



Illicit Drivers of Land Use Change: Narcotrafficking and Forest Loss in Central America

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ABSTRACT

Illegal activity, such as deforestation for illicit crops for cocaine production, has been inferred as a cause of land change. Nonetheless, illicit activity is often overlooked or difficult to incorporate into causal inference models of land change. Evidence continues to build that narcotrafficking plays an important, yet often unreported, role in forest loss. This study presents a novel strategy to meet the challenge of estimating the causal effect of illicit activity in land change using consolidated news media reports to estimate the relationship between drug trafficking and accelerated forest loss in Central America. Drug trafficking organizations engage in illegal land transactions, money laundering, and territorial control that can manifest as forest conversion to agriculture or pasture land uses. Longitudinal data on 50 sub-national units over a period of 16 years (2001–2016) are used in fixed effects regressions to estimate the role of narcotrafficking in forest loss. Two narcotrafficking activity proxies were developed as explanatory variables of forest loss: i) an “official” proxy from drug seizures data within 14 sub-national units; and, ii) an “unofficial” proxy developed from georeferenced news media accounts of narcotrafficking events. The effect of narcotrafficking was systematically compared to the other well-known causes of forest loss, such as rural population growth and other conventional drivers. Both proxies indicate narcotrafficking is a statistically significant ($p < 0.01$) contributor to forest loss in the region, particularly in Nicaragua ($p < 0.05$, official proxy), Honduras ($p < 0.05$, media proxy), and Guatemala ($p < 0.05$, media proxy). Narcotrafficking variables explain an additional 5% (media proxy) and 9% (official proxy) of variance of forest loss not captured by conventional models. This study showed the ability of news media data to capture the signal of illicit activity in land use changes such as forest loss. The methods employed here could be used to estimate the causal effect of illicit activities in other land and environmental systems. Our results suggest that current drug policy, which concentrates drug trafficking in remote areas of very high cultural and environmental value, has helped to accelerate the loss of Central America's remaining forests.

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1. Introduction

Land Systems Science (LSS) is an interdisciplinary field focusing on understanding where, why, and how land systems change (Turner et al., 2007; Verburg et al., 2013) and its consequences on social and environmental systems. One of its major aims is to identify the relevant drivers and establish the causes of land change. Henceforth in this study, a driver constitutes a phenomenon associated with an outcome. A cause is a driver for which processual mechanisms exist that are at least partially responsible for the outcome constituting an explanation (Meyfroidt, 2016). A factor is any variable that mediates an outcome. Establishing a driver as a cause of change requires evidence of both a causal mechanism and an estimated significant causal effect (Meyfroidt, 2016). LSS has addressed individual behavior, collective and state actions, market enterprise, and globalization, among others, as drivers (Meyfroidt et al., 2018; Munroe, McSweeney, Olson, & Mansfield, 2014; Turner et al., 2007). Illicit activity, or activity which is hidden because it either violates legal or widely held social norms, has been inferred as a driver of land change in a few studies including illegal logging (Hosonuma et al., 2012; Lawson et al., 2014), “land grabbing” (Davis et al., 2015; Ruilli et al., 2012), illicit crop production (Dávalos et al., 2011; Grau and Aide, 2008), sand mining (Torres et al., 2017), and cocaine transit (Devine et al., 2018; McSweeney et al., 2018, 2017). One study estimates at least 40% of deforestation globally is linked to illicit activity (Lawson et al., 2014). There have been limited attempts to date, however, to estimate the causal effects of illegal economic activity on land systems (Tellman et al., 2020). Establishing causality is necessary to incorporate illicit activity into existing theory,

modeling, and governance of land systems on which human societies depend.

Illicit activities are intentionally hidden, because the actors involved seek to avoid detection and potential sanctions, creating challenges when quantifying their role in land systems. Illicit land transactions include land uses, transfer of entitlements, permission to access, zoning, and investments and may be either illegal, against social norms, or both (see Tellman et al., 2020 for examples). Examples of illicit land transactions linked to forest loss include land permits for logging or oil palm expansion provided by elected authorities to political supporters in Brazil (Pailler, 2018) and Indonesia (Burgess et al., 2012), illegal gold mining rendered legal in Ghana by using national brokers to sell permits to foreigners (Hausermann et al., 2018), and deforestation from illegal coca production in biodiversity hotspots (Dávalos et al., 2011; Murillo-Sandoval et al., 2020), among others. Illicit activities with less drastic modification to land use, but with large ecosystem impacts include examples such as illegal selective small scale logging in Cameroon (Cerutti et al., 2013), rosewood trafficking in Madagascar (Watts, 2018), and illegal waste dumping in the Netherlands (Navarro et al., 2016).

Quantitative and qualitative observations of illicit transactions are often incomplete, fragmented, or unreliable, whether they are based on ethnographic accounts, tangential information obtained during field surveys, official statistics, data “leaks” (e.g. The Panama Papers), or the media (Hudson, 2014; Rege, 2016). Collecting field data on illicit activities can be dangerous, often precluding researchers from broaching the subject directly (Hall, 2012). Thus, a scarcity or absence of data is a principal limitation for sufficiently testing illicit drivers as a significant

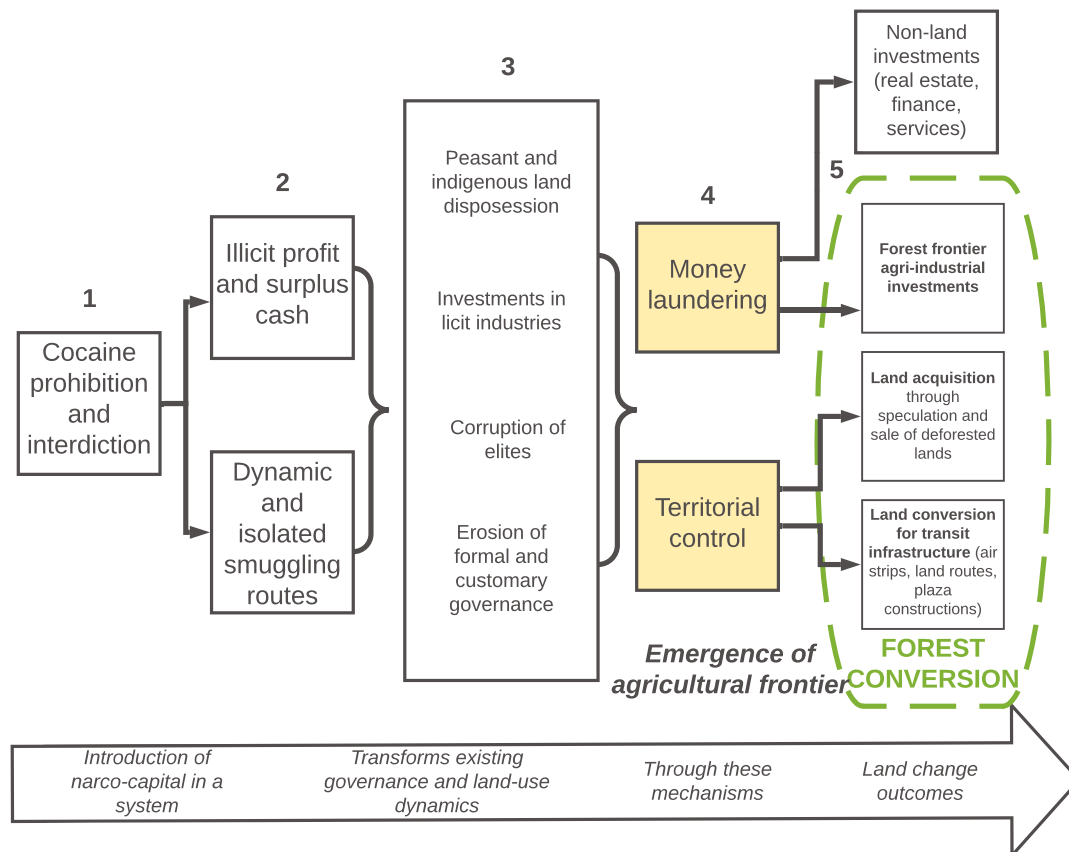


Fig. 1. Causal map explaining plausible mechanisms and relationships between narco-trafficking and forest loss. The central two mechanisms for forest conversion are narco-traffickers' need to launder illicit capital and assert territorial control of dynamic smuggling routes (yellow boxes). Forest conversion (green dotted circle) occurs as some of this narco-capital is expended on labor in forested areas to clear land for cocaine transportation infrastructure (e.g. airstrip construction) and narco-traffickers acquire and clear land for productive or speculative purposes. Drug interdiction (first box) increases the value of cocaine per kilo, generating greater illicit profits and the need to launder money, in turn, causing narco-traffickers to seek new routes (second boxes). Increasing narco-capital, especially in rural areas, may indirectly influence or accelerate forest conversion and shape emerging agricultural frontiers (third and fifth boxes).

cause of land change. New methods are needed to better understand the role of illicit drivers, particularly where illegal activity can exact substantially negative social and environmental impacts. One promising approach to overcome inadequate reporting of official statistics on illicit activities is to generate spatio-temporal data by systematizing data on illicit activities reported in news media. Investigative journalism and media reports are one of the only sources of data documenting illicit activities beyond official statistics (Hudson, 2014), which are known to underreport drug trafficking activity (Magliocca et al. 2019; McSweeney, 2020). However, media reports likely capture large-scale national- and annual-level trends in drug trafficking activity that provide coherent information. News media may also capture fine spatial and temporal scale information, which has been used to effectively monitor the illegal wildlife trade (Basu, 2014; Nijman, 2015; Patel et al., 2015; Siriwat and Nijman, 2018) and illicit soil and sand mining (Rege, 2016; Rege and Lavorgna, 2017). Yet outside of these two examples, to our knowledge, online news media has not been developed as a primary means to investigate the relationship between illicit activities and changes in land use associated with forest loss.

1.2. Study Aims

The goal of our study was to assess whether we could identify a causal relationship between illicit narcotrafficking and deforestation. Previous research has identified a causal mechanism of forest loss accompanying drug transit in Central America as land is cleared for agribusiness to launder money or for territorial control (Fig. 1, below). The mechanism between narcotrafficking and forest loss has not been paired with quantitative hypothesis testing to estimate a causal effect. To address this gap we assessed two primary research questions i) can news media data proxies estimate spatial and temporal changes in narcotrafficking intensity, or the amount of cocaine transited, at sub-national scales? and ii) does narcotrafficking have a significant causal effect on forest loss in addition to well established causes and mediating factors? To answer these questions, news media accounts of spatially explicit drug-related activity (e.g., a law enforcement seizure of cocaine in a named municipality) were consolidated across Central America. We compared a news media event database to official statistics on drug trafficking data at both national and sub-national scales to assess congruence and the potential of media data as a proxy for drug trafficking intensity. Fixed effects regression models, including relevant causes of land change beyond drug trafficking, were used to estimate causal effects of forest loss. With these new data and methods, we sought to determine how illicit activities could *cause* land change instead of merely being a driver.

