnolia cespedesii*. *The IUCN Red List of Threatened Species* 2016: e.T38865A2884422. https://dx.doi.org/10.2305/IUCN.UK.2016-1.RLTS.T38865A2884422.en. Accessed on 11 August 2022.

26. Capinha, C. and Pateiro-López, B., 2014. Predicting species distributions in new areas or time periods with alpha-shapes. *Ecological Informatics*, 24, pp.231-237.

27. Cavelier, J., Aide, T.M., Dupuy, J.M., Eusse, A.M., Santos, C., 1999. Long-term effects of deforestation on soil properties and vegetation in a tropical lowland forest in Colombia. *Ecotropicos*, *12*(2), pp.57-68.

28. Cavers, S., Navarro, C. and Lowe, A.J., 2003. Chloroplast DNA hylogeography reveals colonization history of a Neotropical tree, *Cedrela odorata* L., in Mesoamerica. *Molecular Ecology*, *12*(6), pp.1451-1460.

29. Cintron, B.B., 1990. *Cedrela odorata* L. Cedro hembra, Spanish cedar. *Silvics of North America*, *2*, pp.250-257.

30. CITES. n.d. *Cedrela odorata* | *CITES*. [online] Available at: <https://cites.org/eng/taxonomy/term/12137> [Accessed 15 August 2022].

31. Clerici, N., Armenteras, D., Kareiva, P., Botero, R., Ramírez-Delgado, J.P., Forero-Medina, G., Ochoa, J., Pedraza, C., Schneider, L., Lora, C., Gómez, C., Linares, M., Hirashiki, C., Biggs, D., 2020. Deforestation in Colombian protected areas increased during post-conflict periods. Scientific Reports 10. https://doi.org/10.1038/s41598-020-61861-y.

32. Condit, R. 2021. *Microdesmia arborea*. *The IUCN Red List of Threatened Species* 2021: e.T118223293A176099735. https://dx.doi.org/10.2305/IUCN.UK.2021-1.RLTS.T118223293A176099735.en. Accessed on 11 August 2022.

33. Danielsson, P.E., 1980. Euclidean distance mapping. *Computer Graphics and image processing*, *14*(3), pp.227-248.

34. Dauby, G., Stévart, T., Droissart, V., Cosiaux, A., Deblauwe, V., Simo-Droissart, M., Sosef, M.S., Lowry, P.P., Schatz, G.E., Gereau, R.E. and Couvreur, T.L., 2017. ConR: An R package to assist large-scale multispecies preliminary conservation assessments using distribution data. *Ecology and evolution*, *7*(24), pp.11292-11303.

35. de Leijster, V., Santos, M.J., Wassen, M.W., Camargo García, J.C., Llorca Fernandez, I., Verkuil, L., Scheper, A., Steenhuis, M., Verweij, P.A., 2021.

Ecosystem services trajectories in coffee agroforestry in Colombia over 40 years. Ecosystem Services 48, 101246. https://doi.org/10.1016/j.ecoser.2021.101246.

36. Dempsey, C., 2021. *Types of GIS Data Explored: Vector and Raster*. [online] GIS Lounge. Available at: <https://www.gislounge.com/geodatabases-explored-vector-and-raster-data/> [Accessed 31 May 2022].
37. ESRI. n.d.a *ArcGIS Hub*. [online] Available at: <https://hub.arcgis.com/> [Accessed 31 May 2022].
38. ESRI. n.d.b *Near (Analysis)—ArcMap* | *Documentation*. [online] Available at: <https://desktop.arcgis.com/en/arcmap/latest/tools/analysis-toolbox/near.htm> [Accessed 6 June 2022].
39. Etter, A., McAlpine, C., Pullar, D. and Possingham, H., 2005. Modeling the age of tropical moist forest fragments in heavily-cleared lowland landscapes of Colombia. *Forest Ecology and Management*, *208*(1-3), pp.249-260.

40. Etter, A., McAlpine, C., Pullar, D. and Possingham, H., 2006a. Modelling the conversion of Colombian lowland ecosystems since 1940: Drivers, patterns and rates. *Journal of environmental management*, *79*(1), pp.74-87

41. Etter, A., McAlpine, C., Wilson, K., Phinn, S. and Possingham, H., 2006a. Regional patterns of agricultural land use and deforestation in Colombia. *Agriculture, ecosystems & environment*, *114*(2-4), pp.369-386.

42. Etter, A., McAlpine, C.A., Seabrook, L. and Wilson, K.A., 2011. Incorporating temporality and biophysical vulnerability to quantify the human spatial footprint on ecosystems. *Biological Conservation*, *144*(5), pp.1585-1594.

43. Etter, A., Villa, L.A., 2000. Andean Forests and Farming Systems in part of the Eastern Cordillera (Colombia). Mountain Research and Development 20. https://doi.org/10.1659/0276.

