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# Linking agents, patterns and outcomes of forest disturbances to understand pathways of degradation in the Argentine Dry Chaco

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# Abstract

Tropical dry forests are of great importance for climate regulation, harbour biodiversity and sustain the livelihood of millions of people. Deforestation and degradation pose a global threat to tropical dry forests, creating a pressing need for monitoring and understanding changes in these ecosystems. Research over the last decades has increased our understanding of tropical deforestation tremendously, but knowledge of the patterns, extent and drivers of forest degradation in tropical dry forests is lacking. The overarching goal of this thesis was to advance the current understanding of forest degradation in the Dry Chaco by means of remote sensing. Specifically, using the Landsat archive, I characterized the disturbance history of the remaining Argentine Dry Chaco forest over three decades, assessed spatial and temporal patterns of disturbance agents in general as well as in relation to natural and anthropogenic determinants, and investigated the long-term effect of different agents on forest structure. The results of my analysis show that over 30 years large areas of the Argentine Dry Chaco (about 8%) were affected by disturbances linked to a variety of agents. My findings reveal a strong anthropogenic link to most types of disturbances, while also suggesting complex indirect influence of precipitation patterns, with forest disturbances being particularly widespread during drought years. The analyses of temporal patterns of different agents reveals trends in land-use practices over time, with new land uses emerging, such as silvopastoral systems, and old practices such as logging, affecting a fairly stable share of areas every year. Findings on the long-term impact of forest disturbances indicate that for the most widespread disturbances, forest structure shows little or no recovery over three decades, which suggests forest degradation affecting large areas. This thesis demonstrates that satellite time series have a high potential for robust and consistent characterization of forest dynamics related to degradation also in tropical dry forests, despite the complex conditions that tropical dry forest represent. The maps, approaches and knowledge resulting from this thesis contribute to a better understanding of forest degradation in the Dry Chaco and can inform management strategies leading to a more effective conservation of tropical dry forests.

# Zusammenfassung

Tropische Trockenwälder sind von großer Bedeutung für die Klimaregulierung, beherbergen biologische Vielfalt und sichern den Lebensunterhalt von Millionen von Menschen. Entwaldung und Degradation stellen eine globale Bedrohung für diese Ökosysteme dar, weshalb es dringend notwendig ist, Veränderungen in tropischen Trockenwäldern zu überwachen und zu verstehen. Während die Forschung der letzten Jahrzehnte unser Verständnis über die Abholzung von Tropenwäldern enorm erweitert hat, fehlt es an Wissen über die Muster, das Ausmaß und die Ursachen der Degradation tropischer Trockenwälder. Das übergreifende Ziel dieser Arbeit war es, das derzeitige Verständnis der Walddegradation im Gran Chaco anhand von Fernerkundung zu verbessern. Konkret habe ich mit Hilfe des Landsat-Archivs die Störungsgeschichte des verbleibenden argentinischen Gran Chaco-Waldes über drei Jahrzehnte hinweg charakterisiert, die räumlichen und zeitlichen Muster der Störungsfaktoren im Allgemeinen und in Bezug auf natürliche und anthropogene Faktoren bewertet und die langfristigen Auswirkungen verschiedener Faktoren auf die Waldstruktur untersucht. Die Ergebnisse meiner Analyse zeigen, dass über 30 Jahre hinweg große Gebiete des argentinischen Gran Chaco (etwa 8 %) von Störungen betroffen waren, die mit einer Vielzahl von Ursachen zusammenhängen. Meine Ergebnisse zeigen einen starken anthropogenen Zusammenhang der meisten Störungen, während sie auch auf einen komplexen indirekten Einfluss von Niederschlagsmustern hindeuten, wobei Waldstörungen in Dürrejahren besonders verbreitet sind. Die Analyse der zeitlichen Muster verschiedener Ursachen zeigt Trends in der Landnutzung im Laufe der Zeit, wobei neue Landnutzungsformen wie silvopastorale Systeme entstehen und alte Praktiken wie die Abholzung jedes Jahr einen relativ stabilen Anteil der Flächen betreffen. Die Ergebnisse zu den langfristigen Auswirkungen von Waldstörungen zeigen, dass sich die Waldstruktur bei den am weitesten verbreiteten Störungen über drei Jahrzehnte kaum oder gar nicht erholt, was auf eine großflächige Walddegradation schließen lässt. Insgesamt zeigt meine Arbeit, dass Satellitenbildzeitreihen ein hohes Potenzial für eine robuste und konsistente Charakterisierung von Walddynamiken im Zusammenhang mit der Degradation auch in tropischen Trockenwäldern haben, trotz der komplexen Bedingungen, die tropische Trockenwälder darstellen. Die aus dieser Arbeit resultierenden Karten, Ansätze und Erkenntnisse tragen zu einem besseren Verständnis der Walddegradation im Gran Chaco bei und können als Grundlage für Managementstrategien dienen, die zu einem effektiveren Schutz tropischer Trockenwälder führen.

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# Introduction

## 1 Forest loss and degradation

Land use that has always sustained human societies represents today a major threat to the liveability of the Earth for humans and other species (Jaureguiberry et al., 2022; Steffen et al., 2015). Land use change and intensification, while increasing the short-term supplies of material goods, are undermining many ecosystem services in the long run, even on regional and global scales (Foley et al., 2005). Agricultural expansion, in particular, is the main driver of forest loss (FAO, 2020). Besides directly impacting the livelihoods of millions of forest-dependant people living in poverty, forest loss has far-reaching impacts that extend both to the regional scale, for example disrupting the Amazon hydrological cycle (Lovejoy and Nobre, 2018), and globally. Forest loss is one of the largest drivers of greenhouse gas emissions, biodiversity loss, and the degradation of ecosystem services (IPBES, 2019), ultimately contributing to climate change and affecting biosphere integrity (Rockström et al., 2009; Steffen et al., 2015).

In addition to deforestation, there are many land-use practices that do not result in land use change but still modify forest biomass, stand structure, and species composition and can ultimately lead to degradation. Forest degradation is the process leading to the permanent deterioration in the density, composition or structure of forest cover (Grainger, 1993). These changes can have major impacts on ecosystem functioning, biodiversity (Barlow et al., 2016; Betts et al., 2017; Gibson et al., 2011), carbon storage (Baccini et al., 2017; Brienen et al., 2015; Pan et al., 2011) and ecosystem services (Watson et al., 2018), in turn threatening local livelihoods (Rozzi, 2012). The recognition of the impacts of forest degradation stimulated efforts to measure and quantify it. The push also came from the international mitigation mechanism Reduced Emissions from Deforestation and Forest Degradation (REDD+) adopted by the United Nations Framework Convention on Climate Change (UNFCCC) that requires estimates of changes in forest carbon stocks and emissions also arising from forest degradation. However, until today we still lack methods to reliably monitor forest degradation. This gap is related to the fact that defining forest degradation is in itself a major challenge, as degradation denotes the loss of forest values or characteristics that vary among stakeholders (Meyfroidt et al., 2022; Mitchell et al., 2017; Putz and Redford, 2010), and as a consequence, there is no unified and commonly-agreed definition (Sasaki and Putz, 2009; Thompson et al., 2013). To this adds that degradation is more challenging to detect than deforestation and that it results from a number of land uses.

Although robust global estimations of forest degradation are lacking, studies conducted at the regional and biome scale reveal a concerning scenario. The extent and rate of forest degradation in the Brazilian Amazon was found to be equal to or greater than deforestation (Matricardi et al., 2020), potentially affecting up to 10% of all tropical moist forests (Vancutsem et al., 2021). Carbon loss from degradation exceeds carbon loss from deforestation in Brazilian Amazon (Qin et al., 2021). When accounting also for degradation, tropical forests are a net carbon source (Baccini et al., 2017). These data highlight the importance of integrating measures for reducing degradation in forest conservation and climate mitigation programs and understanding the drivers, extent and mechanisms of forest degradation better.

## 2 Forest degradation in Tropical Dry Forests

Tropical dry forests (TDF) make up roughly half of all world's subtropical and tropical forests (Murphy and Lugo 1986) (1.1 billion ha when applying the UNEP-WCMC definition (FAO, 2019)). They are characterized by low annual rainfall (250-2000 mm) and a strong seasonality (Murphy and Lugo, 1986). TDF are heterogeneous ecosystems that can contain a variety of canopy types, including woodlands dominated by smaller trees and shrubs, woodlands with scattered large trees, savannas with scattered palm trees and shrublands (Baumann et al., 2018; House et al., 2003). Tropical dry forests harbour a unique biodiversity, including many endemic taxa (Banda-R et al., 2016; Mares, 1992; Pennington et al., 2018; Redford et al., 1990) and provide a wide range of ecosystem services that sustain the livelihoods of millions of people (FAO, 2019). Forest resources are especially important for poor people who depend on wood fuel, that is often the only affordable and accessible energy source for their daily cooking and heating (Wells et al., 2022). Furthermore, tropical dry forests are an important resource for construction materials and non-timber forest products, including fruits, vegetables, honey, resins, fibres, edible insects etc. (Blackie et al., 2014).

TDF are under great pressure from a number of multiple and complex threats largely resulting from human activity (FAO, 2019; Miles et al., 2006; Murphy and Lugo, 1986; Sunderland et al., 2015). In particular, the conversion of forests due to agricultural expansion poses a threat to TDF that may even be at greater risk than tropical moist forests (Gillespie et al., 2012; Portillo-Quintero and Sánchez-Azofeifa, 2010) especially because they are weakly protected (Miles et al., 2006). Climate change is expected to worsen the situation with decreased rainfall and more frequent drought events (Siyum,

2020) that will affect TDF both directly and by altering the frequency, intensity and duration of disturbances (Dale et al., 2001).

The resilience of remaining tropical dry forests in the face of these scenarios is challenged by widespread degradation and fragmentation (Sánchez-Azofeifa et al., 2005) resulting from various human activities involving fires, logging, fuelwood collection, mining and forest grazing (Miles et al., 2006; Murdiyarso et al., 2008; Riggio et al., 2020; Sasaki and Putz, 2009). Firewood collection and charcoal production are by far the most important forest resources used in TDF (Murphy and Lugo, 1986; Schröder et al., 2021). Tree harvesting for charcoal production ranges along a continuum from selective cutting to clear cutting (Chidumayo and Gumbo, 2013) with consequences that go from the depletion of the desirable species to a permanent modification of forest structure. Commercial logging of valuable species or for saw wood and construction material frequently affect the structure and composition of TDF (Gobbi et al., 2022; Sánchez-Azofeifa et al., 2005). Wildfires are another major driver of degradation in TDF, especially as human activities altered fire regimes substantially. Fire is used to promote the regrowth of grasses in pastures, to burn waste, to convert forest into agricultural land and to facilitate the extraction of fuelwood and charcoal (Zak et al., 2004) and can easily escape to surrounding forest. Fires also exacerbate the impact of logging and fragmentation leading to the development of degraded secondary forests and scrubs. Free cattle grazing in the forest is an additional cause of degradation in TDF. Grazing pressure alters forest composition by favouring unpalatable species and inhibiting the recruitment of juvenile trees (Agarwala et al., 2016; Chaturvedi et al., 2012; Díaz et al., 2001; Sfair et al., 2018) and can lead to higher shrub cover but also bare soil exposure where heavy trampling compacts the soil. In addition to the direct causes of degradation, the recent agriculture expansion in tropical dry forests reduced forest availability or accessibility for forest-dwelling smallholders (del Giorgio et al., 2021), therefore increasing pressure and degradation on forest remnants.

In addition to anthropogenic activities, various disturbances from natural agents can contribute to forest degradation in TDF. Floods and drought can cause mortality of juveniles trees (Vieira and Scariot, 2006), but also increasing water stress makes impacts from other disturbances more severe (Chaturvedi et al., 2017), salinization, insects outbreaks, tropical storms can damage or kill trees, increase fragmentation leaving the remaining patches vulnerable and more susceptible to fires (Stan and Sanchez-Azofeifa, 2019). Many of these disturbances are increasing in frequency and intensity due to climate change.

Given the importance of TDF for livelihoods, biodiversity and climate regulation, it is critical to address and reverse the loss and degradation of these forests. However, despite the recognition that TDF are a severely threatened ecosystem dates back decades (Janzen, 1988; Murphy and Lugo, 1986), TDF have not yet attracted the same international and scientific attention as tropical moist forests. Although the scientific community has begun to bridge this gap (Pennington et al., 2018; Sunderland et al., 2015), to date the number of publications on TDF are 3.6 times less than the number of articles focussing on tropical moist forests (Schröder et al., 2021). Consequently, our understanding of the extent, rate and impacts of TDF degradation remains limited, although robust figures would be needed to inform conservation actions.

## 3 Opportunities and challenges for remote sensing application to TDF degradation monitoring

The last decade has been an exciting period of rapid development in data availability, techniques and tools for remote sensing application to forest dynamics. Following the opening of the Landsat archive in 2008 (Woodcock et al., 2008), the wealth of information offered by satellite images led to impressive advancements in algorithms and approaches for forest monitoring (Wulder et al., 2012; Zhu et al., 2019), and this remains an active area of development, both in terms of methods and theory (Pasquarella et al., 2022). The opening of the Landsat archive marked only the beginning of a strong momentum for full, free and open access remote sensing data (Zhu et al., 2019). In 2015, ESA launched the first satellite of the Copernicus constellation, providing new imagery, including radar data, at high temporal and spatial resolution and committing from the start to open access policy. Parallel to this stark increase in data availability, the increased availability of cloud computing resources and platforms such Google Earth Engine enabled efficient running of computationally intensive algorithms for large-area mapping and monitoring (Pasquarella et al., 2022).

A large body of research revealed dynamics, patterns and extent of deforestation in many forest types (Hansen et al., 2013; Potapov et al., 2022; Turubanova et al., 2018). In contrast, we still lack robust figures on forest degradation. Forest degradation is more challenging to assess using remote sensing techniques as it occurs within forests, from processes that leave standing biomass and canopy cover (Matricardi et al., 2020) and are therefore more difficult to detect than full clearing related to deforestation. Furthermore, forest degradation is caused by an array of agents or drivers with complex spatial and temporal patterns and dynamics (Hirschmugl et al., 2017), including the extraction of biomass below the canopy such as grazing, firewood and non-timber product extraction (Sfair et al., 2018) that are nearly undetectable with current conventional remote sensing techniques (Peres et al., 2006).

Current remote sensing approaches for forest degradation monitoring can be divided into two main categories (Mitchell et al., 2017): (1) the detection of canopy cover change, and (2) the quantification of loss (or gain) in above-ground biomass (AGB), which the REDD+ scheme requires from countries in their emissions reporting. For accurate canopy cover change, especially small-scale and low-magnitude disturbances, dense time series are essential, and the Landsat time series have proved crucial, thanks to the unmatched temporal extent of its archive. Many algorithms use Landsat time series to detect changes by modelling each pixel's spectral time series as a sequence of linear segments bounded by breakpoints or vertices. Among the most popular algorithms that have been tested for monitoring forest disturbances and degradation are: Change Detection and Classification (CCDC) (Zhang et al., 2022; Zhu and Woodcock, 2014), Landtrendr (Kennedy et al., 2010), and Breaks For Additive Seasonal and Trend (BFAST) (Verbesselt et al., 2012). Spectral Mixture Analysis (SMA) that isolates mixed fractions of vegetation, dead wood, soil and shade has also been used with promising results in time series approaches (Bullock et al., 2020a; Chen et al., 2021). Studies using these algorithms often aim at classifying a diversity of disturbances, but there are also studies focussing on one or few drivers of degradation, with logging and fires being the two most studied forest disturbances (Asner et al., 2009, 2005; Gao et al., 2020; Hethcoat et al., 2019).

Besides disturbances, relevant indicators to assess and quantify forest degradation are obtained by modelling aboveground biomass (Bustamante et al., 2016) and forest structure (Rappaport et al., 2018; Thompson et al., 2013). Various studies demonstrated that multi-sensor approaches are best suited for biomass and forest structure mapping, in particular leveraging the sensitivity of LiDAR (i.e., light detection and ranging) and radar data to forest structural parameters, including tree height, volume and biomass (Bourgoin et al., 2018; Milodowski et al., 2021; Shao and Zhang, 2016). However, the overwhelming majority of studies has been done in the moist tropics.

Adding to the above-mentioned challenges that degradation monitoring pose, TDF are extremely complex and heterogeneous, ranging from more open, savanna-like woodlands to closed-canopy forests (Dexter et al., 2018), which makes it hard to differentiate between natural open forest and degraded forest (Morales-Barquero et al., 2015). For this reason, in such systems time series analysis is the optimal choice for disturbance monitoring because by detecting disturbances and analysing vegetation temporal dynamics can  help distinguishing degraded forest from naturally open forest (Gao et al., 2020). The strong seasonality further complicates the detection of forest cover changes for algorithms that use very dense time series (Gao et al., 2021; Grogan et al., 2016), therefore algorithms that use annual time series might be a better choice, given that the phenology of the system is addressed in the construction of the annual time series. Additionally, tropical dry forests have long been inhabited and used and have recently become hotspot of large-scale agricultural expansion. As a consequence, a wide variety of land uses contribute to shaping forest structure, making it more difficult to design monitoring protocols to capture them all. Machine learning classification algorithms allow leveraging several metrics derived from time series segmentation of different indices, promising  better performances for disturbance detection and capturing of varied disturbances (Cohen et al., 2018; Schultz et al., 2016). Another major challenge resulting from forest heterogeneity and stand complexity is mapping AGB and forest structure. Here as well, the integration of optical and radar data proved to be effective to map sparser woody vegetation and address TDF challenges (Baumann et al., 2018; Pötzschner et al., 2022). In sum, remote sensing tools and techniques offer considerable potential for improving TDF change monitoring, and improving forest degradation estimates, yet, due to the lack of attention TDF received, we still lack both statistics on the extent of forest degradation and knowledge regarding the methods best suited for forest monitoring in these environments.

## 4 Importance of agent attribution

For a better characterization of forest change,+ an understanding of the agent of change or proximate cause is needed, and not just the quantification of the location changes (Kennedy et al., 2015; Shimizu et al., 2019). This is important for various reason: first, different agents impact forests in different ways and result in different long-term outcomes (Chazdon, 2003; Cole et al., 2014; Dale et al., 2001) and therefore characterization of the agent provides an indication of the ecological consequences of disturbances. Second, statistics on disturbance agent occurrences can support policy makers in developing informed management action. For example, which agent is the most widespread, how frequently does each disturbance agent manifest, or what are the spatial determinants of disturbances caused by one type of agent (e.g.  do fires more commonly escape through pastures or roads?). Lastly, an accurate assessment of the proximate causes of forest change can provide an insight to the underlying causes of forest change (Shimizu et al., 2019) that could lead to effective policy actions (Finer et al., 2018).

Remote sensing can assist characterizing agents of disturbances as a number of characteristics that can help distinguishing among agents can be retrieved from remote sensing data. As disturbances rarely affect singular pixels, focusing on disturbance patches is an approach suited for the classification of causal agents (Huo et al., 2019; Kennedy et al., 2015). Spectral characteristics of disturbances are very useful for characterizing agents (Schroeder et al., 2017) and, as for disturbance detections, the use of multiple indices have the potential of enhancing the agent discrimination (Cohen et al., 2018; Nguyen et al., 2018). In addition, disturbance patch characteristics, and their sizes and shapes can help distinguish between agents (Kennedy et al., 2015; Nguyen et al., 2018). However, the attribution of disturbance agents still present open challenges (Sebald et al., 2021; Shimizu et al., 2019) and how well it is possible to separate agents in TDF where many occur and overlap is not well known. Knowledge on the prevalence and dynamics of disturbance agents in TDF is essential to have a thorough understanding of the impacts of change and a critical first step to understand underlying drivers of forest degradation.

## 5 Importance of studying post-disturbance developments

A critical component of forest dynamics is the development of vegetation following disturbance. Anthropogenic and natural disturbances both play important roles in modifying forest structure and different disturbance agents differ substantially in their impact on forest canopy structure and biomass (Chazdon, 2003). Vegetation structure is a key feature that plays an important role in forest ecology. It influences carbon storage, surface energy balance, and ecosystem functioning, and thereby ecosystem services and biodiversity (Asner, 2013; White and Pickett, 1985). Knowledge of responses and recovery rates of TDF structure to past disturbances may help us understand the capacity of these ecosystems to respond to recent and future events (Cole et al., 2014) and inform conservation planning – to decide where to intervene with restoration actions.

Studies exploring the links between disturbance agents and post-disturbance recovery have typically relied on field assessments (Chaturvedi et al., 2012; Colón and Lugo, 2006; Loto and Bravo, 2020; Urquiza-Haas et al., 2007). While such studies have the advantage of typically detailed and high-quality plot-level data, they are laborious and therefore limited to small areas. Moreover, understanding disturbance and recovery trajectories requires long-term assessment over time periods that exceed typical project runtimes and funding cycles. Remote sensing can remedy some of the drawbacks of field-based assessments, as satellite image time series allows for a detailed and retrospective characterization of disturbance and post-disturbance development across larger areas (Cohen et al., 2010; Griffiths et al., 2014; Hermosilla et al., 2019; Meng et al., 2021; Pflugmacher et al., 2012; Shimizu et al., 2022), yet not many studies use remote sensing to assess post-disturbance changes in forest structure, including in TDF.

Understanding the impact of human activities in TDF is very challenging, first because TDF are socio ecological systems (Kalaba, 2014; Quesada et al., 2009) and have been used for centuries, therefore the baseline is already a secondary forest. Second, because of the overlay of different disturbance events, we may not be able to clearly separate the vegetation response to a particular disturbance (Chazdon, 2003). Nonetheless, an effort to close this gap is needed, because information on the potential for recovery after disturbance and the time taken for it is essential to determine the system vulnerability to permanent degradation. Mapping and characterizing forest disturbances give us an important picture of changes in the forest canopy but only linking the history of disturbances with their long-term outcomes on forest structure can lead us to the understanding of pathways of forest degradation.

## 6 The Argentine Dry Chaco

I focused my work on the Argentinean section of the Gran Chaco dry forest (Figure I-1). The Gran Chaco is the largest remaining continuous tropical dry forest in the world (Olson et al., 2001), and the second largest forest in South America. The Chaco forest has been inhabited and used for centuries (Leake, 2016) and became in the last decades a global deforestation hotspot caused by agricultural expansion (Baumann et al., 2017; Hansen et al., 2013; Kuemmerle et al., 2017). Its long history of forest use resulted in widespread alteration and degradation of the remaining forests. However, processes and disturbances leading to forest degradation have never been quantified for larger regions in the Chaco, therefore the extent, trends and patterns of degradation remain poorly understood.

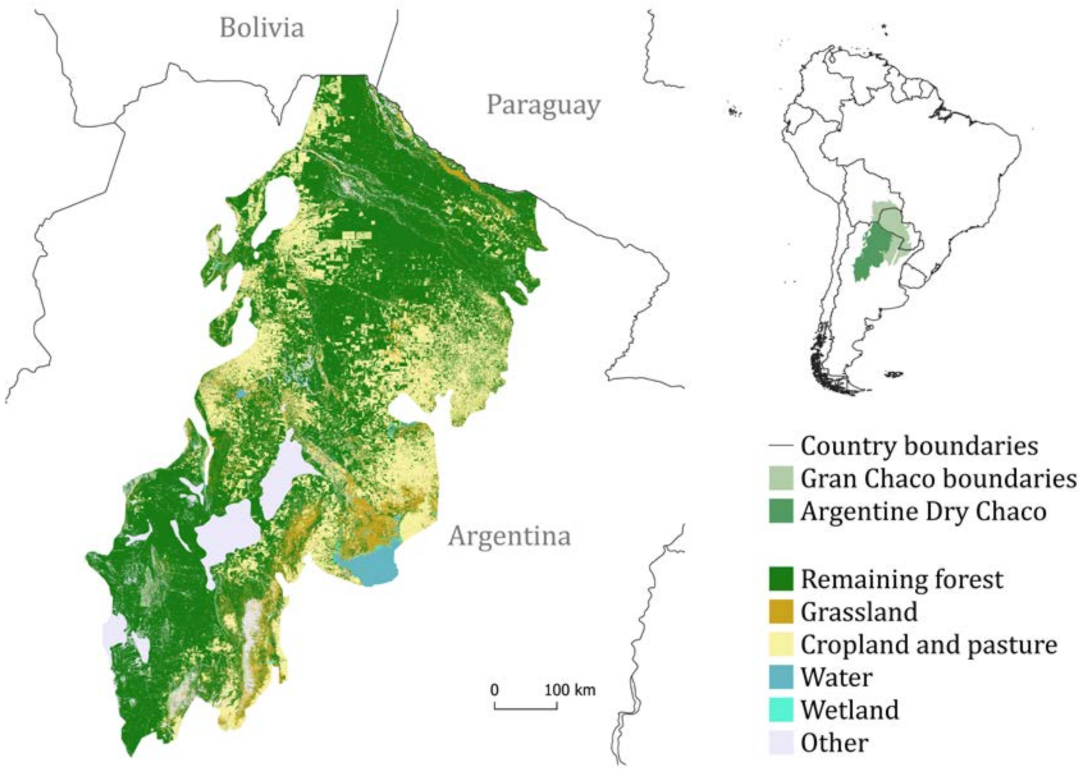


Figure I-1: Location of the Gran Chaco (top right) and of the study area, the Argentine Dry Chaco, in South America.

The Chaco region is mostly flat, except for hilly areas in western and southwestern Chaco. Climate is characterized by strong seasonal variations, with dry winters and hot and rainy summers. Average temperature varies across the area, with mean annual temperature increasing from south to north, varying from 18 to 21°C, and maximum temperatures of up to 48°C (Minetti, 1999). Similarly, rainfall varies across the area, ranging from 1000 mm to less than 450 mm. Soils are mainly mollisols and alfisols, formed from fluvial and aeolian deposits (Panigatti, 2010).

The vegetation of the Dry Chaco consists of a mosaic of forests, woodlands, scrubs, savannas and grasslands. A peculiar feature of the vegetation of the Chaco consists of the dominance by species of the arboreal genus *Schinopsis S. lorentzii* ("quebracho colorado") and *S. hankeana* ("horco quebracho"). Other characteristic tree species are *Gonopterodendron sarmientoi* ("palo santo"), *Aspidosperma quebracho-blanco* ("quebracho blanco") and *Prosopis* spp. and *Neltuma* spp. ("algarrobo") (Prado, 1993). The shrub layer of the Chaco is dominated by *Vachellia, Mimosa, Neltuma* and *Strombocarpa*, and in the driest south-western section cacti *Opuntia* and *Cereus* are abundant. Forests sometimes intermix with natural grasslands and savannas characterized by grasses *Elionorus muticus* or *Spartina argentinensis* (Bucher, 1982).

The Chaco forests have a stratified and long history of use, characterized by various phases and actors. Following Morello et al. (2005), these stages of forest use can be identified: first and until today, various indigenous communities inhabit the Chaco forests. Their livelihoods consist of extensive forms of subsistence agriculture, hunting and gathering, and the widespread use of nontimber forest products (Leake, 2016). Around a century ago, descendants of Europeans (Criollos) settled in the area, where they live practicing extensive cattle ranching, wood collection, small scale agriculture, hunting, and charcoal production. At the beginning of the 20th century, the development of the railway system and the need for wire fencing triggered a high demand for timber that drove major logging activities targeting hardwood species. Around the same time, European forestry production companies established an industrial activity based on extraction of tannin from tannin-rich quebrachos trees (*Schinopsis lorentzii*) and essential oil extracts from rosewood (*Gonopterodendron sarmientoi*). In the 1920s and 1930s, cultivation of cotton became prominent in the region. A phase of exploration for oil in the 70s led to the opening of a network of prospecting roads that simplified the extraction of natural products, invasion of exotics, and access for livestock (Tálamo and Caziani, 2003). Finally, during the past decades, the agricultural system in the Chaco has become dominated by large-scale farms for commodity production, mainly beef and soybeans, both for domestic and, increasingly, for international markets (le Polain de Waroux et al., 2018). Today, crop fields and pastures on farms cover several thousand hectares (Baumann et al., 2016), and are highly mechanized, involving the use of agrochemicals and herbicides. All these forest uses resulted in substantial changes in forest structure and composition. Guided by the relevant literature on forest degradation available for the Chaco, in the following section I will illustrate land-use practices that can lead to degradation and their long-term outcomes on forest structure. This will help construct a first understanding of pathways of degradation that I summarize in the conceptual scheme in Figure I-2.

A key cause of degradation is related to traditional livestock management. Extensive cattle ranching is one of the main activities of smallholders living in the forest, locally referred to as Criollos (i.e. of European descent) (Levers et al., 2021). Livestock, primarily cattle and goats, freely graze and browse in the forest around homesteads ("puestos"), returning for water (Gasparri, 2016). The grazing pressure alters the herbaceous/woody vegetation dynamic by favouring shrubs (Adamoli et al., 1990), thus leading to the virtual elimination of grasses and resulting in the dominance of shrubs and small trees (Torrella and Adámoli, 2005). Hence, vegetation shows gradients of complexity, diversity and biomass decreasing away from the homestead (Adamoli et al., 1990; Macchi and Grau, 2012). Where livestock trampling is intense, soil compaction cause bare soil exposure (Tálamo and Caziani, 2003).