1.3. Narcodeforestation in Central America

Our study of illicit land use change examines the role of narcotrafficking and forest loss (termed narcodeforestation) in Central America (McSweeney et al., 2014). Central America is a primary transit zone in the cocaine supply chain. An estimated 86% of cocaine reaching the USA moves through the region, accruing 9,000-10,000 \$USD of value added per kilo and \$6 billion USD in annual profits despite efforts from the United States government to intercept cocaine shipments (UNODC, 2010). These interdiction activities cause highly adaptive cartels to shift cocaine transport sites within Central America in response to risks in their supply chain (Magliocca et al., 2019). The movement of the cocaine and its associated capital across Central America often occurs in remote forested regions, making these areas increasingly vulnerable to criminal organizations (Devine et al. 2018; Wrathall et al., 2020).

Despite some evidence of a forest transition and regeneration of seasonal, coniferous, and dry tropical forest in Central America (Aide et al., 2013; Hecht and Saatchi, 2007; Portillo-Quintero and Smith, 2018; Redo et al., 2012), forest loss in wet tropical areas remains

high. Identified causes, drivers, and factors of forest loss include the continued expansion of the agricultural frontier, infrastructure development, and human colonization (Armenteras et al., 2017; Bebbington et al., 2018a; Carr et al., 2009; Graesser et al., 2015; Schlesinger et al., 2017; WCS and CONAP, 2018). The Wildlife Conservation Society (2017) estimated that nearly 90% of all deforestation in protected areas in Central America is due to illegal cattle ranching.

Activities associated with narcotrafficking may also make up a substantial portion of forest loss. While production of illegal crops such as coca cultivation in South America can cause forest loss, (Dávalos et al., 2011; Murillo-Sandoval et al., 2020), here we investigate the forest loss that may result from cocaine transit.

Figure 1 illustrates plausible causal mechanisms linking narcotrafficking to forest loss. Note that because this is an illicit transaction, it is difficult to interview the actors directly involved, or access data to confirm these mechanisms. The described mechanism relies on ethnographic evidence collected from key informants by researchers in the region.

Narcotrafficking leads to forest loss through two direct and two indirect causal mechanisms driven by the dynamic nature of drug trafficking nodes (Magliocca et al., 2019) and generation of illicit excess capital at these locations (McSweeney et al., 2018; Wrathall et al., 2020). Direct mechanisms (yellow boxes, Fig. 1) include: 1) using surplus profits to purchase land to launder illicit capital, and 2) acquire land, allowing DTOs (Drug Trafficking Organizations) to establish territorial control for new smuggling routes in remote forested regions. Indirect casual mechanisms include: 1) licit land purchases by DTOs to consolidate holdings in traditional agri-business landscapes and the subsequent capitalization and displacement of landowners into the agricultural frontier, and 2) the accumulation of wealth by local elite operating in frontier regions and their investments in securing land near essential trafficking nodes.

First, legitimizing illegal drug profits can occur through a variety of expenditures that include real estate, finance markets, the service sector, mining, fishing, and agro-industrial investments (Hall, 2018). One of the most secure ways to launder money in predominantly forested areas is through productive and lightly regulated land use activities. Many agro-industrial laundering expenditures occur within already established and licit agro-industrial corridors (e.g. see seized assets of Honduran DTO the Cachiros (US Department of Treasury, 2013)). When this occurs near forest frontiers, sellers are capitalized and incentivized to acquire new lands in the agricultural commodity frontier. However, many DTO investments also occur at the agro-industrial frontier in indigenous territories, and protected areas where local labor is hired to illegally clear remnant forest land (McSweeney et al., 2018).

Forest conversion funded by narco-capital enables investment and money laundering at the nexus between agricultural and forested land, often through cattle-ranching. In Guatemala, a specific type of ranching, known as “narco-cattle ranching” is referred to in news media and previous research to describe large-scale illegal ranches, often inside of protected areas. In such cases, land cleared for cattle maintain few to no cattle. A primary use of these ranches is to launder drug profits (Devine et al., 2020). Drug traffickers also engage in illegal and speculative land acquisition to further increase their profits, using forest clearing to establish usufruct ownership (McSweeney et al., 2017).

The second direct mechanism whereby narcotrafficking may induce forest loss, in addition to money laundering, is the need to establish territorial control (Fig. 1). The construction of airstrips, land routes, and illegal border crossings, called “plazas,” directly contributes to forest conversion. For example, DTOs have constructed over 100 airstrips to land shipments of cocaine from South America in remote forested areas along the Guatemala-Mexican border in the Maya Biosphere Reserve (Michel, 2013). Clearing land along trafficking routes secures ownership (especially in places of insecure tenure), is a sign of

power, and serves as warning to rival DTOs. DTOs may station look-out points or scouts in areas along the routes they have purchased (Wrathall et al., 2020). Narco-cattle ranches, for example, are often found along international borders in protected areas like the Laguna del Tigre National Park in Guatemala (Devine et al. 2018) and the Honduran Mosquitia (McSweeney et al., 2018) to secure air, land, and marine transit nodes.

Interdiction both increases the need to launder money and causes narco-traffickers to adjust their transportation routes (Toth and Mitchell, 2018) (first box and second boxes, Fig. 1). First, new smuggling routes are established in increasingly remote forested areas to avoid interdiction, and DTOs need to acquire and transform additional land to maintain route control (Magliocca et al., 2019). Second, models indicate that interdiction increases the value of cocaine, which we speculate may further increase the need to launder new profits in rural areas through agribusiness (Allen, 2013; Caulkins et al., 1993; Magliocca et al., 2019).

Indirectly, the establishment of narco-trafficking nodes in forest frontiers generates significant economic activity captured by local elites who may or may not be directly involved in DTO activities. This capital accumulation spurs subsequent investment in local land acquisition and development for commercial agricultural activities (McSweeney et al. 2018). This type of land acquisition sometimes displaces or evicts peasant farmers who may otherwise engage in subsistence-level agriculture (Lunstrum and Ybarra, 2018; Devine et al., 2020; McSweeney et al. 2018). Agricultural development and cattle ranching by narco-traffickers may involve illicit transactions which undermine traditional governance structures and norms through bribery, coercion and violence. Illicit transactions weaken local to national controls on illegal forest loss. In indigenous territories, for example, narco-trafficking can increase land consolidation as traffickers acquire more land in regions with collective or uncertain tenure and property rights (PRISMA, 2014). These outcomes are represented in the third box in Figure 1.

When the capital influx from drug trafficking arrives in rural economies such as eastern Honduras and northern Guatemala, it can exacerbate existing pressures to clear remote forestland. Increased demand and the value of land generates a feedback loop, that resembles (or becomes) an agricultural commodity frontier (le Polain de Waroux et al., 2018; Meyfroidt et al., 2014). The dotted lines of the green circle in Figure 1 recognizes that forest conversion is influenced directly by money laundering and territorial control (yellow boxes), as well as indirectly by dynamics (third box) that may accelerate or reshape emerging agricultural frontiers.

The potential scale of narco-deforestation from 2001–2014 in parts of Central America is illuminated by Sesnie and associates (2017) based on analysis of spatial patterns of remotely sensed forest loss and official statistics on U.S. drug seizures. Rapid and unusual forest clearings were correlated with the timing of increased drug shipments in at least five Caribbean departments¹ in Honduras, Nicaragua, and Guatemala. These rapid clearings, assumed associated with narco-trafficking, accounted for 15% to 30% of forest loss in the region (and 30–60% in protected areas). This important research, however, did not establish a causal effect, because it did not account for counterfactuals (rapid deforestation not linked to narcotics) to establish linkages between accelerated narco-trafficking and forest loss. The study was also limited in geographic scope (only 14 of the 50 departments in Central America) and relied solely upon official drug seizure data that contains missing values and bias due in part to inherent underreporting of drug trafficking events (McSweeney, 2020). Here we assessed causal effects of narco-trafficking, compared to conventional drivers of forest loss, across all 50 departments in Central America using news media reports. Our

objective was to draw inference on the potential causal linkage between accelerated narco-trafficking and forest loss by comparing alternative models with and without variables measuring drug trafficking.

2. Materials and Methods

2.1. Narcotrafficking data

We collected official narco-trafficking data at national and subnational scales, collected and coded news media data, and evaluated the quality of media data as a proxy for narco-trafficking. Data were collected for five countries: Honduras, Guatemala, Panama, Nicaragua, and Costa Rica at national and subnational scales (department or province).

2.1.1. Official narco-trafficking data

We collected four country-scale annual measures of narco-trafficking activity in Central America: i) seizures in kilos reported by UNODC 2000–2017 (United Nations Organization on Drug Control) (Unodc, 2017), ii) seizures in kilos reported by INCSR 200–2017 (U.S. International Narcotics and Strategy Control Report), iii) number of cocaine shipments received, recorded in the CCDB (Consolidated Counterdrug database) 2001–2014, and iv) kilos of cocaine seized, lost, or delivered (hereafter, SLD), recorded in the CCDB (summarized in Table 1). UNODC seizure data rely on self-reporting by each country when available, and fills in gaps with information from INCSR (International Narcotics Control Strategy Report), CICAD (InterAmerican Drug Abuse Control Commission), and reports from national drug enforcement agencies. UNODC data may be biased due to country variations in interdiction effort, resources dedicated to data collection, and politically motivated over-reporting (UNODC, 2018). The INCSR data are prepared by the U.S. State Department using a variety of intelligence sources. The CCDB records the number of drug shipments of cocaine into each country in Central America from the cocaine producing country of origin. The CCDB data are considered to be of higher accuracy because of the stringent review process required to include each observation (GAO, 2002), but were only available through 2014, whereas INCSR and UNODC data are available through 2018.

The only official source of data available at subnational scales is the CCDB. The CCDB data are managed by the U.S. Interdiction Coordinator and are the officially vetted and sole source of interdiction and cocaine flows data used by the US government to assess drug policy performance (Joint Drug Control Interagency Policy, 2010, see McSweeney, 2020, for a detailed description). CCDB data have been used in previous studies to analyze anomalous patterns of forest loss (Sesnie et al. 2017) and narco-trafficking route adjustments in response to interdiction with an agent-based model (Magliocca et al. 2019). Here we use CCDB annual detections of cocaine (kg) seized (confiscated by law enforcement), lost (discarded over land or sea during interdiction), or delivered (known to be received) to a destination in Central America, hereafter referred to as CCDB SLD. The vast majority of these data represent cocaine “delivered” at the country scale, and for some regions, department scale (Fig. 2).

The CCDB SLD data have known limitations and biases. We only obtained data for 14 departments in Central America. Among these 14 departments, there are missing data in some years, because the exact location of drug delivery is often unknown, leaving spatial and temporal gaps in information on drug flows. Data are conservative estimates of actual cocaine flows because they focus on non-commercial marine and air traffic routes directly from South America, excluding overland movement of drugs along commercial routes within Central America. Finally, counter narcotics data suffer from bias known as the ‘spotlight effect’, meaning limited resources for law enforcement where data are collected are focused on areas with identified trafficking routes. As a result, data were collected after route establishment in strategic locations with a high likelihood for seizures. This spotlight

¹ Note subnational units in Panama and Costa Rica are provinces not departments, but we use departments to refer to them for simplicity in this paper.

