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Central America's agro-ecological suitability for cultivating coca, *Erythroxylum* spp

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Abstract

We assess how much of Central America is likely to be agriculturally suitable for cultivating coca (*Erythroxylum* spp), the main ingredient in cocaine. Since 2017, organized criminal groups (not smallholders) have been establishing coca plantations in Central America for cocaine production. This has broken South America's long monopoly on coca leaf production for the global cocaine trade and raised concerns about future expansion in the isthmus. Yet it is not clear how much of Central America has suitable biophysical characteristics for a crop domesticated in, and long associated with the Andean region. We combine geo-located data from coca cultivation locations in Colombia with reported coca sites in Central America to model the soil, climate, and topography of Central American landscapes that might be suitable for coca production under standard management practices. We find that 47% of northern Central America (Honduras, Guatemala, and Belize) has biophysical characteristics that appear highly suitable for coca-growing, while most of southern Central America does not. Biophysical factors, then, are unlikely to constrain coca's spread in northern Central America. Whether or not the crop is more widely planted will depend on complex and multi-scalar social, economic, and political factors. Among them is whether Central American countries and their allies will continue to prioritize militarized approaches to the drug trade through coca eradication and drug interdiction, which are likely to induce further expansion, not contain it. Novel approaches to the drug trade will be required to avert this outcome.

1. Introduction

Coca (*Erythroxylum* spp.) is an evergreen shrub domesticated by Holocene peoples in northwestern South America (White *et al* 2021). Today, coca is the continent's most culturally significant pharmaceutical plant, and as the raw ingredient in cocaine it is listed as a Schedule I narcotic globally banned since 1961 (Walsh and Jelsma 2023). 'Supply-side' efforts to curtail cocaine markets since then have prioritized coca eradication. Those efforts have helped to displace coca cultivation within and beyond historical production areas in Bolivia, Peru, and Colombia and into neighboring countries (Casale *et al* 2014, Dávalos *et al* 2016, Mallette *et al* 2016, Rivera-Rhon and Bravo-Grijalva 2020, VIU 2022, Aquino 2023).

Today, Colombia—a marginal coca leaf producer in the 1980s—is the world's top supplier of both coca and cocaine, reaching an historic high of 230 000 ha planted in coca in 2022 (UNODC 2023a).

Until recently, this well-documented 'balloon effect' (the spatial relocation of drug production or trafficking operations following counternarcotic interventions) has played out largely within coca's original domestication area (White *et al* 2021, Murillo Sandoval *et al* 2023). However, in the mid-2010s, authorities began to report their discovery of well-capitalized and reportedly 'experimental' coca-growing operations north of South America: in Mexico in 2014, in Honduras in 2017, and in Guatemala and Costa Rica in 2018 (De La Cruz 2014, Dittmar 2018a). Coca has since become particularly well-established as a cash crop in Honduras and Guatemala, where it is being grown by criminal organizations to supply coca paste to labs manufacturing powder cocaine in Honduras, Mexico, and possibly overseas (Papadovassilakis and Voss 2023, Wrate *et al* 2023).

These plantations represent the first time since 1961 that commercial coca cultivation for illegal cocaine production has been sustained outside of South America, suggesting novel spatial dynamics in the drug's global supply chain (cf UNODC 2023a). They are also the first time that coca cultivation has *ever* been reported for Central America outside of botanical gardens or agricultural research stations; the region does not appear to have been part of the global boom in legal coca cultivation from ca. 1880s–1930s (Karch 2003, Bosman 2012, Van der Hoogte and Pieters 2013).

This makes contemporary coca plantings in Central America both geographical and historical anomalies. While the total area cultivated to date is unknown, eradication reports suggest that the area is tiny compared to more than 200 000 ha under coca in Colombia (UNODC-SIMCI 2022). Nevertheless, the U.S. State Department considers coca's establishment in Central America to be 'troubling' (INCSR 2023:15) and 'could be a sign of bigger things to come' (Voss 2023; see also Casale and Mallette 2016). Meanwhile, other analysts suggest that the isthmus is not ecologically suitable for coca cultivation (Rodríguez 2021), and that coca cultivation north of the Andes may not be scalable (Casas 2022). In fact, Central America's biophysical suitability for growing *Erythroxylum* spp. is unknown. This ignorance derives as much from the novelty of the context as from the fact that coca varieties and their cultivation requirements are understudied (White *et al* 2021).

In this paper, we address this knowledge gap by estimating Central America's agro-ecological suitability for coca—that is, the combined soil, climate and topographic factors that might favor or constrain farming high-alkaloid *Erythroxulum* spp. using standard management practices. We ask: (1) Where are known coca cultivation sites in Central America? (2) What do the agro-ecological contexts of those fields tell us about favorable conditions for coca cultivation? (3) What Central American landscapes—from an agro-ecological perspective alone—appear most suitable for it?

To answer these questions, we use a novel approach to extrapolate Central America's agro-ecological suitability for coca based on its existing range in Colombia. Our aim is not to endorse or condemn the fact of coca's cultivation in Central America, or to predict where coca is likely to be grown in the future, but to advance understanding of coca's current biophysical limits. Below, we offer context on the crop's expansion into Central America and review aspects of its cultivation in Colombia, the likely source for Central American planting stock. Following the Methods and Results in sections 2 and 3, we conclude with the study's scientific and policy implications.

1.1. Central America in the cocaine supply chain

Since the 1980s, Central Americans' role in the global cocaine supply chain has largely been to facilitate bulk transshipments from Colombian suppliers to Mexican distributors (UNODC 2023a). However, in the mid-2010s, some Honduran trafficking groups began to refine imported Colombian coca paste into powder cocaine (UNODC 2012, Pachico 2015). The recent move into coca production seems to be a logical progression in this vertical integration of the supply chain (Ernst 2022, Wrate *et al* 2023). Mexican criminal groups appear to be financing coca plantations in Central America, probably to: (a) diminish their reliance on Colombian exporters; (b) reduce the costs and risks of long-distance drug transshipment given constant interdiction pressures, especially on maritime smuggling; (c) increase profits by producing the drug where its wholesale value is much higher than in Colombia; and (d) take advantage of the relative availability of precursor chemicals, which are less regulated than in Colombia (INCSR 2023, Papadovassilakis and Voss 2023, Wrate *et al* 2023). Mexican organized crime is apparently working with Central American criminal groups to bring in Colombian farmers, agronomists, and chemists to train *in-situ* actors who supply the land, labor, and chemical inputs required for coca growing, coca paste production, and cocaine synthesis (Ernst 2022, Proceso Digital 2023, Wrate *et al* 2023).

It is unclear why coca cultivation has rapidly increased in Honduras and Guatemala in the period since ca. 2017—a time marked by dramatic coca leaf overproduction in Colombia and historically low wholesale coca leaf prices there (Isacson 2023). It is possible that Colombia's production surge and the expansion of coca into Central America were both catalyzed by the 2016 Colombian Peace Accords, which initiated major upheavals in the structure and functioning of the cocaine economy and which have intensified since the election of Colombian President Petro, a drug policy reformer, in 2022 (Noriega 2022, Llanes *et al* 2023). This industry shakeup has created opportunities for new players and novel spatial dynamics within and beyond Colombia (UNODC 2023b, Wrate *et al* 2023). Transnational criminal groups may view investment in Central American coca cultivation as low-risk given their well-documented relationships with politicians, judiciary, and police/military there (UNODC 2012, Rodríguez 2021)—relationships which deepened in Honduras after the 2009 coup and in Guatemala since the presidency of Pérez Molina (2012–2015) (Hite and Montenegro 2020, Estrada 2021). Central America may also have become more attractive for coca cultivation since the US Justice Department's successful prosecution of Honduran and Guatemalan trafficking 'kingpins,' which left organizational vacuums that were filled in Honduras by a newly professionalized MS-13 (the criminal gang Mara Salvatrucha-13), which is now reportedly collaborating with Mexican groups to grow coca in rural areas that they control (Farah and Babineau 2018, Dittmar 2018b, Farah 2023).

1.2. Coca cultivars and production expertise: imported from Colombia

Four taxonomic varieties of coca have been used for cocaine production in South America (White *et al* 2021). Until about 2000, three of these were the principal varieties grown for cocaine production in Colombia: (1) *Erythroxylum novogranatense* var. *Novogranatese*, (2) *E. novogranatense* var. *Truxillense*, and (3) *E. coca* var. *Ipadu* (Casale *et al* 2014). Since then, however, Colombia's estimated 124 000–169 000 coca-growing smallholders (UNODC-SIMCI 2020) have bred at least 15 new cultivars (Casale *et al* 2014), selecting for high alkaloid content, dense biomass, and even resistance to the herbicide glyphosate (Ehleringer *et al* 2000, Casale and Lydon 2007, Casale *et al* 2014). It is unknown to the public if genetically modified strains of coca exist. The U.S. Drug Enforcement Administration (DEA) regularly tests coca from across all known growing regions (Casale *et al* 2014, Mallette *et al* 2018), but has yet to report on the existence of GMO coca. What seems most likely is that the coca plants grown in Honduras and Guatemala include several different Colombian cultivars, which were likely tested *in situ* by Colombian experts (La Prensa 2022, Proceso Digital 2023, Wrate *et al* 2023). For example, the DEA identified coca grown near the Guatemalan border in Chiapas, Mexico in 2014 as 'Pajarito' (*E. novogranatense* var. *Truxillense*), a variety widely planted in Colombia (Casale *et al* 2014, Casale and Mallette 2016).