Selective logging is another activity significantly contributing to forest degradation in the Argentinean Dry Chaco. There are two types of logging practices: first, selective logging of valuable species, such as "quebracho colorado" (*Schinopsis lorentzii*) for fence posts and railroad beams, and “palo santo” (*Gonopterodendron sarmientoi*) for fine furniture, floors, and essential oils, which has occurred for nearly a century. Second, less selective logging of hardwood species (e.g., *S. lorentzii*, *Aspidosperma quebracho-blanco*, *Ziziphus mistol*, *Caesalpinia paraguariensis*, *Acacia furcatispina*) occurs for charcoal production (Rueda et al., 2015; Tálamo et al., 2020). Unsustainable historical logging practices resulted in a reduction in average canopy height (Gobbi et al., 2022) and a simplification of forest structure and composition with a shift to shrub-dominated communities (Torrella and Adámoli, 2005).

Anthropogenic fires are an additional driver of degradation. Fire is used to promote grass regrowth in pastures, burn waste, convert forest into agricultural land (Bachmann et al., 2007), and facilitate the extraction of fuelwood and charcoal (Zak et al., 2004). In combination with overgrazing and logging, unmanaged fires have led to the development of secondary forests and scrubs known as “fachinales” and “peladares” (Cabido et al., 2003).

Additionally, I have included in the conceptual scheme in Figure I-2 forest structural changes related to the establishment and management of silvopastures. In silvopastoral systems part of the canopy is retained, in contrast to pure pasture systems. Silvopastures have become widespread after the passing of the Forest Law, as this land use, presented as a way to reconcile food production with important ecosystem services (Fernandez et al., 2020) is allowed in areas where full conversion became prohibited. However, the regular management interventions carried out to prevent shrub encroachment (e.g., roller chopping, controlled burns) affect the trees, leading to a decline in tree density in the long term (Fernandez et al., 2020; Marquez et al., 2022).

Besides these practices and agents directly impacting forest structure, other land uses indirectly affect the remaining forests. In particular, the recent agriculture expansion led to land acquisition, privatization and conversion, resulting in reduced forest availability or accessibility for forest-dwelling small-holders (del Giorgio et al., 2021; Vallejos et al., 2020), who often lack recognized property rights (Goldfarb and van der

Haar, 2015; Vallejos et al., 2015). This concentrates their activities and forest resource extraction in the remnant patches, thus increasing pressure on forest and degradation (Cotroneo et al., 2021).

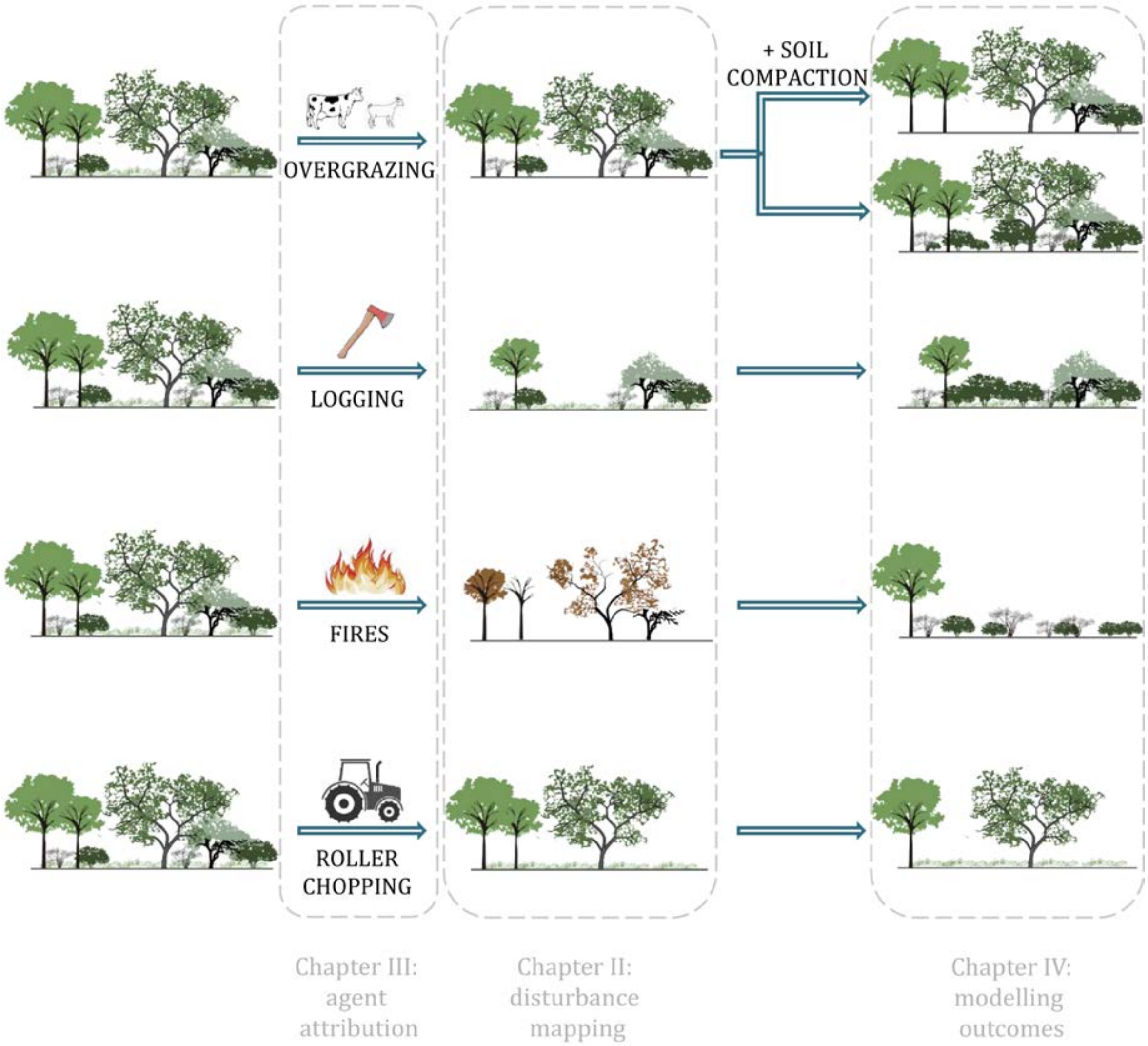


Figure I-2: Conceptual scheme of the degradation pathways related to different land-use practices. The grey boxes point to the thesis chapter of dedicated to the analysis of the highlighted components.

A body of work has studied the causes and effects of forest disturbances and degradation in the Chaco using field-based assessments (Cotroneo et al., 2018; Fernandez et al., 2020; Macchi and Grau, 2012), aerial photographs (Adamoli et al., 1990), unpiloted aerial vehicles (UAV) (Gobbi et al., 2022) and participatory approaches (Cotroneo et al., 2021). Post-disturbance vegetation development following different disturbances has been assessed through field-based studies (Loto and Bravo, 2020; Tálamo et al., 2020; Tálamo and Caziani, 2003) and ground-based LiDAR (Ferraina et al., 2022). A few studies used satellite imagery to investigate degradation related to “puestos” (Grau et al., 2008), fire patterns (Argañaraz et al., 2015; Chen et al., 2013; Fischer et al., 2012) and charcoal production (Rueda et al., 2015). However, the extent, timing and agents of forest disturbances have never been mapped and quantified for the entire Argentine Dry Chaco.

## 7 Research questions and objectives

The overarching goal of my thesis was to advance the current understanding of forest degradation in the Dry Chaco by means of remote sensing. To this purpose, I assessed the agents, patterns, and outcomes of forest disturbances. My research was guided by three main research questions, and each of the three research chapters contributes to answering these questions by focusing on specific research objectives.

***Research Question 1:*** *How can forest disturbances in the Dry Chaco be reliably characterized based on the Landsat image archives?*

A variety of land-use activities that alter forest structure and biomass can lead to declining productivity, canopy cover, and stand complexity. An important step toward understanding forest degradation is thus the monitoring and characterization of disturbances in forest canopies caused by degradation drivers such as selective logging or anthropogenic fires. However, capturing disturbances and characterizing their agent are both challenging. Approaches for analysing long time series of images provide opportunities to improve the detection and mapping of forest disturbances and their respective agents. Yet, such methods have not been tested for mapping disturbances and forest degradation across a large TDF area.

The specific objectives related to Research Question 1 were as follows:

- **Objective 1.1**: Assess the usefulness of a range of Landsat-based spectral indices and time periods over which metrics are calculated to capture forest disturbances in TDF (Chapter II).
- **Objective 1.2:** Characterize forest disturbance agents based on Landsat-derived metrics (Chapter III).

In Chapter II, I compared the performance of a suite of Landsat-derived spectral indices and seasonal windows, and of different classification approaches (single index models versus ensemble) to capture disturbances in the Dry Chaco. Specifically, I built annual time series of Landsat-derived indices to which I applied temporal segmentation to extract disturbance metrics per pixel. These metrics were then used in a random forests classifier to map disturbances for each spectral index, as well as for the ensemble of all indices. I evaluated the performance of the different models.

In Chapter III, I attributed agents to the disturbances identified in Chapter II using Landsat-derived spectral-temporal metrics and shape metrics describing disturbance patches. In particular, I identified disturbance patches from a pixel-level disturbance map produced in Chapter II. Based on these patches, I calculated shape metrics and summarized spectral-temporal metrics per patch. I then used these metrics in a random forest classifier to attribute disturbance agents to each disturbance patch.

***Research Question 2:*** *What are the spatial and temporal patterns of forest disturbances across the Chaco and due to different agents?*

Land-use activities leading to forest degradation in the Argentinean Dry Chaco vary in space and time. Understanding forest disturbance agents and their relationship with natural and anthropogenic determinants can help link disturbance patterns, agents and actor groups as a basis for disturbance management. Because information on the spatial and temporal patterns of forests disturbances is sparse, linking land-use practices and degradation remains a challenge.

The specific objectives related to Research Question 2 were:

- **Objective 2.1:** Assess the extent and temporal patterns of forest disturbances across the Argentine Dry Chaco (Chapter II).
- **Objective 2.2:** Assess the prevalence and dynamics of different disturbance agents in the period from 1990 to 2017 in the Argentine Dry Chaco (Chapter III).
- **Objective 2.3:** Assess the relationship of different disturbances agents to anthropogenic features in the Chaco landscape (Chapter III).

In Chapter II, I estimated yearly disturbed area between 1990 and 2017 based on an independent set of reference locations and used these estimates to investigate the relationship between rainfall and disturbances.

In Chapter III, I analysed the share of disturbed areas attributed to each disturbance agent in absolute terms and over time. To assess the relationship of different disturbance agents to anthropogenic features, I then compared the disturbances to land-cover maps to assess whether some disturbance types were more common close to agricultural fields, forest smallholder homesteads, and roads.

***Research Question 3:*** *What are the outcomes of different disturbance types and histories on current forest structure?*

A wide range of human activities produce disturbances that result in varying ecological responses, but information on how these disturbances impact structure and functioning of forest ecosystems or how forests develop following different types of disturbances, is limited. This results in a lack of knowledge regarding the long-term effects of disturbances on forest structure, as well as which of these effects indicate recovery as opposed to forest degradation.

The specific objective related to Research Question 3 was:

- **Objective 3.1:** Assess how post-disturbance trajectories of forest structure vary across disturbance agents (Chapter IV).

In Chapter IV, I determined how different disturbance types and histories relate to current forest structure variables. Specifically, I combined the disturbance dataset created in Chapter II and III, with dataset of fractional tree and shrub cover and aboveground biomass in a Bayesian multilevel framework to understand the impact of different disturbance types and histories relate to current forest structure.

## 8 Thesis structure

This thesis consists of five chapters: the introduction (Chapter I), three research papers (Chapters II-IV), representing individual studies that contribute to answering the overarching research questions and objectives described above, and a synthesis chapter (Chapter V) that summarizes the main results of the research papers, synthesizes overarching findings, and provides an outlook on potential applications and future research directions. The three research chapters were written as stand-alone publications, and all have been published in international peer-reviewed journals as follows:

Chapter II: Characterizing forest disturbances across the Argentine Dry Chaco based on Landsat time series. *International Journal of Applied Earth Observations and Geoinformation* (2021).
**Teresa De Marzo**, Dirk Pflugmacher, Matthias Baumann, Eric F. Lambin, Nestor Ignacio Gasparri and Tobias Kuemmerle.

Chapter III: Agents of Forest Disturbance in the Argentine Dry Chaco. *Remote sensing* (2022).
**Teresa De Marzo**, Nestor Ignacio Gasparri, Eric F. Lambin and Tobias Kuemmerle.

Chapter IV: Linking disturbance history to current forest structure to assess the impact of disturbances in tropical dry forests**.** *Forest Ecology and Management* (2023).
**Teresa De Marzo**, Marie Pratzer, Matthias Baumann, Nestor Ignacio Gasparri, Florian Pötzschner and Tobias Kuemmerle.

Chapter II:

# Characterizing forest disturbances across the Argentine Dry Chaco based on Landsat time series

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## Abstract

Forest loss in the tropics affects large areas, but whereas full forest conversions are routinely assessed, forest degradation patters remain often unclear. This is particularly so for the world's tropical dry forests, where remote sensing of forest disturbances is challenging due to high canopy complexity, strong phenology and climate variability, and diverse degradation drivers. Here, we used the full depth of the Landsat archive and devised an approach to detect disturbances related to forest degradation across the entire Argentine Dry Chaco (about 489,000 km$^2$) over a 30-year timespan. We used annual time series of different spectral indices, summarized for three seasonal windows, and applied LandTrendr to temporally segment each time series. The resulting pixel-level forest disturbance metrics then served as input for a Random Forests classification which we used to produce an area-wide disturbance map, and associated yearly area estimates of disturbed forest. Finally, we evaluated disturbance trends in relation to climate and soil conditions. Our best model produced a disturbance map with an overall accuracy of 79%, with a balanced error distribution. A total of 8% (24,877 ± 860 km2) of the remaining forest in the Argentine Dry Chaco have been affected by forest disturbances between 1990 and 2017. Diverse spatial patterns of forest disturbances indicate a variety of agents driving disturbances. We also found the disturbed area to vary strongly between years, with larger areas being disturbed during drought years. Our approach shows that it is possible to robustly map forest disturbances in tropical dry forests using Landsat time series, and demonstrates the value of ensemble approaches to capture spectrally-complex and heterogeneous land-change processes. For the Chaco, a global deforestation hotspot, our analyses provide the first Landsat-based assessment of forest disturbance in remaining forests, highlighting the need to better consider such disturbances in assessments of carbon budgets and biodiversity change.


**Keywords:** Ensemble classification, Forest degradation, LandTrendr, Trajectory analyses, Tropical dry forests, Random Forests.

## 1 Introduction

Tropical dry forests (TDF) are widespread but typically receive less attention in research and policy-making than moist rainforests (Miles et al., 2006; Schröder et al., 2021). This is unfortunate, as many TDF regions today contain little forest cover due to the historically widespread conversion of forest to agriculture. Where sizable areas of TDF still exist, they are typically under substantial conversion pressure (Miles et al., 2006; Portillo-Quintero and Sánchez-Azofeifa, 2010). Moreover, even those forests that are spared from conversion are under high, and often rising, human influence, as a range of land-use activities lead to forest degradation within them (Sánchez-Azofeifa et al., 2005). These activities include selective logging, fuelwood collection, charcoal production, mining, forest grazing and anthropogenic fires (Miles et al., 2006; Murdiyarso et al., 2008; Sasaki and Putz, 2009; Schneibel et al., 2017b). Understanding how such land-use activities contribute to tropical dry forest degradation is therefore important, given the critical ecological state of many TDF.

Forest degradation is the process leading to the permanent deterioration in the density, composition or structure of forest canopies (Grainger, 1993). These changes can have widespread and major impacts on ecosystem functioning, biodiversity and ecosystem services (Watson et al., 2018). For instance, degraded forests store and sequester less carbon (Pan et al., 2011) and sustain less biodiversity (Betts et al., 2017; Gibson et al., 2011) than undegraded forests, and forest degradation might threaten indigenous communities that depend on intact forests (Rozzi, 2012). Monitoring forest condition and uncovering drivers of forest degradation is therefore important to understand the wider social-ecological implications of degradation, particularly considering that degradation is a widespread phenomenon in the tropics (Asner et al., 2005; Pearson et al., 2017). Having accurate estimates of forest degradation is furthermore needed to inform and implement global and national climate mitigation initiatives, such as the United Nation's (UN) Reducing Emissions from Deforestation and Forest Degradation (REDD+) programme (Goetz et al., 2015). Nonetheless, we still lack robust information on the extent of degraded forests, mainly due to the conceptual and technical challenges related to detecting and mapping degradation (Da Ponte et al., 2015; Sasaki and Putz, 2009).

Degradation is typically assumed to be caused by an increase in anthropogenic disturbance (Lambin, 1999). A wide range of land-use activities that disturb forest structure and biomass can lead to declining productivity, canopy cover and stand complexity (Grainger, 1993). An important step to understand forest degradation is therefore the reliable monitoring of disturbances in forest canopies that are the result of degradation drivers, such as selective logging or anthropogenic fires (Hethcoat et al., 2019; Hirschmugl et al., 2014; Matricardi et al., 2010; Souza et al., 2005). Detecting such canopy disturbances in tropical forests with remote sensing can be challenging though, as disturbances have diverse impacts on forest structure, leave varying tree cover, and occur in diverse patch sizes, ranging from individual trees taken out to large forest fires. Moreover, some disturbances disappear quickly as forests recover, while others last for a long time (Hirschmugl et al., 2014). Because many forest disturbances associated with forest degradation result in subtle and gradual canopy changes, they can easily be confused with phenology or natural fluctuations in forest condition, for instance due to varying rainfall (Cohen et al., 2010; Lambin, 1999). The latter is particularly important for TDF regions, which experience marked interannual climate variability (Murphy and Lugo, 1986). Robust monitoring of forest degradation in TDF therefore requires appropriate methodologies to deal with this complexity, but such methodologies are overall missing. This translates into a paucity of knowledge on degradation trends in TDF (Morales-Barquero et al., 2015; Sánchez-Azofeifa et al., 2005; Sánchez-Azofeifa and Portillo-Quintero, 2011).

Analysing long time series of images can provide a quasi-continuous history of forest disturbance and regeneration (Da Ponte et al., 2015). Such long, decadal time series are thus potentially well-suited to capture forest degradation trends. With its open data policy and long time span, the Landsat archive provides time series at spatial resolution fine enough to monitor forest degradation (Woodcock et al., 2020). In addition, many algorithms have been developed to automatize forest-disturbance assessments, such as the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr; Kennedy et al., 2010), the Breaks for Additive Season and Trend (BFAST; Verbesselt et al., 2010), the Continuous Change Detection and Classification (CCDC; Zhu and Woodcock, 2014), or the Vegetation Regeneration and Disturbance Estimates through Time (VeRDET; Hughes et al., 2017) algorithms. Application of these algorithms has recently also moved from using time series of individual indices (e.g., band 5, NDVI, NBR) towards employing ensembles approaches that have considerable potential for capturing disturbances (Bullock et al., 2019; Cohen et al., 2018; Healey et al., 2018; Schultz et al., 2016). Two types of ensemble approaches have been tested: spectral ensemble approaches, where individual disturbance-detection runs are done for different spectral bands or indices using one algorithm, and then a classifier derives the final disturbance product (Cohen et al., 2018; Wang et al., 2019), or an algorithm ensemble approach, where the output from multiple disturbance-detection algorithms is used to feed the classification (Healey et al., 2018; Hislop et al., 2019; Saxena et al., 2018). While these studies show that ensemble techniques can produce more accurate forest disturbance maps, such approaches have not been tested to map disturbances and forest degradation for a large TDF area.

One TDF region where trends and patterns of forest degradation remain poorly understood is the South American Gran Chaco. Here, alongside the massive and relatively well-understood conversion of forest to agriculture that has happened since the 1990s (Baumann et al., 2017; Gasparri and Grau, 2009; Grau et al., 2005; Piquer-Rodríguez et al., 2018), a variety of land uses inside remaining forests cause forest degradation (Adamoli et al., 1990; Bachmann et al., 2007; Bucher and Huszar, 1999; Cabido et al., 2018; Grau et al., 2008; Torrella and Adámoli, 2005). However, the extent, severity, and timing of forest disturbances potentially associated with degradation have never been quantified for larger regions in the Chaco. Better information about the broad-scale patterns of forest condition would be important, as forests continue to be lost at alarming rates.

Focussing on the entire Argentine Dry Chaco (489,000 km$^2$), our goal was to identify rates and patterns of forest disturbances in remaining Chaco forests. Specifically, our objectives were to:

1. assess the usefulness of a range of Landsat-based spectral indices and time periods over which metrics are calculated to capture forest disturbances in TDF.
2. map forest disturbances potentially related to forest degradation across the entire Argentinean Dry Chaco.
3. assess the extent and spatiotemporal patterns of forest disturbance across the Dry Chaco, generally and in relation to rainfall and soil patterns.

## 2 Study area

The Gran Chaco is the largest remaining continuous tropical dry forest of the world (Olson et al., 2001). We focus on 489,000 km$^2$ study area in the Dry Chaco in northern Argentina, which was covered by about 370,000 km$^2$ of forest at the beginning of our study period in 1987. Climate in the Dry Chaco is strongly seasonal, with a distinct dry season between May and September, and a hot, rainy season from November to April. Annual rainfall ranges from 1,200 mm in the east to 450 mm in the west and the average temperature is around 22 °C (Minetti, 1999). The area is characterized by flat terrain, except for the west and southwest where hilly terrain prevails. Vegetation consists of a mosaic of xerophytic forests, open woodlands, scrubs, savannas and grasslands. Characteristic tree species belong to the generum *Schinopsis*, in particular *S. balansae* ("Quebracho colorado chaqueño"), *S. quebracho-colorado* ("Quebracho colorado"), *S. hankeana* ("Horco quebracho"). Also forests of *Bulnesia sarmentoi* ("Palo santo") are characteristic and those dominated by *Aspidosperma quebracho-blanco* ("Quebracho blanco"). Trees of Prosopis spp. ("Algarrobos") are also very common. The shrub layer is dominated by species of the genus *Acacia*, *Mimosa*, *Prosopis*, *Celtis*, and cacti *Opuntia* and *Cereus*. Some savannas are also present, dominated by grasses *Elionorus muticus* or *Spartina argentinensis*, and palm savannas of *Copernicia alba*. (Bucher, 1982; Cabido et al., 2018; Prado, 1993).

During the last decades, the Chaco experienced dramatic forest loss caused by agricultural expansion (Fehlenberg et al., 2017; Gasparri and Grau, 2009). In addition, several land-use activities lead to forest degradation. Logging, charcoal production, fires and overgrazing are the main drivers of degradation. Logging can be related to the production of firewood, fence poles, tannin or charcoal (Bachmann et al., 2007; Rueda et al., 2015), typically leading to the extraction of large trees (e.g., *Schinopsis lorentzii* and *Aspidosperma quebracho-blanco*). Because logging historically has often been unsustainable, a simplification of forest structure and composition, and a shift to shrub-dominated communities has happened in many places in the Chaco (Torrella and Adámoli, 2005). Fire, although a natural and ecologically important disturbance agent in the region (Adamoli et al., 1990), is another key driver of forest degradation (Bachmann et al., 2007). Fire is used to promote the regrowth of grasses on pastures, to burn waste on fields, and to convert forest into agricultural land (Bachmann et al., 2007). In all these cases, fires can escape to nearby forest, causing degradation. Likewise, fire is often used as a management tool to clear the shrub layer and to facilitate the extraction of partly burnt trees for fuelwood and charcoal (Zak et al., 2004). Finally, forest grazing exerts considerable pressure on forest in the Chaco. Forest grazing is a traditional management practice related to small-scale cattle ranching that largely affects the forest (Grau et al., 2008; Macchi and Grau, 2012). Grazing pressure alters the herbaceous/woody vegetation dynamic by favouring shrubs (Adamoli et al., 1990) leading to the virtual elimination of grasses and a dominance of shrubs and small trees (Torrella and Adámoli, 2005).

# 3 Data and Methods

Our methodology consisted of four main steps (Figure II-1). In step 1, we built annual time series of Landsat-derived indices to which we then, in step 2, applied temporal segmentation to extract disturbance metrics per pixel. In a third step, we used a random forests classifier, trained with an extensive reference dataset, to map disturbances for each spectral index, as well as for the ensemble of all indices. In our final and fourth step, we used the best-performing model and associated disturbance map to estimate yearly disturbed areas using an unbiased estimator based on an independent set of reference points.

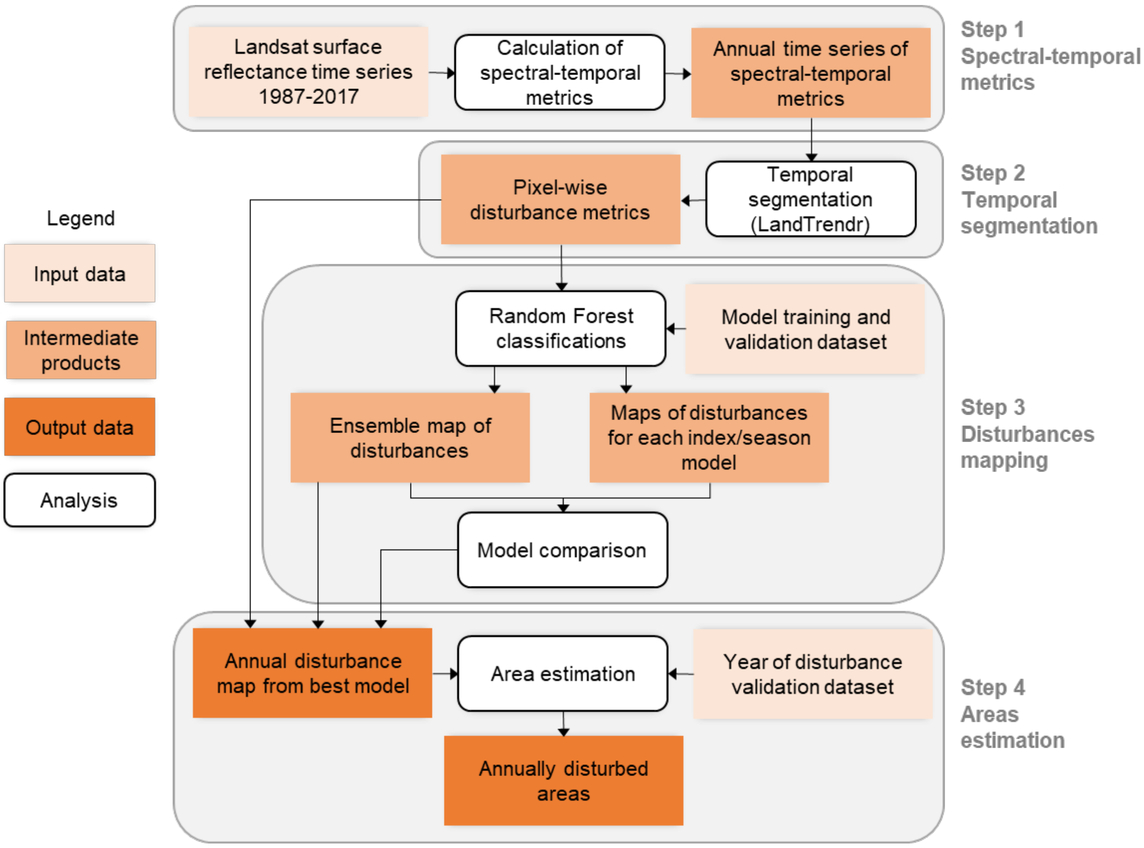


Figure II-1: Workflow of our analysis to map disturbances related to degradation in the tropical dry forest of the Argentine Gran Chaco.

## 3.1 Annual composites of spectral indices

In the first step, we derived consistent time series of a range of spectral-temporal metrics based on all available Landsat imagery. To do that, we collected all available

Landsat TM, ETM+ and OLI images for the period 1987-2017 as Collection 1 Tier 1 surface reflectance data in Google Earth Engine. These data are atmospherically corrected, have the lowest geo-registration errors and come with a pixel Quality Assessment (QA) band based on CFMask (Foga et al., 2017). We masked out all clouds and cloud shadows using the respective QA band values and applied the coefficients by Roy et al. (2016) for cross-calibration of SR-values between OLI and ETM+ data. We also calculated a set of spectral indices, specifically the Tasselled Cap Wetness (TCW, Kauth and Thomas, 1976), the Normalized Burn Ratio (NBR, Key and Benson, 2003), and the Normalized Difference Moisture Index (NDMI, Gao, 1996). We then subdivided for each year of our study period the yearly image collection into three seasonal image collections (February-April, May-July, August-October), and calculated for each period the medoid (Flood, 2013) of our spectral indices. The choice of these intervals resulted from consideration about the phenology of our system: we targeted at the beginning of the dry season (May-July) because this is the time when herbaceous vegetation is dry, but trees have not shed their leaves yet. However, this period is also is also phenologically dynamic, which makes trend analyses more sensitive to false disturbance detections, depending on data availability. Therefore, we decided to also test the interval before and after (February-April and August-October) when vegetation phenology is relatively stable. This resulted in a set of 9 annual medoid time stacks (i.e., 3 indices x 3 seasons), which served as input for the LandTrendr segmentation. We masked all index stacks to exclude areas that had not been forest in our study period using a forest mask from the onset of our study period (Baumann et al., 2017).