Table 1
Official narco-trafficking data sources for Central America from the United Nations Office on Drugs and Crime (UNODC), International Narcotics Control Strategy Report (INCSR) and the Consolidated Counter Drug Database (CCDB) at national and department scales. The unit of observation, and spatial and temporal resolution and availability is reported for each source.

Data	Explanation	Unit and N	Temporal and spatial scale	Source
National Level: seizures	Self-reported country seizures of cocaine in kilos to UNODC	15 observations for 6 countries, Cocaine seized (kg)	2000-2014, annual, country	UNODC
National Level: shipments of cocaine	US intelligence from various sources Detected shipments of cocaine arriving from South America	18 observations for 6 countries, Cocaine seized (kg) 15 observations of shipments for 5 countries	2000-2018, annual 2000-2014, annual, country	INCSR CCDB
Department Level: Drug trafficking and seizure data	Cocaine seized, lost or delivered as tracked by US military	Cocaine seized lost and delivered (kg) 114 observations (some missing years)	2000-2014, annual, select departments (14 of 56)	

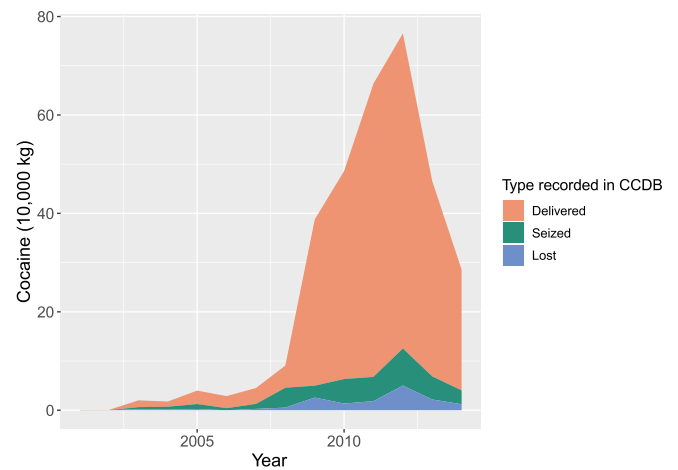


Fig. 2. Kilos of cocaine seized, lost, or delivered from 2001-2014 in Central America recorded in the Consolidated Counter Drug Database.

effect creates a spatial and temporal lag between increased trafficking and interdiction activity. CCDB data have few observations before 2003, and most departments have fewer than 10 years of observations. Together these limitations reduce sample size, power in statistical analyses, and the ability of CCDB data to measure causal effects, increasing the risk of type II statistical error (Crewe et al., 2016).

2.1.2. Media data of narco-trafficking

To address the limitations in official narco-trafficking data, we developed a new and complementary dataset using news media reports of drug trafficking events. We considered relevant media reports from national newspapers (see SI for sources per country) if they documented specific geographic locations of narco-trafficking activity, for example, cocaine traveling over land, capture of property of known narco-traffickers, conflicts in communities with competing DTOs, and discovery of clandestine airstrips. One media report could contain multiple narco-trafficking events occurring in multiple places at different times. For example, if one report identifies locations of four airstrips and two money laundering schemes identified in distinct years and departments, six drug trafficking events and locations were recorded.

Media reports were coded to create a spatio-temporal dataset for drug trafficking activity (see SI for further details on coding protocol). For each country, key search terms were used to scan digital and hard copy media for drug trafficking activity reported in national newspapers. Discrete trafficking events in each media report were coded by date, location, and amount or value of cocaine seized. The data were manually checked by Spanish speaking technicians to ensure no duplicate events were recorded. Media events were summarized per department and year and used as a proxy for narco-trafficking activity in regression models.

Although media data cover a larger spatial and temporal range than the CCDB data, Central American media reports are subject to urban bias, with underreporting in rural areas (Lopez et al., 2019). An additional limitation is that economic elites with powerful political and business connections, who are sometimes involved in narco-trafficking, own some newspapers and may influence the content of coverage to protect drug trafficking routes (Salzman and Salzman, 2009). We therefore conducted validity analyses, detailed below, to assess whether news media could serve as a viable proxy for drug trafficking despite these limitations.

2.1.3. Media data validation

We assessed media data quality by first comparing them to official country and department level drug trafficking data (Table 1) to estimate spatial and temporal correlations and potential temporal lags from

the spotlight effect. Media data were compared to official drug trafficking data at these two scales because while drug trafficking data at the country level are more spatially and temporally complete, departments were the unit of analysis for this study. Often, aggregated data will correlate at coarse spatial scales (countries), but not at finer scales (departments), known as the modifiable areal unit problem (Openshaw, 1984). Spatial agreement was assessed by comparing total number of media events to CCDB SLD. Temporal correlation and lags were assessed using cross-correlation analysis between media events and available narcotrafficking data (Table 3) (R version 3.5.2, 'stats package' [Venables and Ripley, 2002]). The spotlight effect could cause recorded observations to be delayed relative to the actual timing of narcotrafficking intensity by several years in contrast to media reporting, which could identify events earlier than the drug trafficking data. We therefore report correlation coefficients for one to five years, lagging and leading the year of reporting.

Second, spatial representativeness of narcotrafficking as reported in the media was performed to assess urban reporting bias for each country based on methods from Schmill et al., (2014). We compared the spatial distribution of media events to an expected spatial distribution of narcotrafficking activities developed for an existing agent based model (Magliocca et al 2019). This suitability surface assumed narcotrafficking is concentrated in protected areas, near coasts and borders, and in more remote or less developed areas (e.g., forested landscapes distant from law enforcement) (see further details in the SI). The average municipal 'narcosuitability' score was used to generate expected distributions of feasible drug transit for Central America (using 15 equal frequency bins). The media events were summed across municipalities in each of these 15 narcosuitability bins in order to compare the expected narcotrafficking distribution with the observed distribution of narcotrafficking intensity quantified using media events. We also assessed media data based on expert opinion with field-based researchers who helped to interpret the results of the congruence and representativeness analyses.

2.2. Attributing forest loss to narcotrafficking

Attributing the role of narcotrafficking on forest loss in Central America required collecting annual data on forest loss and drivers of deforestation at subnational scales. Fixed effects regression models of forest loss that included and excluded variables representing drug trafficking activity were compared to examine the role of drug trafficking on forest loss.

2.2.1. Forest loss data

We focused on moist tropical forest, the biome that has the highest rates of forest loss in Central America, in comparison to forest types such as seasonal and coniferous forest which has had more stable forest cover over the past two decades (Portillo-Quintero and Smith, 2018). Departments with moist forests were identified by calculating the area of forest with >50% canopy cover in 2000 (Hansen et al., 2013) inside the boundaries of the Moist Tropical Forest Terrestrial Ecoregion (Olson et al., 2001). Departments containing large areas (> 300 km²) of identified moist tropical forest in 2000 (few departments had contiguous moist tropical forest in this year below 300 km²), the starting year of our study, were included in this analysis ($n = 50$ departments, Fig. 3, study area). Annual, spatially explicit (30 m), and validated forest loss data consistent over the Central American region were obtained from the University of Maryland Department of Geographical Sciences Global Forest Change version 1.4 (see: https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.4.html accessed 2/1/2018-4/1/2018; Hansen et al., 2013). Continuous forest patches measuring ≤ 2 ha, representing minor areas of forest loss or potential noise (Sesnie et al., 2017), were removed from the analysis. Forest loss percentages, 2001-2016 (Fig. 3) were aggregated by administrative departments in Central America

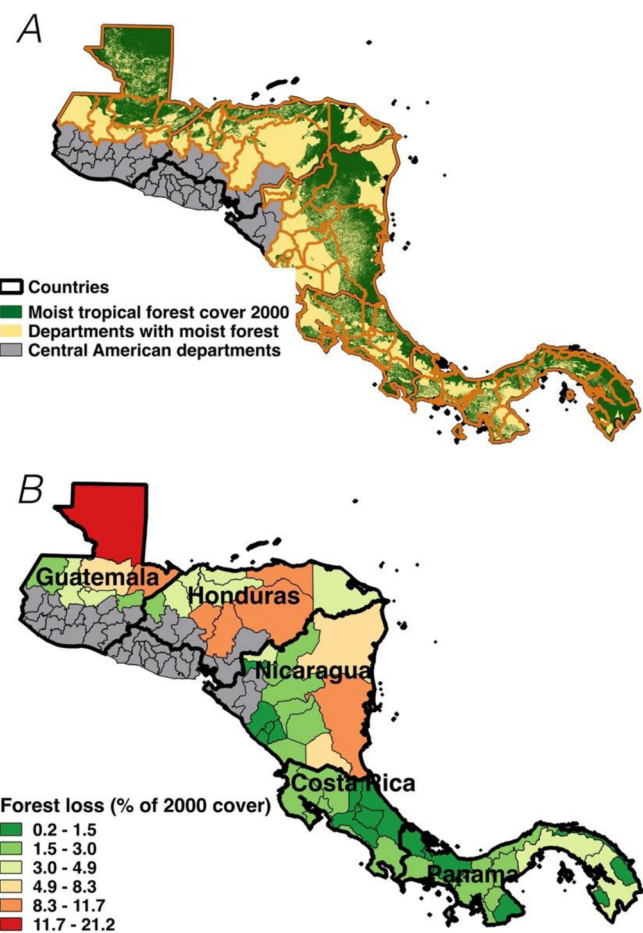


Fig. 3. Forest loss and moist tropical forest cover. A) Study area highlighted in yellow, department outlines in orange with moist tropical forest cover in 2000. B) Total standardized forest loss percentages following Puyravaud (2003) from 2001-2016 for each department in Central America. Calculated by Authors from Hansen et al. (2013) forest loss data.

using the GADM (Global Administrative Unit) Department or Province Areas (GADM, 2015).

2.2.2. Conventional drivers of forest loss in Central America

Previous studies have suggested that conventional land use change drivers and causes include crop and pasture expansion, population (growth and density), road infrastructure, and economic development (Armenteras et al., 2017; Bebbington et al., 2018a; Carr et al., 2009; Graesser et al., 2015; Rudel, 2007; Schlesinger et al., 2017; WCS and CONAP, 2018). Mediating factors include fires, which are primarily anthropogenic (Radachowsky et al., 2012), rainfall patterns, and policy and institutional changes (which include changing boundaries of a protected area (Tesfaw et al., 2018), indigenous tenure/titling (Liscow, 2013), and political changes (Hecht et al., 2006)).