44. Felter, C. and Renwick, D., 2017. *Colombia's Civil Conflict*. [online] Council on Foreign Relations. Available at: <https://www.cfr.org/backgrounder/colombias-civil-conflict> [Accessed 5 July 2022].
45. Feoli, E., Vuerich, L.G. and Zerihun, W., 2002. Evaluation of environmental degradation in northern Ethiopia using GIS to integrate vegetation, geomorphological, erosion and socio-economic factors. *Agriculture, Ecosystems & Environment*, *91*(1-3), pp.313-325.
46. Fernández-Alonso, J.L., Pérez-Zabala, J.A. and Idarraga-Piedrahita, A., 2000. Isidodendron, un nuevo género neotropical de árboles de la familia Trigoniaceae. *Revista de la Academia Colombiana de Ciencias Exactas, Físicas y Naturales*, *24*(92), pp.347-358.
47. Forman, R., 1995. *Land Mosaics: The Ecology of Landscapes and Regions*. Cambridge: Cambridge University Press.
48. Galvis, G. and Iván Mojica, J., 2007. The Magdalena River fresh water fishes and fisheries. *Aquatic ecosystem health & management*, *10*(2), pp.127-139.
49. García-Monroy, J.S., Morales-González, Ó.E. and Carvajal-Cogollo, J.E., 2020. New bird records for the Serranía de Las Quinchas, Colombia: inventory update and comments on distributions in an altitudinal gradient. *Check List*, *16*, p.1475.
50. Gärdenfors, U., Hilton-Taylor, C., Mace, G.M. and Rodriguez, J.P., 2001. The application of IUCN Red List criteria at regional levels. *Conservation biology*, *15*(5), pp.1206-1212.
51. Gasparri, N.I. and Grau, H.R., 2009. Deforestation and fragmentation of Chaco dry forest in NW Argentina (1972–2007). *Forest ecology and Management*, *258*(6), pp.913-921.

52. Gaston, K.J., 1994. Rarity. Chapman anf Hall, London.

53. GBIF.org (2022), *GBIF Home Page*. Available from: https://www.gbif.org [12 August 2022].

54. GBIF.org. n.d. Occurrence Detail 436999488. [online] Available at: <https://www.gbif.org/occurrence/436999488> [Accessed 6 October 2021].

55. Geist, H.J., Lambin, E.F., 2001. What drives tropical deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence (http://www.geo.ucl.ac.be/LUCC/lucc.html). LUCC Report Series, 4. CIACO, Louvain-la-Neuve.

56. Gillies, A.C.M., Cornelius, J.P., Newton, A.C., Navarro, C., Hernández, M. and Wilson, J., 1997. Genetic variation in Costa Rican populations of the tropical timber species *Cedrela odorata* L., assessed using RAPDs. *Molecular Ecology*, *6*(12), pp.1133-1145.

57. Global Trees Campaign. 2020. *Big-leaf Mahogany - Global Trees*. [online] Available at: <https://globaltrees.org/threatened-trees/trees/big-leaf-mahogany/> [Accessed 8 December 2021].

58. González-González, A., Villegas, J.C., Clerici, N. and Salazar, J.F., 2021. Spatial-temporal dynamics of deforestation and its drivers indicate need for locally-adapted environmental governance in Colombia. *Ecological Indicators*, *126*, p.107695.

59. Govaerts, R. (2017). *Magnolia cespedesii* (Triana & Planch.) in Govaerts, R. (2017). World Checklist of Selected Plant Families. In O. Bánki, Y. Roskov, L. Vandepitte, R. E. DeWalt, D. Remsen, P. Schalk, T. Orrell, M. Keping, J. Miller, R. Aalbu, R. Adlard, E. Adriaenssens, C. Aedo, E. Aescht, N. Akkari, M. A. Alonso-

Zarazaga, B. Alvarez, F. Alvarez, G. Anderson, et al., Catalogue of Life Checklist (Aug 2017). https://doi.org/10.48580/d4sl-38c

60. Guisan, A., Weiss, S.B. and Weiss, A.D., 1999. GLM versus CCA spatial modeling of plant species distribution. *Plant ecology*, *143*(1), pp.107-122.

61. Gullison, R.E., Panfil, S.N., Strouse, J.J. and Hubbell, S.P., 1996. Ecology and management of mahogany (*Swietenia macrophylla* King) in the Chimanes Forest, Beni, Bolivia. *Botanical Journal of the Linnean society*, *122*(1), pp.9-34.

62. Hadeel, A., Jabbar, M. and Chen, X., 2011. Remote sensing and GIS application in the detection of environmental degradation indicators. *Geo-spatial Information Science*, *14*(1), pp.39-47.

63. Harris, J.B.C., Reid, J.L., Scheffers, B.R., Wanger, T.C., Sodhi, N.S., Fordham, D.A. and Brook, B.W., 2012. Conserving imperiled species: a comparison of the IUCN Red List and US Endangered Species Act. *Conservation Letters*, *5*(1), pp.64-72.