Unlike in Colombia, however, it appears that smallholding *campesinos* are not (yet) the principal growers. Rather, most coca is being grown under 'work-camp' style labor arrangements, where field managers oversee workers at a remote grow site for prolonged periods. One 4 ha operation in Colón, Honduras, for example, had sleeping arrangements for 30 people (Orellana 2020).

2. Methods

2.1. Coca cultivation locations in Central America

We are unaware of any systematic aerial monitoring of coca cultivation in Central America. To map known coca-growing locations there, we draw from data in press releases and media reports of manual coca eradication operations by police and military forces from first discoveries in 2017 through to late 2022 ($n = 55$). We found these sources by opportunistically searching English and Spanish-language Google using relevant keywords[9] in combination with each Central American country name. Most reports came from Honduras and Guatemala, where the majority of Central American coca has been found (as of late 2022 there were significantly fewer eradication events in southern Mexico or other Central American countries). We also reviewed the available archived social media (Twitter and Facebook) feeds of Guatemala's National Police, the Guatemalan military, Honduras' National Interinstitutional Security Force and Honduras' Armed Forces. Because these agencies are incentivized to publicly report counternarcotic successes, we assume that we captured most instances of coca eradication. We cross-referenced media reports and press releases to remove any instances of double counting.

We used the detailed geographical information contained in the media data to map the approximate locations for each coca field cluster. We also extracted from the media sources any details of the coca operation such as field area, number of seedlings and mature shrubs found, the presence of laboratory facilities for rendering coca paste, and the presence of agrochemicals.

We assume that the coca fields eradicated by law enforcement are not a random sample of all existing coca fields, but rather represent the distribution of law enforcement effort (see Willis *et al* 2011). Given national contexts in which the police and military are known to regularly collude with organized crime, we assume that the coca fields that are eradicated represent a 'negotiation' between both parties

[9] We used Boolean search terms and modifiers with the following keywords (and their English equivalents): *coca* AND *hoja**, *plantación**, *arbusto**, *erradica**, *sembradío**, *cultivo**, *ilicito**, *vivero**, 'NOT *Colombia*.' Asterisks were used to capture all words with a given stem.

(see, e.g. Ávalos 2017, Estrada 2021). Nevertheless, the eradication record provides useful information about the range of agro-environments in which coca cultivation for cocaine production is possible.

2.2. Contexts of coca cultivation

To understand the agro-ecological contexts in which coca is being grown, and by extension the land cover that the crop is replacing, we used complementary qualitative and quantitative approaches: (a) we reviewed the photographs and videos of eradication operations, which depict the land uses and land covers surrounding the coca field; (b) we employed the Dynamic World land cover product from 2020 to 2021 (Brown *et al* 2022) to calculate differences in dominant land cover class probabilities in a 1 km buffer around each coca eradication site.

2.3. Determining agro-ecological suitability

To determine what these eradication sites tell us about Central America's broader agro-ecological suitability for coca, we combine digital data relevant to crop viability (Akinci *et al* 2013) with geo-specific field observations to generate distributions of environmental conditions capable of supporting the crop in question (Estes *et al* 2013). These data then informed machine-learning land suitability models, which have been used for a variety of tropical crops, including oil palm (see, e.g. Paterson *et al* 2015).

We used an ensemble machine learning (ML) modeling approach developed from other recent work (Harris *et al* 2023, Sesnie *et al* 2023, see also appendix A). Our models integrated coca occurrence records with biophysical predictor variables to assess agro-suitability on a scale of 0.0 (lowest) to 1.0 (highest). Coca-growing locations in Colombia were obtained from Colombia's Sistema Integrado de Monitoreo de Cultivos Ilicitos (SIMCI) for 1999–2008, a period that captures coca distribution in Colombia well (www.unodc.org/colombia/es/simci/simci.html). Coca occurrences from Central America ($n = 55$) were alternately included and excluded from suitability models to assess model differences. For each model, we combined spatially referenced occurrences with digital data on bioclimatic, edaphic, and topographic variables (table 1).

These variables are commonly used to assess agricultural viability and production parameters (Taghizadeh-Mehrjardi *et al* 2020). All model co-variable data layers were developed at an $\sim$1 km grid cell size resampled to Worldclim 30 second resolution bioclimate data (Fick and Hijmans 2017; www.worldclim.org/). For the Colombia-only model, herein referred to as COM, we used a 10% random sample of well-distributed coca occurrences (polygon centroids, n = 7,721). We created a polygon hull encompassing the total number of occurrences to develop 8000 random pseudo-absence locations within Colombia, which were confined to areas proximate to coca growing regions. Because of the wide distribution of coca plantations in Colombia, a single minimum convex hull polygon covered most of the country but excluded portions of the Choco, Amazonas, Vaupes, and Guainía departments where there were no coca detections in the dataset. Inside this area, pseudo-random points were eliminated within a 1 km polygon buffer surrounding coca presence locations to avoid presence and absence points from intersecting the same 1 km $\times$ 1 km grid cell. Any presence or absence points sharing the same grid cell number were subsequently removed, retaining only independent samples. The same techniques were applied to combined occurrence records for the models that included the Central America sites, herein referred to as CAM. The two resulting model training and validation data sets included combined Colombian and Central American records ($n = 15\,437$), referenced as CAM, and Colombia only records (n = 14 917) with a near-equal presence-absence distribution.

2.4. Ethical considerations

We considered the possibility that our published results might: (a) be misinterpreted to suggest that coca is already widespread in Central America (it is not); (b) be used by national police and military forces to justify targeting specific rural communities; and/or c) be mobilized by counternarcotics forces to legitimize the ongoing militarization of rural spaces more generally (cf McSweeney 2023, Ciro *et al* 2024). Any of these scenarios could cause reputational or physical harm to rural peoples and lands in Central America. To mitigate these potential harms: (a) we do not reproduce the names of, nor map with any specificity, the locations where coca plantations have been found; (b) we use cartographic devices to express the *hypothetical* nature of coca suitability in Central America; (c) we attempt to head off 'blame the victim' narratives by pointing to dynamics of the drug trade and counternarcotics operations as the driver of coca cultivation in Central America, not its rural residents; (d) we consulted with our Central American co-author and collaborators who approved our approach and agreed that scientists and the general public had a right to know and discuss our findings, especially given that organized criminal networks and the DEA are widely assumed to have independently developed the same insights (see Casas 2022, Casale *et al* 2014).

3. Results

3.1. Spatio-temporal distribution of eradicated coca fields

We tabulated 55 separate eradication operations between 2017 and 2022, the majority of which occurred after 2019 (figure 1). The upward trend

Table 1. Predictor variables used for machine learning agro-ecological suitability models. Worldclim bioclimatic variables were obtained from www.worldclim.org/ using the 'geodata' package v. 0.-5-8 for R statistical software v. 4.3.1 (R Core Team 2023) and soils variables that included t5 cm to 15 cm soil depth layers from www.isric.org/explore/soilgrids. Elevation data were obtained from OpenTopography (https://opentopography.org/developers/) using the 'elevatr' package v. 0.99.0 for R. All data sources were accessed 18 October 2022.

Predictor	Description	Units	References
Bioclimatic variables			
bio1	Annual mean temperature	°C	Fick and Hijmans (2017)
bio2	Mean diurnal range (mean of monthly (max temp—min temp))	°C	"
bio3	Isothermality (bio2/bio7 × 100)	°C	"
bio4	Temperature seasonality (standard deviation × 100)	°C	"
bio5	Max temperature of the warmest month	°C	"
bio6	Min temperature of the coldest month	°C	"
bio7	Temperature annual range (bio5—bio6)	°C	"
bio8	Mean temperature of the wettest quarter	°C	"
bio9	Mean temperature of the driest quarter	°C	"
bio10	Mean temperature of the warmest quarter	°C	"
bio11	Mean temperature of the coldest quarter	°C	"
bio12	Annual precipitation	mm	"
bio13	Precipitation of the wettest month	mm	"
bio14	Precipitation of the driest month	mm	"
bio15	Precipitation seasonality (coefficient of variation)	mm	"
bio16	Precipitation of the wettest quarter	mm	"
bio17	Precipitation of the driest quarter	mm	"
bio18	Precipitation of the warmest quarter	mm	"
bio19	Precipitation of the coldest quarter	mm	"
Edaphic variables			
sand	Proportion of sand particles >0.05 mm	g/100 g (%)	Poggio *et al* (2021)
silt	Proportion of silt particles ⩾0.002 mm and ⩽0.05 mm	g/100 g (%)	"
clay	Proportion of clay particles <0.002 mm	g/100 g (%)	"
cfrac	Volumetric coarse fraction	cm3/100 cm3 (vol%)	"
N	Total nitrogen	g kg^{-1}	"
cec	Cation exchange capacity	cmol(c) kg^{-1}	"
soc	Soil organic carbon	g kg^{-1}	"
snsl	Ratio of sand to silty content	ratio	—
sncl	Ratio of sand to clay content	ratio	—
socn	Ratio of soil organic carbon to nitrogen content	ratio	—
Topographic variables			
el	Elevation	m	Hollister (2023)
slope	Degrees slope		"
trasp	Transformed aspect (1–cos((π/180) * (aspect-30))/2)	—	"