Consistent, annual, spatially explicit data across Central America exist for a subset of these variables (Table 2). All data were summarized annually and at the department scale. Cropland and pasture expansion were estimated by calculating the annual total percent of cropland, plantations, and pasture per department using annual land change data developed from the MODIS satellite (Graesser et al., 2015). Annual estimates of rural population growth were generated by masking out urban areas as defined by the Global Rural-Urban Mapping Project (GRUMP), and summing non-urban population using the annual Landsat population data set (Bright et al., 2016). Annual GDP growth rates at the country scale from the World Bank served as a proxy for changes in economic development. An estimate of annual burned area

Table 2

Annual Central America-wide model covariates attributed to each study area province or department. *Narcotrafficking variables excluded from conventional forest loss models. **Precipitation was summed for the three month period with large fires per country (March-May in Guatemala, Honduras, Nicaragua, and Costa Rica, and February-April in Panama based on Giglio et al (2013)).

Variable	Description	Temporal Scale, Resolution, Unit	Source
Agricultural production	Cropland, pasture, and citrus/coffee (plantations), aggregated as percent per department	2001-2014, 100m, percent area	(Graesser et al., 2015)
Population total	People per department	2001-2016, 1km, people	LandScan (Bright et al., 2016)
Rural population	Rural population calculated by using grump to mask out urban area population	2001-2016, 1km, people	From LandScan and GRUMP (Balk, 2009)
Economic development	GDP growth	2000-2016, country, rate	(The World Bank, 2018)
Fires	MODIS Burned Area (MCD64A1)	2000-2017, monthly data aggregated annually, 500m	NASA (Giglio et al., 2013)
Climate	Peak fire season precipitation	2000-2017, 1km, summed for 3 months of peak fires**, mm	CHRIIPS (Funk et al., 2015)
Drug trafficking and seizure data*	Cocaine seized, lost or, delivered as tracked by US military	2000-2014, department (14), cocaine (kg); 114 observations (some missing years)	Consolidated Counter Drug Database (CCDB)
Media data*	Media reports with department specific narcotrafficking activity events	2000-2017, department (all 56); 700 observations (some missing years) and 2217 total events	Coded newspaper articles from major media outlets

(MCD61A1, see Giglio et al, 2013) and peak fire season precipitation (summing CHRIPS rainfall for the 3 months with largest burned area for each year) were included to address the potential impact of drier periods and opportunistic anthropogenic burning when land was easier to clear, on forest loss. These fires, often associated with agriculture or grasslands, have been observed to be particularly high in the Petén department in Guatemala during seasonally dry periods (Radachowsky et al., 2012; WCS and CONAP, 2018).

Other known factors of forest loss for which data were unavailable at the time of this analysis include road infrastructure and resource extraction (Bebbington et al., 2018b) and land tenure changes such as titling indigenous lands (Liscow, 2013; Stocks et al., 2007). Plantation crops have historically been a strong driver of forest loss in Central America (Fagan et al., 2013; Myers et al., 1987). However, recent studies show some crops, such as oil palm, are not a contemporary driver of forest loss because plantations mostly replace previous cropland and pastureland, except a few plantations replacing forest in the Petén, Guatemala (Furumo and Aide, 2017; Varsha et al., 2016). We thus did not include oil palm as a driver of forest loss in models. Note that because we used fixed effects for political departments in regressions, time invariant variables that may influence forest loss, such as slope, size of the department, and protected areas, are not explicitly incorporated in models as variables, but rather are indirectly incorporated through model intercepts for each department. Two data sources represent drug trafficking activity in regression models (Table 2): data on drug trafficking and seizures, extracted from the Consolidated Counter Drug Database (CCDB), and media reports analyzed and coded by the authors.

2.3.3. Fixed effects panel regression

We used panel regression models to estimate significant causal factors contributing to forest loss. All drivers noted above except those with an asterisk (Table 2) were included in each of four models (Table 4). Separate Central America forest loss models were developed using the two different drug trafficking measures (Table 2, variables

with asterisk) and compared to the R^2 values in conventional models using the same spatial and temporal scale (see Table 3, model summary).

We also ran fixed effects panel regression models for each individual country using media data to determine the relationship between narcotrafficking and forest loss. In all cases, we compared model fit using R^2 to compare models and hypotheses (Burnham and Anderson, 2004) that narcotrafficking does or does not cause forest loss by including and excluding drug trafficking variables. Fixed effects panel statistics were employed to control for any time invariant departmental factors that could influence forest loss (e.g., slope or area). The temporal mean of each independent variable is differenced from the time series to control for time constant differences. We used the *plm* R package (version 2.2-0) (Croissant and Millo, 2008) for computation in a two-way fixed effects model using equation 1:

$$eq. \quad 1Y_{it} = \alpha + B_1x_{it} + C_i + \gamma_t + \varepsilon_{it}$$

Where

Y is the total number of hectares of forest area lost each year (t) per department (i)

γ_t is the time fixed effect at time t

C is the department fixed effect

α is the average of fixed and time effects across all departments

x_{it} are the independent explanatory variables

B is the vector of coefficients to be estimated

ε_{it} is the error term for each year (t) per department (i)

α is an intercept represent the unobserved time invariant individual effects (Gould, 2013), which controlled for variation in forest loss explained by factors or causes in the linear model that were constant over time.

A two-way fixed effects model, including both time invariant factors and year of measurement, was used to test the hypothesis that narcotrafficking increases forest loss. Our expectation was that trafficking

Table 3

Models used to estimate causal effects of narcotrafficking on forest loss.

Name	Explanation	Spatial and Temporal Scale
Conventional	Conventional drivers of forest loss only	50 departments with moist forest (regional), 14 departments with official data, and 3 country subsets; 2001-2016
Drug trafficking with official data	Conventional drivers of forest loss and CCDB data	14 departments with official data; 2001-2014
Drug trafficking with media data 1 (absence of report = 0)	Conventional drivers of forest loss and media data	50 departments with moist forest (regional) and 5 country subsets; 2001-2016
Drug trafficking with media data 2 (absence of report = missing data)		

variables would explain variation in forest loss beyond that already controlled for by the conventional drivers (rural population rates, increases in pasture and cropped area, changes in precipitation and burned area), and by time (e.g. deforestation increases or decreases everywhere in Central America in specific years or in a trend). The two-way fixed effects model reduces the chance that endogeneity or omitted variable bias would influence the results. An omitted variable would have to substantially covary with both departments and temporal trends of deforestation to cause bias and confound results.

Additional robustness checks included lagging and leading forest loss variables. We expected significant explanatory variables to lose significance when the dependent variable is lagged by multiple years. If we were to find, for example, that narcotrafficking remained significant when leading or lagging deforestation several years, it would indicate that narcotrafficking is correlated with places of high deforestation, but that it does not cause deforestation at a specific time point.

We included all variables in the model that we found through literature review to be a possible driver of forest loss, even if the variable is not statistically significant. We discarded models in which variables which were highly correlated, measured through square root of variable inflation factors (VIF) > 2 (Fox, 1991). Residual plots were examined for every model to ensure no outliers were outside of 0.5 of Cook's distance. Forest loss was log transformed to improve normality of residuals. Coefficients in plots were standardized by dividing each variable by two standard deviations, so the magnitude of coefficients can be directly compared (Gelman, 2008; dotwhisker package, Solt and Yue, 2015).

Missing observations in CCDB data were treated as missing data, because the U.S. interdiction coordinator informed us that missing data could be due to the spotlight effect and could not be used as evidence of no cocaine flows. In contrast, observations in departments and years with no media events could either represent missing data (no media reporting was available) or truly indicate no narcotrafficking activity (e.g., 0 narcotrafficking events occurred). To account for this uncertainty, we ran three separate regression models with narcoactivity covariates i) CCDB data, ii) media data with an absence of events coded as a zero, and iii) media data with an absence of events coded as a missing value for that year and department.

3. Results

3.1. Media Events of Drug Trafficking in Central America

Honduras had the greatest number of reported narcotrafficking events (826), followed by Guatemala (566), Panama (327), Nicaragua (165), and Costa Rica (124). Media data increased the sample size relative to CCDB data (700 vs 114 department-year observations, respectively) and enlarged temporal and spatial coverage (SI Fig. 1, Fig. 4). Completeness, as measured by the number of years of non-zero data (e.g. no absence of CCDB data or media reports) available for each department, is shown in panels C and D in Figure 3.

3.2.1. Country Level Media Validation

Media data were spatially and temporally correlated with other drug trafficking data at both the country and department level (R^2 ranging from 0.44 to 0.70, r ranging from 0.35–0.74, respectively, details below). Results of linear regressions comparing the number of media events per year in each country revealed CCDB drug seizures had the highest total correlation (CCDB seizures, $R^2 = 0.70$, UNODC seizures, $R^2 = 0.59$, CCDB shipments, $R^2 = 0.55$, and INCSR seizures, $R^2 = 0.44$, see SI Table 3). The high correlation with CCDB seizure data was influenced by strong outliers in Honduras (Fig. SI 3). Media events and UNODC seizure data showed a significantly greater positive correlation in Guatemala and Honduras than for other countries (SI Table 3, Fig. SI 4).

Cross-correlation analyses revealed media data were temporally

congruent with official national drug trafficking reports (average $r = 0.54$, $SE = 0.1$ years across all countries and datasets) with a 2.14 year lag on average ($SE = 2.15$ years) (Fig. 5). All cross-correlation plots are available in the supplementary materials (Fig SI 6–8) and the results are detailed in Table SI 4 and in Fig. SI 4. Media events were significantly correlated to CCDB shipments in all countries except Guatemala ($r = 0.403$, $SE = 0.349$ years). Media data were correlated with UNODC data at similar levels ($r = 0.424$, $SE = 0.246$ years), yet with little to no temporal lag ($-0.25 = \text{years}$, $SE = 1.26$ years). A one-way ANOVA test revealed no significant difference between correlations or lags per country.

3.2.3. Department Level Media Validation

Media data were temporally correlated ($p < 0.05$) with drug activity data for four of seven departments tested, but with lags in some regions (Fig. 6). Media data were significantly correlated with kilos of cocaine SLD in Gracias a Dios, Honduras ($r = 0.59$), Petén, Guatemala ($r = 0.56$, with 4 year lag), Darien, Panama ($r = 0.79$), and Region de Atlántico Norte, Nicaragua ($r = 0.97$, with 1 year lag), but not significantly correlated in Panama, Panama, Puntarenas, Costa Rica, and Region de Atlántico Sur, Nicaragua.

3.2.4. Media Representativeness Analysis

Countries varied widely by type of bias and the number of narcotrafficking events reported by news media (Table 1 SI and Fig. SI 2). Of all Central American countries, Honduras had the highest proportion of media reports in the highest narco-suitability bin (41%), followed by Costa Rica (31%), Nicaragua (25%), Guatemala (13%), and Panama (6%). Urban bias was strong in Panama and Guatemala (with over 30% of reports coming from the capital city in each country), and to a lesser degree, in Nicaragua, with high reporting in Managua. Under reporting in rural areas was strongest in Petén, Guatemala, and Darien, Panama.