64. He, F. and Gaston, K.J., 2000. Estimating species abundance from occurrence. *The American Naturalist*, 156(5), pp.553-559.

65. Heath, J. and Binswanger, H., 1996. Natural resource degradation effects of poverty and population growth are largely policy-induced: the case of Colombia. *Environment and Development Economics*, *1*(1), pp.65-84.

66. Hernández, H.M. and Navarro, M., 2007. A new method to estimate areas of occupancy using herbarium data. *Biodiversity and Conservation*, *16*(9), pp.2457-2470.

67. HISTORY. 2020. *World Wide Web (WWW) launches in the public domain*. [online] Available at: <https://www.history.com/this-day-in-history/world-wide-web-

launches-in-public-domain#:~:text=On%20April%2030%2C%201993%2C%20four,first%20web%20browser%20and%20editor.> [Accessed 22 June 2022].

68. Hoffmann, C., Márquez, J.R.G. and Krueger, T., 2018. A local perspective on drivers and measures to slow deforestation in the Andean-Amazonian foothills of Colombia. *Land use policy*, *77*, pp.379-391.
69. Ibáñez, A.M. and Vélez, C.E., 2008. Civil conflict and forced migration: The micro determinants and welfare losses of displacement in Colombia. *World Development*, *36*(4), pp.659-676.
70. IDEAM. n.d. *IDEAM Homepage*. [online] Available at: <http://www.ideam.gov.co/> [Accessed 7 June 2022].
71. IGAC. (2011). *Modelo Digital de Elevación. SRTM 30 Metros. Colombia*. Año 2011. https://www.colombiaenmapas.gov.co/?e=-87.99692981445587,-1.3189043097131903,-74.90122668945935,11.026822978285383,4686&b=igac&u=0&t=23&servicio=159.
72. Imre, A.R. and Bogaert, J., 2004. The fractal dimension as a measure of the quality of habitats. *Acta Biotheoretica*, *52*(1), pp.41-56.
73. iNaturalist.ca. n.d. *Isidodendron tripterocarpum*. [online] Available at: <https://inaturalist.ca/taxa/887361-Isidodendron-tripterocarpum> [Accessed 6 October 2021].
74. International Union for Conservation of Nature, International Union for Conservation of Nature, Natural Resources. Species Survival Commission and IUCN Species Survival Commission, 2001. *IUCN Red List categories and criteria*. IUCN.

75. IPCC, 2022: Summary for Policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 3–33, doi:10.1017/9781009325844.001.

76. IUCN Standards and Petitions Committee. 2022. Guidelines for Using the IUCN Red List Categories and Criteria. Version 15.1. Prepared by the Standards and Petitions Committee. Downloadable from https://www.iucnredlist.org/documents/RedListGuidelines.pdf.

77. IUCN. 2021. *About | IUCN*. [online] Available at: <https://www.iucn.org/about> [Accessed 23 November 2021].

78. IUCN. n.d. *Red List of Ecosystems*. [online] Available at: <https://www.iucn.org/theme/ecosystem-management/our-work/red-list-ecosystems> [Accessed 23 June 2022].

79. Jara-Rojas, R., Russy, S., Roco, L., Fleming-Muñoz, D., Engler, A., 2020. Factors affecting the adoption of agroforestry practices: Insights from silvopastoral systems of Colombia. Forests 11. https://doi.org/10.3390/F11060648.

80. Jiang, F., Ma, L., Broyd, T., Chen, W. and Luo, H., 2022a. Digital twin enabled sustainable urban road planning. *Sustainable Cities and Society*, *78*, p.103645.

81. Jiang, X., Jiang, M., Gou, Y., Li, Q. and Zhou, Q., 2022b. Forestry digital twin with machine learning in Landsat 7 data. *arXiv preprint arXiv:2204.01709*.

82. Jiménez-Alfaro, B., Draper, D. and Nogués-Bravo, D., 2012. Modeling the potential area of occupancy at fine resolution may reduce uncertainty in species range estimates. *Biological Conservation*, 147(1), pp.190-196.

83. Kinnaird, M.F., Sanderson, E.W., O'Brien, T.G., Wibisono, H.T. and Woolmer, G., 2003. Deforestation trends in a tropical landscape and implications for endangered large mammals. *Conservation Biology*, *17*(1), pp.245-257.

84. Lamine, S., Petropoulos, G.P., Singh, S.K., Szabó, S., Bachari, N.E.I., Srivastava, P.K. and Suman, S., 2018. Quantifying land use/land cover spatio-temporal landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS®. *Geocarto international*, *33*(8), pp.862-878.

85. Lang, S., Tiede, D., (2003): vLATE Extension für ArcGIS - vektorbasiertes Tool zur quantitativen Landschaftsstrukturanalyse, ESRI Anwenderkonferenz 2003 Innsbruck. CDROM.