### 3.2 Disturbance metrics

We then applied LandTrendr, as implemented in Google Earth Engine, to each of our nine stacks (Kennedy et al., 2018). LandTrendr is a temporal segmentation algorithm that fits spectral trajectories on a pixel-per-pixel basis, using regression methods and point-to-point fitting across the annual time series of values (Kennedy et al., 2010). LandTrendr works by iteratively identifying a set of vertices and then fitting linear segments between them in order to obtain a continuous trajectory through the time series (see Kennedy et al., 2010 for details). The result of this procedure is a simplified, piece-wise representation of the annual time series. Based on these time series, a number of metrics can be derived, such as the number and length (in years) of segments, their slope, and the years corresponding to segment vertices.

LandTrendr requires tuning several parameters (Table II-1). We did this by visually inspecting samples at exemplary regions where key disturbance processes, including selective logging and fire, were known to occur. These exemplary regions were derived from the literature, pointed out by local experts (including co-authors with 10+ years of field experience in the Chaco) or identified on very high-resolution images on Google Earth. We visually evaluated how different parameters changed the trajectory fitting for these exemplary regions, and chose the parameter combination that across samples visually resulted in the best time series segmentations (Table II-1).Thus, this segmentation procedure resulted in a distinct set of disturbance metrics for each of the nine annual time series (in Figure II-2 examples of the TCW segmentation). We selected the following metrics describing the segment with the highest magnitude (in the direction of forest loss): (1) the index value for the year before the beginning of the disturbance (hereafter: *prevalue*), (2) the delta of the values of the index between the beginning and end of the disturbance (*magnitude*) and (3) the segment duration (*duration*). We did not apply a threshold filter for the disturbance magnitude (e.g., to disregard low magnitude disturbances). As such, the disturbance metrics included gradual as well as abrupt disturbances (and noise) at this step in our analyses.

Table II-1: Values used for LandTrendr parametrization on Google Earth Engine.

| Parameter | Value |
|---|---|
| maxSegments | 6 |
| spikeThreshold | 0.9 |
| vertexCountOvershoot | 3 |
| preventOneYearRecovery | true |
| recoveryThreshold | 0.25 |
| pvalThreshold | 0.05 |
| bestModelProportion | 0.75 |
| minObservationsNeeded | 6 |

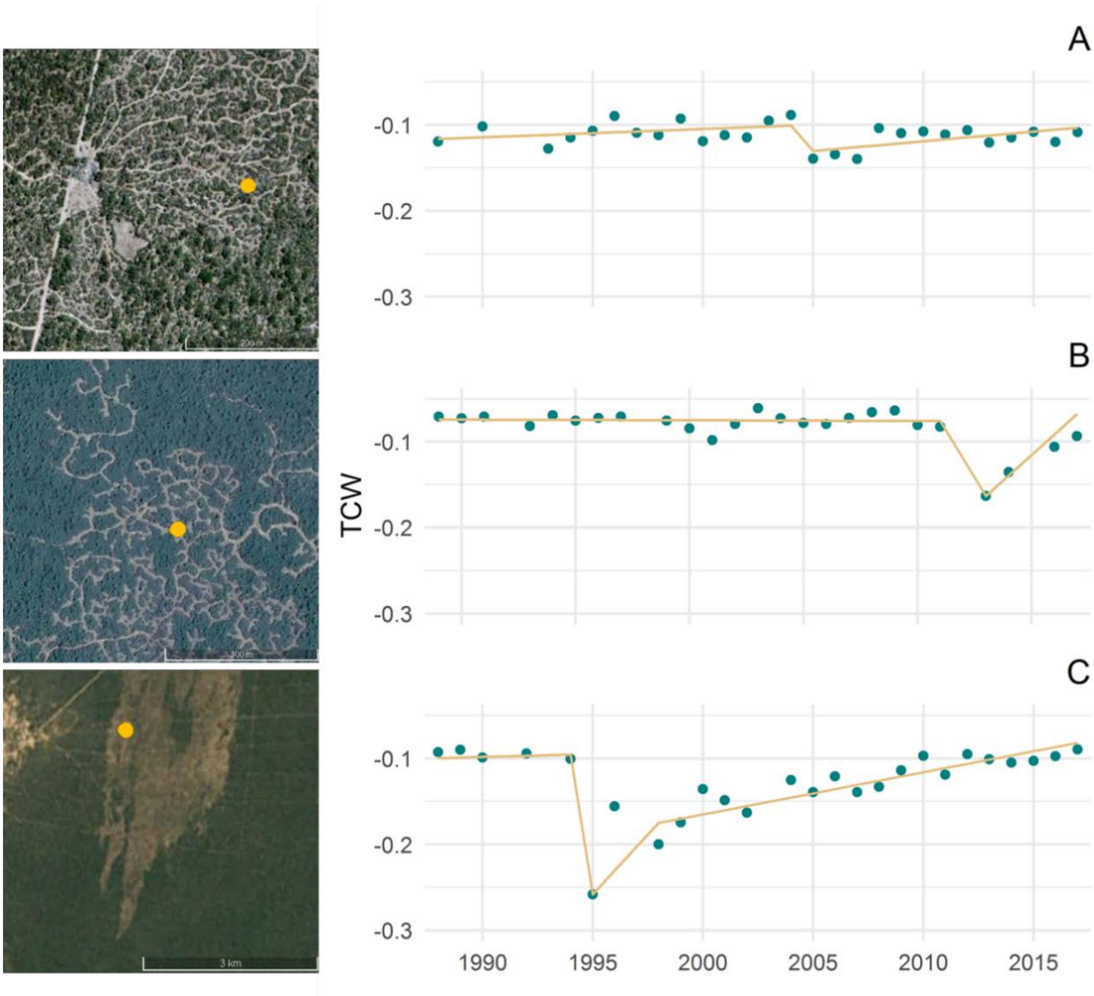


Figure II-2: Three examples of land-use practices leading to forest disturbances, as seen in very-high-resolution satellite images in Google Earth (left), as well as in time series of Tasselled Cap Wetness (TCW) medoids calculated over May-July (right; original annual values in green, values fitted with LandTrendr in yellow). A) logging for charcoal production (note that the charcoal kiln is also visible); B) selective logging of valuable tree species; C) fire.

### 3.3 Disturbance mapping

In our third step, we used our LandTrendr disturbance metrics as input for our forest disturbance classification. To generate the training/validation dataset, we used a stratified sampling design where we first trained an initial random forests classifier with an opportunistically collected training sample and then we used the disturbance magnitude class of this initial classification as strata for our sampling. We did this to ensure that our training/validation dataset contained the full range of disturbance magnitudes and a range of different disturbance severities. We then randomly sampled 80 samples per strata (= 800 samples in total). We then used the visualization and data collection tool TimeSync (Cohen et al. 2010) to interpret the temporal trajectories at the sample locations. TimeSync facilitates visual interpretation of temporal dynamics in time series, allowing the simultaneous visualization of: (a) Landsat image chips of an area of interest around the target pixel, (b) spectral properties of the pixel time series plotted as a trajectory across time, and (c) very-high-resolution imagery available in Google Earth. A total of 781 samples were successfully interpreted, where 377 samples represented disturbances at any point in time and 404 samples represented undisturbed areas (19 samples were discarded as they were inconclusive). We then combined our training data together with the LandTrendr disturbance metrics (i.e., prevalue, magnitude, and duration) in a random forest classification scheme (Breiman, 2001). We refer to this procedure as secondary classification (Cohen et al., 2018; Wang et al., 2019). All classifications were based on the outputs of 500 decision trees.

To evaluate how the choice of the seasonal window and vegetation index influenced detection accuracy, we build separate random forests classification models for each of the nine index-season combinations, as well as one ensemble model based on all nine predictor sets (3 disturbance metrics x 9 combinations = 27 variables). We evaluated the classification performance for all 10 classification models following the good practices for accuracy assessment suggested by Olofsson et al. (2014). We used the out-of-bag (OOB) random forest prediction to generate confusion matrices and estimate the overall accuracy and the omission and commission errors. Because random forests takes a bootstrap sample for every tree, the out-of-bag samples can be used for an unbiased estimate of accuracy (Breiman, 2001) In remote sensing studies, resampling techniques are increasingly used to estimate map accuracy, whereas accuracies estimated from single hold-out test datasets are likely to suffer from large variances (Lyons et al., 2018). Finally, we used the best-performing model to generate our final, binary disturbance map (disturbed vs. undisturbed forest).

### 3.4 Estimating the area of annually disturbed forest

Our ensemble approach provides a consensus map of disturbance happening at any point in our time period, but does not directly yield information on the year of disturbance. To assign a disturbance year to the ensemble map, we used the disturbance year from the LandTrendr segmentation of the best-performing individual disturbance model (i.e., the best performing spectral index and seasonal window).

Since we were interested in forest disturbance, but not the permanent conversion from forest to agriculture, we masked converted areas from our analysis using the map by Baumann et al. (2017). Therefore, for all subsequent analyses, our map did not include converted areas (i.e., areas cleared and followed by agricultural land use), but only forest disturbances happening inside forests, thus forest changes that did not result in a change of the land use. We hence attributed the year of disturbance from the best single model to all disturbed pixels of the map resulting from the ensemble classification. We did this only for disturbances occurring after 1989, as disturbance detection in the first two years of time series is typically unreliable (Cohen et al., 2017).

To estimate the area that was disturbed in each year between 1990 and 2017, we again followed best-practice guidelines (Olofsson et al., 2014) and estimated the area based on an independent set of reference locations. We collected a second stratified random sample because the size of our first reference sample was not sufficiently large to estimate disturbed area annually, using the disturbance years in the final (best) disturbance map as strata, using 30 points per strata (= a total of 840 samples as there were 28 years in our times series where disturbance can occur). Each sample was interpreted with TimeSync, labelling the year of disturbance. We then used an unbiased stratified estimator to adjust for possible sampling bias and calculated unbiased area estimates and associated confidence intervals for each year between 1990 and 2017 (Olofsson et al., 2014; Stehman, 2013).

### 3.5 Comparison with environmental variables

To further assess disturbance patterns, we investigated the relationship between rainfall and soils on the one hand, and disturbances on the other. To assess the relationship of rainfall and disturbance over time, we used the Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) time series, which blends infrared geostationary satellite observations with in situ station observations to produce monthly grids of precipitation (Funk et al., 2014). We calculated total annual precipitation, averaged across the study region, and compared this time series with our time series of disturbed forest area. We fitted a linear regression, using total disturbed area as response and average annual precipitation as explanatory variable, and derived residuals.

To explore this relationship further in space, we used the Standardized Precipitation Index (SPI) (Mckee et al., 1993) derived from CHIRPS data and compared it with our map of disturbances. SPI values are expressed in standard deviations by which the observed anomaly deviates from the long-term mean. Positive SPI values indicate wet conditions and negative values indicate dry conditions. SPI time series based on CHIRPS data were found to accurately reproduce the occurrence and spatial patterns of wet and dry conditions in Central-Western Argentina (Rivera et al., 2019) and in southern South America (Penalba and Rivera, 2015). We created SPI maps using the Climate Engine tool (Huntington et al., 2017) using a 10-month time-scale (covering the 9 months for which we calculated our spectral-temporal metrics, plus one month before). In addition, we also compared total disturbances with general (average) rainfall patterns by summarizing disturbance for 100-mm-rainfall classes, ranging from 200 mm to 1300 mm. Finally, we summarized disturbances for soil classes using a soil map from the Argentine *Instituto Nacional de Tecnología Agropecuaria* (INTA).

## 4 Results

All nine models that we tested for detecting forest disturbances, based on three disturbance metrics derived for one of the combinations of vegetation indices (NDMI, TCW, NBR) and temporal windows (fall, winter, spring), yielded moderate to high detection accuracies. Overall accuracies for individual indices and seasons ranged from 65.7% (NDMI, Feb-Apr) to 75.4% (TCW, May-Jul), with an average accuracy of 71.3 % (Table 2). Model performance was generally highest for TCW-based models and lowest for NDMI-based models. There was also a clear pattern in terms of seasons, with composites derived for May-July generally resulting in higher accuracies than composites from other time periods, regardless of the specific index. Validating these models showed that our disturbance detection generally yielded balanced error distributions, with commission errors ranging between 31.9% (TCW, May-Jul) and 43.4% (NDMI, Feb-Apr), and omission errors ranging between 30.5% (TCW, May-Jul) and 48.4% (NDMI, Feb-Apr). Uncertainty was lower for the undisturbed class, with commission errors ranging between 19.7% (TCW, May-Jul) and 29.2% (NDMI, Feb-Apr), and omission errors ranging between 20.8% (TCW, May-Jul) and 25.2% (NDMI, Feb-Apr).

Combining all indices in an ensemble model outperformed any single-index model. The ensemble classification model, using all 27 variables (3 indices x 3 seasons x 3 disturbance metrics), had the highest overall accuracy (79%) as well as the lowest commission error (27.3% for the disturbed class, 17.5% for the undisturbed class) and omission error (27.4% for the disturbed class, 17.4% for the undisturbed class) compared to the models based on disturbance metrics from a single index and season classifications. Furthermore, the ensemble model also had the most balanced distribution of commission and omission errors, which were almost equal within both the disturbed class (around 27%) and the undisturbed class (around 17%). We also explored if LandTrendr results among individual metrics varied more for samples incorrectly classified versus those correctly classified, but found no difference (results not shown.

Table II-2: Overall accuracy, omission and commission errors of the disturbance detection. The detection of disturbances was based on random forest classifications of LandTrendr-based disturbance metrics, derived for nine combinations of three spectral indices (Tasseled Cap Wetness, Normalized Burn Ratio and Normalized Difference Moisture Index) and three time intervals, as well as an ensemble model over all these variables.

| Index/season model | Overall accuracy (%) | Class errors (%) | | | |
|---|---|---|---|---|---|
| | | Disturbed | | Undisturbed | |
| | | Commission | Omission | Commission | Omission |
| TCW_Feb_Apr | 73.0 | 35.2 | 33.0 | 21.5 | 23.2 |
| TCW_May_Jul | 75.4 | 31.9 | 30.5 | 19.7 | 20.8 |
| TCW_Aug_Oct | 72.6 | 35.3 | 34.7 | 22.3 | 22.7 |
| NBR_Feb_Apr | 69.0 | 39.2 | 42.4 | 26.1 | 23.7 |
| NBR_May_Jul | 71.8 | 35.2 | 39.5 | 24.2 | 20.9 |
| NBR_Aug_Oct | 71.2 | 36.1 | 39.9 | 24.5 | 21.6 |
| NDMI_Feb_Apr | 65.7 | 43.4 | 48.4 | 29.2 | 25.2 |
| NDMI_May_Jul | 69.4 | 37.8 | 45.2 | 26.8 | 21.2 |
| NDMI_Aug_Oct | 66.4 | 42.4 | 47.8 | 27.9 | 24.6 |
| Ensemble model | 78.7 | 27.3 | 27.4 | 17.5 | 17.4 |

The final disturbance map, showing disturbed vs. undisturbed areas, highlighted distinct spatial patterns across the Argentine Dry Chaco (Figure II-3). Disturbances between 1990 and 2017 were generally more widespread at the interfaces of larger forested and non-forested patches (e.g., in the southernmost section of the study area corresponding to the province of San Luis), inside fragmented forest patches (e.g., in the south-western part of Chaco province, eastern side of Santiago del Estero province, north-eastern part of Córdoba province), as well as close to water bodies such as major rivers (e.g., the Pilcomayo river in the north of Formosa, or along the Río Dulce in

Santiago del Estero). In contrast, large, continuous patches of remaining forest appear less affected by disturbance, particularly in the southwest of the study region (provinces of San Luis, San Juan and western La Rioja) and in the north-western Chaco province. Provinces of Córdoba, Santiago del Estero and Catamarca showed the highest disturbance rates (respectively 13%, 12% and 11%). Examining the disturbance map also show distinct and diverse spatial patterns of detected disturbances from larger, continuous patches (e.g., Figure II-3, A) to more dispersed and irregular patterns (e.g., Figure II-3, B), pointing to diverse disturbance agents.

Taking a closer look at the timing of disturbance, based on the best-performing model for any combination of spectral index and season (i.e., TCW, May-July) provided further insights into the spatiotemporal patterns of forest disturbance across the Argentine Chaco (Figure II-3). Larger disturbance patches occurred predominately in the beginning of our observation period, in the 1990s, with several large, irregularly shaped patches (e.g., at the border between La Rioja and Córdoba provinces and in central Santiago del Estero). More recently, disturbances patches became generally smaller and had more geometrical shapes (indicated in our map by warmer colours, Figure II-3). Such disturbances occurred mainly close to existing agricultural fields, for example at the southern border between Salta and Chaco provinces and in the north-western part of Cordoba and south-western Catamarca. In addition, clear overall spatiotemporal patterns were visible with disturbances more prevalent in the south in the early 1990s, but progressively moving towards the more interior Chaco over time.

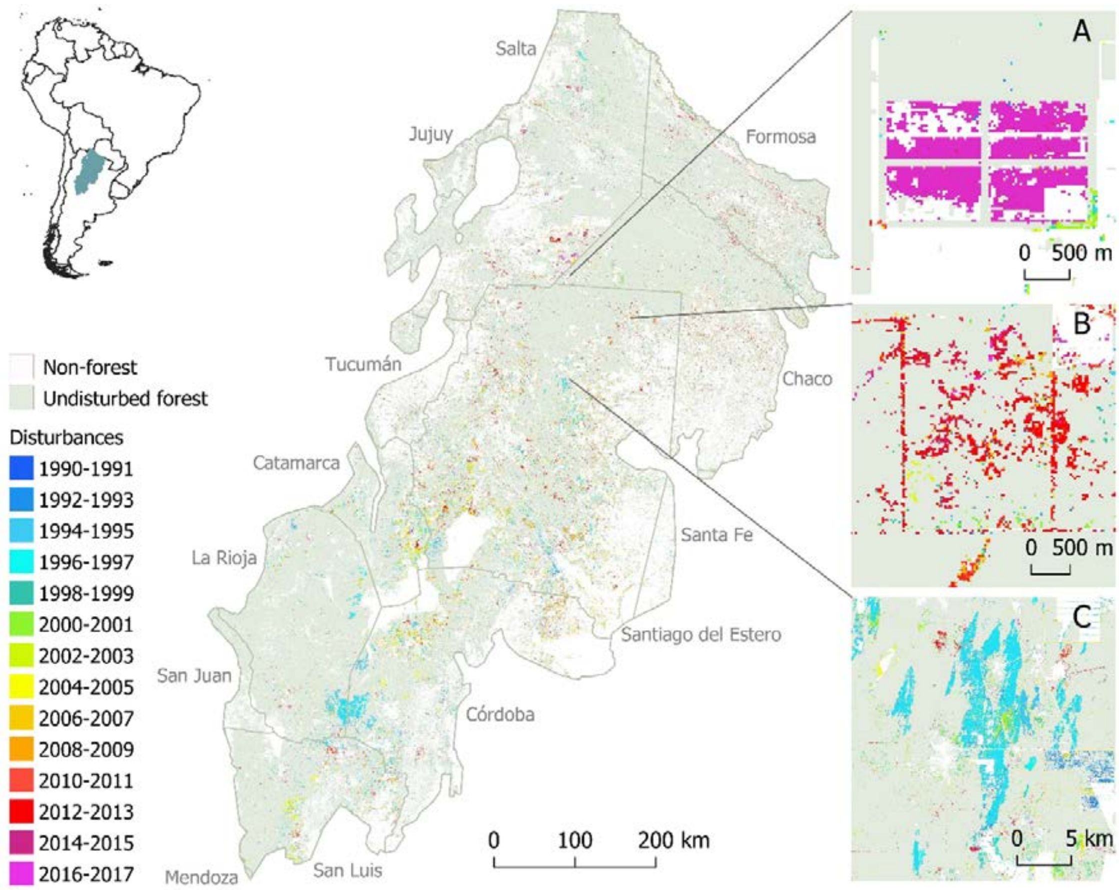


Figure II-3: Year of detection of disturbances map produced by merging the disturbance map from the ensemble model and the best single index model (TCW, May-July.)

The estimated annual area of forest disturbances, based on an independent set of ground truth points not used in model training, showed a variable pattern over time (Figure II-4, B). On average, about 888 km$^2$ (standard deviation = 581 km$^2$) of the remaining forest in 2018 was disturbed over time, yet this varied in magnitude from year to year. Highest disturbed areas occurred in 1995, 2004, 2009 and 2013 with more than 1,500 km$^2$ of disturbed areas, with a remarkable peak in 2013 when 2,647 km$^2$ were disturbed (95% confidence interval = ±488 km$^2$). Conversely, we found very small areas of disturbance for the years 1990 to 1993, 1998, 2002 and 2014 to 2016 (all <500 km$^2$), with the lowest area estimated for 1990 (48 ±42 km$^2$). The total area of disturbed forest across our entire study period was 24,877 ± 860 km$^2$.

Comparing the temporal patterns of disturbed area with precipitation time series revealed synced patterns (Figure II-4) between estimated annual disturbed area (panel B) and cumulative annual precipitation (panel A). In particular, peaks in the disturbance time series typically corresponded to years with particularly low precipitation (e.g., in 1995 and 2013). Conversely, the three years with highest rainfall (1991, 2002, and 2015) had very low levels of disturbed areas (all below 400 km$^2$). However, plotting the residuals of a simple linear regression model (Figure II-5) between annual disturbed area and annual precipitation may suggest that the effect of precipitation on forest disturbances was not consistent over time (Figure II-4, panel C). The coefficient of determination also corroborates that precipitation alone does not explain disturbed area ($R^2$= 0.41).

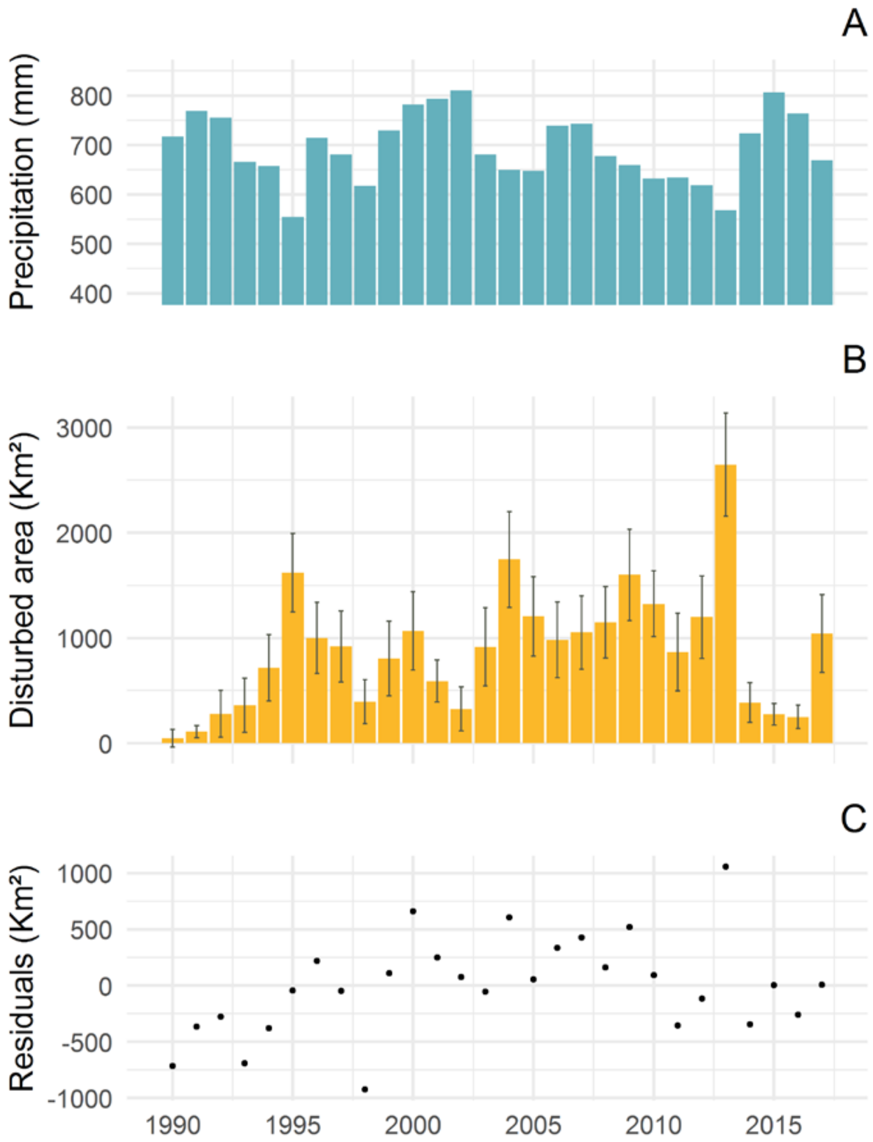


Figure II-4: Comparison between disturbances and annual precipitation patterns. A) annual precipitation sums derived from CHIRPS data. B) annual disturbance area estimated from Landsat composites. C) residuals between the observed (Landsat) and predicted disturbed area (predicted based on a linear regression between observed area and precipitations, see Figure II-5).

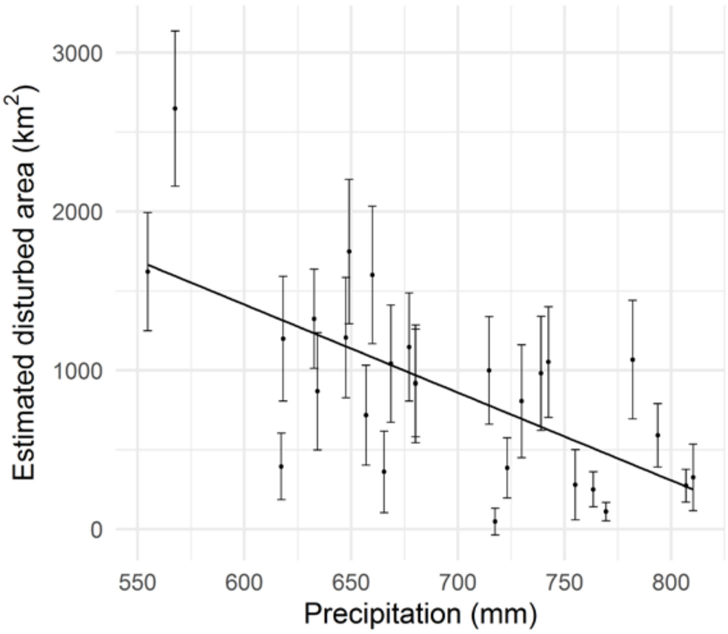


Figure II-5: Linear regression model fitted to annual precipitation sums derived from CHIRPS data and annual disturbance area estimated from Landsat composites.

Comparing the spatial disturbance patterns with maps of drought indices (SPI; Figure II-6) provided further insights into the relationship between precipitation and disturbances. The drought indices revealed a remarkably high spatial variability, with hotspots occurring in distinct regions of the Argentine Dry Chaco (e.g., 1995, 2004 and 2013, when rainfall was lowest). For instance, drought hotspots in 1995 occurred in the central and southern part of the study area, whereas the northern part of the study region was hit hardest in 2013. Interestingly, some of these spatial patterns were also reflected in the disturbance maps (Figure II-6, lower row), with regions with relatively high disturbance densities occurring where drought impacts were particularly high in a given year. Yet, disturbances also occur in areas not affected by drought.

