Coca Cultivation After the Colombia-FARC Peace Agreement

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Introduction

Rebel group's illicit drug economy has been considered as a major factor that prolongs the conflict duration, worsens the violence, and complicates the peace negotiation (Bhatia 2021; Cornell 2005; Fearon 2004; Lujala 2009). However, it is yet unclear how the rebel's illicit drug economy plays a role *after* the post-peace agreement period. If a peace agreement fails to address rebel's illicit economies adequately, the rebel groups may easily re-mobilize and hamper settling the peace in the long run.

For this reason, this paper examines how a rebel's illicit drug economy affects the implementation of the peace agreement. Particularly, this paper examines how the Colombia's 2016 peace agreement and subsequent power-sharing with the rebel group FARC (The Revolutionary Armed Forces of Colombia—People's Army) affected coca cultivation in the territory once controlled by the FARC and nationally. We argue that signing a peace-agreement and power-sharing with rebel groups that are heavily dependent on illicit drug production ironically enlarges the drug productions which may promotes a war recurrence. This is because the incentive from the peace agreement and power-sharing disproportionately benefit members, which leads non-elites to continue seeking money from drug cultivation. It is also possible that other rebel groups may take up drug cultivation when the absence of the major rebel group is absent. In this paper, we explore the relationship between 2016 peace agreement in Colombia and the amount of coca cultivation, using panel data collected from satellite images.

A second aim of this paper is to evaluate satellite images as a mechanism for drug enforcement or detection. Agricultural land use has been a traditional research topic for social scientists using the satellite images since the first National Aeronautics and Space Administration (NASA)/US Geological Survey (USGS)'s Landsat satellite launch in 1972. Particularly, scholars use satellite image to measure the size of agricultural output and to identify the types of crop (Farmaha et al. 2016; Kudamatsu et al. 2012). NASA/USGS's Landsat and European Space Agency (ESA)'s Sentinel publicly provide petabytes of data with 10–30m spatial resolution, multiple spectral information in visible-to-thermal and microwave wavelengths, with 3–5 days to biweekly revisit frequency (Song et al. 2021). Moreover, the development of image classification algorithms, including convolutional neural networks and deep learning, has dramatically improved crop classification accuracy (Inglada et al. 2015). Saddler (1990) and Chuinsiri et al. (1997) pioneered applying the method to detect cannabis growth in Afghanistan and Thailand. In 1999, UNODC's illicit crop monitoring program adopted satellite imagery to oversee coca and poppy production, and other institutions like European Commission followed. For instance, Pesaresi (2008) shared coca detection results using ikonos satellite 1m resolution data with UNODC on behalf of the European Commission. Afghan Ministry of Counter Narcotics also cooperated with UNODC to detect and react cannabis production (Kelly and Kelly 2014). Building upon this strand of research, this paper suggests that satellite imagery can provide comprehensive, (near-) real-time, low-cost data on illicit drug production, and thus can be potentially utilized in conflict studies.

Literature Review and Theory: Illicit Drugs and Peace Agreements

The illicit drug economy has emerged as a major factor that can exacerbate violence, complicate peace negotiations, and corrupt transitions from war to peace (Bhatia 2021). Several studies explored the impacts of drugs on conflict duration (Cornell 2005; Fearon 2004; Jonsson et al. 2016), intensity (Lujala 2009), rebel recruitment (Gates 2002; Weinstein 2006), and conflict initiation (Fjelde and Nilsson 2012; Ross 2003). Illicit drugs are especially important in conflicts because they tend to prolong the duration of conflicts and prevent successful peace-building (Cornell 2005; Fearon 2004). Being an illicit good with strong demand, high-profit margins, limited barriers to entry, and few interdiction opportunities, drugs creates war economies that benefit rebel groups, making them reluctant to engage in peace negotiations (Jonsson et al. 2016).

While the existing studies clearly show how the illicit drug market worsens the conflicts and complicates the peace agreement process, it is yet unclear how the pre-existing illicit drug market plays a role in the post-peace agreement period. If a peace agreement fails to adequately address illicit economies by rebel groups, it means that the rebel groups can easily re-mobilize and harm successful peace-building in the long term. For this reason, this paper aims to fill the gap by examining how the Colombia's 2016 peace agreement and subsequent power-sharing with the rebel group FARC affected rebel group's illicit drug cultivation–particularly the coca production which has been the main monetary source of the FARC for the last decades. This paper does not try to make a prediction on conflict recurrence in Colombia, but theorizes how the pre-existing rebel's illicit drug cultivation plays a role in peace-building efforts. We also show how the satellite image can be a useful tool to evaluate the implementation of a peace agreement in conflict studies.

How do Peace Agreements Facilitate Drug Cultivation?

Building upon the existing literature, we argue that the power-sharing with a rebel group with illicit drug economy monetary source destabilize the peace effort by bringing a backlash: an expansion of drug production. In the Colombia's case, we argue that the peacemaking and power-sharing with the FARC would lead ex-rebel members to retain and even expand pre-possessed coca production.