86. Lee-Grant, C. (2021). *Seeing the forest for the trees: Exploring the abundance-range size relationship of woody flora in the seasonally dry tropical forests of Colombia and Venezuela*. Undergraduate Dissertation, University of Exeter.

87. Liévano-Latorre, L.F., Brum, F.T., Loyola, R., 2021. How effective have been guerrilla occupation and protected areas in avoiding deforestation in Colombia? Biological Conservation 253. https://doi.org/10.1016/j.biocon.2020.108916.

88. Lindström, A.J. and Idárraga, A., 2009. *Zamia incognita* (Zamiaceae): the exciting discovery of a new gymnosperm from Colombia. *Phytotaxa*, *2*(1), pp.29-34.

89. Link, A., Galvis, N., Marquez, M., Guerrero, J., Solano, C. and Stevenson, P.R., 2012. Diet of the critically endangered brown spider monkey (Ateles hybridus) in

an inter-Andean lowland rainforest in Colombia. *American journal of primatology*, *74*(12), pp.1097-1105.

90. Lira, P.K., de Souza Leite, M. and Metzger, J.P., 2019. Temporal lag in ecological responses to landscape change: Where are we now?. *Current Landscape Ecology Reports*, *4*(3), pp.70-82.
91. Lopatin, J., Dolos, K., Hernández, H.J., Galleguillos, M. and Fassnacht, F.E., 2016. Comparing generalized linear models and random forest to model vascular plant species richness using LiDAR data in a natural forest in central Chile. *Remote Sensing of Environment*, *173*, pp.200-210.
92. Lopez-Gallego, C. & Morales M, P. 2020. *Isidodendron tripterocarpum*. *The IUCN Red List of Threatened Species* 2020: e.T153331254A153331257. https://dx.doi.org/10.2305/IUCN.UK.2020-2.RLTS.T153331254A153331257.es. Accessed on 11 August 2022.
93. Lopez-Gallego, C. 2022. *Zamia incognita*. *The IUCN Red List of Threatened Species* 2022: e.T187838A1829016. https://dx.doi.org/10.2305/IUCN.UK.2022-1.RLTS.T187838A1829016.en. Accessed on 11 August 2022.
94. Lopez-Gonzalez, G., Lewis, S.L., Burkitt, M. and Phillips, O.L. 2011. ForestPlots.net: a web application and research tool to manage and analyse tropical forest plot data. Journal of Vegetation Science 22: 610–613. doi: 10.1111/j.1654-1103.2011.01312.x
95. Lopez-Gonzalez, G., Lewis, S.L., Burkitt, M., Baker T.R. and Phillips, O.L. 2009. ForestPlots.net Database. www.forestplots.net. Date of extraction [21,10,21].
96. Malerba, D., 2020. Poverty alleviation and local environmental degradation: An empirical analysis in Colombia. *World Development*, *127*, p.104776.

97. Mark, J. & Rivers, M.C. 2017. *Cedrela odorata*. *The IUCN Red List of Threatened Species* 2017: e.T32292A68080590. https://dx.doi.org/10.2305/IUCN.UK.2017-3.RLTS.T32292A68080590.en. Accessed on 11 August 2022.

98. Mas, J.F., Puig, H., Palacio, J.L. and Sosa-López, A., 2004. Modelling deforestation using GIS and artificial neural networks. *Environmental Modelling & Software*, *19*(5), pp.461-471.

99. McGarigal, K., 1995. *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure* (Vol. 351). US Department of Agriculture, Forest Service, Pacific Northwest Research Station.

100. Meli, P., Herrera, F.F., Melo, F., Pinto, S., Aguirre, N., Musálem, K., Minaverry, C., Ramírez, W. and Brancalion, P.H., 2017. Four approaches to guide ecological restoration in Latin America. *Restoration Ecology*, *25*(2), pp.156-163.

101. Mendoza-Cifuentes, H., Celis, A., Tovar, E. and Gonzalez, M.A., 2020. Lintersemina (Rubiaceae: Condamineeae), a new and enigmatic genus from the Magdalena Medio Region of Colombia. *Phytotaxa*, *451*(1), pp.1-20.

102. Meyer, L., Diniz-Filho, J.A. and Lohmann, L.G., 2017. A comparison of hull methods for estimating species ranges and richness maps. *Plant Ecology & Diversity*, *10*(5-6), pp.389-401.

103. Monti, M.M., 2011. Statistical analysis of fMRI time-series: a critical review of the GLM approach. *Frontiers in human neuroscience*, *5*, p.28.

104. Moonlight, P.W., Banda-r, K., Phillips, O.L., Dexter, K.G., Pennington, R.T., Baker, T.R., C. de Lima, H., Fajardo, L., González-m, R., Linares-Palomino, R. and Lloyd, J., 2021. Expanding tropical forest monitoring into Dry Forests: The DRYFLOR protocol for permanent plots. *Plants, People, Planet*, *3*(3), pp.295-300.