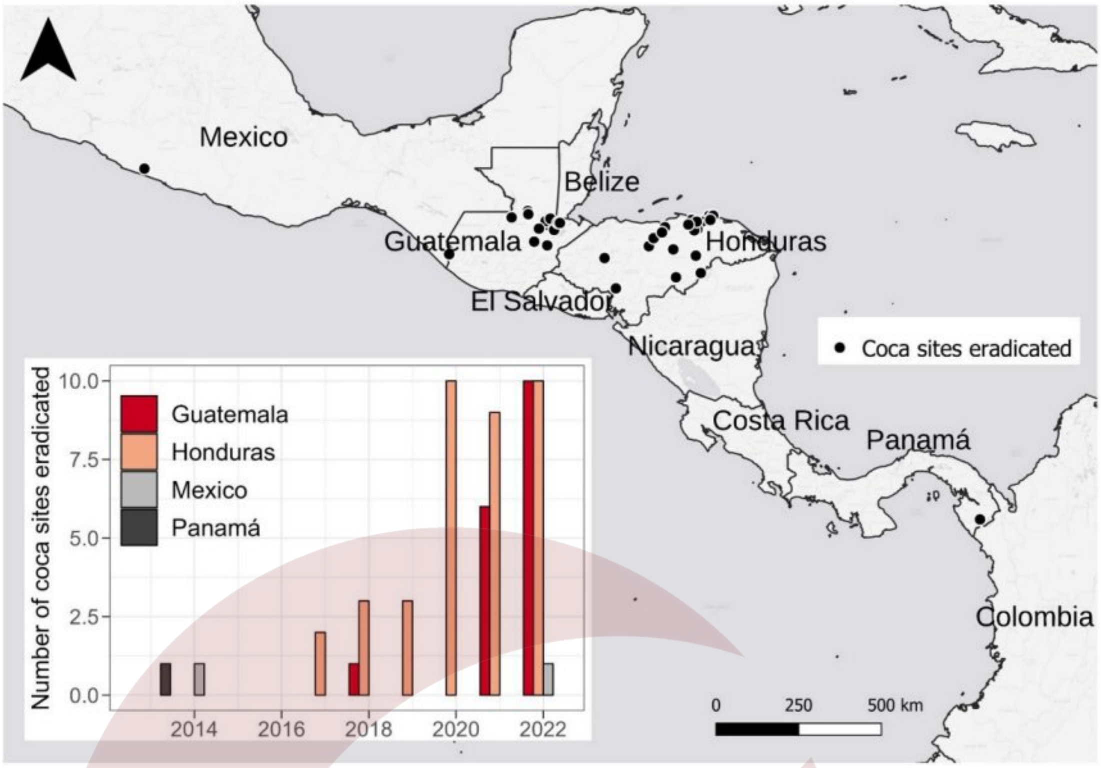

Figure 1. Approximate location of coca eradication sites, with eradication events reported by year and country (inset).

should be interpreted with care. Eradication events necessarily lag field establishment, and so may not match trends in coca expansion. For example, one site eradicated in 2022 in northern Honduras included coca bushes estimated to have been in production for 5 years (Ministerio Público 2022).

There was some clustering of coca eradication sites in both Honduras and Guatemala. In Honduras, coca fields were found in the departments of Colón (28 sites), Olancho (7 sites), and Yoro (1 site). In Guatemala, coca fields were found in Izabal (6 sites), Petén (5 sites), Alta Verapaz (5 sites), and Zacapa (1 site). All are departments through which cocaine has been trafficked regularly for the last two decades (UNODC 2012).

Law enforcement and media reports offered only rough areal estimates of individual coca fields and farming operations. Most showed that monocropped coca fields are 1–2 ha in size, which is similar to the mean patch size in frontier coca farms in Colombia (1 ha, $\sigma = 0.7$ ha) (Murillo Sandoval *et al* 2023) and seems designed to make field detection more difficult (Robbins 2022). While individual plots were small, some operations were quite large overall, with one in eastern Honduras exceeding 45 ha.

Thousands of mature plants (ranging in height between 0.5 and 4.5 m) were reported at the majority of sites. At a site in Guatemala, for example, national police incinerated 247 075 mature coca bushes (Muñoz 2022). The maturity of the bushes indicates that the sites had been in production for a year or more and harvested at least once. Most media mentioned the presence of on-site nurseries with thousands of coca seedlings. Photos and videos of eradication operations also showed rudimentary laboratories on site, with supplies of urea and gasoline used to process the leaf into coca paste, and sheds with stored agrochemicals, including Proteogreen (fertilizer), Rootex (for root growth and phosphorous uptake), and Fertig Forte (fertilizer and leaf growth stimulant) (e.g. FUSINA 2021).

3.2. Land cover contexts for coca cultivation

In both Guatemala and Honduras, law enforcement reports indicate that eradicated coca fields are concentrated in remote and sparsely populated areas, including those within protected areas and indigenous territories (see also Proceso Digital 2023). Many law enforcement images showed coca fields surrounded by high forest or secondary forest, as indicated by the presence of successional tree species (*Attalea* spp., *Cecropia* spp.). Some grow sites, however, appeared to be adjacent to or incorporated within subsistence and commercial agricultural systems, as when photos depicted coca intercropped with maize, beans, coconut, bananas, and coffee, and planted on the margins of what appear to be cattle pastures. At one

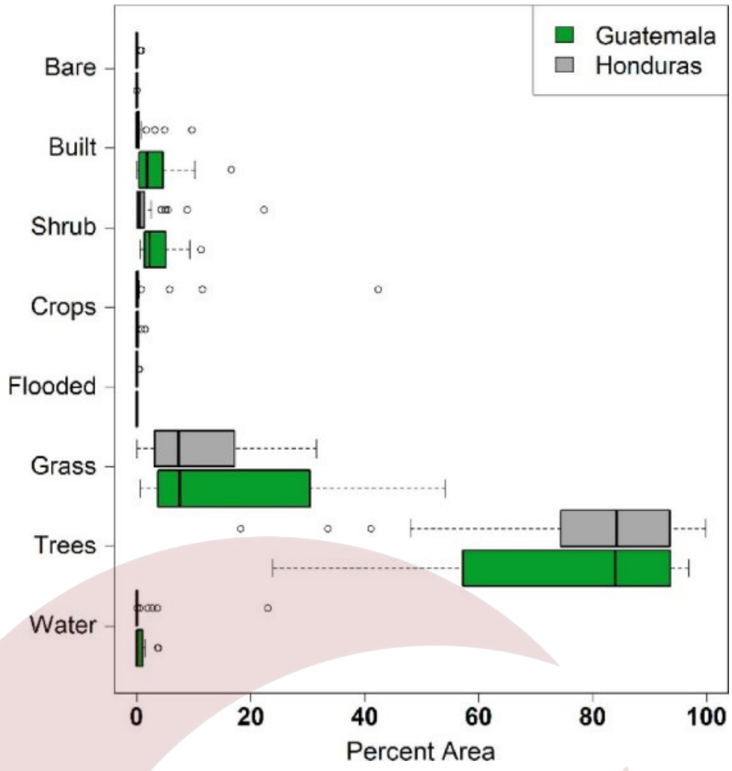

Figure 2. Land cover categories in 1 km-buffer arounds eradicated coca cultivation sites in Guatemala and Honduras.

site in Guatemala, coca was being grown directly adjacent to an oil palm nursery.

Dynamic World-based analysis confirms that >80% of the buffer areas around grow sites were in tree cover (which includes natural forest but not oil palm plantations), followed by <10% under grass—which likely represent cattle pasture, given the absence of natural grasslands in these areas (figure 2).

3.3. Landscape suitability for coca cultivation

Model performance. Performance and variable selection were similar among COM (Colombia data only) and CAM (Colombia and Central American data) models. In each case, ensemble coca suitability models out-performed single ML approaches showing lower RMSE and better goodness-of-fit (appendix B, table B2). The CAM and COM model ensembles produced high area under the curve (AUC) values (0.96 and 0.89 respectively) from independent validation data, likely because of the greater contribution of coca occurrences for Colombia relative to Central America. The CAM model ensemble had an RMSE and MAE of 0.27 and 0.15 respectively and an $R^2 = 0.71$, which was nearly identical to the COM model (RMSE = 0.27, $R^2 = 0.72$) from 10-fold cross-validation with model training data. Additional model evaluation statistics are reported in appendix B, tables B1 and B2.

We found that relatively important variables were also similar between ensemble models, such as the annual amount of precipitation (bio12), mean diurnal temperature range (bio2) and elevation (appendix B, figure B3). Two soil variables—cation exchange capacity (CEC) and volumetric coarse fraction (cfrac)—intermittently showed higher importance for individual ML models and final ensemble models.

Variables associated with coca-growing. In most cases, coca occurrences from Colombia and Central America showed overlapping environmental conditions for important variables (figures 3(a)–(f)). Notably, Central American coca production is distributed over a similar elevation range to Colombian coca occurrences: mean elevation for Central American coca ($\bar{x} = 364$ m, SD 314.1) was similar to Colombia ($\bar{x} = 329$ m, SD 326.2). However, the maximum elevation for coca occurrences was twice as great in Colombia (2864 m v. 1398 m).