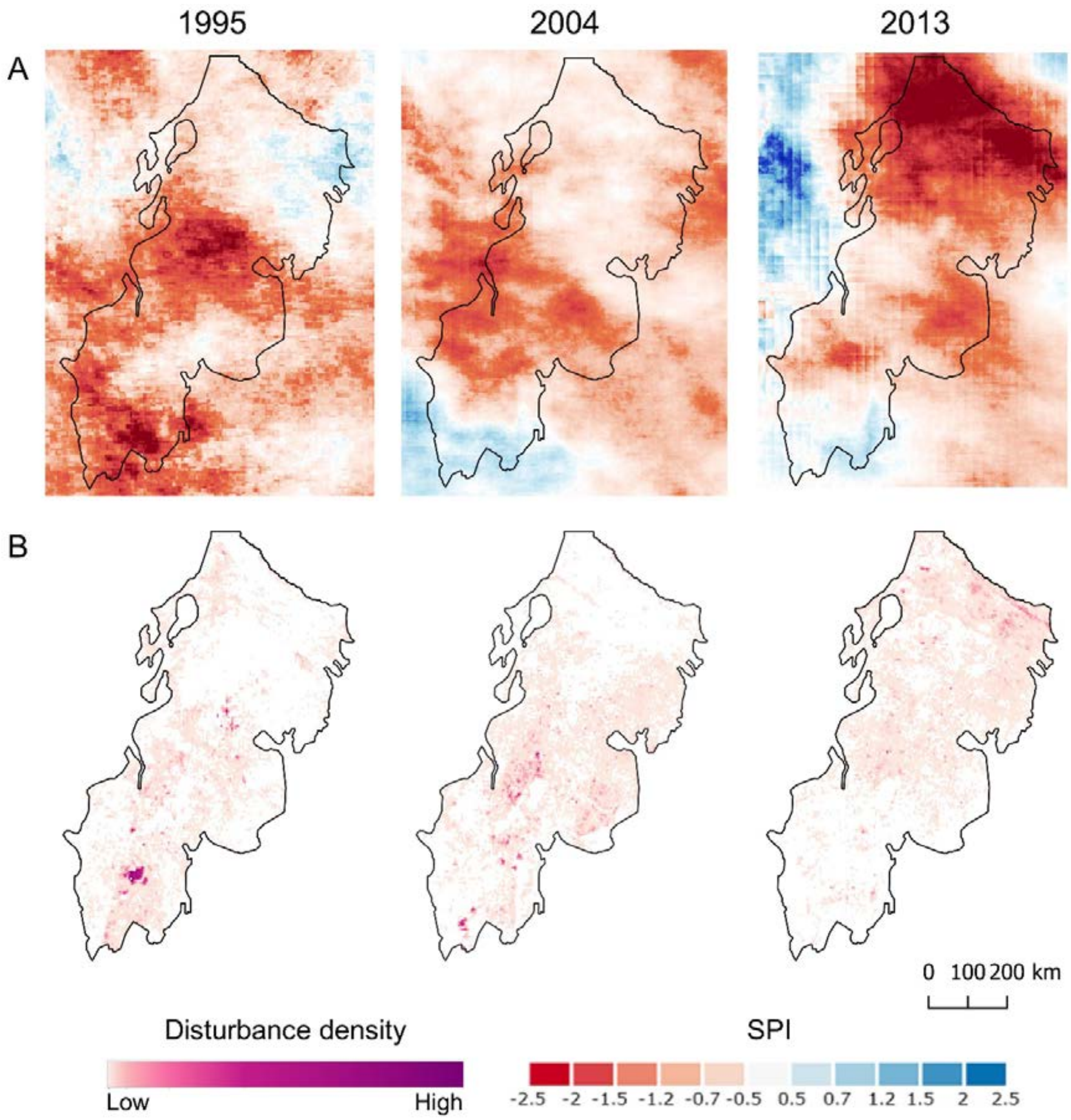


Figure II-6: Spatial comparison between drought impact and disturbance patterns for the years 1995 (left), 2004 (centre), and 2013 (right). A) Standardized Precipitation Index maps based on CHIRPS data; B) disturbance density maps. These three years had particularly low rainfall and large disturbed areas.

Finally, summarizing disturbances along a gradient of average rainfall over the entire observation period (1990-2017) showed clear association of disturbance with average rainfall in our study region (Figure II-7). In absolute terms, disturbed areas followed a clearly hump-shaped distribution, with largest forest disturbance areas found at average rainfall around 700 mm (Figure II-7, A), where also forest cover in the Dry Chaco is still the highest. Putting the disturbed area in relation to the remaining forest extent in these rainfall zones showed that highest disturbance rates occurred above 500 mm (constantly above 8-10% across the entire observation period). At lower average rainfall, disturbance rates were much lower (<4%). In terms of soil types, disturbed areas were highest in Mollisols (Figure II-7, C), with Alfisols and Mollisols having the highest disturbance rates (around 9%). Generally, disturbance rates varied less in relation to soil types than in relation to average precipitation patterns.

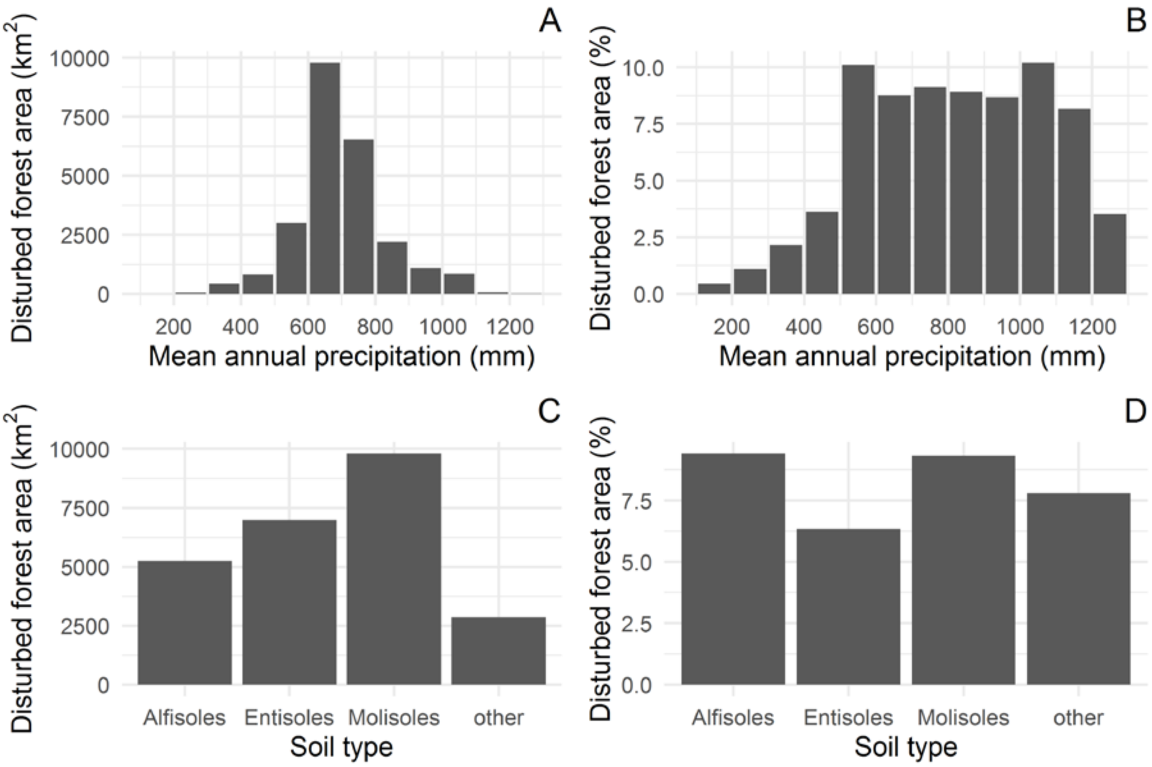


Figure II-7: Forest disturbances between 1990 and 2017 in the Argentine Dry Chaco in relation to average annual precipitation rainfall gradient and soil types. A) Total disturbed area (24,877 km$^2$) by average precipitation zone; B) Percentage of forest disturbed over total forest area by average precipitation zone; C) Total disturbed area by soil type; D) Percentage of forest disturbed by soil type.

## 5 Discussion

Tropical dry forests experience high human pressure, but monitoring forest degradation in these systems is challenging due to high canopy complexity, strong phenology, high climate variability, and diverse degradation drivers. Making full use of the opportunities that the Landsat archive provides, we here provide an assessment of forest degradation in the Dry Chaco, a large tropical dry forest region (489,000 km$^2$), over a 30-year time span using dense Landsat time series, temporal segmentation, and an ensemble disturbance detection algorithm. Methodologically, our study showed that forest disturbances associated with forest degradation can be mapped reliably and that a multispectral ensemble approach is preferable to time series analyses based on individual spectral indices. Thematically, our study yielded three main insights. First, we found major areas (about 25,000 $km^2$, 8% of the study region) of the remaining forests in the Argentine Dry Chaco have been disturbed since 1990, suggesting degradation is a widespread phenomenon that deserves more attention in discussions of environmental sustainability in the Chaco. Second, we found diverse spatial patterns of forest disturbances, which appear to be driven by different disturbance agents, including both natural (e.g., drought) and anthropogenic ones (e.g., logging, agricultural fires). This suggests disturbance attribution is central for understanding the drivers and impacts of forest degradation. Third, we found a clear association between forest disturbance and precipitation. Temporally, forest disturbance was particularly widespread during drought years. Our disturbance maps suggest a possible link of drought and increased fire activities can explain this pattern. Spatially, forest disturbance was most widespread in areas with average rainfall around 700 mm (Figure II-6, A). These are areas that are too dry for cropping, and therefore still contain considerable shares of forest, yet are inhabited by more people than the even drier parts of the Chaco. Together, this can explain the hump-shaped disturbance distribution we find. More generally, our analyses suggest that an improved degradation monitoring is urgently needed in the world's tropical dry forests. Our approach based on the Landsat archives and trajectory analyses, both readily implemented in Google Earth Engine, are promising for scaling up monitoring efforts.

Our study demonstrates the feasibility of mapping disturbances robustly across a large tropical and subtropical dry forest. Our overall accuracy (about 79%) is comparable to the only other study adopting a similar approach for a tropical dry forest (Wang et al. (2019). In this study a spectral ensemble was used to map disturbances in different forest types in Mato Grosso, yielding an overall accuracy of about 83% for the tropical dry forest area assessed (a much smaller area than in our study). Likewise, our overall accuracies are comparable to those obtained in moist tropical forests, such as in Brazil, Ethiopia and Vietnam (Schultz et al., 2016). All of this further attests to the robustness of our approach. However, it should be noted that the Chaco is relatively homogeneous in terms of topography (Bucher, 1982) and transferring our approach to topographically more complex woodlands, such as in Central America or Colombia, might therefore bring new challenges due to complexity arising from illumination differences.

Our study adds to growing evidence that a multispectral ensemble approach outperforms traditional algorithms for disturbance detection. The ensemble performed better than any single index with improved classification accuracy and error balance, a finding consistent with studies by Cohen et al. (2018), Schultz et al. (2016) and Wang et al. (2019). In terms of the performance of single indices, our study suggests that particularly the Tasseled Cap Wetness component has considerable potential for advancing degradation monitoring in tropical dry forests. This index outperformed all other indices in our change detection model comparison, in line with prior work on different forest types (Cohen et al., 2018; Czerwinski et al., 2014; DeVries et al., 2016). For tropical dry forests, Grogan et al. (2015) found TCW to be best-performing for monitoring forest disturbances, while other studies found NDMI (the least-performing index in our case) or NBR to be useful for detecting disturbances (Schneibel et al., 2017b; Smith et al., 2019). This diversity of findings, not always from studies that compared across multiple indices, further highlights a strength of an ensemble approach, which does not force an *a priori* selection of a specific spectral metric. Given the diversity of disturbance signatures we found in our case, using multiple spectral indices in an ensemble approach might also provide opportunities to capture this diversity (as different indices might detect different disturbances best), though quantifying this requires further work.

Our assessment of disturbed areas indicates that a large share, about 8% (= 24,877 ± 860 $km^2$) of the forests spared so far from agricultural conversion were affected by forest disturbances in the period 1990-2017. This area represents roughly one third of the area that was converted to agriculture during that time. For instance, forest conversion to agriculture in our study area in the period 1985 to 2013 amounted to 74,351 $km^2$ (Baumann et al., 2017). These forest losses are associated with globally-relevant carbon emissions (Baldassini et al., 2020; Baumann et al., 2017; Gasparri et al., 2008) and biodiversity loss (Romero-Muñoz et al., 2020, 2019b; Semper-Pascual et al., 2020, 2018). Yet all impact assessments so far have exclusively focused on full forest conversion, as ours is to the best of our knowledge the first study quantifying the extent of forest disturbance within remaining forests. As a result, a key finding of our work is that, unfortunately, the strong environmental impacts of forest loss and transformation reported for the Chaco (Barral et al., 2020; Baumann et al., 2017; Piquer-Rodríguez et al., 2015) still represent a substantial underestimation of the real impacts, and simple forest vs non-forest maps might heavily overestimate the quality of the remaining Chaco forests. Impact assessments must therefore urgently include forest-degradation indicators, such as the extent and severity of disturbances that we derive here. This seems particularly relevant for assessments of Reducing Emissions from Deforestation and forest Degradation (REDD+) implementation, particularly when setting baselines against which to measure reduction in forest conversion and degradation. These baselines do so far not consider degradation footprints and extent (SAyDS, 2019), which is to a large extent due to missing disturbance maps prior to our study.

Although we did not attempt here to differentiate between disturbance agents, both the shape and context of disturbance patterns hint to the processes causing disturbances. For example, irregular, continuous patches might be attributable to fires (e.g., Figure II-3, C). Such patches often occurred next to agricultural fields, suggesting that post-harvest burns and fires escaping to nearby forests are a major driver of forest disturbance in the Chaco. In contrast, we found many large, rectangular patches of disturbed forest (e.g., Figure II-3, A) – typically in areas where the agricultural frontiers are advancing (le Polain de Waroux et al., 2018). This can be interpreted as evidence for forest clearing with the intention to establish agriculture, but this intention was never realized. As a result, forests were only cleared partially and/or cleared areas were abandoned with subsequent woodland recovery, a pattern so far not documented for the Chaco. In addition to these larger disturbance patches, we found many small disturbances (e.g., Figure II-3, B) which appear to be related to selective logging or charcoal production (Rueda et al., 2015). Finally, linear disturbances were frequent, likely due to the construction or maintenance of forest roads. In sum, the spatial features of disturbance suggest diverse disturbance agents, and combining our data with ancillary data on these agents would be a beneficial follow-up step that can provide insights into the underlying causes and possible policy responses of forest degradation (Finer et al., 2018).

A key finding of our work was a possible link between the forest disturbance and drought years, with the largest area of disturbance corresponded to the most extreme droughts in our study area (Figure II-5). Similar patterns were found in the Amazon, possibly due to drought-related fires (Bullock et al. 2020). This link has been suggested for the Chaco too (Argañaraz et al., 2015; Fischer et al., 2012), and is further corroborated by our work as we found fire-like disturbance patterns particularly in drought years and particularly in areas highlighted in the SPI maps as drought hotspots (Figure II-5). We speculate that fires are more likely to occur and escape (e.g., when fields are burned), and likely larger, during drought years. However, droughts impact forest also directly (Corlett, 2016) and our analyses suggest that particularly forests along rivers are susceptible to drought impacts, possibly because these forest are more dependent on water resources and vulnerable to water stress.

Focussing on the link between disturbance and average rainfall across the Chaco, our results suggest the majority of disturbances occurred around 700 mm annual precipitation. This is perhaps not surprising, as this precipitation amount represents the lower limit for major crops (e.g. soybean, maize) in the Chaco (Grau et al., 2005), and thus deforestation occurs mainly in areas with higher precipitation (Zak et al., 2008). Several processes suggest this could be changing in the future. First, the silvopastoral cattle ranching systems mentioned above are economically feasible at precipitation levels below 700 mm and we already find evidence for their expansion (Peri et al., 2017). Second, new soybean strains that can tolerate drier climates are being developed, and this would likely shift the deforestation frontiers in major ways (Leguizamón, 2014). That the bulk of the forest disturbances in the remaining forest occurred in relatively wet areas (i.e. between 500 mm and 1200 mm) can likely be explained by the higher presence of people (both farmers and forest smallholders) in these, relatively-speaking, more favourable areas compared to the driest parts of the Chaco. Also, this pattern might be explained by the lower availability or quality of forest resources in extremely dry areas, where some valuable species disappear and vegetation grows slower and less high (Powell et al., 2018; Prado, 1993).

While our methodology resulted in relatively high detection probability and an overall robust forest disturbances map across a large region, three limitations need to be mentioned. First, our classification was based on training and validation data that were visually interpreted from Landsat image trajectories and very high-resolution images on Google Earth. Subtle disturbances (e.g., selective logging) are not easy to identify in such a way and might be missed. This suggests our estimate of forest disturbance is likely conservative. Second, and related to this, our disturbance map does not capture the impact of forest grazing on forest understory, which is a key driver of forest degradation in the Chaco (Adamoli et al., 1990; Bucher and Huszar, 1999; Torrella and Adámoli, 2005). Combining our approach with approaches that use radar or lidar data (Dubayah et al., 2020) may help to monitor such more subtle disturbances in the future. It is also worth mentioning that by considering only disturbances and not recovery, our map gives a partial picture of forest dynamics. Taking into account regrowth would be important for carbon budget estimates. However, both in the context of forest degradation and for carbon accounting, assessing recovery would require separating trees and shrubs, as the latter often dominates in recovering forests that had contained tall trees before they were disturbed. Our segments are based on spectral recovery only and do therfore not readily separate shrub from tree cover. Interpreting them as forest recovery could therefore hide ongoing degradation, which is why we refrain from showing them here. Lastly, we cannot rule out a systematic bias in the finding of higher disturbances found in dry years. Detection, however, could be both positively biased (e.g., better detectability due to lower cloud cover) or negatively biased (e.g., less contrast between vegetation and background). Generally, we are convinced our estimates in dry years are reliable, because cloud cover is lowest and image availability very good for dry seasons across our observation period.

In this study, we demonstrated the benefit of a Landsat-based, spectral ensemble approach to map forest disturbances in tropical dry forests. Most elements of our approach are implemented in Google Earth Engine, providing considerable potential for upscaling and thus for degradation-related forest disturbance monitoring. Our study highlights that such monitoring is important and timely, given the rapid pace at which tropical dry forests around the globe are disappearing, and the so far overlooked extent of disturbances related to degradation in our case. The Gran Chaco is a global hotspot of deforestation (Hansen et al., 2013), and our work suggests this is still an underestimation of the real impact of land use on forest loss and transformation. Stepping up forest disturbance monitoring in tropical dry forests is urgently needed to better understand carbon emissions and biodiversity loss associated with forest loss – and to identify effective strategies to mitigate these losses.

## Acknowledgements

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# Chapter III:

# **Agents of forest disturbance in the Argentine Dry Chaco**

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## Abstract

Forest degradation in the tropics is a widespread, yet poorly understood phenomenon. This is particularly so for tropical and subtropical dry forests, where a variety of disturbances, both natural and anthropogenic, affect forest canopies. Addressing forest degradation thus requires a spatially-explicit understanding of the causes of disturbances. Here, we apply an approach for attributing agents of forest disturbance across large areas of tropical dry forests, based on Landsat image time series. Focusing on the 489,000 $km^2$ Argentine Dry Chaco, we derived metrics on the spectral characteristics and shape of disturbance patches. We then used these metrics in a random forests classification framework to estimate the area of logging, fire, partial clearing, riparian changes, and drought. Our results highlight that partial clearing was the most widespread type of forest disturbance in 1990-2017, extending over 5,520 $km^2$ (± 407 $km^2$), followed by fire (4,562 ± 388 $km^2$) and logging (3,891± 341 $km^2$). Our analyses also reveal marked trends over time, with partial clearing generally becoming more prevalent, whereas fires declined. Comparing the spatial patterns of different disturbance types against accessibility indicators showed that fire and logging prevalence was higher closer to fields, while smallholder homesteads were associated with less burning. Roads were, surprisingly, not associated with clear trends in disturbance prevalence. To our knowledge, this is the first attribution of disturbances agents in tropical dry forests based on satellite-based indicators. While our study reveals remaining uncertainties in this attribution process, our framework has considerable potential for monitoring tropical dry forest disturbances at scale. Tropical dry forests in South America, Africa and Southeast Asia are some of the fastest disappearing ecosystems on the planet, and a more robust monitoring of forest degradation in these regions is urgently needed.

**Keywords:** Disturbance agents; Disturbance regimes; Forest degradation; Landsat time series; Land use; LandTrendr; Tropical dry forests.

## 1 Introduction

Tropical and Subtropical Dry Forests (hereafter: dry forests or TDF) occur on all continents and are among the most threatened ecosystems globally (Miles et al., 2006; Sunderland et al., 2015). Many TDF are deforestation hotspots, due to the expansion and intensification of different forms of agriculture and forest use (Hasnat and Hossain, 2020). At the same time, TDF remain weakly protected in many regions (Miles et al., 2006). TDF harbor unique biodiversity, including a great number of endemic taxa(Banda-R et al., 2016; Mares, 1992; Redford et al., 1990), and support the livelihood of many million people (Byron and Arnold, 1999; Newton et al., 2020). Understanding patterns, drivers and outcomes of forest changes in TDF is therefore important. Despite this, TDF have received far less attention than tropical rainforests. Available studies have mostly focused on agricultural expansion and deforestation, while the status of those forests that are spared from conversion is unclear.

Processes related to forest degradation remain weakly understood, although forest degradation likely affects large tracts of TDF (Siyum, 2020). The consequences of forest degradation are also significant. For example, forest degradation contributes in major ways to carbon emissions (Chidumayo, 2013; Pearson et al., 2017; Sedano et al., 2016) and increases forests' susceptibility to fires and droughts (Cochrane, 2003; Matricardi et al., 2010). Fires also exacerbate the impact of logging and fragmentation on biodiversity, and can eventually lead to a shift in forest state, including a simplification of forest structure, domination by shrubs and pioneer species, loss of important ecological functions, or increase in invasive species (Veldman et al., 2009). A better monitoring of forest degradation in TDF is thus key to improve our understanding of their status and threats, and to inform conservation and land-use planning.

A variety of disturbances have an impact on TDF and can be linked to degradation. These disturbances include both natural ones (e.g., drought, fires, storm events, floods) and anthropogenic ones (e.g., selective logging of valuable timber, logging for fuelwood collection or charcoal, mining, forest grazing, shifting cultivation) (Miles et al., 2006; Murdiyarso et al., 2008; Sasaki and Putz, 2009; Schneibel et al., 2017a). Disturbance agents can be natural processes or anthropogenic activities (e.g., natural fires vs. fire used as a management tool). Depending on the disturbance characteristics, different post-disturbance development trajectories can unfold, from full recovery to degradation cascades when disturbance frequency is high (Vieira and Scariot, 2006). Thus, to understand forest changes and their impacts, it is important to identify and attribute disturbance agents to mapped areas of forest disturbances.

The recent rapid developments in satellite image access, algorithms, and computing power now allow to map forest disturbance at high spatial and temporal resolutions, and across large extents (Zhu, 2017). Although most applications have so far focused on boreal, temperate or tropical moist forest ecosystems, the mapping of forest disturbances in TDF has only recently received increasing attention (De Marzo et al., 2021; Gao et al., 2021; Grogan et al., 2016; Hamunyela et al., 2016; Reiche et al., 2017; Smith et al., 2019). A research frontier remains in the attribution of disturbance agents, for TDF and forest disturbance generally (Sebald et al., 2021; Shimizu et al., 2019). A promising approach is to derive spectral-temporal metrics from Landsat time series segmentation, and then using these metrics in machine-learning algorithms to identify and map disturbance types or agents (Kennedy et al., 2015; Nguyen et al., 2018; Oeser et al., 2017; Senf and Seidl, 2021; Shimizu et al., 2017). For example, the spectral magnitude, duration, rate of change, or spectral values before and after the disturbance all can help differentiate disturbance agents such as fires, selective logging, clear-fell, storms, or insects (Huo et al., 2019; Nguyen et al., 2018; Senf et al., 2015; Senf and Seidl, 2021). Likewise, metrics describing the spectral recovery of the signal can be informative (Schroeder et al., 2017) For example, the gap caused by a cut single tree or single skid trail might disappear quickly, while the scar of a forest fire might take decades to fade. The segmentation algorithm LandTrendr (Kennedy et al., 2010) has been extensively tested for describing such spectral-temporal characteristics of disturbances (Cohen et al., 2018; Kennedy et al., 2012; Main-Knorn et al., 2013; Schneibel et al., 2017b; Senf et al., 2017) and is implemented in Google Earth Engine, allowing for its wide application (Kennedy et al., 2018). However, the capability of LandTrendr to identify disturbance agents in TDF has so far not been tested.

In addition to the spectral-temporal properties of disturbances, the spatial characteristics of disturbance patches provide an additional source of information for characterizing disturbance agents. Disturbance events, both natural and anthropogenic, typically affect areas larger than a single pixel, making the disturbance patch a useful unit to study (Kennedy et al., 2015; Shimizu et al., 2017). Once disturbance patches are identified, their sizes and shapes can be derived to help distinguish agents (Nguyen et al., 2018; Schroeder et al., 2017). For example, clear-cutting often results in geometrically shaped, large patches of tree loss, fire scars are large and irregularly shaped; and selective logging produces small disturbance patches. Once disturbances have been attributed to agents, analyses of their spatial determinants can provide insights into what drives disturbance regimes (Kumar et al., 2014). Most TDF have been inhabited and used over long periods of time and a variety of actors operate, use and shape these forests today (Blackie et al., 2014; Sunderland et al., 2015; Sunderlin et al., 2008). For example, where forest fires occur predominantly inside large forest patches, they could be part of natural disturbance dynamics or a result of indigenous and management practices, whereas fires adjacent to agricultural fields or settlements are likely of different origin (Cano-Crespo et al., 2015). Understanding relationships between forest disturbance agents and spatial determinants thus help to link disturbance patterns, agents and actor groups as a basis for disturbance management.

Here, we employed a methodology to detect and map disturbance agents in tropical dry forests based on satellite-based metrics. We applied this approach to the entire Argentine Dry Chaco, a vast region with a long history of forest use and degradation (Cabido et al., 2018). Forest conversion has been a key land change recently in the Argentine Dry Chaco, mainly due to the expansion of agribusinesses. However, the status of, and recent trends in forest condition of remaining, still sizeable dry forests in this region are unclear. Existing studies point to considerable forest degradation (Grau et al., 2008; Macchi and Grau, 2012; Rueda et al., 2015), as evidenced by woody cover decreasing close to fields, smallholder homesteads, and roads (Baumann et al., 2018). However, the prevalence and spatial patterns of the main disturbance agents have never been analysed in the Chaco.

Building on a temporally- and spatially-detailed mapping of forest disturbance across the entire Argentine Dry Chaco from our own previous research (De Marzo et al., 2021), here we aimed at identifying major disturbances agents in this system. Specifically, we combined multiple metrics describing disturbances spectrally and spatially into a random forests classifier to identify disturbance agents at the patch level. We then compared the identified disturbance agents to a range of features associated with key land-use actors potentially driving disturbance patterns. Specifically, we asked:

1. What was the prevalence of different disturbance agents in the period 1990 to 2017 in the Argentine Dry Chaco?
2. What were the dynamics of different types of forest disturbances in this time period?
3. How do different disturbances agents relate to anthropogenic features in the Chaco landscape, namely agricultural fields, forest smallholder homesteads and roads?

## 2 Study area

The Gran Chaco in South America is among the largest remaining continuous tropical dry forest of the world (Olson et al., 2001). The majority of the ecoregion is located in northern Argentina, where it covers an area of 489,000 $km^2$. The Argentine Chaco stretches through a mostly flat terrain characterized by a strongly seasonal climate, with average temperature around 22 °C. The cooler, dry season is between May and September, and the hot, wet season from November to April. Annual rainfall decreases from east to west from 1,200mm to 450mm in the centre of the region, with an again westward increase closer to the Andes as result of the orographic effect (Minetti 1999). Vegetation consists of a mosaic of xerophytic forests, open woodlands, scrubs, savannas, and grasslands. Characteristic tree species belong to the generum *Schinopsis*, in particular *S. balansae* ("Quebracho colorado chaqueño"), *S. quebracho-colorado* ("Quebracho colorado"), *S. hankeana* ("Horco quebracho"). Also, Chaco forests include *Bulnesia sarmentoi* ("Palo santo"), *Aspidosperma quebracho-blanco* ("Quebracho blanco"), and *Prosopis spp.* ("Algarrobo"). The shrub layer of the Chaco is dominated by *Acacia*, *Mimosa*, *Prosopis*, and *Celtis*, as well as the cacti *Opuntia* and *Cereus*. Forests sometimes intermix with natural grasslands and savannas, dominated by the grasses *Elionorus musitcus* or *Spartina argentinensis*. Finally, palm savannas with the palm *Copernicia alba* can occur in wetter parts of the Chaco (Bucher, 1982; Cabido et al., 2018; Prado, 1993).