105. Moreno, B., 2020. *Rural Community Tourism for the Area of Influence of the: Serranía Regional Natural Park of Las Quinchas in Otanche, Boyacá, Colombia* (No. 3163). EasyChair.

106. Moreno-Sanchez, R., Kraybill, D.S., Thompson, S.R., 2003. An Econometric Analysis of Coca Eradication Policy in Colombia. *World Development* 31, 375–383.

107. Murcia, C., Guariguata, M.R., Andrade, Á., Andrade, G.I., Aronson, J., Escobar, E.M., Etter, A., Moreno, F.H., Ramírez, W., Montes, E., 2016. Challenges and Prospects for Scaling-up Ecological Restoration to Meet International Commitments: Colombia as a Case Study. Conservation Letters 9, 213–220. https://doi.org/10.1111/conl.12199.

108. Murcia, C., Kattan, G.H. and Andrade-Pérez, G.I., 2013. Conserving biodiversity in a complex biological and social setting: The case of Colombia. *Conservation biology: voices from the tropics*, pp.86-96.

109. Myneni, R.B., Keeling, C.D., Tucker, C.J., Asrar, G. and Nemani, R.R., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature*, *386*(6626), pp.698-702.

110. Naing Tun, Z., Dargusch, P., McMoran, D.J., McAlpine, C. and Hill, G., 2021. Patterns and Drivers of Deforestation and Forest Degradation in Myanmar. *Sustainability*, *13*(14), p.7539.

111. NASA. n.d. *Landsat 7* **|** *Landsat Science*. [online] Available at: <https://landsat.gsfc.nasa.gov/satellites/landsat-7/#:~:text=The%20government%2Downed%20Landsat%207,Delta%2DII%20expendable%20launch%20vehicle.> [Accessed 1 June 2022].

112. Negret, P.J., Sonter, L., Watson, J.E.M., Possingham, H.P., Jones, K.R., Suarez, C., Ochoa-Quintero, J.M., Maron, M., 2019. Emerging evidence that armed conflict and coca cultivation influence deforestation patterns. *Biological Conservation* 239. https://doi.org/10.1016/j.biocon.2019.07.021.

113. Noreña, A.P., González Muñoz, A., Mosquera-Rendón, J., Botero, K., Cristancho, M.A., 2018. Colombia, an unknown genetic diversity in the era of Big Data. *BMC Genomics* 19. https://doi.org/10.1186/s12864-018-5194-8.

114. O'Neill, R.V., Krummel, J.R., Gardner, R.E.A., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W. and Dale, V.H., 1988. Indices of landscape pattern. *Landscape ecology*, *1*(3), pp.153-162.

115. Orwa C., A Mutua, Kindt R., Jamnadass R., S Anthony. 2009 Agroforestree Database: a tree reference and selection guide version 4.0 (http://www.worldagroforestry.org/sites/treedbs/treedatabases.asp). [Accessed 6th September 2022].

116. Ovalle-Pacheco, A., Camacho-Rozo, C. and Arroyo, S., 2019. Amphibians from Serrania de Las Quinchas, in the mid-Magdalena river valley, Colombia. *Check List*, *15*(3), pp.387-404.

117. Pacheco-Angulo, C., Plata-Rocha, W., Serrano, J., Vilanova, E., Monjardin-Armenta, S., González, A. and Camargo, C., 2021. A low-cost and robust landsat-based approach to study forest degradation and carbon emissions from selective logging in the Venezuelan Amazon. *Remote Sensing*, *13*(8), p.1435.

118. Panchal, A., Rai, N. and Kumar, N., 2021. Assessment of forest land degradation by remote sensing and GIS: a case study of Jaisamand Wildlife Sanctuary, Udaipur (Rajasthan). *Eco. Env. & Cons.*, *27*(1), pp.447-454.

119. Panta, M., Kim, K. and Joshi, C., 2008. Temporal mapping of deforestation and forest degradation in Nepal: Applications to forest conservation. *Forest Ecology and Management*, *256*(9), pp.1587-1595.

120. Paul, C. and Weber, M., 2013. Intercropping *Cedrela odorata* with shrubby crop species to reduce infestation with Hypsipyla grandella and improve the quality of timber. *International Scholarly Research Notices*, *2013*.

121. Pavlov, I., 2022. *7-Zip*. [online] 7-Zip. Available at: <https://www.7-zip.org/> [Accessed 7 June 2022].

122. Pelaez, J.J., Prato, A.I., Zapata, L.P. and Zaraté, D.A., 2018. Phenology of *Cariniana pyriformis* in the Magdalena Medio region of Santander, northeastern Colombia. *Pesquisa Florestal Brasileira*, *38*, pp.1-6.