In terms of climatological and edaphic variables, annual precipitation for each region was between approximately 2000 mm and 4000 mm, and minimum temperatures were typically >15 °C. These values coincide with the climate characteristics of coca-growing locations assessed in other parts of South America, such as Peru and Bolivia (USDOJ 1991, Bax and Francesconi 2018). We also observed that Central American coca overlapped at somewhat lower minimum temperatures than in Colombia and during cooler months and was found across a higher range of soil CEC. The differences in these

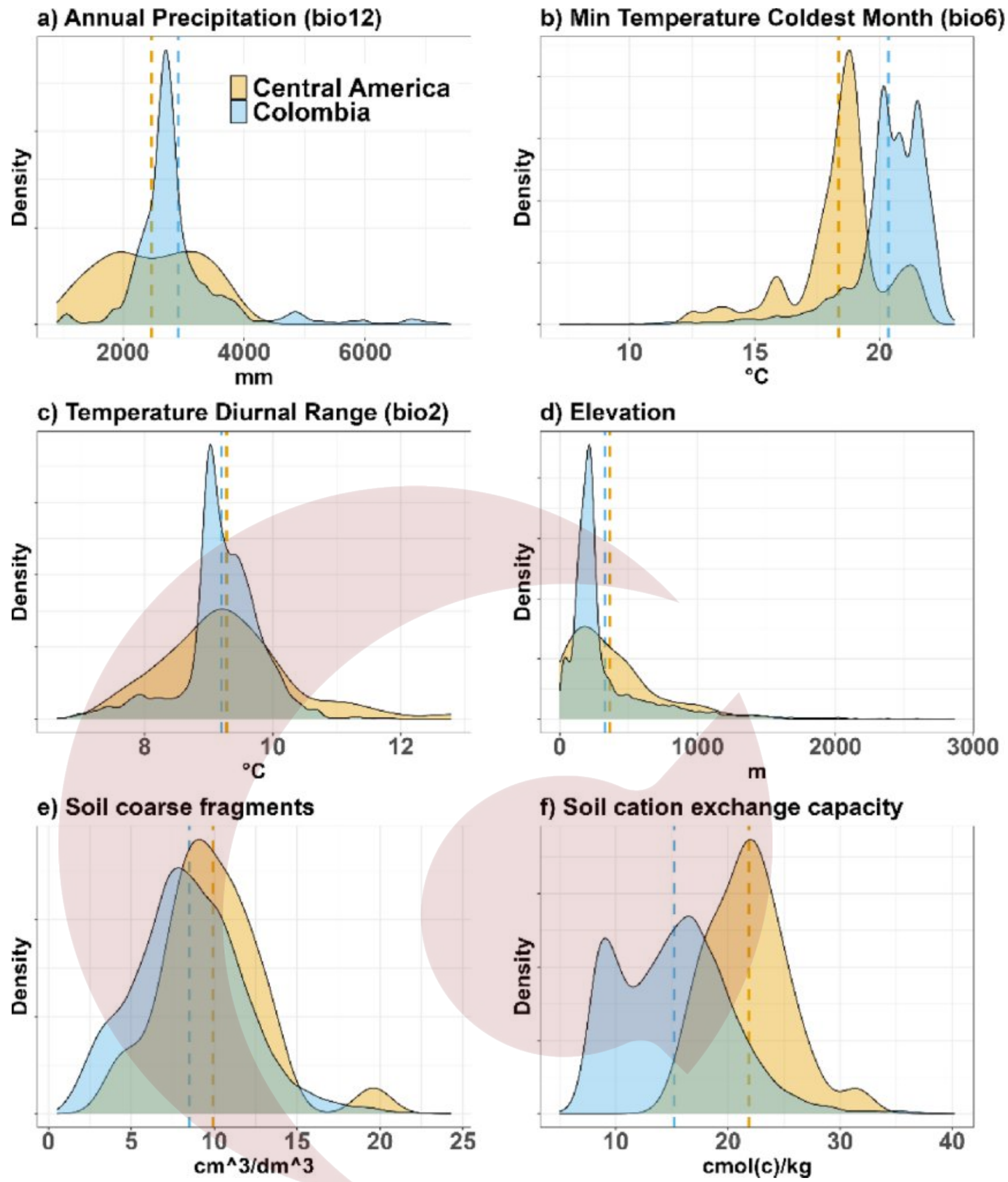

Figure 3. Density distribution of spatially explicit coca occurrences intersected with important environmental variables used in COM and CAM ensemble models, separating records from Central America and Colombia. Variables that either component or final ensemble models identified as important included: (a) annual precipitation, (b) minimum temperature of the coldest month, (c) mean annual temperature diurnal range, (d) elevation above sea-level, (e) soil coarse fragment content, and (f) soil cation exchange capacity. Colored vertical lines in each graph represent mean values for Central America (orange) and Colombia (light blue).

variables (minimum temperature values and soil CEC) between regions could account for differences in suitability predictions between COM and CAM models. We observed a higher range of CEC values for Central America (figure 3(f)) but from a relatively low number of occurrences ($n = 55$) compared to occurrences from Colombia ($n = 7721$)[10].

We performed a post-hoc assessment of Colombian and Central American occurrence records comparing environmental variables using non-metric multidimensional scaling (NMDS) and permutational multivariate analysis of variance (Permanova) assessing

[10] Broadscale soil classifications where coca occurs in both regions were similar for soil groups such as Acrisols, Ferralsols and Cambisols. These are generally acidic and highly leached low-fertility soils, but the two latter soil types are particularly rich in iron oxides, which are important for coca production (USDOJ 1991, Bax and Francesconi 2018) but, depending on soil pH, can limit coca productivity in acid soils (Johnson and Foy 1996).

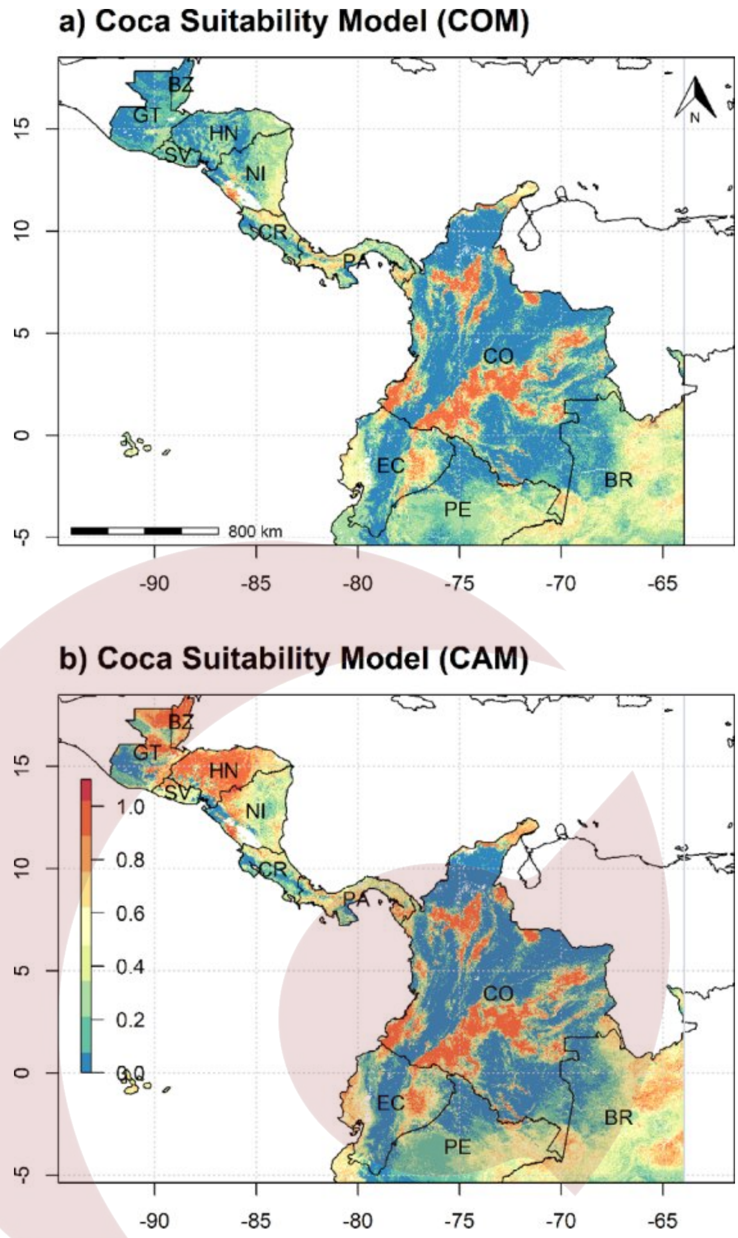

Figure 4. Mapped predictions for coca agro-suitability from (a) COM and (b) CAM model ensembles with the locations of coca occurrences for Central America only ($n = 55$). Countries in white were excluded from analysis. The warmer the color (towards red) the higher the modeled suitability for coca cultivation.

overall differences (appendix B). NMDS ordination indicated high overlap between Central and South American coca occurrences according to Bray–Curtis similarity but were significantly different from one another. This was likely because of soil differences observed for coca plantations in both Honduras and Guatemala, but also warmer and wetter equatorial conditions for many coca plantations in Colombia (see appendix B, figure B4).