Until recently, the Chaco was largely forested. Beginning in the 1980s, but especially in the 2000s, large-scale conversion of the Chaco's forests to agriculture occurred (Gasparri and Grau, 2009; Vallejos et al., 2015) leaving about 72% forest cover today for the Chaco as a whole (Baumann et al., 2022). Most of the remaining Chaco forest is used, with many regions considered degraded due to historically unsustainable exploitation. This resulted in a substantial simplification of forest structure and composition, with a loss of trees in the upper layer, loss of the herb layer or shrub encroachment (Torrella and Adámoli, 2005). Furthermore, the expansion of industrial agricultural also caused an intensification of forest use, worsening forest degradation (Cotroneo et al., 2021). Different land-use activities have contributed to the degradation of the Chaco forest. First, the tannin and wood industry has targeted valuable tree species such as Quebracho Colorado, Palosanto and Algarrobo, leading to extractive logging for timber across wide swaths of the Argentine Chaco (Torrella and Adámoli, 2005). Second, much logging is linked to charcoal production, a common economic activity of poorer rural people (Krapovickas et al., 2016; Rueda et al., 2015). Third, the Chaco harbours many forest smallholders, locally referred to as *'puesteros'* or *'criollos',* who live inside the forest and use the surroundings of their homesteads for sustenance (e.g., fuelwood collection, timber for construction) (Levers et al., 2021). The livestock of these smallholders typically roam freely around homesteads and has considerable impact on forest structure (Adamoli et al., 1990). Fourth, crop field and pasture management techniques in areas where forest was replaced by agriculture include the use of fire, which can spread into the surrounding forest. The prevalence, frequency and spatial patterns of these anthropogenic disturbances, however, remains weakly understood at the regional scale. The same is true for natural disturbances, which include natural fires, droughts or flooding (Bachmann et al., 2007; Bucher, 1982; Kunst, 2011).

## 3 Materials and Methods

Our overall workflow (Figure III-1) consisted of four steps. First, we derived spectral-temporal metrics at the pixel level from the temporal segmentation of time series of Tasseled Cap Wetness and Normalized Burn Ratio composites. Second, we identified disturbance patches from a pixel-level disturbance map. Based on these patches we calculated shape metrics and summarized the spectral-temporal metrics per patch. Third, we used these metrics in a random forest classifier to attribute disturbance agents to each disturbance patch. Finally, we assessed the spatial relationships of disturbance agents with anthropogenic features in the Chaco landscape, specifically agricultural fields, forest-smallholders homesteads and roads.

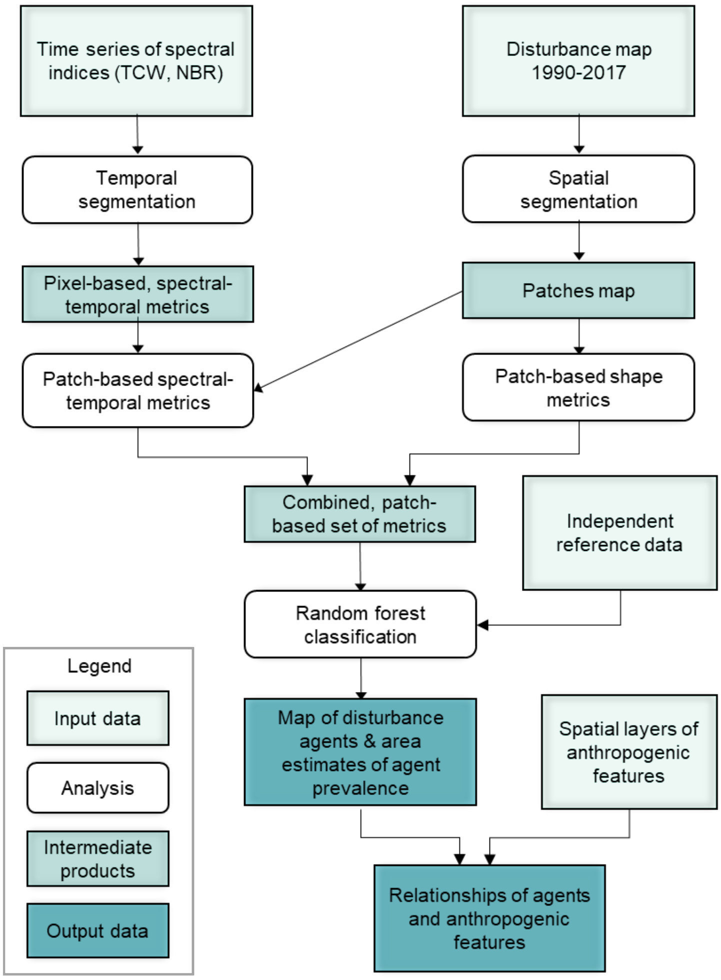


Figure III-1: Overall workflow of the research methodology employed to identify and map disturbance agents in the Argentine Dry Chaco.

## 3.1 Forest disturbance map

We used a detailed forest disturbance map (Figure III-2) for the Argentine Dry Chaco for the period 1990-2017 at 30m resolution (De Marzo et al., 2021). The map was produced using all available Landsat imagery and a time series change detection methodology. Specifically, our methodology was based on calculating annual image composites of a set of spectral indices (i.e., Tasselled Cap Wetness - TCW, the Normalized Burn Ratio - NBR, and the Normalized Difference Moisture Index - NDMI) and then using trajectory analyses per pixel to identify disturbance years, as well as disturbance metrics. We then used an ensemble classification across these composites to derive a consensus disturbance map for all areas that were forested in 2017. The final map showing the location and timing of forest disturbances was rigorously validated following best-practice accuracy assessment protocols, using independent reference data. This disturbance map had an overall accuracy of about 79% and a user's accuracy of the disturbance class of 73% (De Marzo et al., 2021). This map focuses on forest disturbances not deforestation. In other words, we investigated forest loss that did not result in a change of land use. All deforested areas (i.e., forest areas cleared and converted to agricultural land use) were masked.

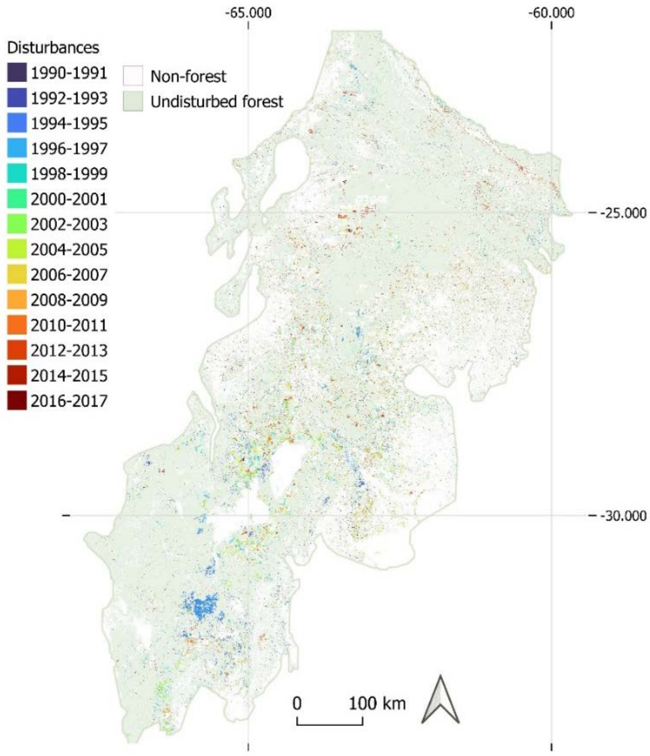


Figure III-2: Disturbance map for the Argentine Dry Chaco showing the timing of individual disturbed pixels.

## 3.2 Spectral-temporal metrics

As a first step to further characterize disturbances, we calculated spectral-temporal metrics at the pixel level using the temporal segmentation algorithm LandTrendr (Kennedy et al., 2010). LandTrendr fits simplified trajectories by first iteratively identifying a set of vertices (i.e., breakpoints) in the time series of a spectral index, and then fitting linear segments between these vertices (see (Kennedy et al., 2010) for details). Consistent with our prior work, and to match the forest disturbance maps described above, we derived time series from all available Landsat TM, ETM+ and OLI images for the period 1987–2017 as Collection 1 Tier 1 surface reflectance data. Pre-processing consisted of clouds and cloud shadow masking and harmonization of surface reflectance values between OLI and ETM+ sensors (Roy et al., 2016). For a more detailed description of the data and preprocessing, we refer to (De Marzo et al., 2021). We did this based on annual Tasselled Cap Wetness composites, as it was the single best-performing index for disturbance detection in the Chaco in our prior work (De Marzo et al., 2021) and has been used for discriminating disturbance agents elsewhere (Senf et al., 2015; Shimizu et al., 2017). From the resulting fitted segments, a number of metrics that characterize change over time can be derived – e.g., the length and numbers of segments, spectral values at the beginning and end of segments, values and sign of the spectral change along segments. We derived those metrics using the same settings and parameters used to produce the forest disturbance map (De Marzo et al., 2021). In other words, we used the same segments and timing of disturbance to ensure agreement of the datasets. Individual disturbance types might be better captured by different spectral indices, and using more than one index could therefore improve disturbance agent attribution. Specifically, the Normalized Burn Ratio (NBR) could be useful for attributing fire as an agent. We therefore also extracted NBR values for our disturbances and pre- and post-disturbance segments. We did this based on the TCW LandTrendr fitting procedure to obtain a comparable dataset (i.e., a fitted time series with vertices matching the vertex timing identified from TCW time series segmentation), with two spectral dimensions (TCW and NBR), as suggested by Kennedy et al. (Kennedy et al., 2015). From these fitted time series, we derived metrics describing the state prior to the disturbance (i.e., spectral value in the year before the disturbance), the disturbance magnitude and duration, the state after the disturbance (i.e., post-disturbance spectral value), and the magnitude and duration of the post-disturbance segment (i.e., indicating recovery trajectories).

### 3.3 Identifying and characterizing disturbance patches

To identify disturbance patches from our pixel-based disturbance map (De Marzo et al., 2021) we aggregated spatially-adjacent, disturbed pixels into patches using an 8-neighbor adjacency rule and a minimum mapping unit of 1ha (11 pixels). We assume in all subsequent analyses, that adjacent disturbance pixels can be attributed to the same disturbance agent. Based on these patches, we then calculated the following spatial metrics per patch in Google Earth Engine: patch area, patch perimeter, perimeter-area ratio, and the fractal dimension index. The latter reflects shape complexity across a range of spatial scales and was calculated as described in (McGarigal et al., 2012). Next, we summarized the spectral-temporal predictor variables per disturbance patch by calculating average and standard deviation metric values, yielding a patch-based dataset of 22 metrics (18 spectral-temporal and 4 spatial metrics; Table III-1).

Table III-1: Predictor variables calculated for each disturbance patch used for random forests modeling of disturbance agents.

| Patch-based metric | | Variable (# metrics) | Description |
|---|---|---|---|
| *Spectral-temporal metrics* | | | |
| | *Pre-disturbance* | Prevalue (2) | Mean of the spectral value before the disturbance of Tasselled Cap Wetness (TCW) and Normalized Burn Ratio (NBR) |
| | *Disturbance* | Magnitude (4) | Mean and STDV of the spectral magnitude (difference between spectral values at the end and beginning of the disturbance segment) of TCW and NBR |
| | | Relative magnitude (2) | Mean of the ratio between Magnitude and Prevalue TCW and NBR |
| | | Duration (1) | Mean of the duration in years of the disturbance segment (same for TCW and NBR time series) |
| | *Post-disturbance* | Endvalue (2) | Mean of the spectral value at the end of the disturbance of TCW and NBR |
| | *Recovery* | Magnitude (4) | Mean and STDV of the difference between spectral values at the end and beginning of the recovery segment TCW and NBR |
| | | Duration (1) | Mean of the duration in years of the recovery segment (same for TCW and NBR time series) |
| *Spatial metrics* | | | |
| | | Area (1) | Patch area |
| | | Perimeter (1) | Patch perimeter |
| | | Perimeter/area (1) | Ratio between patch perimeter and area |
| | | Fractal index (1) | Patch fractal index |

## 3.4 Disturbance attribution

To attribute each disturbance patch to its disturbance agent, we used a random forests classification. Based on the literature on forest disturbance and degradation in the Chaco, our extensive field knowledge from the region, as well as an initial scoping exercise where we examined disturbance patches in high-resolution imagery in Google Earth, we sought to attribute disturbance patches to one out of five possible agents: (1) logging, (2) fire, (3) partial clearing, (4) riparian changes, and (5) drought. To train our attribution algorithm, we collected 308 training patches across the study area (i.e., 70 logging, 70 fire, 77 partial clearing, 40 riparian changes, and 51 drought patches), where disturbance agents had been observed in the field and/or where disturbance agents could be clearly identified in Google Earth imagery.

“Logging” included selective logging for timber and logging for fuelwood collection or charcoal production. These activities typically leave a characteristic signature of a maze of irregular skid trails inside the forests, which can be easily identified on high-resolution imagery (Figure III-3). The “fire” category included any fire (natural or anthropogenic) occurring inside forests. Fires are easily recognizable by the irregularly-shaped patches, often an elongated shape in the north-south direction (due to the prevailing wind directions in the Chaco), and the spectrally-distinct signal of burned areas in the year of the fire. Our agent class “partial clearing” contained areas of forest where part of the canopy was removed as agriculture expanded. Partial clearing can occur because: (1) the conversion from forest to an agricultural field or pasture was initiated but never completed; (2) forests was converted but then abandoned, with subsequent forest regrowth; or (3) forest was converted to silvopastures, where some of the canopy is left on pastures. The agent class “riparian” refers to situations where the meandering of rivers in the Chaco (i.e., the Salado, Dulce, Pilcomayo and Bermejo rivers) leads to the erosion of riverbanks and therefore the degradation of riparian forests found on them. Given the highly dynamic fluvial systems in the Chaco, this can be common (Prieto and Rojas, 2015a). Finally, our agent “drought” included areas where a severe rainfall deficit leads to a disturbance signal as the vitality and productivity of the canopy is reduced in the drought and subsequent years.

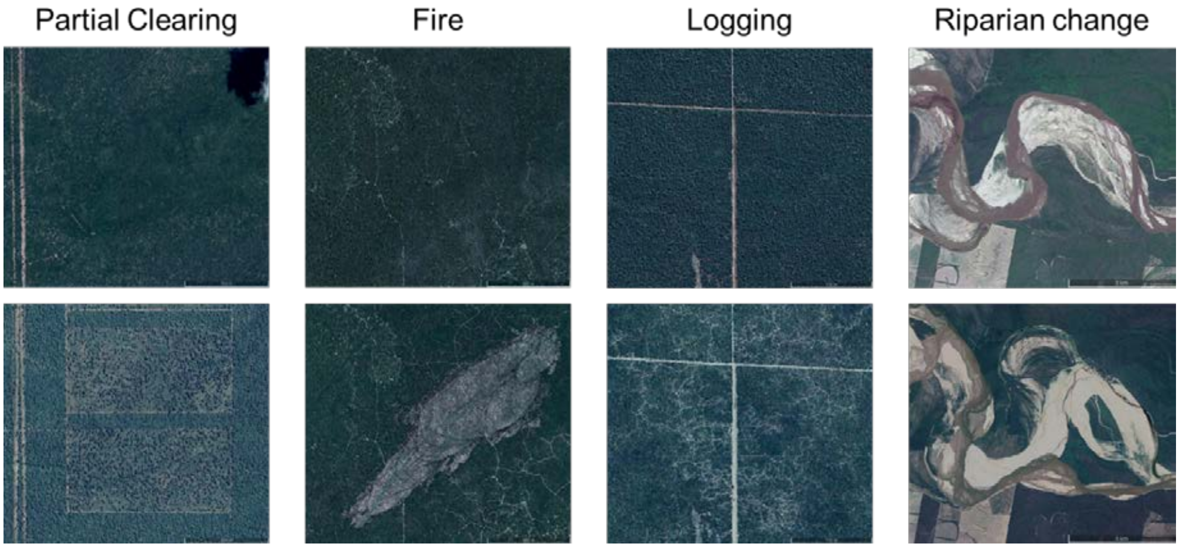


Figure III-3: Examples of different disturbance agents as seen on very high-resolution images from Google Earth. Top row: forests prior to the disturbance; Bottom row: post-disturbance situations. Columns: Partial clearing (in the example a silvopasture field); Fire; Logging; Riparian change (in the example, the Bermejo river. Note how mutable the river meanders are).

We used our set of patch-level metrics together with our training data to train a random forests classifier (RF, Breiman, 2001) to assign disturbance agents per patch. Random forests are a non-parametric classifier that consist of many individual decision trees that together determine class attribution. Individual decision trees are built using a bootstrap aggregation technique (i.e., bagging), which randomly samples a subset from the full training dataset to derive a tree, resulting in a 'forest' of many different decision trees. This has the advantage of reducing overfitting problems. Random forests classifiers are a powerful tool for remote sensing classifications generally, and particularly for attributing disturbance agents (Kennedy et al., 2015; Nguyen et al., 2018; Shimizu et al., 2017). Here, we applied the algorithm at the patch level, assigning one of the five agents to each patch. Our classification was based on 500 decision trees.

We validated our resulting disturbance agent map with a pixel-based accuracy assessment. We used a two-stage sampling strategy. First, we randomly sampled patches form a list of all patches, stratified by disturbance agent. Because our disturbance agents resulting in differently sized patches (e.g., fire had typically large patches), this ensured representation of all agent types and a diversity of patch sizes in our sample. Moreover, reliable labelling of disturbed pixels to agents requires considering patch context (i.e., size and shape of patches) and sampling patches randomly as a first step thus avoids bias. Second, we further sampled 70 pixels per stratum with a minimum distance of 100m between them. We then inspected each pixel visually on-screen in: (1) high-resolution Google Earth imagery, and (2) Landsat images time series of raw spectral and TCW using the Time series app in Google Earth Engine (https://github.com/jdbcode/ee-rgb-timeseries). We labelled the disturbance agent corresponding to the disturbance that occurred in the year indicated by our disturbance map (De Marzo et al., 2021). In other words, in case of multiple disturbance per pixel, we assigned the agent based on the year of detection (i.e., dominant disturbance) and in case of multi-year disturbances we assigned the dominant year for the entire patch. This allowed to assign a disturbance agent to each pixel. In total, we could label 326 pixels. We then used this reference dataset to calculate a confusion matrix, from which we estimated area estimates as well as overall and class-wise accuracies, using the estimator for stratified random sampling, following best-practice protocols (Olofsson et al., 2014; Stehman, 2013).

### 3.5 Analysing disturbances in relation to agricultural fields, homesteads and roads

To further understand the distribution of disturbance agents in space and time, we carried out a number of geospatial analyses. First, we analysed the share of disturbed areas attributed to our different disturbance agents over time, based on our disturbance agent map. This resulted in trend graphs per agent. Second, we compared our disturbances to land-cover maps to assess whether some disturbance types were more common close to agricultural fields. As agriculture has been expanding rapidly into forests in the Argentine Chaco over our observation period, this required us to match the timing of each disturbance with an agricultural map from that time period. To do so, we used a time series of land-cover maps in 5-year intervals (1990, 1995, 2000, 2005, 2010, and 2015) based on Landsat satellite imagery ((Baumann et al., 2017). We then calculated 500m buffers up to a maximum distance of 4,000m around fields and summarized the area of disturbance patches by agent and buffer. This allowed to assess the distribution of disturbance agents relative to the distance to agricultural land.

Third, we compared our disturbance agent map to a dataset of locations of forest-smallholder homesteads, obtained by screen-digitalizing about 24,000 individual homesteads from Landsat and Google Earth very-high resolution imagery for our entire study region (Levers et al., 2021). This database includes temporal information, specifically on which homesteads where persistent over the time period 1985-2015, and which homesteads disappeared or emerged (and when). Using the same procedure as above, we summarized areas of disturbances by agent around buffers surrounding homesteads (i.e., considering which homesteads were present when the disturbance had taken place).

Finally, we analysed disturbance agents relative to the distance to roads. We used a time series of road networks for the years 1995, 2000, 2005, 2010, 2015, reconstructed from OpenStreetMap data, historical road atlases, and historical imagery in Google Earth. Our dataset contained all major paved and unpaved roads. We then derived areas of disturbances by agent in relation to distance, again considering when roads were constructed.

Table III-2: Anthropogenic features in the Chaco landscape used for the analysis the spatial distribution of disturbance agents.

| **Variable** | **Source** | **Reference** |
|---|---|---|
| Distance to agricultural fields | Land-cover maps for the years 1990, 1995, 2000, 2005, 2010, and 2015 | Baumann et al., 2017) |
| Distance to smallholders homesteads | Homesteads screen digitalization based on the Landsat archive and very-high-resolution imagery in Google Earth | (Levers et al., 2021) |
| Distance to roads | Road network for the years 1995, 2000, 2005, 2010, 2015 | openstreetmap.org, (Romero-Muñoz et al., 2020) |

# 4 Results

## 4.1 Prevalence and estimated areas of different disturbance agents

Our best random forests model of disturbance agents had an area-adjusted overall accuracy of 56.6%. Class-wise user's accuracies where highest for partial clearing (85.5%), followed by fire (64.3%), whereas user's accuracy was lower for drought and logging (60.9% and 36.5%, respectively). Riparian changes had the lowest accuracies (20.0%). In terms of producer's accuracy, the class fire was most reliable (70.6%), although there was some confusion, particularly with logging. Partial clearing had a producer's accuracy of 48.9%, with pixels misclassified with all other classes (Table III-3). Logging pixels were mostly misclassified with riparian and fire. For the drought class, a number of reference pixels were attributed to logging in our classification. The class riparian changes had again the lowest accuracy (38.5%). Generally, our accuracy assessment revealed a fairly even error distributions (i.e., between user's and producer's accuracies). We used the model to generate our disturbance agent map (Figure III-4).

Table III-3: Population error matrix showing the estimated percentage of pixels attributed to each agent class in the reference (columns) and by the model predictions (rows) and the estimated user's and producer's accuracies per disturbance agent class with the relative standard error.

| | | Observed | | | | | |
|---|---|---|---|---|---|---|---|
| | | *Partial clearing* | *Fire* | *Logging* | *Riparian* | *Drought* | *User's accurac y* |
| **Predicted** | *Partial clearing* | 16.1 | 1.4 | 1.1 | 0.0 | 0.3 | 85.5 (± 4.3) |
| | *Fire* | 5.4 | 21.9 | 4.9 | 0.0 | 1.9 | 64.3 (± 5.8) |
| | *Logging* | 6.9 | 6.0 | 10.6 | 1.8 | 3.7 | 36.5 (± 6.1) |
| | *Riparian* | 2.2 | 1.1 | 1.8 | 1.5 | 0.7 | 20.0 (± 5.2) |
| | *Drought* | 2.3 | 0.7 | 0.7 | 0.5 | 6.5 | 60.9 (± 6.1) |
| | *Producer's accuracy* | 48.9 (± 3.6) | 70.6 (± 4.2) | 55.6 (± 6.3) | 38.5 (± 11.3) | 49.4 (± 6.5) | |

Although our classification of disturbance agents contained, as can be expected, considerable uncertainty, it is important to note that our area estimates are associated with narrow confidence intervals (Figure III-5). These area estimates, derived using independent reference data, revealed that partial clearing, a disturbance associated with the wave of agricultural expansion in the region, was most widespread disturbance agent (Figure III-5), covering 5476 ± 789 $km^2$. The second most-widespread agent was fire (5171 ± 843 $km^2$) followed by logging (3176± 785 $km^2$). Smaller areas were affected by drought (2189 ± 566 $km^2$) and the least widespread disturbance agent was riparian changes (635 ± 170 $km^2$). In total, disturbances that can be clearly attributed to natural causes (i.e., drought and riparian changes) accounted for 17% of the disturbed area (2824 ± 898 $km^2$), whereas disturbance agents that can be clearly attributed to anthropogenic activities (i.e., partial clearing and logging) accounted for 52% of the disturbed area (8652 ± 1574 km$^2$). Note that fires could be both, of natural or anthropogenic origin.

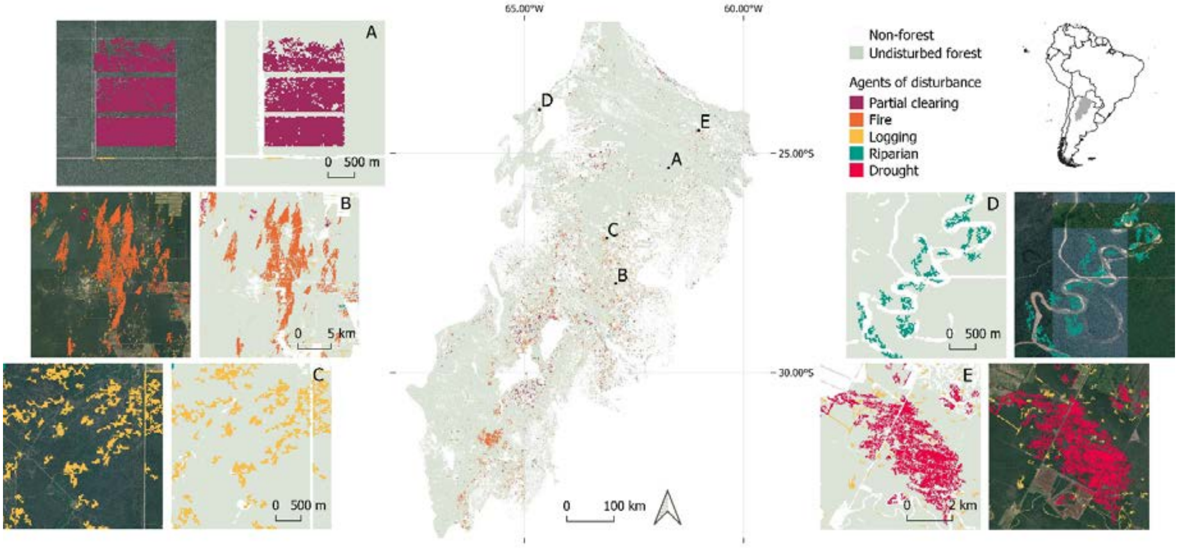


Figure III-4: Map of forest disturbance agents for the Argentine Dry Chaco. Insets show examples for the five disturbance agents identified in our analyses (Google Earth Imagery as background).

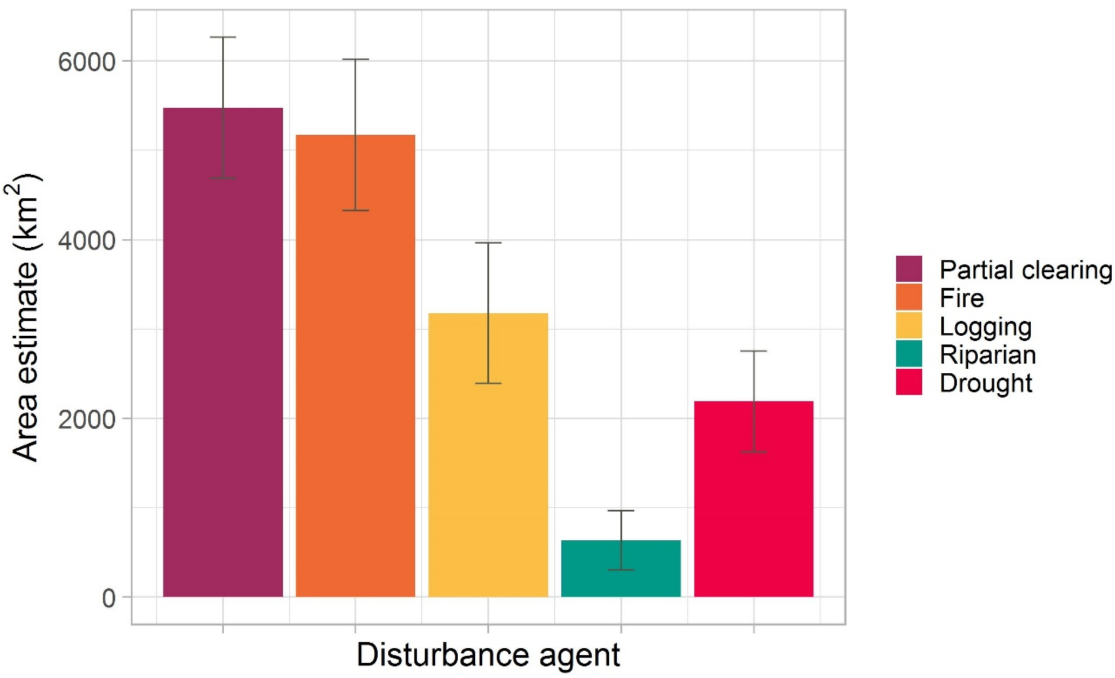


Figure III-5: Area estimates including uncertainty range (i.e., confidence intervals) for five major forest disturbance agents for the Argentine Chaco for the period 1990 to 2017.

## 4.2 Trends in disturbance agents

Summarizing disturbance agents over time showed interesting trends (Figure III-6). Analyzing trends in absolute agent distribution (i.e., based on map estimates; Figure III-6, A) revealed that the partial clearing, a disturbance connected to agricultural expansion, was overall not very widespread (<70 km$^2$/year) until the mid-2000s, when it abruptly increased 2- to 4-fold, with a maximum area of 285 km$^2$ in 2004. Logging was relatively widespread in the period 1992-1997 (around 190 km$^2$/year), then lower in 1998-2003, yet much more widespread between 2004 and 2013 (around 330 km$^2$/year). The highest area of logging occurred in 2013. Areas affected by fire fluctuated more heavily, with peaks around 1995 (1090 km$^2$ in 1995, 666 km$^2$ in 1996) and 2004 (608 km$^2$ in 2004 and 420 km$^2$ in 2005). Minimum fire years where 1990 (only 1 km$^2$) and 2015-2017 (3-9 km$^2$). Drought was overall a not very widespread disturbance agent, with drought-affected areas particularly prevalent in 1993, 2000, 2005, and 2012-2013.