123. Pennington, R.T., Lehmann, C.E. and Rowland, L.M., 2018. Tropical savannas and dry forests. *Current Biology*, *28*(9), pp.R541-R545.

124. Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.M., Tucker, C.J. and Stenseth, N.C., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in ecology & evolution*, *20*(9), pp.503-510.

125. Pisek, J., Rautiainen, M., Nikopensius, M. and Raabe, K., 2015. Estimation of seasonal dynamics of understory NDVI in northern forests using MODIS BRDF data: Semi-empirical versus physically-based approach. *Remote Sensing of Environment*, *163*, pp.42-47.

126. Prance, G.T., 2021. Sixty Years with the Chrysobalanaceae. *The Botanical Review*, 87(2), pp.197-232.

127. Prem, M., Saavedra, S., Vargas, J.F., 2020. End-of-conflict deforestation: Evidence from Colombia’s peace agreement. World Development 129. https://doi.org/10.1016/j.worlddev.2019.104852.

128. RAINFOR (2021). *In the field*. [online] University of Leeds. Available at: <https://rainfor.org/en/manuals/in-the-field/> [Accessed 30 March 2023].

129. Rainforest Trust. n.d. *Protect Colombia’s Middle Magdalena Valley - Rainforest Trust Saves Rainforest*. [online] Available at: <https://www.rainforesttrust.org/projects/protect-colombias-middle-magdalena-valley/> [Accessed 28 October 2021].

130. Restrepo, J.D., Kjerfve, B., Hermelin, M. and Restrepo, J.C., 2006. Factors controlling sediment yield in a major South American drainage basin: the Magdalena River, Colombia. *Journal of Hydrology*, *316*(1-4), pp.213-232.

131. Reusing, M., 2000. Change detection of natural high forests in Ethiopia using remote sensing and GIS techniques. *International archives of photogrammetry and remote sensing*, *33*(B7/3; PART 7), pp.1253-1258.

132. Riebau, A.R. and Qu, J.J., 2005. Application of remote sensing and GIS for analysis of forest fire risk and assessment of forest degradation. In *Natural Disasters and Extreme Events in Agriculture* (pp. 335-350). Springer, Berlin, Heidelberg.

133. Ríos-García, C.A., Orantes-García, C. and Sánchez-Cortés, M.S., 2014. Aprovechamiento del árbol tropical Licania arborea Seem (Chrysobalanaceae) en una comunidad campesina de Chiapas, México. *Revista iberoamericana deficiencias*, *6*(1), pp.27-31.

134. Robbins, N., 2012. *When Should I Use Logarithmic Scales in My Charts and Graphs?*. [online] Forbes. Available at: <https://www.forbes.com/sites/naomirobbins/2012/01/19/when-should-i-use-logarithmic-scales-in-my-charts-and-graphs/?sh=4df2b0f35e67> [Accessed 26 May 2022].

135. Rodrigues, A.S., Pilgrim, J.D., Lamoreux, J.F., Hoffmann, M. and Brooks, T.M., 2006. The value of the IUCN Red List for conservation. *Trends in ecology & evolution*, *21*(2), pp.71-76.

136. Rodríguez, J.P., RODRÍGUEZ-CLARK, K.M., Baillie, J.E., Ash, N., Benson, J., Boucher, T., Brown, C., Burgess, N.D., Collen, B.E.N., Jennings, M. and Keith, D.A., 2011. Establishing IUCN red list criteria for threatened ecosystems. *Conservation Biology*, *25*(1), pp.21-29.

137. Rodríguez, N., Armenteras, D., Retana, J., 2013. Effectiveness of protected areas in the Colombian Andes: Deforestation, fire and land-use changes. Regional Environmental Change 13, 423–435. https://doi.org/10.1007/s10113-012-0356-8.

138. Rodríguez-Mahecha, J. V., P. Salaman, P. Jørgensen, T. Consiglio, E. Forno, A. Telesca, L. Suárez, F. Arjona, F. Rojas, R. Bensted-Smith, and V. H. Inchausty. 2004. Tumbez– Chóco–Magdalena. Pp. 80-84 in Hotspots revisited: Earth’s biologically richest and most endangered ecoregions, edited by R. A. Mittermeier, P. Robles-Gil, M. Hoffmann, J. D. Pilgrim, T. M. Brooks, C. G. Mittermeier, and G. Fonseca. Mexico City: CEMEX

139. Romero, J., 2022. *Serious damage to Puerto Pinzón and the villages of Puerto Boyacá due to flooding*. [online] W Radio. Available at:

<https://www.wradio.com.co/2022/06/07/graves-afectaciones-en-puerto-pinzon-y-veredas-de-puerto-boyaca-por-inundaciones/> [Accessed 19 September 2022].

140. Rondinini, C., Di Marco, M., Visconti, P., Butchart, S.H. and Boitani, L., 2014. Update or outdate: long-term viability of the IUCN Red List. *Conservation Letters*, *7*(2), pp.126-130.