3.3. Fixed Effects Panel Regressions of Forest Loss

Fixed effects panel regressions of forest loss were developed at both national (individual country) and regional scales (Central America wide) and are discussed in turn.

3.3.1. Regional Models

In the conventional model (RM1), agricultural production (crop and pasture) and rural population growth showed a significant and positive relationship with forest loss (Table 4). Narcotrafficking activity had a significant positive causal effect on forest loss ($p < 0.01$) using both official data (RM5) and the media proxy data (RM3, RM4) (Table 4, Fig. 7). Forest loss models that included narcotrafficking data explained an additional 5% of variation over conventional models using the media proxy data ($R^2 = 0.11$ and $R^2 = 0.06$, RM4 and RM1, respectively, $n = 50$ departments) and 9% of variance using official data ($R^2 = 0.27$ and $R^2 = 0.18$, RM5 and RM2, respectively, $n = 14$ departments).

In the conventional model subset (RM2), reduced economic development was significantly correlated with forest loss, but this effect became insignificant in models that included official data measures of kilos of cocaine SLD (RM5). Robustness checks (Table 7 SI) reveal media data were significantly correlated with a 1 year lag ($p < 0.05$) and 1 year lead of forest loss ($p < 0.01$). These results indicate that either media data, or the relationship between narcotrafficking and forest loss, were slightly imprecise temporally. Correlations between official trafficking data and forest loss were robust (no significant correlation found) to leads and lags.

3.3.2. Country Level Models

Narcotrafficking activity had a causal effect on forest loss in Nicaragua as measured by official data ($p < 0.05$, Table 5), and in Honduras and Guatemala as measured by media proxy data ($p < 0.05$, Table 6). Models with official drug trafficking data had insignificant F

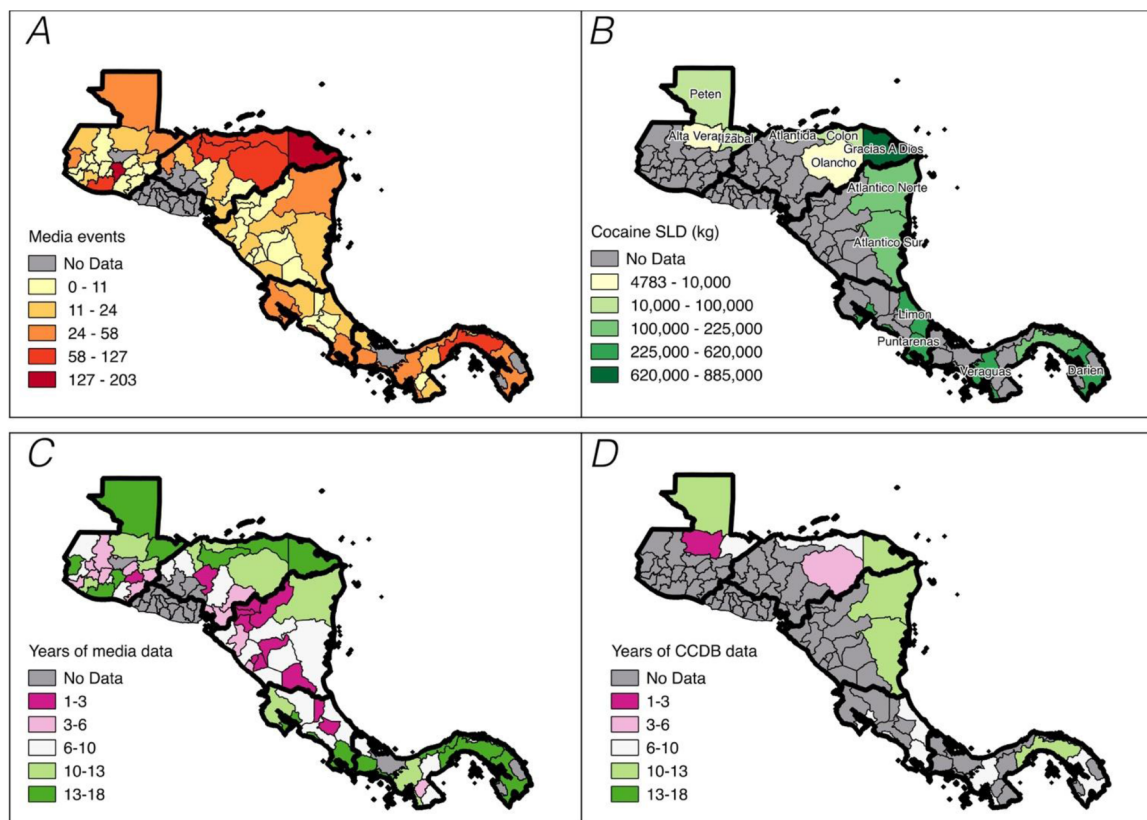


Fig. 4. Media and CCDB data coverage and completeness over Central America. A) Total media events per department from 2000-2017. B) Total kilos of cocaine seized, lost, or delivered from 2000-2014, with labeled names of departments. C) Completeness measured in years of media observations present per department. D) Completeness measured in years of CCDB data per department.

statistics, suggesting little explanatory power (Table 5, robustness checks in Table SI 7), and no results could be assessed for Guatemala or Costa Rica because there were too few observations of official data at the department scale ($n=14$ and 18 respectively). Narcotrafficking measured by official data had a positive causal effect on forest loss only in Nicaragua (CMM1). In Nicaragua, narcotrafficking had a relatively smaller effect on forest loss in comparison to other significant forest loss predictors: agricultural production and rainfall (CMM1, $p<0.05$ for crops, $p<0.1$ for pasture and rainfall, standardized coefficients in Fig. 8).

Media data proxies indicate narcotrafficking has a positive causal effect on forest loss in Honduras (CMM2, $F=4.08$, $p<0.05$) and Guatemala (CMM6, $F=4.54$, $p<0.05$), but only after 2005). Robustness checks in Honduras (Table SI 8) reveal that, as in the regional models, media proxies are significantly correlated with forest loss ($p<0.01$) with one year of lagging and leading the dependent variable. Robustness checks in Guatemala (Table SI 10) reveal narcotrafficking has a causal effect on forest loss with a 2-year lag only and after 2005. Other countries showed no relationship between trafficking and forest loss (Table 6).

Significant conventional causes and factors of forest loss differ by country. Expanded agricultural crops and pasture land were a primary cause of forest loss in Nicaragua (CMM1, $p<0.1$ and $p<0.05$), and expanding cropland caused forest loss in Guatemala (CMM6, $p<0.1$, after 2005 only). In Costa Rica, decreased cropland and rural population growth were associated with forest loss (CMM4, $p<0.1$ for both). In Guatemala, fire impacts as measured by annual burned area was significantly correlated with forest loss ($p<0.1$, SI tables 8 and 9) in both conventional models and those that include narcotrafficking variables (CMM5). However, in the Guatemala model subset after 2005 (CMM6) burned area was no longer significantly correlated with forest loss. The relationship between burned area and forest loss is strongest

in the Petén, Guatemala from between 2000 and 2009 (Fig. 9). In Honduras, forest loss was associated with rural population decrease.

4. Discussion

4.1. Narcotrafficking and forest loss in Central America

Among a set of common drivers of tropical forest loss, we found a significant causal effect between narcotrafficking intensity and increased annual forest loss in Central America at the department scale. Models of forest loss that included narcotrafficking as an explanatory variable explained more variance than models that only included conventional drivers of forest loss. These results are consistent with two independent measures of annual narcotrafficking - official statistics and media data. Our results showed that forest loss was consistently higher in areas of increased drug trafficking. This study makes an empirical contribution by extending previous studies that found narcotrafficking, as reported in official statistics, to be correlated with anomalous patterns of forest loss in 14 departments of Central America for 14 years (Sesnie et al 2017). A methodological contribution is also made by demonstrating the utility of news media data for establishing a causal effect of narcotrafficking on forest loss across a wider spatial (50 departments) and temporal extent (16 years).

The increased spatial and temporal coverage of media data, as compared to official statistics measuring narcotrafficking, provided the advantage of estimating country scale causal effects on forest loss. Country model results are consistent with established causal mechanisms in Honduras and Guatemala, where drug trafficking activities have been linked to forest loss when land is cleared for agribusiness for money laundering (McSweeney et al., 2018), narco-cattle ranching (Devine et al., 2018), or to establish territorial control along land based supply routes. Our results provide evidence of narcotrafficking as a

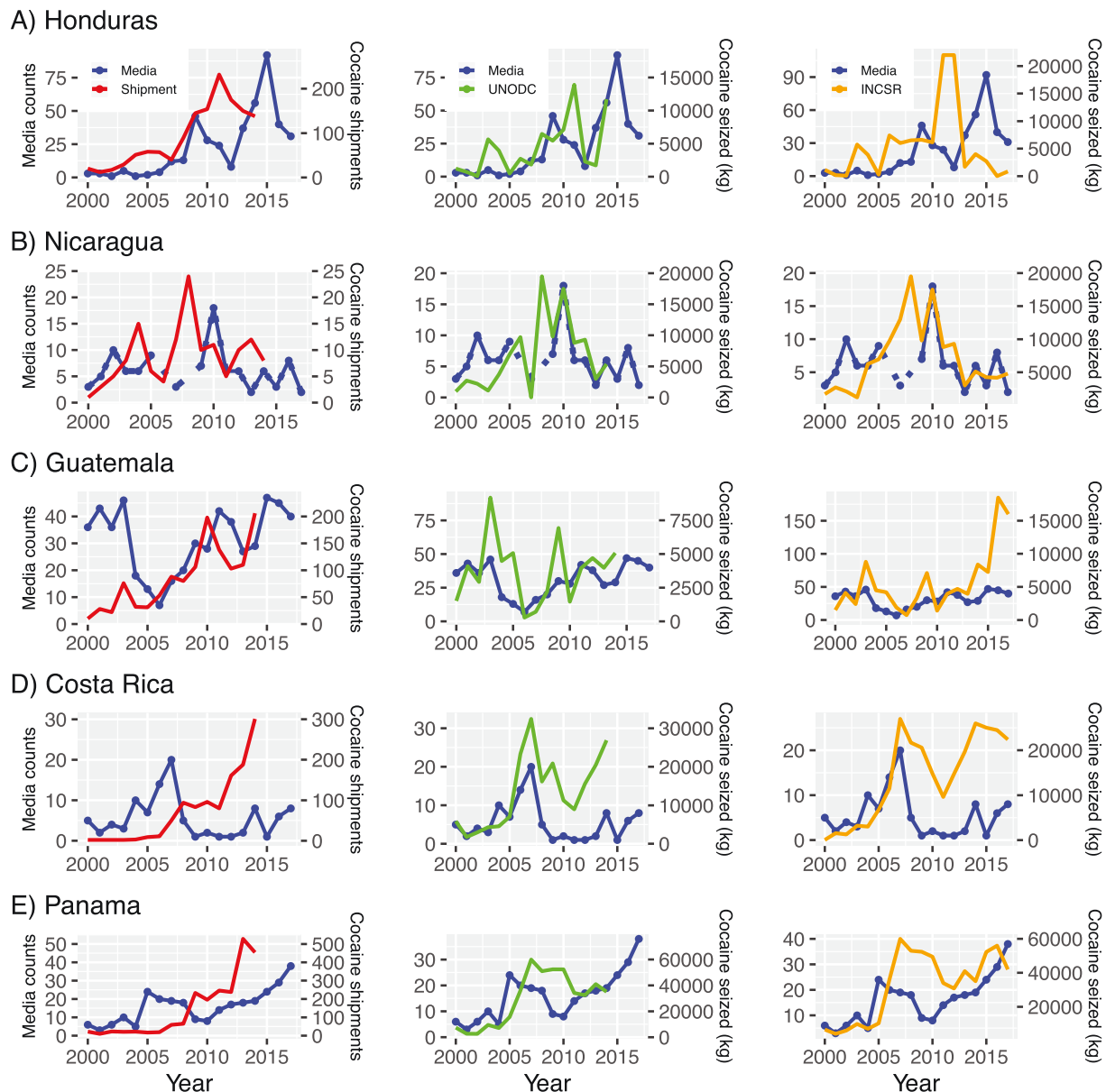


Fig. 5. Country comparisons of media events to official measures of drug trafficking activity for A) Honduras, B) Nicaragua, C) Guatemala, D) Costa Rica, and E) Panama. Dotted blue line represents missing data with linear interpolation..