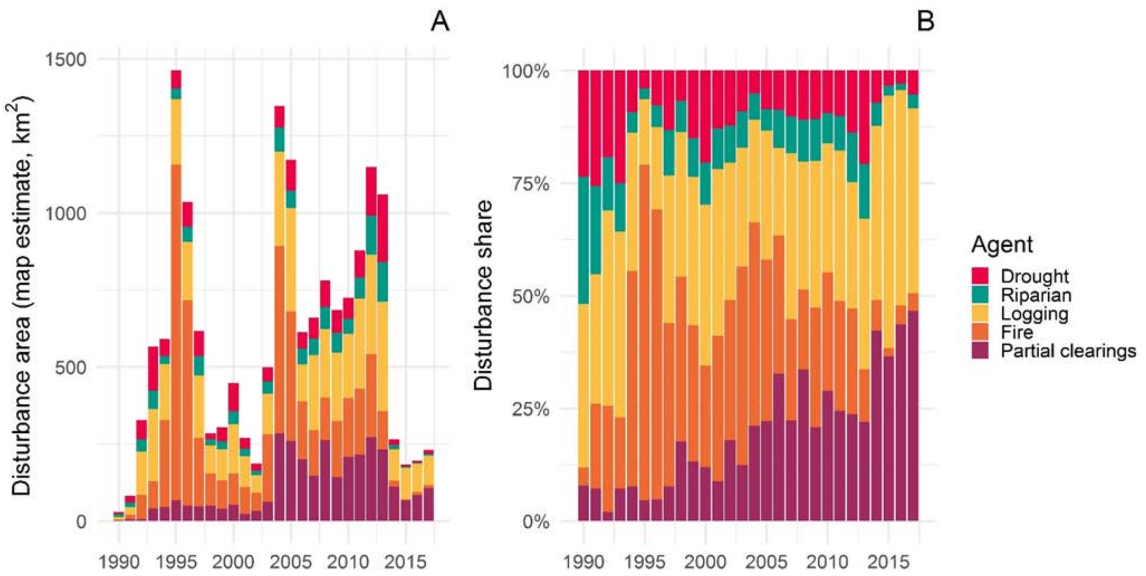


Figure III-6: Disturbance areas by year, and areas proportion of the five agents by year.

Assessing the relative share of disturbance agents over time showed clear trends in disturbance importance (Figure III-6, B). Most importantly, the share of partial clearing steadily increased, with shares rising from <10% in the early 1990s to >40% after 2010. The share of fire decreased over time in contrast, yet with major fluctuations over our observation period. Fire-prone periods were in 1994 to 1996 (between 47% to 74%), 2003-2004 (around 45%) and 2009-2010 (around 26%), whereas fire became less important in the Argentine Dry Chaco after 2015. Logging prevalence stayed relatively stable, with shares around 30%, although the area of Chaco forest declined substantially over our observation period. According to our map, drought prevalence was higher in the early years of our study period, as well as in 2000-2013.

## 4.3 Disturbance agents in relation to anthropogenic features

Analysing the spatial patterns of our disturbance agents in relation to anthropogenic features, specifically agricultural fields, smallholder homestead and roads, revealed interesting trends away from these features (Figure III-7). Trends were overall fairly similar across disturbance agents (columns in Figure III-7) and within specific anthropogenic features (rows in Figure III-7). In terms of agricultural fields, we found the clearest patterns, with all disturbances declining away from fields. For partial clearing and fire, we found an initial increase away from fields, with peaks of these disturbances about 1 km away from fields. These patterns were different when analysing disturbances in relation to smallholder homesteads. Here, we found an initial increase of disturbances, particularly for partial clearing and fire, with a peak around 1-2km, but a much more gradual decline further away. These patterns were similar for partial clearing, fire, and logging, which however differ from the patterns found for riparian changes and drought (less decline away from smallholder homesteads than for the other agents, Figure III-7, middle row). For roads, we found similar patterns with smallholder homesteads, with an initial peak at 1-2 km and a subsequent gradual decline. Again, this pattern was clearer for anthropogenic compared to natural disturbance agents (Figure III-7).

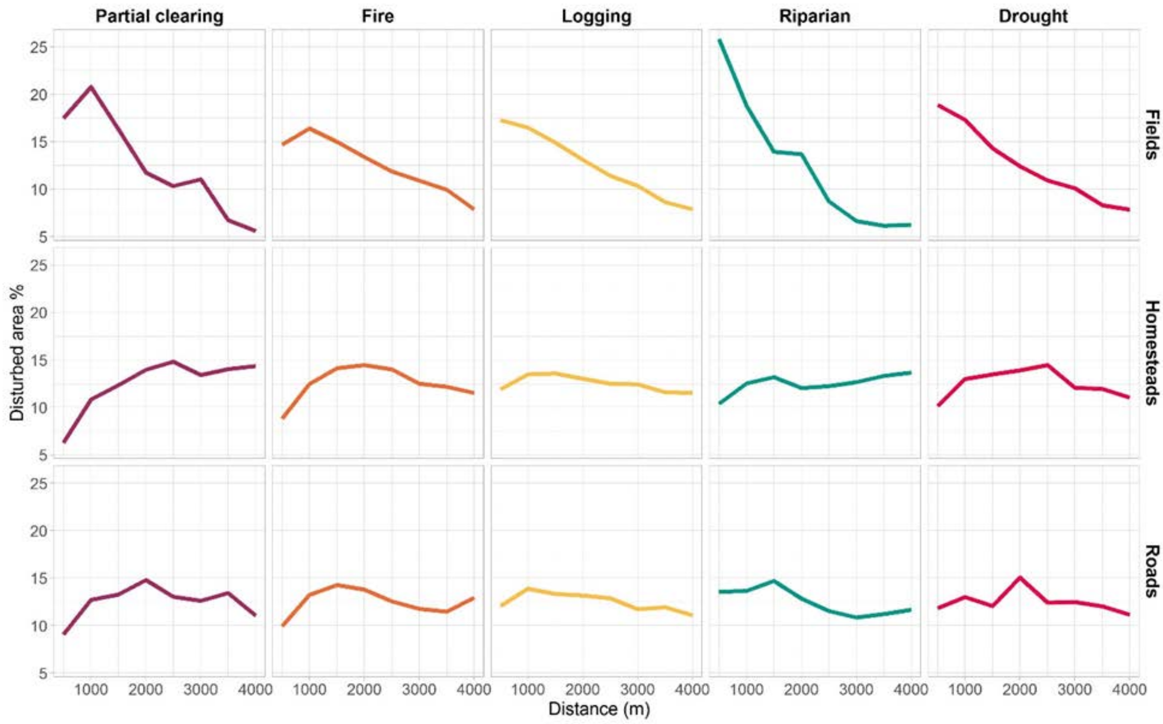


Figure III-7: Disturbance agents in relation to distance to agricultural fields, smallholders homesteads and roads.

## 5 Discussion

Understanding the agents of forest disturbances is important for avoiding and addressing forest degradation, biodiversity loss and climate change. This is particularly so for the world's widespread, often threatened, but frequently neglected tropical and subtropical dry forests. Using Landsat time series and a patch-based classification framework, we here reconstruct the prevalence and dynamics of five forest disturbance agents over a 30-year time span across the entire Argentine Dry Chaco, a vast dry forest region (489,000 km2) and global deforestation hotspot. This suggested that multiple, cooccurring disturbance agents contribute to forest degradation trends in the Chaco. Specifically, our main findings were, first, that partial clearing was the most widespread disturbance agent, pointing to a so far largely overlooked outcome of agricultural expansion processes. Second, fire and logging affected sizeable areas of the remaining forests, with most fires likely of anthropogenic origin, pointing to an urgent need for fire management strategies to preserve the remaining Dry Chaco forest. Third, most disturbances, particularly fire and logging, decreasing markedly away from agricultural areas (i.e., crop fields and pastures), highlighting so far undocumented edge effects and an indirect outcome of the recent agricultural expansion wave. Finally, we demonstrate a considerable impact of forest smallholders on disturbance prevalence, but also that this impact is spatially restricted to the vicinity of their farms. More generally, our study highlights that an improved degradation monitoring of disturbance agents is needed to sustainably manage dry forests, in the Chaco and elsewhere. Our approach based on readily available Landsat archives is promising for improving understanding of the links between disturbance patterns and actors.

Partial clearing was the most widespread disturbance agent we identified, and the prevalence of partial disturbances increased particularly after 2000. Two factors can explain this finding. First, partial clearing likely includes forests that were initially cleared for agriculture, but later abandoned, allowing the regrowth of a secondary forest. Initial clearing may be carried out to ensure land claims, yet sometimes farmers might not be able to afford establishing agriculture subsequently, agricultural operations fail, or the initial clearing is carried out for speculation purposes (i.e., to re-sell cleared land). The Argentine Forest Law (Law 26.331, Ministerio de Agricultura Ganadería y Pesca, 2015) was discussed and finally implemented in 2007, enacting considerable land-use restrictions over large areas of forests. Many land owners might have converted forest in fear of not being able to do so later, which likely led many situations where land was not put to use due to the reasons outlined above. Second, silvopastures, where part of the canopy is retained on pastures, became widespread after the passing of the Forest Law, as this land use was still allowed in areas where full conversion became prohibited. This incentivized silvopastures (Fernandez et al., 2020) which is likely captured in our partial clearing class. Generally, the strong increase of partial clearings we found for the 2000s corresponds well with other findings (Baumann et al., 2017; Vallejos et al., 2015) that highlight an acceleration of forest loss due to the agriculture boom in this period.

Fire was the second most important disturbance agent. Although natural fires can occur, most of fires in the Argentine Chaco result from human ignition source (Bravo et al., 2010; Kunst, 2011). Fire is used for vegetation clearing and as a management tool to control shrub encroachment and to promote grass growth on pastures (Boletta et al., 2006; Tálamo and Caziani, 2003). Where fire is used for management, fire can easily spread into neighbouring forests, especially in dry years, and affect very large areas (Fischer et al., 2012). Indeed, some of the largest patches in our disturbance map were due to fires (i.e., of the ten largest patches, eight were attributed to fires, with areas ranging between 35 $km^2$ and 660 $km^2$). A link between fire and drought has been suggested by prior studies for the Chaco (Argañaraz et al., 2015; Fischer et al., 2012) and South America more generally (Di Bella et al., 2006), and indeed the two peak fire years we found in our analysis were also years of documented severe drought (1995 and 2004, Figure III-6). Interestingly, fire seems to be a better way to map drought impact than our drought class, as the extremely dry years in 1995 and 2004 were captured in our time series of fire-affected area, but less so in our drought-affected areas. Overall though, fire prevalence in the Chaco's forests decreased over time, which might represent higher levels of control of fires, particularly in areas where cropping takes place and farmers are investing in fire prevention/restriction (Di Bella et al., 2006). Likewise, declining fire can be explained by less (full) conversion of forests to agriculture, as fire has historically been used for clearing land, but this is no longer compatible with land-use restrictions that require keeping part of the canopy.

Logging was the third most-widespread disturbance type we found, with a fairly constant share of forest affected over our study period. Logging can be related to the harvesting of valuable timber, production of firewood, fence poles, tannin or charcoal and these activities relate to different actors ranging from wood industries to smallholders using the selling of forest product as a safety net during economically hard times (Krapovickas et al., 2016). The large area affected by this disturbance type, and the fact that logging activities remained important despite major forest losses and an 'agriculturization' of the region, highlights the importance of considering logging in assessments of forest integrity, pressure on biodiversity, or emission assessments – which has so far not been possible due to a lack of spatially-detailed and area-wide maps. We note that our estimates of logging are likely conservative, as logging normally affects smaller patches and we had a minimum mapping unit of 1ha.

Our disturbance attribution was less reliable for the natural disturbances of riparian-change and drought. Disturbances due to meandering rivers are important, but a locally, restricted phenomena, and therefore do not cover a large area. Integrating our disturbance analyses with an assessment of changes in water surface would likely increase the reliability of this class in major ways. Drought-related disturbance also affect a smaller area, however, it must be noted that our analysis likely does not capture all drought-related vegetation stress on Chaco forests. Mapping drought impact was not our main objective, and we therefore see this class mainly as separating out strong drought impacts to avoid confusion with other disturbance agents. A more complete assessment of drought impact on vegetation would likely benefit from a temporally more resolved time series (e.g., MODIS time series). Interestingly, many of our mapped drought disturbances were found in paleochannels, indicate that vegetation occurring on these sandy soils is likely more sensitive to drought.

A striking pattern we observed was the decreasing disturbance prevalence away from agriculture. For partial clearing, this is an expected trend as distance to prior deforestation has the highest explanatory power for new land clearance (Volante et al., 2016). The distinct initial increase in partial clearing prevalence away from fields is likely related to the average distance between fields, in between there is still some forest in the form of narrow forest stripes left to prevent wind erosion ("cortinas"), which are often degraded (but overall cover a small area). Fire as well as logging decrease strongly away from fields, particularly beyond 1 km. This likely reflects accessibility of forest, relevant for extractive activities but also as a predictor of human activities and thus human ignition. Furthermore, where fires are used for management purposes, they can escape into adjacent forests, as highlighted above.

We also found marked effects of smallholder homesteads in relation to disturbance prevalence. The decreasing partial clearing closer to smallholder homesteads likely indicates that homesteads persist only they have sizeable forests in the surrounding, with many homesteads abandoned as industrialized agriculture expands around them (Levers et al., 2021). Fire occurrence was lower closer to homesteads, on the one hand because of higher fire control, on the other hand likely because livestock reduces woody cover and herbaceous fuel loads in the close surrounding of homesteads (Baumann et al., 2018; Macchi and Grau, 2012). This might also explain the increase in logging further away from homesteads, as wood availability should increase further away. We note that we found similar, though somewhat less conclusive patters for distances to roads in line with prior work (Baumann et al., 2018), which can be explained by roads being a less clear indicator of human presence than settlements. Yet, this might also point to shortcomings in our road dataset, which was perhaps too coarse (mainly paved roads only) and did not include small roads opened for the purpose of logging or (historically) oil prospecting (Tálamo and Caziani, 2003). Our findings on the relationship of disturbances to anthropogenic features are based on analysis of the whole area, while different context might result in local difference. For example, the collection of firewood is influenced by household income and access to forestland and therefore varies in different regions (Krapovickas et al., 2016). Charcoal ovens are concentrated in some provinces and rare in others (Rueda et al., 2015). Pastures, where fire is used as a management tool, prevails over crops in drier areas (Baldi et al., 2015). These factors might produce different local patterns of disturbances prevalence in relation to anthropogenic features.

Our analyses yielded robust area estimates and maps of disturbance agents, yet also highlighted the challenges of accurately attributing disturbance agents. The level of accuracy we achieved was comparable to other studies. For example, we obtained user's accuracies of 77.0% for disturbances caused by partial clearing and 46% for our logging class, comparable to a harvest disturbance accuracy of 68% for Central Europe (Sebald et al., 2021), or between 63% and 87% for the USA (Schroeder et al., 2017). Our fire class had a user's accuracy of 59.3%, which is lower what is often reported from other biomes (i.e., the Boreal), although fire mapping is easier there (Hermosilla et al., 2015). Interestingly, we did not find any study that provides robust error estimates for disturbance agents in dry forests, limiting comparability, and we found no study at all independently evaluating the performance of riparian change disturbances or drought (typically included in classes like "other" (Nguyen et al., 2018) or "stress" (Schroeder et al., 2017), with widely varying error estimates, such as 29%-88% in the latter study). These highlights the complexity of disturbances agent attribution in tropical dry forest, and the urgent need for more studies in this biome. In our case, confusion was highest among partial clearing, fire and logging, disturbances that in reality blend on the ground as they are all connected to both the deforestation process and to management (e.g., silvopastures, charcoal production). Better understanding agent complexes (i.e., co-occurring or sequential disturbances) would therefore be a useful next step. A deeper consideration of landscape context (Sebald et al., 2021) could help in this regard, in addition to the spectral-temporal and patch shape metrics we used here.

Although our methodology resulted in a reliable disturbance agent attribution and robust area estimates for these agents across a large region, a few limitations need to be mentioned. First, we carried out the most comprehensive attribution of disturbance agents so far for the Chaco or any dry forest region, but we could not find reliable reference data for some disturbance types that are consequently not identified here. These might include, disturbance due to salinization (Maertens et al., n.d.), insect disturbance, or herbicide drift due to heavy pesticide use on some crops (i.e., soybean, cotton). Second, we applied a minimum mapping unit of 11 pixels, equalling approximately 1ha. This helped to remove scattered, small patches many of which likely represent misclassification, but we cannot rule out that this not also filtered out some disturbance types connected to very small patches, such as logging, more than others, such as fire. Third, our disturbance map likely is a conservative estimated as we did not map low-severity disturbances (De Marzo et al., 2021) and our map does not capture sub-canopy disturbances, such as forest grazing and resulting forest understory degradation, a common process of forest degradation in the Chaco. Fourth, our disturbance map had by itself some level of uncertainty (see De Marzo et al., 2021) that are not fully captured in the accuracies metrics we report here, as these only capture the reliability of the agent attribution. However, our disturbance map had very balanced omission and commission errors, and we therefore do not expect uncertainty in disturbance detection to strongly affect our disturbance agent area estimates.

## 6 Conclusion

Going beyond only mapping forest conversion in tropical and subtropical dry forests to more deeply consider forest disturbance and forest degradation is urgently needed to better understand human pressure on these systems. Remote sensing is an essential tool for deforestation monitoring, and should be a key tool for assessing disturbance and more subtle changes in these forests as well, but has so far not been widely used for this purpose. In this study, we demonstrated the benefit of the unique Landsat archive to assess and map, at high spatial and temporal resolution, different forest disturbance agents and to separate anthropogenic from natural disturbances for the entire Argentine Dry Chaco. A number of studies focused on mapping or quantifying conversion of forest to agriculture [e.g., 56,57,72], and a few investigated changes in the remaining forests, such as degradation (Grau et al., 2008), logging (Rueda et al., 2015), fires (Argañaraz et al., 2015) in regions of the Chaco. However, this is, to our knowledge, the first forest disturbance agent attribution for the whole Argentine Dry Chaco. Given that our workflow is implemented in Google Earth Engine, there is considerable potential for consistent, repetitive forest disturbance monitoring, as well as for upscaling to larger areas – given appropriate training and validation data can be gathered. Thus, our workflow can be a start for a monitoring tool supporting land managers, planners, and policymakers. Thematically, our work suggests that a large proportion of the forest so far spared from deforestation is affected by anthropogenic disturbances, related to a diversity of land-use actors. This highlights the need to better capture and address forest degradation in order to maintain ecological integrity. Forest degradation as an important group of processes should not be neglected in tropical dry forests undergoing deforestation due to the expansion of commodity agriculture, such as the Chaco.

## Acknowledgements

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Chapter IV:

# Linking disturbance history to current forest structure to assess the impact of disturbances in tropical dry forests

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## Abstract

Tropical dry forests are widespread, harbour vast amounts of carbon and unique biodiversity, and underpin the livelihoods of millions. A variety of natural and anthropogenic disturbances affect tropical dry forest canopy, yet our understanding of how these disturbances impact on forest structure and ecosystem functioning, and how forests develop after different disturbances, is partial. This translates into knowledge gaps regarding long-term outcomes of disturbances on forest structure as well as which of these outcomes signify recovery vs forest degradation. Here, we use a rich dataset of remotely-sensed, high-resolution forest indicators in a multilevel Bayesian regression framework to understand the effect of different disturbance agents (partial clearing, fire, logging, drought and riparian changes) on aboveground biomass, and woody cover in the Argentine Dry Chaco. Our models show that post-disturbance trajectories of forest structural indicators differ markedly among different disturbance agents. For example, riparian changes affected biomass most strongly but had the fastest recovery, whereas logging had a generally lower impact and mostly affected tree cover, but recovery was slow or never occurred. Importantly, even three decades after the disturbance event, woody cover and biomass exhibited higher values for natural disturbances compared to anthropogenic disturbances. Furthermore, anthropogenic disturbances had slower recovery rates than natural disturbances. Overall, our approach shows the potential of remote-sensing indicators and space-for-time substitution to unravel the diverse vegetation response of different disturbance agents. Given the high and rising human pressure on dry forests in the Chaco and globally, our findings also show the long-lasting effects that anthropogenic disturbances have on these valuable forests.


**Keywords**: Above-ground biomass, Woody cover, Bayesian multilevel models, Dry Chaco, Forest degradation

## 1 Introduction

Tropical dry forests (TDF) are widespread, but have received much less attention than tropical humid forests in research, policy-making and the wider public (Miles et al., 2006; Schröder et al., 2021). This is unfortunate, as tropical dry forests harbour high and unique biodiversity (Banda-R et al., 2016; Pennington et al., 2018; Powers et al., 2018; Redford et al., 1990), are globally important carbon stocks, and provide a myriad of ecosystem services to local communities (Blackie et al., 2014). Yet, these forests are under substantial pressure from agricultural expansion, timber extraction, charcoal production, livestock grazing and infrastructure development (Baumann et al., 2022). As a result, TDF in many regions have been disappearing or are now heavily degraded, making the protection and restoration of remaining dry forests a global priority (Banda-R et al., 2016; Kuemmerle et al., 2017; Miles et al., 2006).

Forest disturbances can substantially alter the structure and composition of remaining forests (Agarwala et al., 2016; Fajardo et al., 2013; Villela et al., 2006). These disturbances include, for example: selective logging of valuable timber; logging for fuelwood or charcoal production; small-scale clearing for mining; livestock production in forests or silvopastoral systems (Fajardo et al., 2013; Miles et al., 2006; Murdiyarso et al., 2008; Sánchez-Romero et al., 2021; Sasaki and Putz, 2009). In addition, tropical dry forest frequently experience natural disturbances, including fires, storm events, flood events or droughts, all of which substantially affect tropical dry forest canopies (Chazdon, 2003). Both anthropogenic and natural disturbances play major roles in reshaping forest structure and ecosystem functioning, affecting carbon storage and sequestration, as well as moisture recycling and, in turn ecosystems services and biodiversity (Asner, 2013; White and Pickett, 1985). What remains unclear is how different types of forest disturbances affect structural parameters directly, and how forest structures may recover over time.

This is not a trivial task, as different disturbances affect forest structure and composition in different ways (Frolking et al., 2009), therefore potentially leading to different post-disturbance development trajectories and different long-term outcomes in forest structure (Giovanini et al., 2013; Urquiza-Haas et al., 2007). For example, selective logging typically targets valuable species and larger trees, while logging for fuelwood or for charcoal production targets trees less selectively in terms of species or age groups (Rueda et al., 2015). In addition, the natural complexity and heterogeneity of tropical dry forests, containing more closed-canopy or open forests, coupled with specific disturbance agents, can lead to multiple post-disturbance pathways that might result in different outcomes. For instance, the removal of trees can lead to shrub encroachment where livestock is allowed to enter forests, or even semi-open shrublands with low vegetation cover, and bare soil exposure, where overgrazing is heavy (i.e., due to animal trampling) (Gobbi et al., 2022). Given that these outcomes will have very different effects on ecosystem functioning, it is important to understand how disturbance alters forest structure.

Furthermore, post-disturbance forest recovery can differ between natural versus anthropogenic disturbances (Chazdon, 2003). Namely, recovery after a natural disturbance (e.g., a storm event) differs from succession on abandoned fields or pastures in terms of species composition. This is due to differences in seed banks, lack of dispersing fauna in landscapes that underwent extensive deforestation, or the overabundance of seed predators in such landscape (Janzen, 1990). Likewise, the speed of forest regrowth can vary considerably among disturbance types: in general, forest structure and composition can recover relatively rapidly following disturbances that impact mainly forest canopies, such as storms or drought, while recovery is considerably slower following disturbances that heavily impact soils, such as ploughing or bull-dozing (Chazdon, 2003). Despite these differences in post-disturbance recovery and the strong implications these differences should have for tropical dry forest ecology and biodiversity (Jara-Guerrero et al., 2021; Yuan et al., 2018), our understanding of post-disturbance dynamics in tropical dry forest is weak (Quesada et al., 2009). In particular, it remains unclear whether forest recover differently after disturbances depending on the type of disturbance. This is problematic as slower recovery or a permanent change in forest structure leads to a reduction in ecological functioning which can signal forest degradation (Grainger, 1993; Schröder et al., 2021; Siyum, 2020). Better understanding potential links between disturbance and post-disturbance recovery across different disturbance agents would thus be beneficial, but we are unaware of any study in TDF that has done so.

One barrier for assessing post-disturbance recovery trajectories is typically the lack of repeated measurements of forest structure. Existing studies exploring the links between disturbance agents and post-disturbance recovery have typically relied on field assessments (Chaturvedi et al., 2012; Colón and Lugo, 2006; Loto and Bravo, 2020; Urquiza-Haas et al., 2007), which come with the trade-offs of being laborious and hence often limited in their spatial extent and/or their number of plots. Overcoming this limitation requires approaches that can characterize the structural composition of TDF across larger areas at high accuracy and spatial detail, while at the same time allowing to understand change over long time periods. Remote sensing is an excellent methodology to remedy some of the drawbacks of field-based assessments to allow for spatially consistent assessments, as satellite imagery allow for a detailed and retrospective characterization of disturbance and post-disturbance development across larger areas and back in time (Hermosilla et al., 2019; Meng et al., 2021; Shimizu et al., 2022). Forest disturbance detection itself is now fairly operational, thanks to open access to high-resolution satellite image archives extending back to the 1980s, new algorithms, and ever-increasing cloud-processing capabilities (Banskota et al., 2014; Frazier et al., 2014; Pasquarella et al., 2022; Wulder et al., 2012; Zhu, 2017). Disturbances and disturbance agents can be robustly characterized thanks to temporal segmentation algorithms and machine-learning methods (De Marzo et al., 2022; Kennedy et al., 2015; Nguyen et al., 2018; Shimizu et al., 2017; Zhang et al., 2022). In addition, multi-sensor approaches allow to reliably characterize forest structural composition, including biomass or fractional woody cover (Baumann et al., 2018; Bourgoin et al., 2018; Pötzschner et al., 2022; Shao and Zhang, 2016).

A challenge for understanding post-disturbance recovery trajectories, however, is a lack of longitudinal data on forest disturbances and structure. For example, while optical remote sensing data (e.g., Landsat, which is often used to detect forest disturbance) reach back to the 1980 s, radar or Lidar data from (e.g., Sentinel-1 or GEDI, which can be used to describe structural parameters) became only available recently. As a result, quantify changes in forest structure over time with repeat measurements at the same sites is often not possible. Space-for-time substitution can help to fill this gap (Blois et al., 2013; Pickett, 1989). Such space-for-time approaches seek to overcome missing repeated measurements by inferring on past trajectories from contemporary spatial patterns, by comparing contemporary data from different sites (e.g., in terms of forest structure) at different times since an event has happened (e.g., a forest fire) (Blois et al., 2013). Thus, space-for-time comparisons may allow to combine detailed reconstructions of historical forest disturbances with characterizations of contemporary forest structure to assess post-disturbance changes in forest structure in tropical dry forests. To our knowledge, no study has applied such an approach in any TDF so far.

We focused here on the Argentine Dry Chaco, a global deforestation hotspot and a TDF region with a long history of forest use, resulting in widespread degradation of remaining forests (Adamoli et al., 1990; Cotroneo et al., 2021; Torrella and Adámoli, 2005). Forest degradation in the Chaco is the result of processes connected to agricultural expansion in the region (e.g., escaping fire used for managing pastures, knock-on effects of pesticide application), as well as to a diversity of forest uses, some of which are traditional for the region (e.g., selective logging, fuelwood collection, charcoal production), whereas others have emerged only recently (e.g., silvopastoral ranching). This diversity makes the Argentine Dry Chaco a very interesting case to assess forest disturbances and post-disturbance recovery. In previous work, we mapped forest disturbance extent, timing and agents for the time period 1990 to 2017 (De Marzo et al., 2022, 2021), fractional tree and shrub cover for the year 2015 (Baumann et al., 2018) and aboveground biomass for the year 2019 (Pötzschner et al., 2022) at high spatial and temporal resolution. Building on these datasets, we here use a Bayesian multilevel framework to understand how different disturbance types and histories relate to current forest structure. Specifically, we asked the following research questions:

1. How does contemporary forest structure vary in relation to the time since disturbance across different disturbance agents?
2. How do post-disturbance trajectories vary across disturbance agents?