141. RStudio Team (2021). RStudio: Integrated Development Environment for R. RStudio, *PBC,* Boston, MA URL http://www.rstudio.com/.

142. Ruiz-Jaén, M.C. and Aide, T.M., 2005. Vegetation structure, species diversity, and ecosystem processes as measures of restoration success. *Forest Ecology and Management*, *218*(1-3), pp.159-173.

143. Sader, S.A. and Joyce, A.T., 1988. Deforestation rates and trends in Costa Rica, 1940 to 1983. *Biotropica*, pp.11-19.

144. Sanchez-Cuervo, A.M., Aide, T.M., 2013. Identifying hotspots of deforestation and reforestation in Colombia (2001-2010): Implications for protected areas. Ecosphere 4. https://doi.org/10.1890/ES13-00207.1.

145. Sanchez-Guzman, G., Velasquez, W. and Alvarez-Alvarado, M.S., 2022, January. Modeling a simulated Forest to get Burning Times of Tree Species using a Digital Twin. In *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 0639-0643). IEEE.

146. Serrano, J., Richardson, J.E., Milne, R.I., Mondragon, G.A., Hawkins, J.A., Bartish, I.V., Gonzalez, M., Chave, J., Madriñán, S., Cárdenas, D. and Sanchez, S.D., 2021. Andean orogeny and the diversification of lowland neotropical rain forest trees: A case study in Sapotaceae. *Global and Planetary Change*, *201*, p.103481.

147. SIAC. 2022. *CATÁLOGO DE MAPAS - IDEAM*. [online] Available at: <http://www.siac.gov.co/catalogo-de-mapas> [Accessed 7 June 2022].

148. Singh, S.K., Pandey, A.C. and Singh, D., 2014. Land use fragmentation analysis using remote sensing and Fragstats. In *Remote sensing applications in environmental research* (pp. 151-176). Springer, Cham.

149. Snipes, M. and Taylor, D.C., 2014. Model selection and Akaike Information Criteria: An example from wine ratings and prices. *Wine Economics and Policy*, *3*(1), pp.3-9.

150. Snook, L.K., 1996. Catastrophic disturbance, logging and the ecology of mahogany (*Swietenia macrophylla* King): grounds for listing a major tropical timber species in CITES. *Botanical Journal of the Linnean Society*, *122*(1), pp.35-46.

151. SRTM. 2022. *SRTM Data – CGIAR-CSI SRTM*. [online] Available at: <https://srtm.csi.cgiar.org/srtmdata/> [Accessed 6 June 2022].

152. Statology. 2021. *How to Interpret glm Output in R (With Example) - Statology*. [online] Available at: <https://www.statology.org/interpret-glm-output-in-r/> [Accessed 27 May 2022].

153. Stevenson, P.R., 2011. The abundance of large ateline monkeys is positively associated with the diversity of plants regenerating in neotropical forests. *Biotropica*, *43*(4), pp.512-519.

154. Stevenson, P.R., Suescún, M., Aldana, A.M., Cano, A., Umaña, M.N., Correa, D., Casas, L.F. and Villanueva, B., 2012. Diversidad arbórea en bosques de tierras bajas en Colombia: Efectos del ambiente, las perturbaciones y la geografía. *Hipótesis*, *12*, pp.29-35.

155. Stiles Hurd, F. G. and Bohórquez, C. I. (2000) «Evaluando el estado de la biodiversidad: el caso de la avifauna de la Serranía de las Quinchas, Boyacá, Colombia», *Caldasia,*22(1), pp. 61-92. Available in: https://revistas.unal.edu.co/index.php/cal/article/view/17551 (Accessed: 24 November 2021).

156. Subedi, P.B., Ojha, P., Mahara, S. and Gautam, D., 2022. Assessment of rate and drivers of deforestation and forest degradation in the lower-tropical region: a case of Punarbas Municipality, Nepal. *Our Nature*, *20*(1), pp.27-40.

157. Tenorio, C. and Moya, R., 2019. Evaluation of wood properties of four ages of *Cedrela odorata* trees growing in agroforestry systems with Theobroma cacao in Costa Rica. *Agroforestry Systems*, *93*(3), pp.973-988.

158. The Nature Conservancy. n.d. *Magdalena River Basin*. [online] Available at: <https://www.nature.org/en-us/about-us/where-we-work/latin-america/colombia/stories-in-colombia/magdalena-river/> [Accessed 26 October 2021].

159. The World Bank. 2022. *Forest area (sq. km) - Colombia* | *Data*. [online] Available at: <https://data.worldbank.org/indicator/AG.LND.FRST.K2?locations=CO> [Accessed 25 July 2022].

160. Tiede, D., n.d. *Vector-based Landscape Analysis Tools (Extension for ArcGIS 10.8): V-LATE 2.0*. [online] ArcGIS Hub. Available at: <https://hub.arcgis.com/content/69963ab422d04e649b64ac11cbadafed/about> [Accessed 31 May 2022].