cause of forest loss in these two countries. While a causal effect of narco trafficking on forest loss was also found in Nicaragua, as yet, no published studies have sought to explain how drug trafficking is a contributing factor to forest loss particularly in RAAN and RAAS departments with moist tropical forest that are currently experiencing very high rates of forest clearing (Volckhausen, 2019). Narcotrafficking may be accelerating or adding to already high deforestation rates in places in Nicaragua with a rapidly expanding agricultural frontier.

Consistent with previous studies, we also found that increasing agricultural production, pastureland expansion, and rural population growth have a significant casual effect on increased forest loss in Central America (Aide et al., 2013; Carr et al., 2009; Graesser et al., 2015). In contrast to this regional trend, country level models in Honduras revealed a negative relationship with rural population and forest loss, potentially due to outmigration that increases with drug trafficking intensity in Eastern Honduras (McSweeney et al., 2018).

Drug trafficking had no causal effect on forest loss in two countries - Costa Rica and Panama. This confirms previous studies finding no

correlation between anomalous deforestation and narco trafficking in either country (Sesnie et al 2017). Drug trafficking generates less profit for land-based laundering or investment in these southernmost Central American countries because the monetary value of cocaine increases as it moves northward through various drug trafficking nodes in Central America (Magliocca et al., 2019). In addition, illegal land markets and forest loss are not always a by-product of trafficking where other investments are more attractive or strategic for laundering money or controlling network territory. For example, money laundering in Panama is common via the financial sector, because its currency is the US dollar (Warf, 2002). In Costa Rica, tourism could provide a money laundering avenue. Territorial control strategies may also differ in these two countries, where drug shipments primarily arrive by sea instead of by land (McIlwaine and Moses, 2012).

Model results in Guatemala reveal that narco trafficking had a causal effect on forest loss only after 2005. The dominant factor of forest loss in regions like the Petén in the early 2000s were forest fires (Fig. 9). The mid 2000s have been identified as the period that the majority of

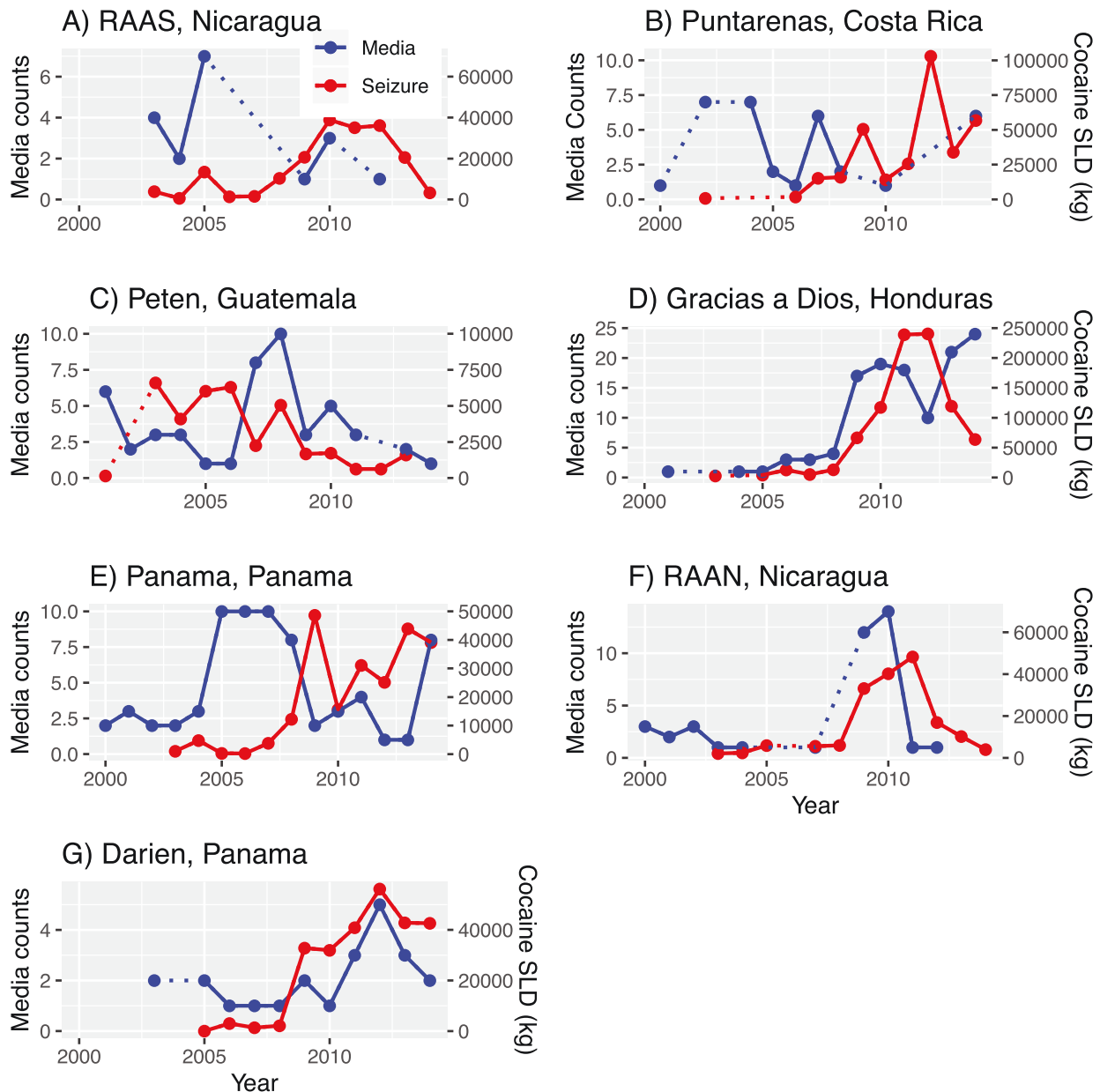


Fig. 6. CCDB kilos of cocaine SLD versus media event counts in departments with 7 years or more of CCDB data. Red lines are annual kilos SLD of cocaine in the CCDB, blue line is the sum of media events per year. Dotted lines interpolate between years of no data.

cocaine transit shifted from the Caribbean to Central America (McSweeney et al., 2014; Sesnie et al., 2017). Studies in Guatemala also point out that narco-traffickers established airstrips and border territories in the Laguna del Tigre national park, where narco-cattle ranching has been documented (Devine et al 2018) in the early 2000s. Rival DTOs also began to compete for territory in the mid 2000s. We believe the lack of CCDB interdiction data in the Petén reflects the spotlight effect, and the lack of seizure data reflects a lack of interdiction efforts rather than decreased drug flows. The lack of causal effect in Guatemala prior to 2005 using the media proxy data might also reflect bias in media reporting or data collection, although coverage in 2004 suggests narco-deforestation is widespread and fueling increased forest fires (Hemeroteca Prensa Libre, 2004). Ethnographic work examining reserve governance further suggests narco-deforestation began in the early 2000s, however, the scale of narco-cattle ranching expanded in the mid 2000s as drug traffickers accumulated and then began laundering profits through agribusinesses (Wrathall et al., 2020). Further

work is required to better understand the relationship between narco-trafficking, fires, and forest loss in Guatemala.

Drug trafficking models revealed that forest loss may increase up to one year before, and up to two years after narco-trafficking activity is detected and reported by news media. This indicated that either media data were temporally imprecise, or the relationship between narco-trafficking and forest loss is not immediate. Clearing forest land for money laundering or investment likely occurs sometime after drug trafficking capital accumulates and must eventually find an outlet as asset investments either in land or other commodities identified as legitimate. Dynamic and reverberating effects of narco-trafficking catalyzing frontier spaces were not captured in the modeling approach used in this study, and should be investigated in future work. The coefficient for media and official data proxies are likely biased downward, because the proxies capture a signal of, but do not completely represent, the spatial and temporal intensity of narco-trafficking activities. Non-linear econometric models capable of incorporating these dynamics and Agent

Table 4

Regional model comparisons with conventional and narcotrafficking variables for the number of hectares of forest loss per year between 2001 and 2016. The conventional subset is for the 14 departments and years for which CCDB kilos SLD data were available. NA = 0 when with no media observations were given a value of 0. RM = Regional Model. RM2 and RM5 models are of forest loss in 2001–2014 (years for which official kilos of cocaine seized are available).

	Regional Forest Loss Models: Forest Loss 2001–2016 (log)		Media NA = 0	Media	CCDB Kilos SLD
	Conventional (RM1)	Conventional Subset (RM2)	(RM3)	(RM4)	(RM5)
crop	0.0519*** (0.012)	-0.0414 (0.0320)	0.0553*** (0.0116)	0.0190 (0.0207)	0.0173 (0.0449)
pasture	0.0328*** (0.0091)	-0.0265* (0.0159)	0.0359*** (0.0090)	0.0170 (0.0118)	-0.0274 (0.0253)
rural pop	4.1e-6** (1.8e-6)	3.2e-6 (2.1e-6)	3.7e-6** (1.8e-6)	3.4e-6(2.5e-6)	7.5e-6* (4.1e-6)
precip	-0.0003 (0.0005)	0.0003 (0.0006)	-0.0005 (0.0005)	1.22 e-5 (6.2e-4)	0.0001 (0.0011)
burned	2.5e-6 (2.5e-6)	1.2e-6 (2.0e-6)	3.3e-6 (2.5e-6)	1.5e-6 (2.4e-)	5e-7 (2.3e-6)
GDP	-0.0043 (0.0231)	-0.0842** (0.0338)	0.0068 (0.0229)	-0.0104 (0.0330)	-0.0027 (0.0568)
media NA = 0			0.0520*** (0.0118)		
media				0.0318*** (0.011)	
kilos cocaine					6.5e-6*** (2.1e-6)
precip*burned	3.43e-9 (9.13e-9)	8.66e-9 (7.18e-9)	1.9e-11 (903.1e-11)	6.63e-9 (8.70e-9)	10.33e-9 (8.26e-9)
Observations	700	196	700	292	114
R ²	0.0597	0.1771	0.0877	0.1091	0.2656
F Statistic	5.7094*** (df = 7; 630)	4.9817*** (df = 7; 162)	7.5617*** (df = 8; 629)	3.4912*** (df = 8; 228)	3.5716*** (df = 8; 79)

Note: Standard errors given in parentheses * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Based Models (ABM) could build off of this study, for example, by testing the conditions under which narcotraffickers clear forest land versus making other opportunistic investments for laundering illicit profits.