While ensemble model performances were nearly identical, environmental differences in soil and climate conditions showed strong differences in mapped agro-suitability for coca, with the COM model showing lower suitability for Central America (figures 4(a) and (b)). Not surprisingly, the addition of Central American coca occurrences to the models greatly increased the area determined to be suitable for coca in countries in that region. Coca suitability showed the greatest increase in countries in northern Central America (Honduras, Guatemala, El Salvador, and Belize) (figures 5(a) and (b)). Honduras (mean increase $= 0.60 \pm 0.26$) and Belize (mean increase $= 0.62 \pm 0.23$) showed the greatest overall increases in suitability under the CAM model. Countries to the south of Honduras showed a low to moderate increase in coca suitability, with negligible change for Colombia (mean increase $= 0.006 \pm 0.11$).

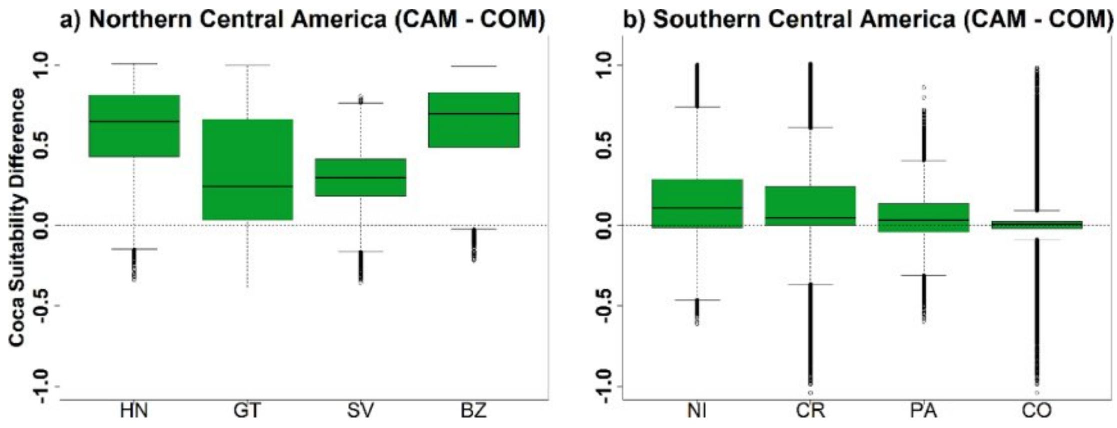

Figure 5. Boxplots of the difference in coca agro-suitability from model ensembles subtracting COM from CAM predicted values, divided into countries from (a) northern Central America (Honduras, Guatemala, El Salvador, Belize) and (b) southern Central America (Nicaragua, Costa Rica, Panama) plus Colombia.

For evaluating differences between the two models and suitability by country, we set a conservatively high coca suitability threshold of >75%. These values were more than one standard deviation above mean suitability values for COM and CAM models, which represented 6.2% and 15.3% of mapped values respectively. Overall, landscapes with ideal biophysical conditions for growing coca were, logically, the most extensive for Colombia for COM models (figures 4(a) and (b)). CAM model predictions highlighted both Honduras and Guatemala as having large areas potentially suitable for coca production that were represented by 64% ($n = 35$) and 31% ($n = 17$) of the coca occurrences in the training and validation sample data, respectively. Belize had no occurrence records but had approximately 60% of its land area predicted as highly suited for coca cultivation from the CAM model (figure 4(c))[11]. In total land area, Honduras and Guatemala had the largest area of suitable lands for coca production according to the CAM model (figure 6(d))—both more than 60% of the countries' total area.

4. Discussion

Our research concerns a 'severely understudied crop' (White *et al* 2021) which cannot be readily investigated *in situ* (criminal groups control production areas). Our methods rely on media reports and derived land cover products from satellite imagery. We find that while southern Central America is not agro-ecologically well-suited to coca cultivation, extensive portions (47% or 127 278 km^2) of northern Central America show high modeled suitability ($\geqslant$0.75) for the cultivation of the same coca varieties that are grown in Colombia, assuming standard crop management practices. The latitudinal and altitudinal gradients of Honduras, Belize and Guatemala appear particularly analogous to the altitudinal diversity of Colombia's coca cultivation zones, although their soil conditions tend towards the upper limit of coca-ready Colombian soils, suggesting coca's ability to adapt to novel environments outside of Colombia (appendix B; figure B3; cf Casale and Mallette 2016).

4.1. Land cover contexts of current coca cultivation

In Central America, only Guatemala and Honduras had sufficient locations to assess the land cover context proximate to coca cultivation sites, which was primarily a matrix of tree cover and likely pasture cleared from forest. Overall, it appears that, as in Colombia, coca production in northern Central America is near or within forest frontiers, where it is likely synergistic with processes associated with the (illegal) conversion of forest to cattle pasture (Armenteras *et al* 2013, Murillo Sandoval 2023, Murillo Sandoval *et al* 2023). More research is needed to better understand the Central American landcovers most vulnerable to conversion for coca in the future.

4.2. Agro-ecological suitability models

Our ensemble models performed well. Both COM and CAM models were based on coca distributions in Colombia from SIMCI's 1999–2008 maps. We found that the agro-ecological conditions that our model predicted as suitable for coca did in fact strongly overlap with coca growing regions mapped in previous studies (UNODC 2005, Mallette *et al* 2016). Moreover, our models also indicated highly suitable environments outside of the region sampled by SIMCI, including areas into which coca has since expanded (see CRS 2017, UNODC-SIMCI 2022).

We also found that our ensemble model approach enhanced performance and mapped suitability assessments above that of individual ML models

[11] Since we conducted our analysis, a half-million coca plants were discovered in southern Belize in an area that our analysis identified as highly suitable.

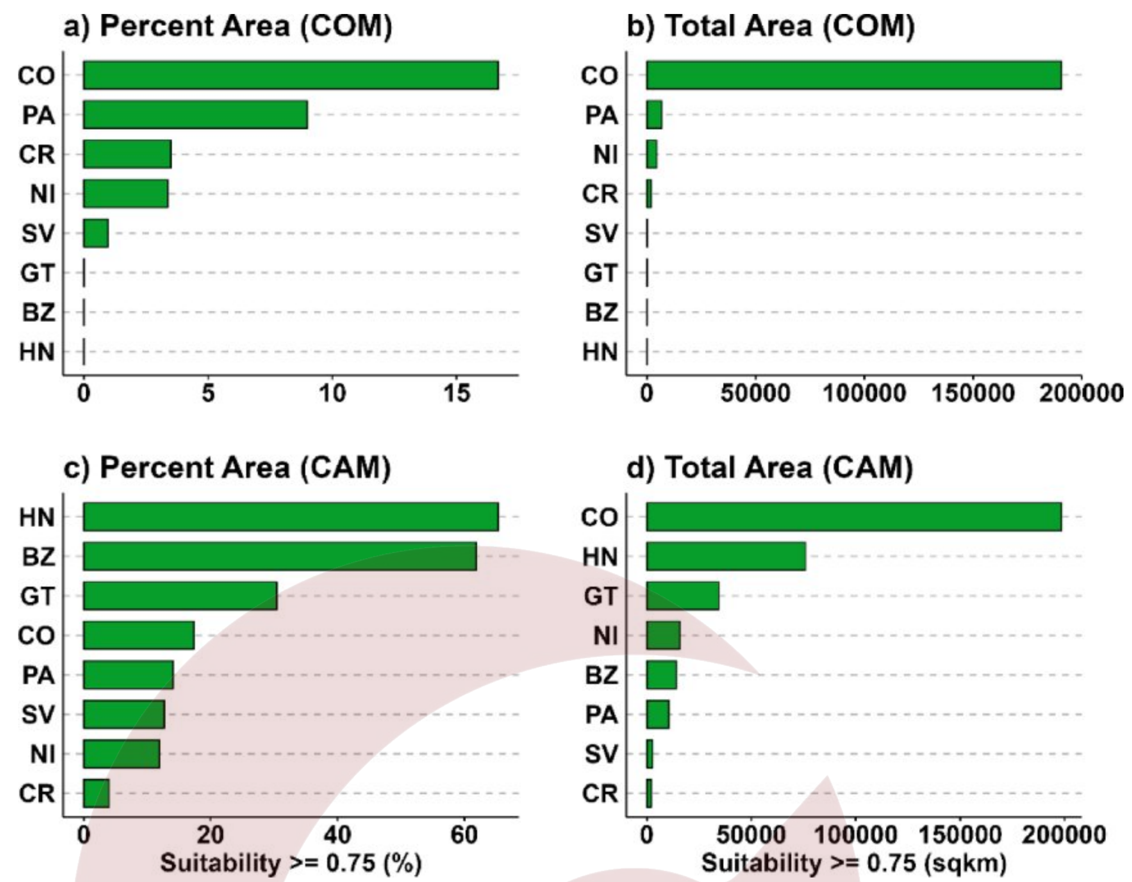

Figure 6. Country-by-country comparison of high coca suitability ($\geqslant 0.75$) areas according to the (a) COM percent area, (b) COM total area, (c) CAM percent area, (d) CAM total area. Country abbreviations are CO = Colombia, PA = Panama, CR = Costa Rica, NI = Nicaragua, SV = El Salvador, GT = Guatemala, BZ = Belize, HN = Honduras.