## 2 Study area

Our study area encompasses the entire Argentine Dry Chaco, covering around 489,000 km$^2$ (Figure IV-1). The region is mostly flat except for the more hilly western and southwestern Chaco. Climate is characterized by strong seasonal variations, with dry winters and hot and rainy summers. Average temperature varies across the area, with mean annual temperature increasing from south to north, varying from 18 to 21°C, and maximum temperatures of up to 48°C (Rubí Bianchi and Cravero, 2010). Similarly, rainfall varies across the area, ranging from 800 mm in the northeastern and northwestern Argentine Chaco, to less than 450 mm in the centre and southwest of the region. Soils are mainly mollisols and alfisols, formed by fluvial and aeolian deposits (Panigatti, 2010).

The natural vegetation of the Dry Chaco consists of xerophytic forests, open woodlands, scrubs, savannas and grasslands. Dominant tree species are *Schinopsis lorentzii* (“Quebracho colorado”), *Aspidosperma quebracho-blanco* (“Quebracho blanco”) and *Gonopterodendron sarmentoi* (“Palo santo”) and fabacea (Prosopis Spp., *Neltuma* spp. and *Strombocarpa* spp.) are also very common. The shrub layer is dominated by species of the genus *Vachellia*, *Mimosa*, *Neltuma, Strombocarpa,* and *Celtis*, as well as cacti of the genus *Opuntia* and *Cereus*. Vast saline areas exists that are covered by halophytic scrubs dominated by *Allenrolfea* spp. and *Heterostachys* spp. Savannas are also present, dominated by the grasses *Elionorus muticus* or *Spartina argentinensis* (Bucher, 1982).

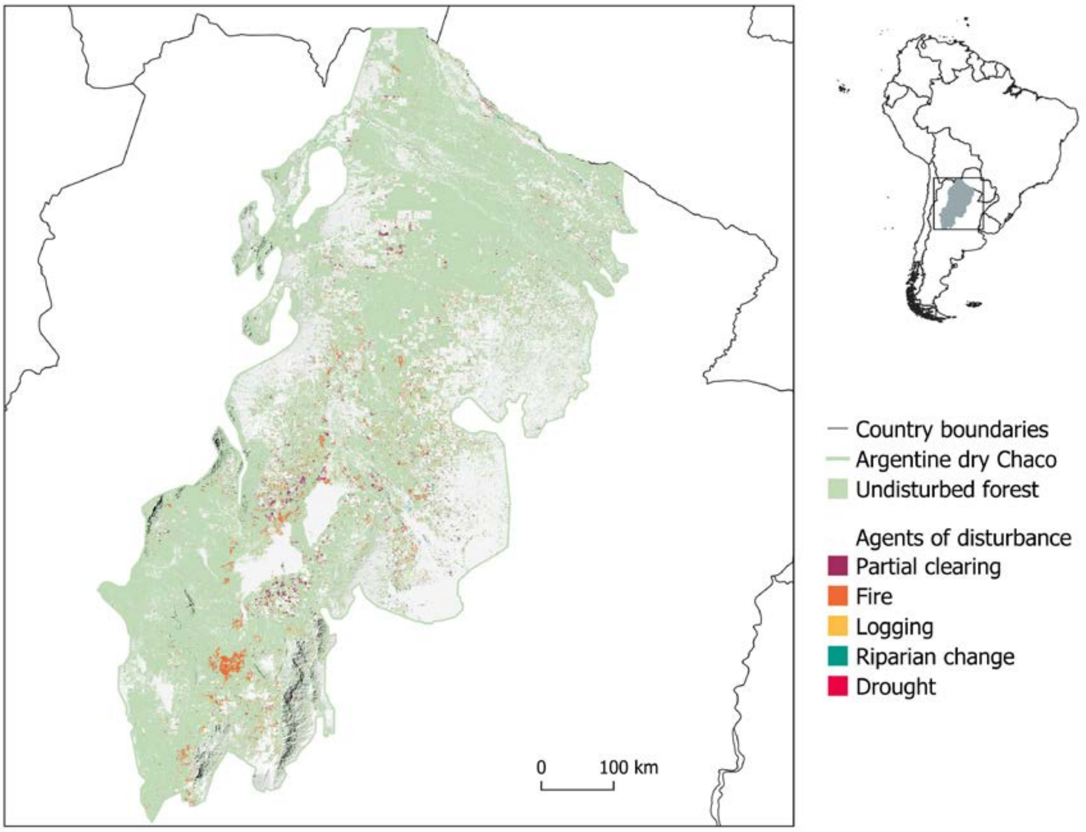


Figure IV-1: Location of the study area, the Argentine Dry Chaco, in South America, and distribution of disturbances (1990-2017) by agent.

Natural disturbances in the dry Chaco include droughts (Murgida et al., 2014), flooding (Prieto and Rojas, 2015b) and some rare natural fires (Fischer et al., 2012; Kunst, 2011). Moreover, forests in the Argentine Dry Chaco have a long history of use, resulting in substantial changes in forest structure and composition (Torrella and Adámoli, 2005). Two types of logging are carried out in our study area. First, selective logging of valuable species has occurred for close to a century, in particular of quebracho colorado for fence posts and railroad beams, as well as of palo santo for fine furniture, floors, and essential oils. Second, less selective logging of hardwood species (e.g., *S. lorentzii*, *Aspidosperma quebracho-blanco*, *Ziziphus mistol*, *Libidibia paraguariensis*, *Acacia furcatispina*) occurs for charcoal production (Tálamo et al., 2020). Relatedly, the Argentine Dry Chaco is inhabited by large numbers of forest-dependent people, including Indigenous communities as well as 'criollo' settlers living in homesteads inside the forest (Levers et al., 2021). Particularly the latter have considerable impact on Chaco forests, logging for fuelwood and construction material, and allowing their livestock (i.e., mostly cattle and goats) to graze and browse freely around homesteads. As a result, forest degradation is widespread around homesteads, characterized by a general loss of larger trees and a dominance of shrubs with defence mechanisms against herbivory (Adamoli et al., 1990; Macchi and Grau, 2012).

Anthropogenic fires are an additional driver of degradation. Fire is used to promote the regrowth of grasses in pastures, to burn waste, to convert forest into agricultural land (Bachmann et al., 2007) and to facilitate the extraction of fuelwood and charcoal (Zak et al., 2004). In combination with overgrazing and logging, unmanaged fires led to the development of secondary forests and scrubs ("fachinales" and "peladares") (Cabido et al., 2003). Significantly, the recent agribusiness expansion has led to a number of social-ecological changes that have fostered the regrowth of secondary forests (Grau et al., 2008), including (1) rural-urban migration and the abandonment of smallholder agriculture (Matteucci et al., 2016), (2) conflicts over land and tenure insecurity (Seghezzo et al., 2017) that have resulted in some plots being abandoned after only a few years of cultivation (Basualdo et al., 2019), and (3) soil erosion and salinization that forced farmers to abandon the land (Boletta et al., 2006).

## 3 Methods

### 3.1 Variable selection and dataset used

We used a comprehensive forest disturbance dataset, including the timing and agents of disturbance, for the Argentine Dry Chaco from our own previous work (De Marzo et al., 2022, 2021). Our maps, produced using Landsat TM/ETM+OLI time series, covered the period 1990 to 2017 at 30-m spatial resolution, providing detailed information about forest disturbances at annual temporal resolution. Specifically, these maps contain (a) information about the location, extent and timing of forest disturbances, and (b) information on one of five disturbance agents (i.e., logging, fire, partial clearing, riparian changes, and drought). *Logging* includes selective logging for fuelwood and charcoal production. *Fire* includes any natural or anthropogenic fire occurring inside forests. *Partial clearing* refers to incomplete canopy removal, because of establishing silvopastures or because of incomplete deforestation (Pendrill et al., 2022). *Riparian* *changes* are disturbances due to meandering rivers, and *droughts* refers to areas where rainfall deficits substantially affected forest vitality (De Marzo et al., 2022).

To characterize contemporary forest structure, we used a map of aboveground biomass at 231-m resolution for the year 2019 (hereafter: AGB map, Pötzschner et al., 2022) and maps of tree cover (TC) and shrub cover (SC) at 30 m resolution (Baumann et al., 2018) updated for the year 2019. These variables served as response variables in our statistical analysis (see next section). The AGB map was obtained combining optical (MODIS) and radar (Sentinel-1) time series and an extensive ground dataset of forest inventory plots. Tree cover and shrub cover maps were produced making use of all available Landsat-8 optical and Sentinel-1 synthetic aperture radar (SAR) images and a large training dataset digitized from very-high resolution imagery.

In addition, we used a suite of control variables for other factors potentially influencing forest structure, including environmental conditions (total annual precipitation) and land-use history (distance to railroads). The former is essential as vegetation structure in the Chaco is strongly influenced by precipitation; we calculated total annual precipitation using the Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) time series (Funk et al., 2014). Concerning the latter, current forest structure might be influenced by historical land use from before our monitoring period (Bourgoin et al., 2021). Hence we chose distance to railways as a proxy for accessibility and historical land use; at the beginning of the $20^{th}$ century the need of wood for the construction of railway sleepers drove intensive logging of Quebracho colorado (*Schinopsis lorentzii*) trees in close proximity to railways (Natenzon and Olivera, 1994; Zak et al., 2004). The railroad was later abandoned, but as a result of the unsustainable extraction, tree cover today is still lower closer to railways (Baumann et al., 2018).

## 3.2 Statistical analysis

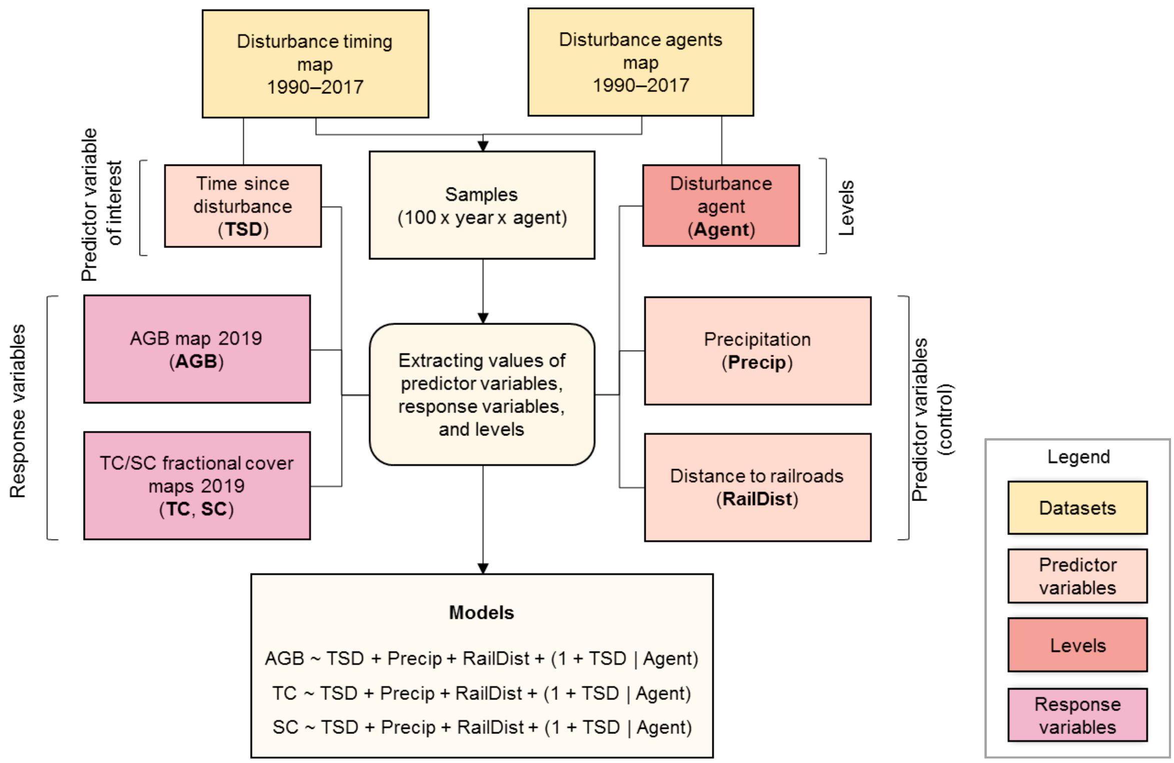


Figure IV-2: Workflow of our analysis to investigate the effects of the time since disturbance on variables related to forest structure for different disturbance agents. The model formulas indicate that we assume both the intercept and the effect of TSD to vary across agents, while Precip and RailDist are assumed to have a constant effect across agents.

The main steps and components of our analysis are illustrated in Figure IV-2. First, we generated a stratified random sample consisting of 100 points per combination of disturbance timing and agent (100 samples per agent per year), resulting in a total of 14,000 points. We then calculated the time since disturbance (TSD) as [2019 minus the year of disturbance] (since the above-ground biomass and fractional woody cover maps were produced for the year 2019). Next, we extracted for each point a total of three dependent variables (i.e., AGB, TC and SC), as well as a suite of other factors that we hypothesized to control the location of forest disturbance (i.e., precipitation and distance to railroads). We discarded samples with missing values resulting in a final sample of 11,144 samples to use for our models.

To relate forest disturbance and forest structural variables, we adopted a multilevel Bayesian analysis framework (van de Schoot et al., 2021). Multilevel (also referred to as hierarchical or mixed-effects) Bayesian methods allow for handling and modelling dependency structure in the data, such as measurements taken at the same time, yet grouped by different levels (Bürkner, 2017). They are particularly suitable for investigating disturbance events (Giovanini et al., 2013; Koutecký et al., 2022; McMahon et al., 2009; Seidl et al., 2011). In our case, we used a multilevel model to investigate how different disturbance agents diversify the relationship between time since disturbances and our structural variables. Therefore, we fitted a multilevel regression model with varying effects among five agents of disturbances (partial clearing, fire, logging, riparian changes and drought) for each of the response variables of our interest (i.e., separate models for AGB, TC, and SC). We further added logarithmic terms to enable the model to fit non-linear relationships of time since disturbance and our structural variables, representing non-linear recovery patterns.

One advantage of Bayesian models is the flexibility in choosing an outcome distribution for the response variable that incorporates our knowledge about the data. To model tree cover, we specified a zero-inflated Beta distribution as likelihood function for the outcome. As our response variable was continuously distributed between 0 and 1, as well as zero-inflated, this probability distribution is appropriate for matching data features to model assumptions. To model shrub cover, which is also continuously distributed between 0 and 1, we specified a Beta distribution, and aboveground biomass is modelled based on a Gaussian likelihood function. We ran the models using the R package *brms* (version 2.17.0, Bürkner, 2017). We drew from the posterior distribution using Monte Carlo Markov Chain sampling to explore model estimations. Two sampling chains ran for 2,000 iterations with a warm-up period of 500 iterations for each model, thereby yielding 3000 samples for each parameter coefficient. We assessed convergence using the Gelman-Rubin statistic ($\hat{R}$) and visual inspection of the trace plots regarding stationarity, mixing and convergence (van de Schoot et al., 2021). To assess the model predictive performance, we used posterior predictive checks (i.e., we compare simulated data from the model with a random draw of the observed data).

## 4 Results

Our models indicated that generally all forest structure variables (TC, SC, AGB) had increasing values with increasingly older disturbances. However, there was considerable variation in post-disturbance trajectories, both among structural metrics and among the different disturbance agents we assessed (Figure IV-3). Post-disturbance trends showed the most marked difference in trends in above-ground biomass (AGB). Importantly, initial values short after disturbance already differed markedly between agents, with lower values for riparian changes, fire and partial clearing, and higher AGB values for logging and drought. Riparian change had the fastest regeneration trajectory, as highlighted by the steepest slope in our space-for-time comparison. Fire, drought and partial clearing also showed considerable regrowth. This was different for logging, where we did not find a clear effect of time since disturbance on AGB values (the 95% credibility interval of the slope estimate include 0, Table SI IV-1). After three decades since disturbance, the values for plots affected by strictly natural disturbances (drought and riparian changes) were generally higher than the AGB of anthropogenic disturbances (i.e., partial clearing and logging).

In the case of the tree cover (TC) model, the agent-related trend curves between TC and time since disturbance mostly differed in terms of intercepts, while rates of change were overall very similar. As the trend curves for different disturbance agents showed (Figure IV-3), initial values were the highest for drought disturbances followed by riparian changes, logging, partial clearing and fires. Slopes did not differ strongly, but were somewhat steeper for partial clearing followed by riparian change and fire, and somewhat lower for drought and logging disturbances (Table SI IV-1).

The shrub cover (SC) model showed similar patterns as the AGB model, with higher SC values right after the disturbance for drought and logging, and lower SC values right after disturbances for fire, partial clearing, and riparian changes. Fire and partial clearing curves almost perfectly overlapped. Riparian change recovered fastest in terms of shrub cover, as indicated by the highest positive slope we found for this disturbance agent. This was followed by drought and partial clearing as well as fire. Logging had again the slowest rate of regrowth among all disturbance agents. For plots that were disturbed in the early 1990s, shrub cover values are higher for the disturbances due to drought and riparian changes, and lower for logging, fire and partial clearing (Table SI IV-2).

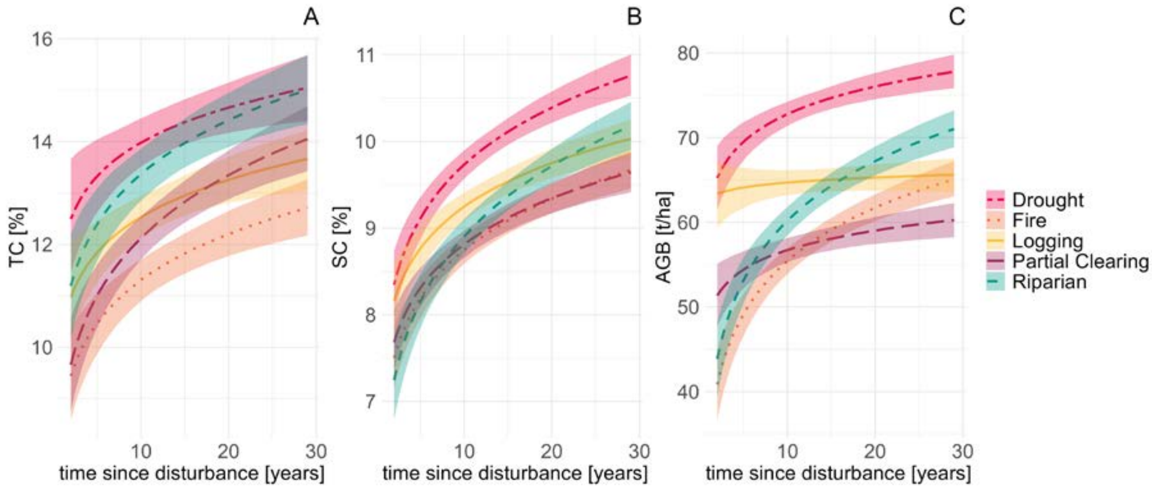


Figure IV-3: Estimated mean agent-level conditional effect of the time since disturbance on A) tree cover (TC); B) shrub cover (SC); C) above-ground biomass (AGB). Shaded area represents the 95% credible intervals around mean values.

Our modelling setup worked well in predicting our response variables (TC, SC, and AGB): the sampling process worked well as values of $\widehat{R}$ were close to one for all parameters; quantities of interest suggest that the chain has converged to the stationary distribution; and trace plots indicate good mixing (Van de Schoot et al., 2014). To assess the power of our models in predicting the response variables, we compared the posterior predictive distribution to the distribution of the observed data. These two distributions were well aligned (Figure IV-4), indicating that all models were robust in predicting the response variables. Moreover, our analytical framework was robust; the choice of precipitation and distance to railroads proved to be good predictors of our response variables and therefore suitable controlling variables. As we assumed, precipitation and distance to railroads had a consistent positive effect (Table IV-1), suggesting these are good predictors for our response variables.

Table IV-1: Model summary statistics for Precipitation (Precip) and distance to railroads (RailDist). Parameters are summarized using mean (estimate) and standard error (SE) of the posterior distribution.

| Model | Parameter | Estimate | SE |
|---|---|---|---|
| TC | RailDist | 0.51 | 0.0003 |
| | Precip | 0.51 | 0.0005 |
| SC | RailDist | 0.51 | 0.002 |
| | Precip | 0.52 | 0.0003 |
| AGB | RailDist | 2.80 | 0.27 |
| | Precip | 6.30 | 0.28 |

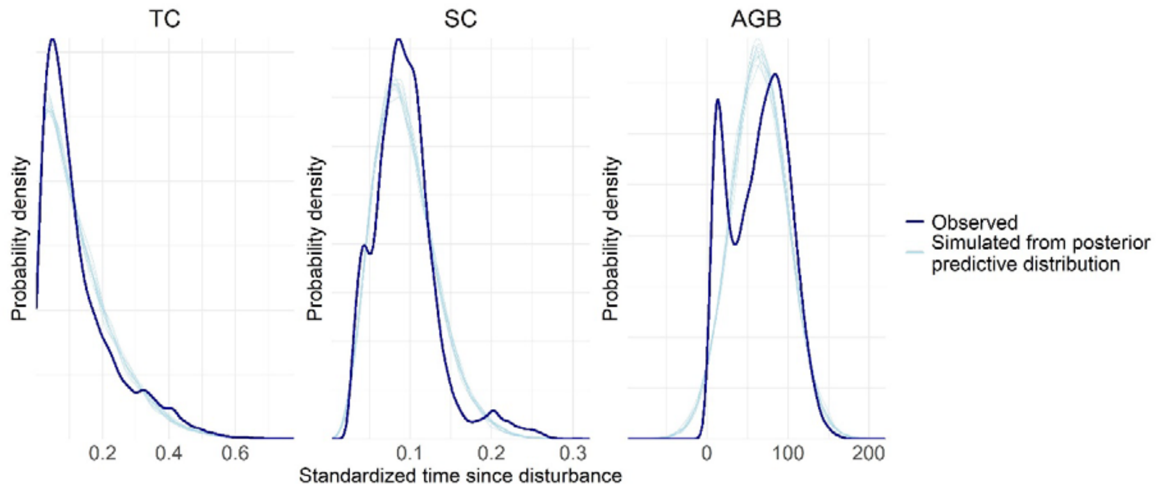


Figure IV-4: Comparison of the posterior predictive distributions (light blue line) and the observed data distribution (dark blue) for the tree cover (TC, left), shrub cover (SC, centre) and aboveground biomass (AGB, right) models. The alignment between the observation and posterior predictive distribution curves suggests good model performance in terms of explaining the data.

## 5 Discussion

Tropical dry forests have high social-ecological value yet, in many parts of the world, these forests are under high and rising human pressure. Forest disturbances affect forest cover and structure in these systems; but how diverse types of disturbance determine the long-term outcome in terms of forest structure remains weakly understood. Using a rich dataset on forest disturbances histories as well as a range of forest structure indicators in a Bayesian multilevel regression framework, we assessed post-disturbance forest structure for five disturbance agents across the Argentine Dry Chaco. Our space-for-time approach to understand 30 years of post-disturbance histories provided three main insights. First, post-disturbance forest structure differed markedly among disturbance agents, which can be explained well by the nature of the disturbance and suggests different outcomes of disturbance agents for ecological functioning more generally. Second, anthropogenic and natural disturbances showed highly different disturbance outcomes, with anthropogenic disturbances leading to lower woody cover and biomass compared to natural disturbances. Third, disturbances connected to logging and partial clearing had slower regrowth rates for tree and shrub cover, and almost no recovery regarding biomass, suggesting a process of forest degradation. Given that all types of disturbance we assessed are widespread in the

Chaco (De Marzo et al., 2022) disturbances likely occurred also before the start of our time series (1987), much of the remaining forests in this region are likely in degraded states. More generally, our study highlights how satellite-based indicators can further our understanding of post-disturbance vegetation structure and recovery, thereby providing information needed to sustainably manage tropical dry forests, in the Chaco and elsewhere.

Post-disturbance forest structure differed markedly among disturbance agents, both in terms of magnitude and regrowth trajectories. The differences we found are in line with prior knowledge about how different agents impact on different aspects of forest structure (Ferraina et al., 2022; Loto and Bravo, 2020; Tálamo and Caziani, 2003). For example, many partial clearings we identified in the Argentinean Chaco may represent areas that were deforested with the intention to secure land or prepare land for resale, which then may never happened (Baumann et al., 2022; Pendrill et al., 2022; Seghezzo et al., 2011). This would explain the increase across all structural parameters in our analysis for this disturbance type. Likewise, partial clearings may represent silvopastoral systems, (Fernandez et al., 2020), but such pastures where the shrub layer is removed are not yet common, as our results also suggest. Similarly, logging reduces mainly tree cover and larger shrubs, thus biomass. Logging often happens in harvesting cycles, slowing down regrowth (Figure IV-3). Conversely, particularly the region's shrubs may recover faster and are more tolerant to drought (Jaureguiberry and Díaz, 2015), which fits to our results with relatively shorter recovery time for shrub cover than for tree cover (Figure IV-3). Finally, disturbance due to riparian changes can be strong, as reflected in the low values of shrub cover and biomass after the disturbance (Figure IV-3). Both shrub cover and biomass showed fast recovery, but never reached a plateau, suggesting that while shrub regeneration is swift on the exposed riverbanks following such disturbances that provide good conditions for colonizer species due to the deposited nutrient-rich sediment (Puhakka et al., 1992), returning to pre-disturbance conditions may need longer. Surprisingly, we found relatively high values of tree cover after riparian changes, which might indicate that larger trees can withstand temporary flooding and inundation.

The difference in post-disturbance trends of forest structural indicators reveal that the considered agents have different impacts on vegetation structure, and possibly on other components influencing vegetation regrowth (e.g., soil, seed banks - see Chazdon, 2003). Forest disturbances can influence species distributions, community composition, and ecosystem processes (Ghazoul, 2002; Turner, 2010). For example, logging has been shown to promote alien grass invasion (Veldman et al., 2009) or change vertebrate and invertebrate populations (Ghazoul, 2002; Shahabuddin and Kumar, 2006). Intense fires cause nutrient losses that likely require a century to recover (Kauffman et al., 1993). Therefore, although we cannot assess this directly with our remote-sensing indicators, the strong differences in post-disturbance changes we find are likely an indication of lasting differences in a range of ecological functions.

Our second main finding was that post-disturbance forest structure and regrowth differed substantially between anthropogenic and natural disturbances. Even three decades after the disturbance events, natural disturbances (i.e., drought and riparian changes) had higher contemporary values in all three forest structural variables we measured. Three factors might explain this finding. First, natural disturbances (e.g., droughts) are frequent in tropical dry forests, with many species adapted to these disturbance (i.e., drought tolerance), indicating high resilience to and recovery potential of TDF from these disturbances (Stan and Sanchez-Azofeifa, 2019). Second, in some cases, sites affected by natural disturbances might provide better conditions for regrowth (e.g., seed dispersal is often a major limitation in areas experiencing anthropogenic disturbances (Turner et al., 1997; Wijdeven and Kuzee, 2000)), allowing for faster regrowth. Finally, natural disturbances might impact sites less frequently, and some anthropogenic disturbances might be persistent, particularly near human settlements (Lhoest et al., 2020; Popradit et al., 2015). For example, we found regrowth rates of above-ground biomass to be slowest for logging and partial clearing, which might reflect multiple anthropogenic interventions (e.g., continued logging), or other overlapping disturbances (e.g., overgrazing by livestock). Generally, these findings are well in line with other studies from tropical environments finding vegetation in moist forests to recover faster after natural disturbances than after anthropogenic disturbances (Cole et al., 2014).

Fire is a disturbance that cannot be easily classified as anthropogenic or natural in the Chaco. Few natural fires are documented, yet many species in the Chaco and other dry forest exhibit adaptions to fire (Bravo et al., 2014; Kunst, 2011). However, the use of fire has a long history in the Chaco as well (e.g., by indigenous people to establish open areas for hunting – the term 'Chaco' itself refers to such open hunting grounds). Today, fires occur almost exclusively through human actions: fire escaping into nearby forests when fire is used for 'cleaning' pastures from old vegetation and shrubs (Kunst, 2011); the use of fire for clearing land to establish agriculture; or accidental ignitions near human settlements (Bachmann et al., 2007). Moreover, forests in the Argentinean Chaco are heavily used for smallholder cattle grazing (Levers et al., 2021). This favours grazing adapted shrubs (e.g., Prosopis spp.) and results in a denser shrub layer than in natural, ungrazed forests (Adamoli et al., 1990), leading to higher fuel loads and therefore likely more severe fires in such used forest. Furthermore, fire is often used in such situations to control shrub encroachment (Kunst, 2011). Our models revealed a generally strong impact of fires on the woody vegetation of the Chaco, with slow regrowth of particularly shrubs (Figure IV-3). This is in line with prior, field-based work (Adamoli et al., 1990; Kunst et al., 2012; Tálamo and Caziani, 2003), suggesting that burned area are mainly colonized by herbs, facilitating subsequent fire outbreaks. Given the high initial impact of fire on this component, values after three decades remain low (Figure IV-3), revealing the long-lasting effects of fires in this region.