Guatemala, Nicaragua, and Honduras maintain some of the last remaining contiguous primary moist tropical forest in Central America, which are being substantially reduced by drug trafficking impacts. Drug trafficking is an underlying driver of forest loss in what can appear to be a business-as-usual explanation of an agricultural frontier (e.g. forest clearing for pasture development and cattle grazing). Illegal cattle ranching has been considered a proximate driver of forest loss (WCS and CONAP, 2018), but this study shows narcotrafficking in some cases may be the root cause of deforestation in parts of Honduras, Nicaragua, and Guatemala.

This study confirms that drug trafficking is a cause of forest loss within moist tropical forest areas of Central America, in the context of other more commonly identified factors. This study reaffirms that international drug policy intersects with national and international conservation policy (McSweeney et al., 2014) because US led interdiction efforts influence the location and intensity of narco-trafficking (Magliocca et al., 2019). By extension, US led interdiction efforts that

force traffickers to establish alternative transportation routes effectively redistributes agents of forest change to new areas that can intensify forest loss in critical areas. From ours and previous assessments, these areas overlap with indigenous lands, protected areas, and other key forested regions that currently maintain core wildlife habitat and connectivity that sustain human livelihoods and biodiversity. Barring substantial changes in supply-side drug trafficking policy and interventions, remote regions of intact forest along major trafficking routes will likely continue to be vulnerable to high deforestation rates.

4.2. News media as a measure of illicit activity

Media data are a promising proxy for illicit activity. We found that media data was an indicator of the location and intensity of illicit activity, complementary to official statistics that suffered from coarse spatial resolution, low sample size, and the “spotlight effect”. Consolidated news media data, when appropriately validated and used, can provide spatio-temporal data of high profile illicit activities that influence environmental change, including corruption, illegal logging, and wildlife trafficking (Patel et al., 2015; Siriwat and Nijman, 2018) for which official data are unavailable or of poor quality. Media data

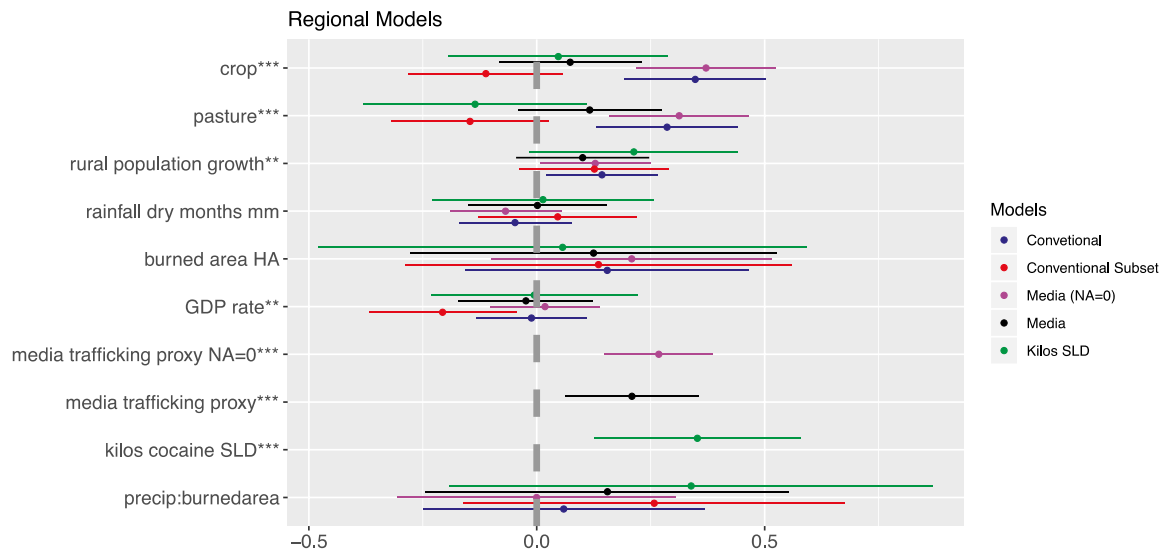


Fig. 7. Coefficient plot of regional models with point estimates and standard deviations, variables rescaled to 2 standard deviations for each variable to directly compare coefficients. Explanatory variables that do not cross the “0” line are significant at the $p < 0.05$ level. Left axis also identifies significance in at least one model from table 4, with * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table 5

Country model comparisons with narcotrafficking variable of kilos SLD from CCDB data to predict hectares of forest loss per year from 2001-2014. Guatemala and Costa Rica did not have a sufficient number of observation units to produce model results. CMO = Country model with official data.

	Country Forest Loss Models with Official Narcotrafficking Data: Forest Loss 2001-2014 (log)			
	Nicaragua (CMO1)	Nicaragua Conventional (CMO2)	Honduras (CMO3)	Panama (CMO4)
crop	154.9599* (64.8436)	0.068*** (0.0195)	-0.4888 (0.4602)	0.3046* (0.1676)
pasture	0.4489** (0.0974)	0.0407** (0.0188)	-0.0142 (0.0690)	0.1543 (0.1407)
precip	0.0109* (0.0039)	-0.0011 (0.0016)	-0.0019 (0.005)	-0.0016 (0.0046)
burned	1.34e-6 (8.3e-6)	8.5e-5 (.74e-5)	.36e-5 (.65e-6)	-4.93e-5 (4.35e-5)
rural pop	1.19e-5 (.86e-5)	.34e-5 (.44e-5)	-1.29e-5 (3.76e-5)	2.35e-5 (2.76e-5)
kilos cocaine	12.2e-4** (.337e-4)		5.5e-6 (4.8e-6)	3.5e-6 (5.2e-6)
precip*burned	7.94e-9 (24.11e98)	-10.03e-9(18.97e-9)	.825e-9 (26.4e-9)	3e-7 (4e-7)
Observations	23	196	30	31
R ²	0.9213	0.1059	0.4802	0.4718
F Statistic	5.0194 (df = 7; 3)	3.2166*** (df = 6; 163)	1.0565 (df = 7; 8)	1.2762 (df = 7; 10)

Note: Standard errors given in parentheses *p < 0.1 **p < 0.05 ***p < 0.01.

can illuminate processes absent from official statistics on drug trafficking and seizures. Media reports captured laundering strategies, conflicts between DTOs, violence, and corruption activities that influence environmental changes such as forest loss related to the movement of drugs. Media reports are already used, for example, to understand public discourses of environmental change (Cody et al., 2017; Dolšák and Houston, 2014; Le Nghiem et al., 2016), but we show that they can also be leveraged to generate data about drivers of environmental change that are difficult to measure, such as illicit activity.

Media data must be compared to independent data of illicit activity to ensure quantitative measures represent spatial and temporal dynamics at the same scale as the causal inference model. This represents a significant challenge as official data on illicit activity are often fragmented or unavailable at sub-national scales. Obtaining spatially explicit drug trafficking data, from clandestine airstrips to land seizures, required developing relationships with law enforcement to know what data exist, what they represent, and navigating transparency laws to obtain them. Efforts to make interdiction data more publicly available would allow researchers to develop more robust illicit proxies from media and other sources, echoing recommendations by the National Research Council (National Research Council, 2001). Access to data on cocaine production in Colombia has been used to analyze forest loss, fires, and other dynamics (Armenteras et al., 2013; Dávalos et al., 2016).

Larger samples sizes, temporal accuracy, and bias in reporting must be addressed if media data are used to measure illicit activity. Cross correlation analysis with independent data can help estimate potential temporal lags in media or interdiction data. Representativeness analysis, developed to address sampling bias in meta-analysis for land change science (Schmill et al. 2014), was useful in this study to

understand urban reporting bias. Future studies should address spatial displacement of urban media reports from the rural social-ecological systems where the impacts of illicit activity are embedded. New approaches may necessarily seek to replace manual coding in order to fill gaps when national newspapers show consecutive years of missing data, as occurred in some countries in this study (El Heraldo in Honduras and La Prensa in Guatemala). Future studies could use natural language processing (NLP) or machine learning trained on the media reports manually coded in this study to automatically extract patterns in news media databases such as GDELT (Global Database of Events, Language, and Tone; GDELT 2018) (Kwak and An, 2016; Rönqvist and Sarlin, 2017).

Country experts should also be called on to interpret results of media validity analyses and help to qualitatively explain political and economic circumstances that affect media reporting dynamics. This study benefited from insights from authors with more than 10 years of field experience in each country. We considered Honduras media data to capture the temporal and spatial variability of trafficking, notwithstanding reduced reports in 2011 attributable to the consolidated power and stability of DTOs and lack of interdiction activity. We noted potential underreporting in western Nicaragua, for example. Costa Rica, Guatemala, and Panama media all showed increased trafficking intensity starting in the mid-2000s congruent with UNODC seizures data, but in contradiction to CCDB shipment data (Fig. 3). Finally, and most importantly, journalists covering drug trafficking in Central America are under constant threat, and often killed, by DTOs (Rafsky, 2019; Shirk, 2010). Violence and impunity influence the spatio-temporal distributions of reporting, causing self-censorship (Reporters without Borders, 2018). The representativeness analyses revealed lower than expected media reports from Petén, Guatemala, for example,

Table 6

Country model comparisons using annual narcotrafficking media counts to predict hectares of forest loss per year from 2001-2016. NA = 0 when department years with no media observations were filled with 0. CMM = country model with media data.