(appendix B). Araujo and New (2007) found that individual ML approaches can increase tuning and computation time and have the potential to overfit data, while Hao *et al* (2020) suggest that combined models may not always show appreciable gains, and that samples external to model development should be used to assess performance. We found we could produce a superior model by limiting model tuning by combining robust boosting and bagging techniques. Indeed, we observed that individual models performed well, which likely contributed to improved overall ensemble performance according to validation samples held out from modeling (appendix B, table B1). This was also reflected in 10-fold cross validation statistics from model training where the best individual COM model (RF) showed lower goodness fit ($R^2 = 0.69$) and greater error (RMSE = 0.283) compared to the ensemble model ($R^2 = 0.72$, RMSE = 0.266). This was also the case for the CAM model (appendix B, table B2).

Other factors may limit our agro-ecological model's capacity to predict the suitability of locations beyond Colombia. Despite the similarities we found between Colombian and Central American bioclimatic conditions, our addition of Central American occurrence locations to the models greatly increased the area of higher suitability predictions. This is partly the result of the imbalance in sample sizes, combined with the fact that the CAM model has limited representation of environmental conditions where coca is currently grown but which to date have avoided eradication (Robbins 2022). In this, our experience is analogous to modeling the potential distribution of invasive species or other novel agricultural crops, which is limited when realized niche factors have low environmental representation from occurrence data obtained (Gallien *et al* 2010). We also lack data on the *Erythroxylum* varieties planted in Central America, and the Colombian data only captured the extent of *Erythroxylum* varieties grown there until 2008. Given that new varieties have been developed in Colombia since, some of which are likely being grown in Central America, our results should be considered a conservative estimate of the isthmus' biophysical capacity to support coca cultivation for cocaine production (see also Ehleringer *et al* 2000).

4.3. Research and policy implications

4.3.1. If biophysical factors are not limiting for coca expansion in northern Central America, what is?

The total area planted in coca in northern Central America is currently tiny compared to South

American coca acreage. While this study suggests that any future expansion of coca growing in the region is unlikely to be constrained by biophysical factors, much further research is required to model the range of social, economic, or political factors that might do so. What is clear, however, is that the geography of coca expansion is very likely to be shaped by the degree to which Guatemala, Honduras, and Belizean governments pursue crop eradication and cocaine interdiction as their primary approaches to cocaine markets, rather than alternatives (see Ciro *et al* 2024). Both strategies, long endorsed and financed by the U.S., have been repeatedly shown to spread illicit coca crop production and cocaine trafficking more widely, not contain it (the 'balloon effect'). On the other hand, suspension of those strategies could stymie the crop's spread and stabilize production areas, with associated social and ecological benefits (Garzón Vergara 2016). Studies in Peru and Bolivia, for example, have found that in the absence of large-scale, intensive eradication campaigns (such as those implemented in Colombia), coca cultivation areas have remained relatively static and concentrated (UNODC 2022).

4.3.2. South America's long monopoly on coca production for the international cocaine market is over

The cessation of Colombia's internal armed conflict in 2016 initiated major re-arrangement of coca production geographies within and beyond Colombia. President Duque's government (2018–2022) invested in forced coca eradication, with little support for coca-growing families seeking alternatives. Combined with the exit of guerilla groups from their long dominance of the coca business, new local and foreign actors have reconfigured it. The development of Central American coca seems to be an extension of these processes and is particularly notable as the first 'leap' of sustained coca cultivation beyond South America in the past 60+ years.

However, coca beyond South America is not new. Through the 1910s, the bulk of the world's cocaine came from legal coca cultivated by Dutch companies in what is now the Indonesian island of Java, and up until the 1930s, other colonial powers sowed coca in Taiwan, Sri Lanka, India, Africa and the Caribbean (Karch 2003, Bosman 2012, Van der Hoogte and Pieters 2013). Given this, what is surprising from a historical perspective is the mid-20th century *retraction* of coca cultivation to South America. Much about this process remains obscure, including how commercial coca cultivation was so effectively eradicated around the world, for so long. For other illicit crops, such as opium poppy and cannabis, the norm has been sustained global expansion, even under aggressive counternarcotics regimes. Coca plantations in Central America draw attention to this history and the many questions that it raises.

4.3.3. Colombian coca farmers have diversified and improved an already generalist crop. Central America's marginalized farmers are primed to adopt it

In Colombia, coca farmers have developed at least 34 cultivars of *Erythroxylum* spp., many with high alkaloid content (Galindo Bonilla and Fernández-Alonso 2010, White *et al* 2021). That agronomic innovation has created a diverse source of planting stock that is likely to do well under a host of conditions—in Central America and elsewhere.

However, to date it does not appear that Central American smallholders are individually investing in coca production. How long this will endure is an open question. Across Central America, *campesino* and indigenous smallholders are in crisis due to, inter alia, hostile social and trade policies that exacerbate pre-existing land inequality, land tenure insecurity, rural underemployment, and labor migration, all of which are compounded by the effects of climate change (Penel *et al* 2023). Under these conditions, it is reasonable to assume that marginalized small farmers might be desperate enough—or vulnerable enough to be coerced into—coca-growing, as has occurred in some areas with cannabis and opium poppy (Anon 2019, Rodríguez 2021, Casas 2022, Penel *et al* 2023). As is well-demonstrated in other contexts, for the marginalized rural poor scraping by under highly adverse conditions, growing prohibited plants can be an economic lifeline that is even worth the risk of violent repression (Gutierrez 2020, Kay 2022).

5. Conclusion

This work provides a first description and analysis of the nascent expansion of coca production in Central America, a region that until recently had functioned only as 'transit zone' in the cocaine supply chain.

Our analysis does not *predict* that illicit coca cultivation will extend into all or even some of the Central American landscapes that our models indicate to be currently agro-ecologically suitable for it. In fact, our hope is that this analytical exercise will inspire drug policy analysts and policymakers across the hemisphere to seriously and urgently consider policy and law-enforcement approaches that would *not* encourage this outcome—i.e. anything *but* the ongoing adherence to orthodox supply-side approaches (see, e.g. Ciro *et al* 2024).

Towards that end, future research should disentangle how coca cultivation in northern Central America is influenced by the drug war-driven 'balloon effect' relative to the ongoing decentralization and diversification of economic power among key players in the transnational cocaine supply chain. Both dynamics are responses to orthodox supply-side counternarcotic approaches (primarily crop eradication and the interception of cocaine exports by the U.S. and its partner nations). As long as these *status* *quo* approaches continue, they will perpetuate a predictable and violent dynamic: increasing profits for organized criminal groups, ongoing spatial expansion of cocaine production and trafficking, and the continued spread of associated violence and corruption. As promising global initiatives are seeking to dismantle parts of this prohibitionary drug regime (see, e.g. Llanes *et al* 2023, Ciro *et al* 2024), understanding how those reforms might influence where and by whom drug crops are grown becomes an increasingly urgent science need.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://heima.ua.edu/data.html. Data will be available from 01 January 2027.

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Appendix A

Individual and ensemble model development, also described in Sesnie *et al* (2023), is briefly outlined here because explanatory and response variables differ from previous work.

Model ensembles can be advantageous by combining separate and distinctly different ML approaches without extensive model tuning that can reduce overfitting and help make generalize predictions (Civantos-Gómez *et al* 2021). That is, we used a set of four component ML models that were tuned using default parameters and ultimately combined into a single meta-model or 'ensemble' (ENS) for prediction. We applied a standard gradient-boosted regression tree model (GBM) in addition to extreme gradient regression trees (XGBT) and extreme gradient boosted linear models (XGBL). We used random forest (RF) regression trees, which apply a 'bagging' approach and are known to perform well with a variety of data sets (Breiman 2001). Each selected component model was developed independently and then combined using a gradient-boosted model with the 'caretStack' function in the caretEnsemble package v. 2.0.2 (Deane-Mayer and Knowles 2019) for R statistical software v. 4.3.1 (R Core Team 2023). Therefore, each model, weighted according to performance, contributed to COM and CAM model prediction probability. Model performance was assessed using 10-fold cross validation during model training.

Prior to ML and ensemble model development, we used recursive feature elimination (RFE), a backwards variable selection technique using RF functions ("rfFuncs), to retain a subset of explanatory variables that contributed most to model prediction (Bazi and Melgani 2006). We used the point at which a minimum RMSE was reached for optimized variable selection. RFE and base ML models were developed using the 'caret' package v. 6.0–94 for R statistical software (Kuhn 2008). We used permutational variable importance and partial dependence plots to interpret explanatory variables contributing to coca suitability model predictions using the DALEX package v. 2.4.3 (Biecek 2018) for R. Trained models were assessed using independent validation data. A 30% partition of each COM ($n = 4614$) and CAM ($n = 4490$) data set was held out of model training for independent validation, using the receiver operating characteristic and AUC to assess the true versus false positive rate of each model. AUC values close to 0.80 were considered good model performance (Komac *et al* 2016). AUC values close to 0.50 were considered poor performance and model predictions that are no better than chance. In the main text, we have limited our performance reporting to AUC using independent validation data, and root mean squared error, mean absolute error and R^2 values using 10-fold cross validation during model training. Further model performance evaluations are reported in appendix B.

Appendix B

Agro-suitability model validation and statistical evaluations for COM (Colombia coca occurrence data only) and CAM (Colombia and Central American coca occurrence data combined) models.