Partial clearing had among the strongest and the most persistent impacts on forest structure, in particular biomass which did not recover much, but also with regards to shrub cover which showed overall lowest values after disturbance. It includes the establishment and management of silvopastures, where a major share of the canopy is removed and where regular management intervention are performed to prevent shrub encroachment (e.g., roller chopping, controlled burns). Moreover, trees in silvopastoral systems recover little over time (Kunst et al., 2012; Marquez et al., 2022; Steinaker et al., 2016), or even decline (Fernandez et al., 2020). Partial clearings also may involve areas where forest was cleared partly or fully for agriculture, but that were eventually not used, possibly due to failed investments, land tenure conflicts, or because the clearing was in first place due to land speculation (Pendrill et al., 2022) and became abandoned (De Marzo et al., 2022). This might be a widespread process in the Chaco (Baumann et al., 2022), but how post-abandonment regeneration takes places is unknown. Nonetheless, given the large size of agricultural plots and the removal of the entire vegetation with bulldozers during deforestation (Matteucci et al., 2016), regeneration can be expected to be slow in such situations (Chazdon, 2003).

Logging stands out for the very slow recovery of all forest structural variables. Wood harvesting, including of small trees (typical for charcoal and firewood production) should lower forest canopy height and move the system gradually towards semi-open systems (Gobbi et al., 2022) and this could be reflected in our trajectories. However, it is also common that overgrazing happens in logged sites, due to the traditional extensive cattle ranching leading to shrub encroachment and, in turn, dense shrub cover (Adamoli et al., 1990; Gobbi et al., 2022). This does not seem to be captured by our results, where shrub cover remains low following disturbance. The slow regrowth patterns we found can be explained by two factors. First, logging, particularly for charcoal or fuelwood, is a continuous activity and sites are often not left to rest (Figure IV-3). Second, the negative impact of wood extraction and logging road construction might simply outweigh the positive effects of tree removal on the shrub layer (e.g., more light availability; Tálamo et al., 2020).

We used the most detailed and fine-scale data available for describing forest disturbance and structure in the Chaco and our Bayesian multi-level model of agent-related effects on forest structure performed well. Nevertheless, a few limitations need to be discussed. First, our results rely on the accuracy of the satellite-based maps of disturbance: AGB, TC and SC. These maps are of high quality, but as with any remote-sensing analyses, contain remaining uncertainty (see Baumann et al., 2018; De Marzo et al., 2022, 2021; Pötzschner et al., 2022). Second, it must be noted that our disturbance maps covered the time span from 1990 to 2017, while the TC, SC and AGB maps were produced for 2019. Therefore, our model could miss the effect of disturbance affecting our sample plots during 2018 and 2019. Third, we were unable to control for multiple, sequential disturbances by different agents at the same site, such as fire or logging, but due to the nature of our data we were limited to analysing the first recorded disturbance. Based on our knowledge of the system as well as the literature, we hypothesize that slower regrowth rates are indeed sometimes related to recurrent disturbances, but we could not investigate this here. Fourth, disturbance intensity influences post-disturbance forest structure and recovery (Kennard et al., 2002; Tálamo et al., 2020), as does the proximity of disturbed patches to other forest patches (Chazdon, 2003; Ioki et al., 2022). Both might be worth investigating further. Finally, our space-for-time approach allowed to assess relative recovery of a site compared to other disturbed sites over a 30 year time frame. We caution that this should not be interpreted as recovery compared to a natural (undisturbed) situation, as we neither had pre-disturbance forest structure data nor would it be easy to identify truly undisturbed forests in the Chaco, given the long land-use history and environmental heterogeneity of the region.

Better understanding forest degradation in the world's tropical dry forests is important as it is becoming increasingly clear that in addition to the major waves of forest conversion to agriculture, dry forests are under immense pressure. Clearer awareness of where and how forest disturbances impact on forest structure is important in this context, and investigating post-disturbance vegetation development is a useful approach. Our study for the Argentinean Chaco highlights the potential of remote sensing indicators and space-for-time approaches to unravel the long-term impacts of anthropogenic versus natural disturbances. In prior work, we have shown that large areas of forest in the Gran Chaco are affected by a wide range of both anthropogenic and natural disturbances (De Marzo et al., 2022, 2021). Here, we show that these disturbances have diverse and long-lasting impacts on forest biomass and structure, and that forests recovery fairly slowly, particularly from logging and fires. This highlights an urgent need for disturbance management: by limiting areas where forest grazing leads to fuel accumulation and to more intense fires; by preventing fire used for managing pastures to 'escape' into nearby forests; and by shifting to sustainable logging schemes that maintain forest structure in the long term. More generally, routinely assessing forest structure and post-disturbance vegetation development is urgently needed to better understand the status of the dry Chaco and other tropical dry forests, and thus for an enhanced knowledge of the long term impacts of human pressure on these systems and their capacity to recover.

**Acknowledgements**

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## Supplementary Information

Text SI IV-1: Specifying prior distribution

The prior distributions for the unknown coefficients were optimized in an iterative process of prior predictive checks, i.e., predicting the data only based on the chosen priors, and subsequently adjusting those prior distributions to yield realistic predictions based on information obtained from sampling diagnostics and predictive checks. In this way, we derived weakly informative priors that were on one hand, regularizing enough to facilitate model convergence, and on the other hand, resulted in plausible predictive simulations while not restricting the outcome distribution in a biasing way. Consequentially, priors for the effect of the predictor variables Precip, RailDist and TSD, were chosen as normally distributed, centred on 0 with a standard deviation of 0.1 for all three models. For the mean of the outcome distribution (Beta distribution for TC and SC; Gaussian distribution for AGB), each disturbance agent was given a unique intercept issued from a Gaussian distribution centred on 0 with a standard deviation of 0.2. The prior distribution for the probability for zero-responses predicted by a Bernoulli distribution as part of the zero-inflated TC model was defined by a logistic distribution with mean 0 and standard deviation 0.1. The Gaussian ABG model as well as all distributions of varying intercepts and slopes had exponentially distributed prior standard deviations, thus restricting the range of possible values to positive ones. Internally, the covariance, i.e., correlation between varying intercepts and slopes was modelled by a multivariate normal distribution with an uninformative correlation prior representing flat covariance assumptions.

Table SI IV-1: Model summary statistics for the tree cover model.

Parameters are summarized using mean (estimate) and standard error (SE) of the posterior distribution as well as central 95% credible intervals. Note that all numbers are given in model scale (untransformed logit/log scale).

| Parameter | Estimate | SE | Q2.5 | Q97.5 | R-hat |
|---|---|---|---|---|---|
| *Regression coefficients* | | | | | |
| b_Intercept | -2.12 | 0.17 | -2.36 | -1.63 | 1.00 |
| b_tsd | 0.12 | 0.03 | 0.06 | 0.20 | 1.00 |
| b_RailDist | 0.06 | 0.01 | 0.04 | 0.07 | 1.00 |
| b_Precip | 0.04 | 0.01 | 0.03 | 0.06 | 1.00 |
| sd_Agent__Intercept | 0.27 | 0.20 | 0.08 | 0.81 | 1.01 |
| sd_Agent__tsd | 0.06 | 0.04 | 0.01 | 0.16 | 1.01 |

| | | | | | |
|---|---|---|---|---|---|
| cor_Agent__Intercept__tsd | -0.49 | 0.45 | -0.98 | 0.63 | 1.00 |
| phi | 9.08 | 0.13 | 8.84 | 9.34 | 1.00 |
| zi | 0.06 | 0.00 | 0.05 | 0.06 | 1.00 |
| *Agent-level effects* | | | | | |
| r_Agent[Partial.Clearing,Intercept] | -0.23 | 0.19 | -0.74 | 0.03 | 1.00 |
| r_Agent[Fire,Intercept] | -0.23 | 0.18 | -0.74 | 0.02 | 1.00 |
| r_Agent[Logging,Intercept] | -0.04 | 0.18 | -0.54 | 0.23 | 1.00 |
| r_Agent[Riparian,Intercept] | -0.04 | 0.18 | -0.52 | 0.23 | 1.00 |
| r_Agent[Drought,Intercept] | 0.12 | 0.18 | -0.35 | 0.40 | 1.00 |
| r_Agent[Partial.Clearing,tsd] | 0.04 | 0.04 | -0.04 | 0.12 | 1.00 |
| r_Agent[Fire,tsd] | 0.01 | 0.04 | -0.08 | 0.09 | 1.00 |
| r_Agent[Logging,tsd] | -0.03 | 0.04 | -0.12 | 0.04 | 1.00 |
| r_Agent[Riparian,tsd] | 0.01 | 0.04 | -0.08 | 0.08 | 1.00 |
| r_Agent[Drought,tsd] | -0.04 | 0.04 | -0.13 | 0.02 | 1.00 |

Table SI IV-2: Model summary statistics for the shrub cover model.

| Parameter | Estimate | SE | Q2.5 | Q97.5 | R-hat |
|---|---|---|---|---|---|
| *Regression coefficients* | | | | | |
| b_Intercept | -2.52 | 0.06 | -2.64 | -2.36 | 1.01 |
| b_tsd | 0.11 | 0.02 | 0.07 | 0.15 | 1.00 |
| b_RailDist | 0.07 | 0.00 | 0.06 | 0.08 | 1.00 |
| b_Precip | 0.04 | 0.00 | 0.03 | 0.05 | 1.00 |
| sd_Agent__Intercept | 0.13 | 0.08 | 0.04 | 0.35 | 1.01 |
| sd_Agent__tsd | 0.03 | 0.02 | 0.01 | 0.09 | 1.01 |
| cor_Agent__Intercept__tsd | -0.45 | 0.42 | -0.96 | 0.59 | 1.00 |
| phi | 61.97 | 0.87 | 60.27 | 63.64 | 1.00 |
| *Agent-level effects* | | | | | |
| r_Agent[Partial.Clearing,Intercept] | -0.03 | 0.07 | -0.19 | 0.10 | 1.00 |
| r_Agent[Fire,Intercept] | -0.06 | 0.07 | -0.23 | 0.06 | 1.00 |
| r_Agent[Logging,Intercept] | 0.04 | 0.07 | -0.12 | 0.17 | 1.00 |
| r_Agent[Riparian,Intercept] | -0.12 | 0.08 | -0.31 | 0.01 | 1.00 |
| r_Agent[Drought,Intercept] | 0.05 | 0.07 | -0.11 | 0.18 | 1.00 |
| r_Agent[Partial.Clearing,tsd] | -0.01 | 0.02 | -0.06 | 0.02 | 1.00 |
| r_Agent[Fire,tsd] | 0.00 | 0.02 | -0.05 | 0.04 | 1.00 |
| r_Agent[Logging,tsd] | -0.02 | 0.02 | -0.07 | 0.01 | 1.00 |
| r_Agent[Riparian,tsd] | 0.03 | 0.02 | -0.01 | 0.08 | 1.00 |
| r_Agent[Drought,tsd] | 0.00 | 0.02 | -0.05 | 0.03 | 1.00 |

Table SI IV-3: Model summary statistics for the above-ground biomass model.

| Parameter | Estimate | SE | Q2.5 | Q97.5 | R-hat |
|---|---|---|---|---|---|
| *Regression coefficients* | | | | | |
| b_Intercept | -0.01 | 1.36 | -2.69 | 2.65 | 1.00 |
| b_tsd | 0.01 | 0.49 | -0.94 | 0.97 | 1.00 |
| b_RailDist | 6.30 | 0.28 | 5.74 | 6.84 | 1.00 |
| b_Precip | 2.80 | 0.27 | 2.29 | 3.33 | 1.00 |
| sd_Agent__Intercept | 55.27 | 18.02 | 31.30 | 101.24 | 1.00 |
| sd_Agent__tsd | 8.71 | 3.41 | 4.38 | 17.53 | 1.00 |
| cor_Agent__Intercept__tsd | 0.47 | 0.32 | -0.31 | 0.89 | 1.00 |
| sigma | 33.14 | 0.22 | 32.71 | 33.57 | 1.00 |
| *Agent-level effects* | | | | | |
| r_Agent[Partial.Clearing,Intercept] | 49.09 | 2.84 | 43.47 | 54.56 | 1.00 |
| r_Agent[Fire,Intercept] | 34.54 | 3.11 | 28.59 | 40.53 | 1.00 |
| r_Agent[Logging,Intercept] | 62.62 | 2.91 | 56.89 | 68.43 | 1.00 |
| r_Agent[Riparian,Intercept] | 36.79 | 3.38 | 30.13 | 43.40 | 1.00 |
| r_Agent[Drought,Intercept] | 61.96 | 2.84 | 56.42 | 67.63 | 1.00 |
| r_Agent[Partial.Clearing,tsd] | 3.31 | 1.06 | 1.26 | 5.42 | 1.00 |
| r_Agent[Fire,tsd] | 9.08 | 1.15 | 6.90 | 11.35 | 1.00 |
| r_Agent[Logging,tsd] | 0.89 | 1.08 | -1.24 | 2.95 | 1.00 |
| r_Agent[Riparian,tsd] | 10.15 | 1.24 | 7.70 | 12.57 | 1.00 |
| r_Agent[Drought,tsd] | 4.70 | 1.06 | 2.61 | 6.78 | 1.00 |

Chapter V:

# Synthesis

## 1 Summary and conclusions

Deforestation and degradation pose a global threat to tropical forests, particularly tropical dry forests, which are often overlooked in research, policymaking, and public attention. But while we have increasingly accurate data and maps on deforestation, we still lack assessments on degradation, largely due to the challenges associated with degradation monitoring. This not only limits our understanding but also weakens conservation actions, forcing policymakers to make decisions without taking degradation into account. Remote sensing techniques have a great potential for assisting our understanding of forest changes, and recent time series analysis algorithms and protocols allow for reliable mapping of forest disturbances. However, these have been mostly tested and used in moist forests, limiting our knowledge of changes in tropical dry forests, and of methods suitable for monitoring them. Furthermore, monitoring disturbances is just the initial step in assessing degradation. A central challenge is developing approaches that allow to move further disturbances assessment towards a deeper understanding of pathways leading to forest degradation.

My thesis contributes towards the overarching goal of advancing the current understanding of forest degradation in the Dry Chaco by means of remote sensing. Specifically, I (1) tested remote sensing tools for disturbances detection and agent classification in the Chaco; (2) assessed spatial and temporal patterns of disturbances in general and in relation to natural and anthropogenic determinants; (3) modelled post-disturbance vegetation structure trajectories for the different agents to better understand impacts of different agents and assess recovery or degradation trajectories.

In Chapter II, I mapped forest disturbances in remaining Chaco forests using Landsat-based spectral-temporal metrics and assessed their rates and patterns. In Chapter III, I further characterized disturbances by identifying their agents and assessed their temporal dynamic and their spatial relation to anthropogenic features. In Chapter IV, I built on the reconstruction of disturbance history from the first two chapters to model the relation between forest structural variables and time since disturbance across the identified agents to understand the impact of different disturbance on contemporary forest structure and biomass. Overall, this thesis contributes to answering each of the main research questions.

***Research Question 1:*** *How can forest disturbances in the Dry Chaco be reliably characterized based on the Landsat image archives?*

The results of the first two research chapters (Chapters II and III) demonstrate that spectral-temporal metrics derived from Landsat time series offer a reliable approach for mapping and characterizing disturbances related to degradation in the Dry Chaco. The use of spectral-temporal metrics in a random forest classification scheme allowed for the reconstruction of disturbance history for the entire Argentine Dry Chaco, and the identification of the relative disturbance agents. In Chapter II, I showed that the Tasseled Cap Wetness component has, among single indices, the highest potential for advancing degradation monitoring in tropical dry forests. However, I also found that a multispectral ensemble approach outperforms the single-index modelling approach for disturbance detection, demonstrating that multiple indices have better potential for capturing disturbances.

In Chapter III, I adopted a patch-based classification approach and integrated spectral variables related to disturbances and spectral recovery with variables describing patch shape for classifying agents of disturbances. With this approach I could distinguish among five natural and anthropogenic disturbance agents. My analyses yielded robust area estimates and maps while also revealing challenges with regard to accurately attributing disturbance agents, highlighting the complexity of disturbance agent attribution in tropical dry forests.

***Research Question 2:*** *What are the spatial and temporal patterns of forest disturbances across the Chaco and due to different agents?*

In Chapters II and III, I described spatial and temporal patterns of disturbances in general and in relation to environmental variables and anthropogenic determinants. In Chapter II, I found that disturbances affected 8% of the remaining Chaco forest between 1990 and 2017, with large annual variations in the affected area. Forest disturbances were particularly widespread during drought years, revealing an association between forest disturbance and precipitation. The analysis in Chapter III revealed that the Chaco forests are affected by a wide range of anthropogenic and natural disturbances. I found that partial clearing was the most widespread type of forest disturbance, uncovering two phenomena: the agriculture-driven deforestation resulting in abandoned fields (Pendrill et al., 2022) and the expansion of silvopastural systems (Fernandez et al., 2020). Fires were also widespread, pointing to an urgent need for fire management strategies to preserve the remaining Dry Chaco forests. Regarding temporal trends, I found an increase in partial clearing, as expected given the general increase in forest loss in the same period (Baumann et al., 2017; Vallejos et al., 2015) and the incentivization of silvopastoral systems. Fires showed large annual variability, being in some years the agent responsible for the largest affected areas. Interestingly, logging remained relatively constant during the study period, pointing at the fact that this is an important agent of pressure for the Chaco forests, even in the context of the expansion of large-scale agriculture and rural depopulation. In Chapter III, I also found that all disturbances strongly decrease further away from agricultural fields, likely reflecting that established fields grant accessibility to forest, relevant for extractive activities but also predictor of other human activities. Taken together, these results reveal that disturbances are widespread in the Chaco and suggest a strong anthropogenic link to most types of disturbances, including fire. These findings also highlight the importance of quantifying the extent of the different types of forest disturbances for both better assessing their impacts and guiding management actions.

***Research Question 3:*** *What are the outcomes of different disturbance types and histories on current forest structure?*

In Chapter VI, I showed that the post-disturbance forest structure differed markedly among disturbance agents, likely denoting different ecological outcomes resulting from the different agents. Disturbances connected to logging and partial clearing exhibited particularly slow regrowth, suggesting they might result in forest degradation. In particular, my analysis revealed differences in the long-term outcomes of anthropogenic versus natural disturbances, with anthropogenic disturbances leading to lower woody cover and biomass compared to natural disturbances, stressing the need for measures to reduce impacts of land-use practices on forests.

## 2 Crosscutting insights

In addition to answering the thesis's main research questions, more general insights emerged from my research chapters, that are relevant to the overarching goal of my thesis: advancing the current understanding of forest degradation in the Dry Chaco by means of remote sensing. Specifically, my research contributed three cross-cutting insights:

First, by assessing agents, patterns and outcomes of forest disturbances, my work led to an increased understanding of threats and challenges to forest persistence and resilience. Previous research largely focused on mapping of disturbances only; a growing but still small body of studies on attributing agents of disturbances; few studies linked disturbance history to current biomass and forest structure. This work provides a more comprehensive assessment of the proximate drivers, how important and widespread they are, which are their spatial determinants and how they impact the forests in the long-term. The analysis of Chapter III demonstrates that untangling of the diverse agents of disturbance is critical to both understanding the prevalence of each agent and how it evolved over time. This revealed that logging is a constant forest use in the Chaco context, that partial clearing is increasingly important and that fires have wide variation. Furthermore, categorizing agents was a key step for discerning their distinct impact on forest cover and therefore uncovering trajectories that likely point to degradation, which I did in Chapter IV. The approach of reconstructing pathways of degradation through remote sensing has the potential of upscaling studies that otherwise need labour-intensive local field data.

Second, coupling the assessment of long-term outcomes of forest disturbances of Chapter IV with the prevalence of disturbance agents assessed in Chapter III revealed a worrisome picture. In fact, fires and logging, which are among the most widespread disturbances, showed a particularly slow forest regrowth and long-lasting effects on forest structure. These results suggest that much of the forest structure of the area disturbed during the three decades of my analysis might still manifest effects of old disturbance or be bound to remain affected for longer if no restoration interventions are made. Furthermore, logging showed fairly constant contribution to yearly disturbance affected area and, while area affected by fires show a decline towards the end of my study period, it was only a transient reduction, and the following years larger areas of Argentina were affected by fire (Bonfanti and Sánchez, 2021) and forest loss due to fires is generally increasing in the region (Romero-Muñoz et al., 2019a; Tyukavina et al., 2022). This suggests that the contribution of these impactful agents is possibly only increasing if not staying constant and, with the long-lasting effect they have on forests, forest degradation is also headed for expansion.

A third insight regards the links and the multiple interactions of drought with other natural and anthropogenic disturbances. In Chapter II, I found a strong link between annual disturbed area and drought and speculate that this is a consequence of a larger burned area, as fires are more likely to occur and spread during drought years. The findings of Chapter III confirm this hypothesis, uncovering large areas affected by fires in the very dry years and in the following one (1995, 1996, 2004, 2005). However, these findings also reveal that fires are not the only agent underlying the drought-disturbance link. For instance, the peak in disturbed area of 2013, a year characterized by severe drought (Chapter II), is not the consequence of an exceptionally large area affected by fires (Chapter III), but rather of a combination of the other disturbances, including a larger-than-usual area affected by logging. A possible explanation is that drought causes critical economic struggle for forest dependent people, by increasing pest incidence, exacerbating summer overgrazing, winter forage deficit, causing deaths of lambs and goatlings and, as a consequence, leads to heavy logging to offset lower income (Cotroneo et al., 2021). While these connections need to be further investigated, they warn us about the indirect impacts of droughts. Results from Chapter IV show that the direct impacts of natural disturbances on forests, especially drought, are light and short-lived in comparison with impacts of anthropogenic disturbances. However, understanding its indirect impacts (e.g., more logging) is important for designing prevention measures against additional forest degradation in a world going toward more extreme droughts.

## 3 Implications for forest conservation

The findings of this thesis highlight key implications for the conservation and management of the Dry Chaco and other tropical dry forests. In general, they point to the overlooked extent of disturbances in the remaining Chaco forest and provide a broader understanding of the human impact on dry forests, that can be useful for expanding assessments of threats to wildlife. More specifically, this assessment sheds light on the extent and long-term consequences of different disturbance agents, calling for necessary management action. Finally, and more holistically, my study reveals complex interactions amongst agents — relating to different local actors — which need to be taken into account for effective conservation.

My work provides the first-ever forest disturbance maps for the Argentine Dry Chaco. These maps uncovered major areas affected by disturbances, highlighting the overlooked nature of degradation in the Chaco, and suggesting that degradation is a widespread phenomenon, deserving more attention. My maps can be used for a better assessment of the availability of quality habitats for wildlife (Romero-Muñoz et al., 2021, 2020). So far, these assessments could only build on forest loss maps, which might lead to heavily underestimating the human impact on biodiversity.

Accordingly, Chapter III and IV indicate that fires pose a serious threat to the Chaco forest, being the second most widespread disturbance and having lasting effects on forest structure. This highlights an urgent need for fire management: for example, planning interventions to reduce fuel accumulation that causes more intense fires; or by limiting fires used for managing pastures, to prevent escapes into nearby forests. In addition, my analysis reveals large areas of forest affected by logging and that forest structure after logging areas show almost no recovery. This suggests the need for active restoration measures and the promotion of sustainable logging schemes that maintain forest structure in the long term, like selective harvesting of rapidly regenerating species (Wells et al., 2022).

Highlighted above are suggestions for necessary action towards the management of specific, singular threats. However, taking a step back, what emerges is the interconnected nature of forest disturbances and degradation. My results contribute to a broader body of literature on degradation pathways in the Chaco, from which we get a glance of complex and interconnected dynamics: grazing affects biomass accumulation by promoting shrubs (Adamoli et al., 1990); biomass accumulation cause fires to be more intense, therefore impactful, particularly in dry years; and drought also affects peoples' livelihoods that turn to logging as a safety net to sustain themselves (Cotroneo et al., 2021; Krapovickas et al., 2016). At the same time, people have less access to forests (del Giorgio et al., 2021; Levers et al., 2021) which intensifies the pressure on remaining forest (Vallejos et al., 2020). All this suggests a spiral of forest degradation and impoverishment. While my results provide evidence, in part, of this interconnected dynamic, other components need further investigation to be clarified. Nonetheless, they suggest that forest management actions that only focus on controlling fires or logging would miss the point. To address forest degradation, these entangled processes need to be taken into account. Moreover, addressing the needs of forest-dependent communities in rural areas, securing equitable access to ecosystem services, and increasing their adaptive capacity and resilience (Vallejos et al., 2020), can make forest conservation more effective and just.

## 4 Future research and outlook

This thesis improves the understanding of the temporal and spatial forest changes linked to degradation. In the course of this work, several interesting questions emerged that are beyond the scope of this thesis, but can point the way for future research.

The Landsat archive potential for assessing long-term forest changes is unmatched, however Landsat imagery capacity to detect small-scale disturbances, for example, those caused by low intensity selective logging, is limited. Consequently, the areas affected by disturbances are likely still underestimated. Open challenges remain regarding agent attribution: agent classification accuracy is affected by the overlapping footprint of some disturbances, like heavy logging and clearing or fires and partial clearing. Further research in refining and methods for disturbance detection and agent attribution could explore radar and lidar data. Data products from lidar sensors, such as the spaceborne Global Ecosystem Dynamics Investigation (GEDI) data, which captures three-dimensional canopy structures, could further improve the detectability of forest disturbances or the monitoring of carbon stock changes (Goetz et al., 2022; Potapov et al., 2021).

The contribution of forest grazing to forest degradation in the Chaco remains an open question. The literature of the Chaco forest shows that extensive cattle grazing is a significant contributor to forest degradation in the Chaco, but also points at different effects on the forest structure: one leading to open forest due to heavy trampling and the other leading to closed shrubland due to the ecological advantage shrubs gain from grass removals (Adamoli et al., 1990; Gobbi et al., 2022). It is unclear to what extent these two processes are active in the Chaco, how much forest is affected and how they interact with other disturbances. Since grazing occurs under the canopy, it mostly belongs to the category of forest disturbances that are almost undetectable with current remote sensing techniques, and so far no one has tried to close this gap (Gao et al., 2020). However, because dry forests are relatively open, it might be possible to detect changes in species composition (i.e., increased shrub cover in the understory due to grazing) by monitoring changes in the phenological signal since distinct plant species have distinct phenology (Helman, 2018) or again by using lidar that is highly sensitive to sub-canopy. Developing approaches to monitor livestock-related changes in the forest would be critical for a system like the Chaco, as well as other dry forests where extensive cattle grazing is widespread and has a significant impact on forest structure and ecosystem services (Agarwala et al., 2016; Jara-Guerrero et al., 2021; Sfair et al., 2018).

Another question that arises from my findings concerns the interaction between drought and disturbances. As previously described, larger disturbed areas in drought years can be attributed to a combination of larger burned areas in some cases and more logging in others. These results account for droughts as annual events. However, in Chapter II, I investigated where drought had impacts by mapping precipitation anomalies. This spatial analysis revealed that different areas were affected by drought in different periods: in 1995, and in 2004 drought hit the centre and south of my study area, while in 2013 it affected the north quite severely. Interestingly, in the former two years, large areas were affected by fires, while in 2013, the peak in disturbed area resulted from different agents, including logging and drought itself. Whether this is a coincidence, or it hides ecological or social differences between the two areas remains an open question and answering it might increase our understanding of the forest and potentially reveal peculiar vulnerabilities of the areas important for conservation planning.

Furthermore, a natural extension of this work would involve investigating the links between the agents of disturbances I found to different land-use actors, as well as underlying drivers of these disturbances. TDF are socio-ecological systems, therefore understanding transformation by human activities in these systems requires not only the analysis of impacts on ecosystems, but also an analysis of the social processes that drive decision-making and how perceptions of their environment affect forest management decisions (Quesada et al., 2009). In the Argentinean Dry Chaco, key actors include big landholder, capitalized medium-sized producers, entrepreneur producers, small-scale producers and forest-dwelling smallholders, as well as indigenous people (Gasparri, 2016). These actors practice a diverse set of land-use practices, but how these actors relate to trends in forest degradation is debated (Grau et al., 2008; Matteucci et al., 2016) and has never been comprehensively analysed. In my work I shed light on the relationship of disturbances to some spatial determinants that can be related to some actors. Future studies could assess the direct and, importantly, the indirect contributions of different actors to forest degradation. Loss of entitlement to natural resources leads to ecological marginalization of the poor (Lambin et al., 2003). Smallholders find themselves in ecological fragile areas because they have been expelled by large farmers. While making use of the surrounding forest for sustaining their livelihoods, they intensify the degradation of natural resources, which in turn feeds back the level of poverty, creating a poverty trap (Barrett, 2008; Vallejos et al., 2019). Top-down conservation policies only directed at banning forest uses that directly cause degradation will be ineffective: driving 'underground' resource extraction, thus losing regulatory control, and unfair: making the livelihoods of many people illegal (Wells et al., 2022). Only a thorough understanding and consideration of the indirect and underlying drivers of forest degradation can form the basis of just and effective policies for halting forest degradation.

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## Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Teresa Rita De Marzo

Berlin, den 23.11.2022