	Country Forest Loss Models with Narcoactivity Measured by Media Proxy: Forest Loss 2001-2016 (log)					
	Nicaragua (CMM1)	Honduras (CMM2)	Panama (CMM3)	Costa Rica (CMM4)	Guatemala (CMM5)	Guatemala > 2005 (CMM6)
crop	0.0682*** (0.0195)	0.0733 (0.056)	0.0049 (0.0493)	-0.1083* (0.0587)	0.0757 (0.0538)	0.1775* (0.0879)
pasture	0.0409** (0.0189)	0.0102 (0.0185)	0.0268 (0.0303)	-0.0388 (0.0308)	-0.0082 (0.0182)	-0.0892 (0.0629)
precip	-0.0010 (0.0016)	-0.0022 (0.0014)	-0.0014 (0.0012)	-0.0012 (0.0009)	0.0022 (0.0018)	0.0023 (0.0018)
burned	1.09e-5 (8.4e-5)	.9e-6 (3.3e-6)	8.6e-6 (36.8e-6)	-13.0e-6 (29.4e-6)	5.0e-6* (2.7e-6)	5.9e-6 (4.5e-6)
rural pop	3.2e-6 (4.4e-6)	-9.0e-6* (5.2e-6)	5.2e-6 (5.6e-6)	13.2e-6* (6.9e-6)	-5.3e-6 (3.1e-6)	4.5e-6 (6.4)
media NA = 0	0.0387 (0.0537)	0.0316** (0.0126)	0.0242 (0.0437)	0.0312 (0.0495)	0.0144 (0.0314)	
media lag 2 yrs						0.0788** (0.0369)
precip*burnedarea	- 2e-8 (2e-8)	1.13e-8 (1.28e-8)	-5e-8 (20e-8)	-3e-8 (10e-8)	-2.64e08 (9.01e-8)	-2e-8 (1.44e08)
Observations	196	140	168	98	52	62
R ²	0.1087	0.2044	0.0369	0.0898	0.4377	0.5144
F Statistic	2.8230*** (df = 7; 162)	4.0380*** (df = 7; 110)	0.7453 (df = 7; 136)	1.0005 (df = 7; 71)	2.8908** (df = 7; 26)	4.5404*** (df = 7; 30)

Note: Standard errors given in parentheses *p < 0.1 **p < 0.05 ***p < 0.01

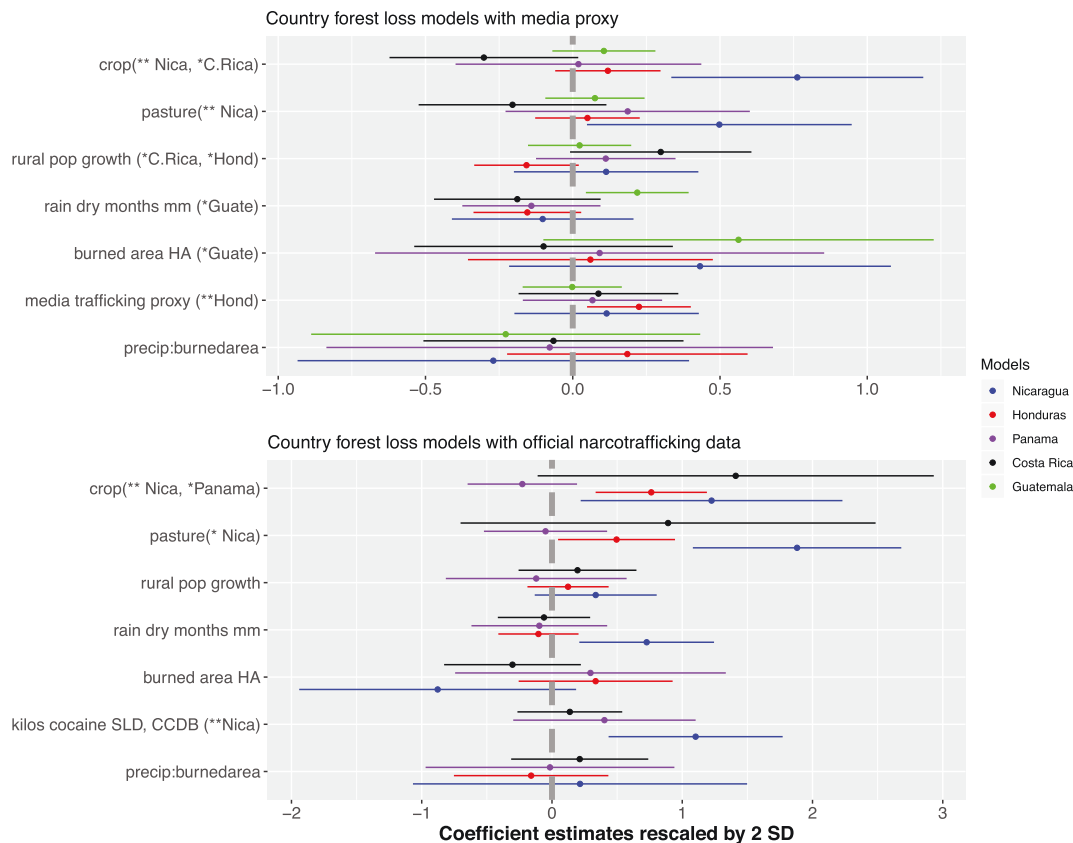


Fig. 8. Coefficient plot of country models with point estimates and standard deviations. Variables that do not cross the “0” dashed grey line are not significant at the $p < 0.05$ level. Left axis also identifies significance, with * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$ for the country model in which each is significant.

potentially due to DTOs intimidating journalists after coverage of a 2011 massacre of farm workers by the a drug trafficking organization, the Zetas, hanging banners stating “Tone it down, before the war is with you” (Rafsky, 2019). These conditions reduce reports of illicit activity in the region where and when it may actually increase.

5. Conclusion

Narcotrafficking constitutes a cause (evidence for both a causal mechanism and a causal effect), as opposed to a driver, of moist tropical forest loss in portions of the Central American isthmus since 2000. Significant forest loss has been attributed to cycles of increased agricultural expansion and frontier development, which this study shows may be accelerated or caused by drug trafficking organizations. Narcotrafficking variables explain an additional 5% - 9% of the variance in forest loss not captured by conventional models. This study illustrates the role of illicit activities on land change and the need to account for them in light of other commonly related factors. In addition, we found that consolidated and geographically explicit media events can partially overcome data limitations, demonstrating their ability to capture illicit activity and serve as a powerful tool to help researchers estimate the causal effects of drug trafficking on forest loss. Identifying and quantifying the role of illicit activity in deforestation is sometimes overlooked because of data shortfalls, but we show how media data can fill this gap. Accounting for illicit activity as a significant cause of forest loss is important because drug trafficking continues to increase, in spite of several decades of supply-side drug interdiction policies and the US war on drugs. Existing drug policy has resulted in concentrating drug trafficking into Central America's remaining contiguous forest areas of very high cultural and environmental value. Loss of governance and local authority to maintain ancestral lands formerly protected by law and indigenous sovereignty is

likely to have long lasting consequences for remaining moist forest areas targeted by traffickers. Continued supply side drug policies are likely to compromise decades of forest conservation investments in these same locations. Revising national and international drug policy in ways that favor more effective forest protection are vital to Central American conservation efforts.

CRedit authorship contribution statement

Beth Tellman: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Steven E. Sesnie:** Conceptualization, Software, Formal analysis, Writing - original draft, Writing - review & editing, Supervision. **Nicholas R. Magliocca:** Conceptualization, Formal analysis, Writing - review & editing. **Erik A. Nielsen:** Conceptualization, Investigation, Resources, Writing - review & editing, Project administration, Funding acquisition. **Jennifer A. Devine:** Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition. **Kendra McSweeney:** Conceptualization, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Meha Jain:** Methodology, Software, Writing - review & editing. **David J. Wrathall:** Investigation, Resources, Funding acquisition. **Anayasi Dávila:** . **Karina Benessaiah:** Investigation, Resources, Writing - review & editing, Visualization. **Bernardo Aguilar-Gonzalez:** Investigation, Resources, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

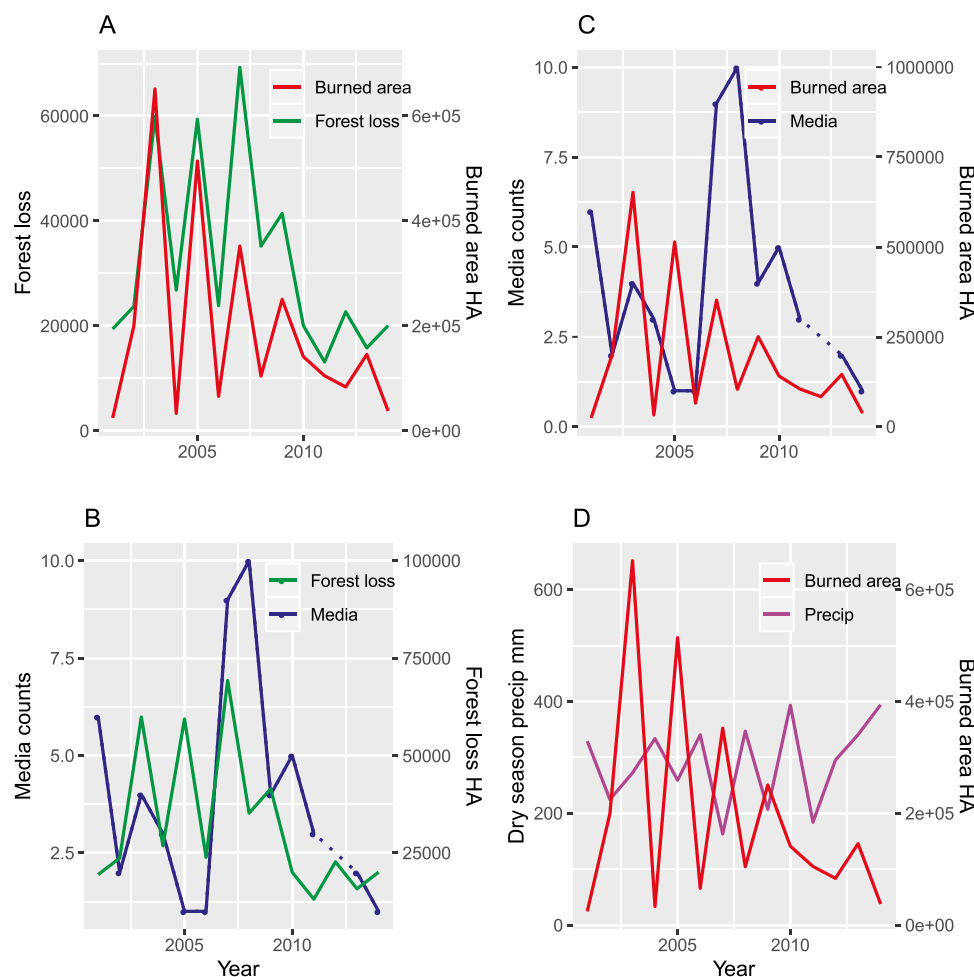


Fig. 9. Petén, Guatemala time series for A) forest loss and burned area, B) narcotrafficking measured by media events and forest loss, C) burned area and media events, and D) burned area and dry season precipitation. Dotted blue line represents missing data with linear interpolation.

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Supplementary materials

Supplementary material associated with this article can be found, in

the online version, at [doi:10.1016/j.gloenvcha.2020.102092](https://doi.org/10.1016/j.gloenvcha.2020.102092).

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