1. Supplementary individual and ensemble model validation statistics were used to assess performance based on independent validation samples (table B1). In general, we considered models with >0.80 area under the receiver operator characteristic curve (AUC) and a Sorensen's Similarity Index (SOR) > 0.60 to have sufficiently good performance (Komac *et al* 2016, Leroy *et al* 2018, Konowalik and Nosol 2021). All individual models used in the ensemble met these criteria, with the COM and CAM ensemble models showing as good or better performance than individual models in each case (table B1). ML and model ensemble training performance

Table B1. Ensemble model performance statistics evaluated from independent validation data (30%, $n = 4490$). Abbreviations are ENS = ensemble model, PCC = percent classified correct, AUC = area under the ROC curve, SN = Sensitivity, SP = Specificity, TSS = True skill statistic, JAC = Jaccard Similarity, SOR = Sorensen's Similarity, OPR = over prediction rate, UPR = under prediction rate (see descriptions below).

Name	Model	Threshold	PCC	AUC	SN	SP	Kappa	TSS	JAC	SOR	OPR	UPR	Observed Prevalence	Predicted Prevalence
COM	**ENS**	**0.50**	**0.83**	**0.89**	**0.89**	**0.76**	**0.65**	**0.65**	**0.72**	**0.84**	**0.11**	**0.21**	**0.5**	**0.57**
COM	RF	0.50	0.83	0.89	0.88	0.77	0.65	0.65	0.72	0.84	0.12	0.20	0.5	0.56
COM	XGBL	0.50	0.81	0.87	0.87	0.74	0.61	0.61	0.69	0.82	0.13	0.22	0.5	0.57
COM	XGBT	0.50	0.80	0.87	0.86	0.74	0.61	0.61	0.69	0.82	0.14	0.22	0.5	0.56
COM	GBM	0.50	0.79	0.85	0.85	0.73	0.57	0.57	0.67	0.80	0.15	0.24	0.5	0.56
CAM	**ENS**	**0.50**	**0.90**	**0.96**	**0.91**	**0.89**	**0.80**	**0.80**	**0.82**	**0.90**	**0.09**	**0.10**	**0.51**	**0.52**
CAM	RF	0.50	0.89	0.96	0.92	0.87	0.79	0.79	0.82	0.90	0.08	0.12	0.51	0.54
CAM	XGBL	0.50	0.88	0.94	0.91	0.85	0.76	0.76	0.80	0.89	0.09	0.13	0.51	0.54
CAM	XGBT	0.50	0.89	0.95	0.91	0.86	0.77	0.77	0.80	0.89	0.09	0.13	0.51	0.54
CAM	GBM	0.50	0.85	0.92	0.88	0.81	0.69	0.69	0.74	0.85	0.12	0.17	0.51	0.54

Performance variable descriptions: Threshold = threshold model prediction used to estimate true positive (TP), false positive (FP), true negative (TN), and false negative (FN) validation samples. Observed positive samples (P) = 1 and negative samples (N) = 0.

PCC = Percent correctly classified, TP + TN/P + N

Sn = TP/N

Sp = FP/N

Kappa = Kappa statistic

TSS = Sn

JAC = TP/(FN + TP + FP)

SOR = 2FP/(FN + 2TP + FP)

OPR = FP/(TP + FP)

UPR = FN/TP + FN

Prevalence = Frequency of occurrences.

Table B2. Model training performance statistics using 70% of the sample data and 10-fold cross validation for model ensembles and contributing models indicating the best performing model with lower error and greatest model fit were for COM and CAM ensemble models. Model abbreviations are extreme gradient boosted regression trees (XGBT), random forests (RF), extreme gradient boosted linear model (XGBL), gradient boosted regression trees (GBM) and the ensemble model (ENS) used for predictions in grey and bold that was developed using gradient boosted regression trees.

Model	Model Name	RMSE[a]	MAE[b]	R2[c]
XGBT	COM	0.307	0.219	0.624
RF	COM	0.283	0.198	0.689
XGBL	COM	0.297	0.206	0.649
GBM	COM	0.338	0.261	0.545
ENS	**COM**	**0.266**	**0.145**	**0.717**
XGBT	CAM	0.305	0.217	0.629
RF	CAM	0.286	0.200	0.681
XGBL	CAM	0.307	0.210	0.624
GBM	CAM	0.339	0.262	0.545
ENS	**CAM**	**0.271**	**0.147**	**0.706**

[a] Root mean squared error.
[b] Mean absolute error.
[c] Coefficient of determination.

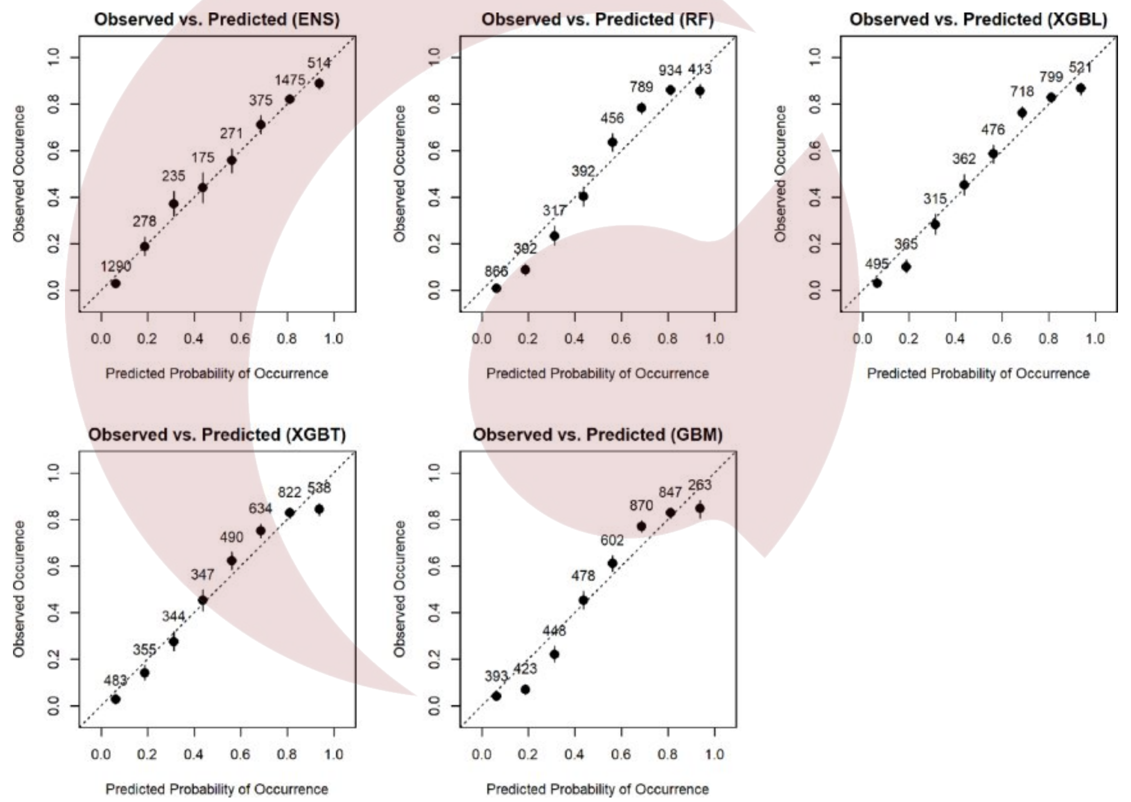

Figure B1. Individual and ensemble COM model comparisons for predicted versus observed coca agro-ecological suitability values using validation samples held out of model development ($n = 4{,}614$) that were 30% of all samples. Plots are grouped into 8 bins according to their predicted values and compared to binned 'prevalence' which is the ratio of presence plots in each bin versus the total number of plots in a bin. Confidence intervals (alpha = 0.5) were calculated for the binomial counts using the F-distribution. The dashed diagonal line indicates perfect agreement between observed and predicted probability of occurrence for validation data.

was also evaluated from 10-fold cross validation that showed good model performance by each individual model, but enhanced performance for COM and CAM ensemble models that had lower model error and greater goodness of fit (table B2). Additional goodness of fit plots with validation data also indicated improved ensemble predictions over that of individual models (figures B1 and B2). All performance measures were evaluated using the 'PresenceAbsense' package v. 1.1.11 (Freeman and Moisen 2008) for R Statistical Software (R Core Team 2023). Important variables assess using the DALEX R package v. 2.4.3 for all ML approaches applied