161. Turner, M.G. and Ruscher, C.L., 1988. Changes in landscape patterns in Georgia, USA. *Landscape ecology*, *1*(4), pp.241-251.

162. Universidad Nacional de Colombia. 2017. *Lycania arborea*. [online] Available at: <http://www.biovirtual.unal.edu.co/floradecolombia/en/description/735/> [Accessed 7 September 2022].

163. USGS. 2022. *EarthExplorer*. [online] Available at: <https://earthexplorer.usgs.gov/> [Accessed 1 June 2022].

164. USGS. n.d.a *Landsat 7* **|** *U.S. Geological Survey*. [online] Available at: <https://www.usgs.gov/landsat-missions/landsat-7#:~:text=Band%201%20Blue%20(0.45%20%2D%200.52,0.77%20%2D%200.90%20%C2%B5m)%2030%20m> [Accessed 3 June 2022].

165. USGS. n.d.b *Landsat 8* **|** *U.S. Geological Survey*. [online] Available at: <https://www.usgs.gov/landsat-missions/landsat-8> [Accessed 7 June 2022].

166. USGS. n.d.c *What is the Landsat satellite program and why is it important?* **|** *U.S. Geological Survey*. [online] Available at: <https://www.usgs.gov/faqs/what-landsat-satellite-program-and-why-it-important> [Accessed 25 July 2022].

167. Valencia-Montoya, W.A., Tuberquia, D., Guzmán, P.A. and Cardona-Duque, J., 2017. Pollination of the cycad *Zamia incognita* A. Lindstr. & Idárraga by Pharaxonotha beetles in the Magdalena Medio Valley, Colombia: a mutualism dependent on a specific pollinator and its significance for conservation. *Arthropod-Plant Interactions*, *11*(5), pp.717-729.

168. Van Ausdal, S., 2009. Pasture, profit, and power: An environmental history of cattle ranching in Colombia, 1850–1950. *Geoforum*, *40*(5), pp.707-719.

169. Vargas, G., León, N. and Hernández, Y., 2019. Agricultural socio-economic effects in Colombia due to degradation of soils. In *Sustainable Management of Soil and Environment* (pp. 289-337). Springer, Singapore.

170. Vié, J.C., Hilton-Taylor, C. and Stuart, S.N. eds., 2009. *Wildlife in a changing world: an analysis of the 2008 IUCN Red List of threatened species*. IUCN.

171. Villa, D. and García, N., 2017. Food plants in home gardens of the Middle Magdalena basin of Colombia. *Caldasia*, *39*(2), pp.292-309.

172. Wallgrün, J.O., Huang, J., Zhao, J., Brede, B., Lau, A. and Klippel, A., 2021. Embodied digital twins of forest environments.

173. Wheeler, C., 2018. *Back to Basics*. [online] ESRI. Available at: <https://www.esri.com/about/newsroom/arcwatch/back-to-basics/> [Accessed 22 June 2022].

174. Wikispecies. n.d. *Microdesmia arborea* - Wikispecies. [online] Available at: <https://species.wikimedia.org/wiki/Microdesmia_arborea> [Accessed 6 October 2021].

175. World Conservation Monitoring Centre. 1998a. *Cariniana pyriformis*. *The IUCN Red List of Threatened Species* 1998: e.T33961A9824874. https://dx.doi.org/10.2305/IUCN.UK.1998.RLTS.T33961A9824874.en. Accessed on 11 August 2022.

176. World Conservation Monitoring Centre. 1998b. *Swietenia macrophylla*. *The IUCN Red List of Threatened Species* 1998: e.T32293A9688025. https://dx.doi.org/10.2305/IUCN.UK.1998.RLTS.T32293A9688025.en. Accessed on 11 August 2022.

177. World Land Trust. n.d.a Big-Leaf Mahogany - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/big-leaf-mahogany/> [Accessed 6 October 2021].

178. World Land Trust. n.d.b Colombian Mahogany - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/colombian-mahogany/> [Accessed 6 October 2021].

179. World Land Trust. n.d.c Spanish Cedar - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/spanish-cedar/> [Accessed 6 October 2021].

180. World Land Trust. n.d.d *Zamia incognita* - World Land Trust. [online] Available at: <https://www.worldlandtrust.org/species/zamia-incognita/> [Accessed 6 October 2021].

181. WWF. 2012. *Colombian Amazon gets reprieve from mining; WWF supports precautionary principle for future development*. [online] Available at: <https://wwf.panda.org/?206793/Colombian-Amazon-gets-reprieve-from-mining-WWF-supports-precautionary-principle-for-future-development> [Accessed 25 July 2022].

182. Yin, D. and He, F., 2014. A simple method for estimating species abundance from occurrence maps. *Methods in Ecology and Evolution*, *5*(4), pp.336-343.