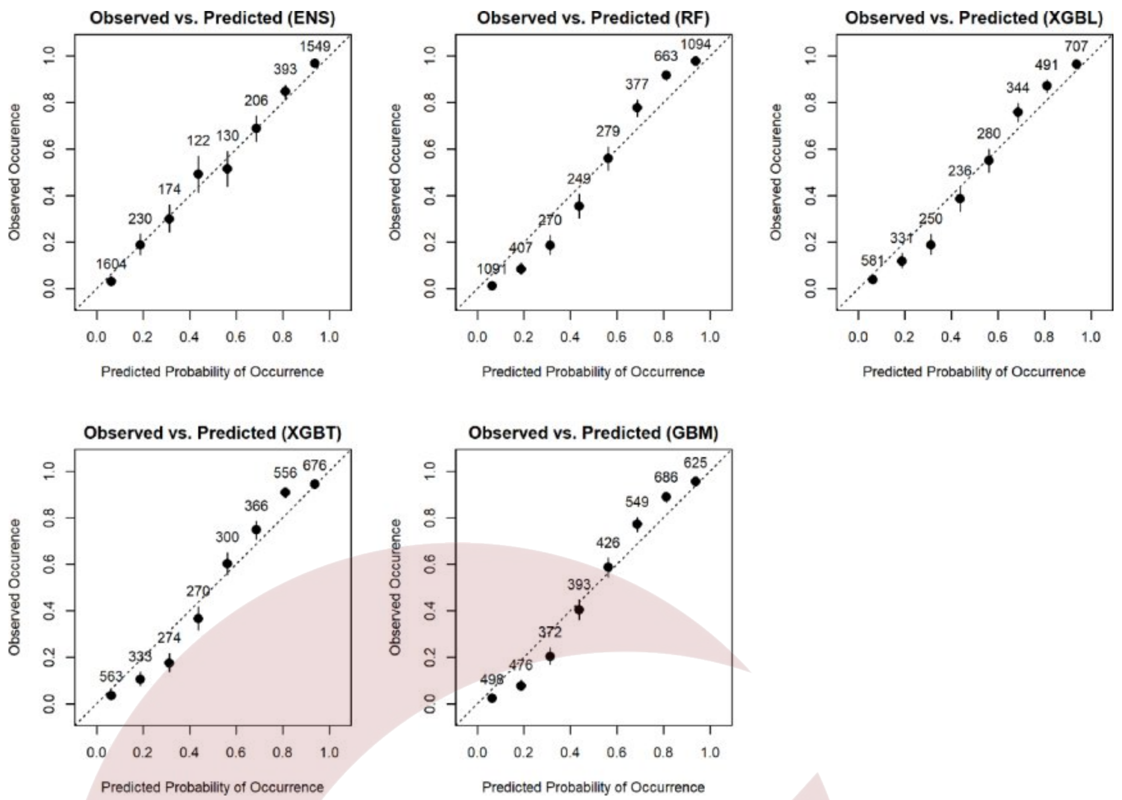

Figure B2. Individual and ensemble CAM model comparisons for predicted versus observed coca agro-ecological suitability values using validation samples held out of model development ($n = 4490$) that were 30% of all samples. Plots are grouped into 8 bins according to their predicted values and compared to binned 'prevalence' which is the ratio of presence plots in each bin versus the total number of plots in a bin. Confidence intervals (alpha = 0.5) were calculated for the binomial counts using the F-distribution. The dashed diagonal line indicates perfect agreement between observed and predicted probability of occurrence for validation data.

and both COM and CAM models are shown in figure B3.

2. Important variables assessed using the DALEX R package v. 2.4.3 for all ML approaches applied and both COM and CAM models are shown in figure B2.
3. NMDS and permutational multivariate analysis of variance (Permanova) showed agroecological similarities and differences for coca grown in Colombia and Central America (figure B4). A random sample of $n = 1000$ Colombian coca occurrences was used for this comparison with Honduran and Guatemalan coca occurrences. The 'vegan' package v. 2.6–4 for R statistical software was use for these analyses (Oksanen *et al* 2022) using Bray-Curtis similarity for each comparison. A two-dimensional NMDS solution was reached after 20 tries with a stress factor of 0.1098903. Permanova was performed by grouping Honduras and Guatemala occurrences together and comparing them with Colombia environmental data that showed a significant difference between the two regions ($A = 0.07725$, $p = 0.001$) after 999 permutations where A is the chance corrected within-group agreement statistic. A small number of occurrence records for Honduras showing a higher percent volume of coarse soil grain sizes (particle size >0.075 mm) as well as bio2 (mean temperature diurnal range = mean of monthly(max temp—min temp) may account for significant differences observed between Central and South American coca occurrences.

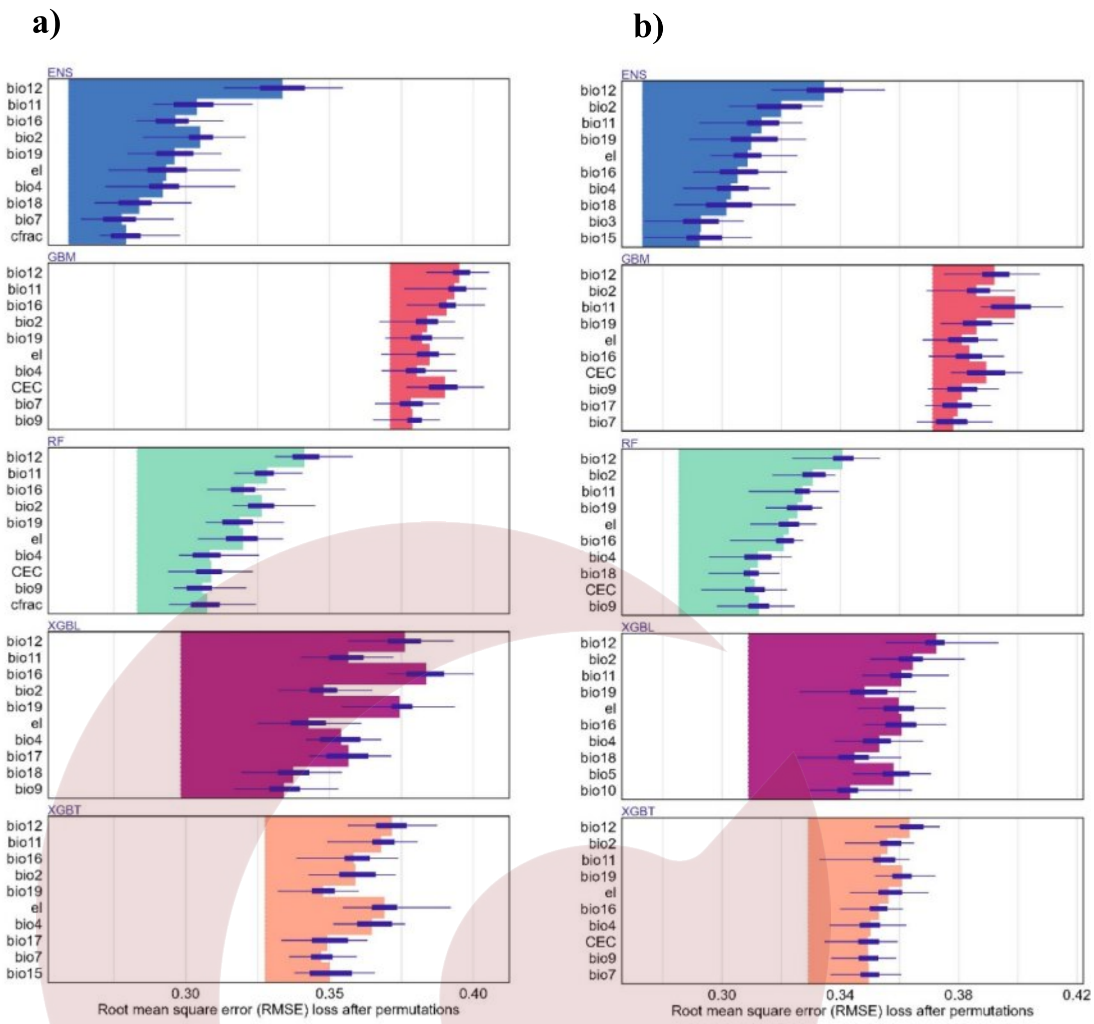

Figure B3. Variable importance plots for all ML ensemble (a) COM and (b) CAM models using the increase in root mean squared error with a variable removed as a measure of its importance from 25 separate iterations. Spatial predictions and reporting of results in the main text are from Ensemble models only. Predictor variable abbreviations are given in table 1 of the main text.

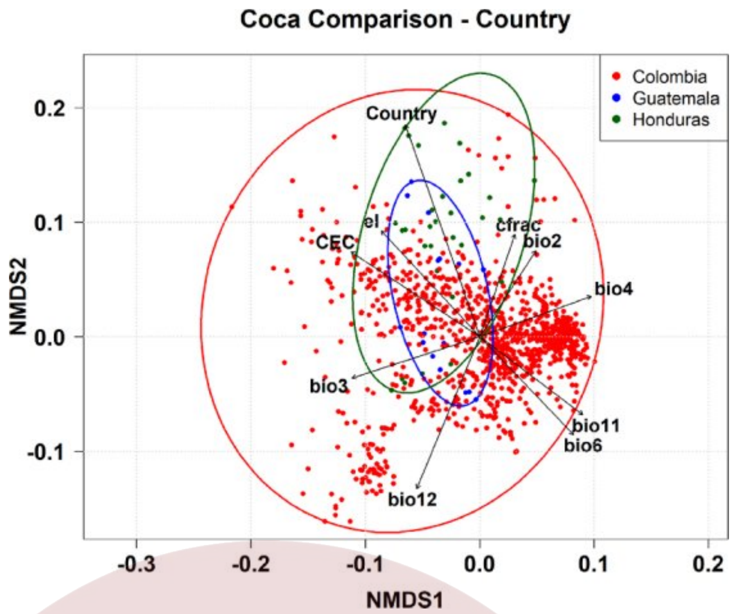

Figure B4. NMDS plot indicating the distribution of coca occurrences according to environmental variables used for estimating agro-ecological suitability with the CAM model. Only Guatemala and Honduras occurrences were used to represent Central American Environmental data. Occurrence data from each country was encompassed by an ellipse, fitting environmental data to each ordination axis. We retained only the environmental variables at the $p \leqslant 0.001$ significance level represented by vectors showing the direction and magnitude of each one. Predictor variable abbreviations are given in table 1 of the main text.

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