There are four main factors that drive this result. First, the distribution of incentives from the peace agreement and power-sharing is heavily concentrated to rebel leaders. This concentration of rewards can lead the middle managers, who have "territorial control over demarcated zones but are of insufficient rank to be present in the peace negotiations" (Daly 2014), and other subordinates to sustain their monetary incentives from the existing illicit drug economy. They possess the highly specialized training and knowledge, operational and tactical experience, and the direct contact with and loyalty of the foot soldiers necessary to either remobilize or fully demilitarize the armed units. For example, Daly (2014) argues that the power-sharing arrangements in a peace agreement can cause a return to violence because the power-sharing only satisfies the top elites, while it does not provide much incentive to middle managers and subordinates that may re-mobilize. To maintain benefits of peace agreements and power-sharing, thus, rebel leaders have motives to provide incentives for the past members of rebel group. One of the easiest way to provide incentives is to allow the illicit drug production which had long been served as their crucial financial source. As illicit drugs tend to have constant high demand and create high-profit margins, it would be difficult for the rebel leader to completely eradicate this important monetary source for former members.

Second, former rebel leaders also have an incentive to earn public support for successful peace-building and the eradication of illicit drug economy is very unpopular among the residents. Illicit drug markets constitute one of the largest and most lucrative shares of worldwide illicit flows. The illicit drug economy not only provides positive economic benefits to rebel groups but also plays a significant role as a means for civilians affected by war to survive. Forced eradication policies may be deeply unpopular and potentially destabilizing (Bhatia 2021). Illicit drug cultivation indeed requires tight collaboration with the local civilians than mining any other resources (Lujala 2009, 54 - 55). In Colombia, where early indications suggest that attempts to displace the coca economy with alternative livelihoods as part of the peace agreement have been ineffective and poorly received (Eventon 2016).

Third, the power-sharing guarantees a certain level of political power to the ex-rebel groups, which might lead a country to adopt a less restrictive anti-drug policy. Considering the existing networks and connections between the ex-rebel politicians and former rebel members, we can expect that ex-rebel politicians may prefer favorable policies to their former members. Moreover, it is difficult to entirely rule out the possibility that the ex-rebel politicians would still receive financial backing from overlooking their former comrades' illicit activities. Even without this dirty money, the personal connection would still prevent them from fully committing to the drug eradication program. Connecting to the first reason, it would be hard to completely ignore the interests of middle managers or members of the former rebel groups. Thus, the middle managers and subordinates in the coca business would expect less risk to sustain the coca production.

Lastly, in the absence of the major rebel group after the peace agreement, other groups often take place. For example, Murillo-Sandoval et al. (2020) found that following the 2016 peace agreement and the withdrawal of FARC, key actors, including drug cartels, large landowners, Campesinos, and dissidents, swept into the region with expectations of favorable land tenure policies. This ultimately led to the increase in large-scale cattle ranching, coca cultivation dispersal, and speculative illegal land markets.

Drawing upon these factors, the power-sharing with the FARC would strengthen the coca production by providing a *de facto* guarantee to the FARC middle managers and subordinates to maintain the coca business, and opportunities for other groups to join the industry. Therefore, we expect that after the peace agreement, the coca production will increase in the municipalities where FARC was present.

Hypothesis 1 *The amount of coca production would have increased after the the Colombia-FARC peace agreement.*

Research Design

To examine whether the peace agreement promotes more coca production in the areas where the coca production was led by the FARC rebel group, we first categorize the coca cultivation regions into two: regions under the FARC's control and those not. We expect to see that the coca production in the FARC's region increased after the signing the 2016 peace agreement, while the impact of the peace agreement on the coca production is less in the region that was free from the FARC control.

Colombian peace agreement with FARC

On 24 November 2016, the Colombian government and FARC signed the Final Accord for the Termination of the Conflict and the Construction of a Stable and Durable Peace. The agreement contains six key agenda items, which include solutions to illicit drugs. The Peace Agreement also provides implementation mechanisms that support the insurgency's formal transition from armed group to political party (Phelan 2019, 836). Thus, our main focus would be the amount of coca production after the 2016 peace agreement. Our research design accomplishes two aims: first, we will compare the overall coca cultivation between areas coded as FARC-controlled or not from 2002 to 2019; second, we compare the results of the satellite-generated coca production data and see if they follow trends reported from Colombia by separate NGOs to assess the accuracy of and potential for such generated data. We trace the change in the amount of coca cultivation by Colombian municipality and see whether the peace agreement has a different effect on the amount of coca production in formerly FARC-controlled (after the agreement) and non-controlled municipality.

Coca cultivation

The response variable is the hectares cultivated with coca. This data provides information on the hectares cultivated with coca by municipality, and covers from 1993 to 2019. In this paper, we will only focus on the period from 2002 to 2019, due to the availability of FARC data, which will be explained below.

FARC presence

For the measure of FARC presence, we use the dummy variable created by Prem et al. (2020), originally compiled by Restrepo et al. (2003), and updated by Universidad del Rosario. They created the database using events listed in the periodicals *Justicia y Paz* and *Noche y Niebla* published quarterly by the Colombian NGO'S *CINEP* and the *Comisión Intercongregacional de Justicia y Paz*. These publications present a detailed description of chronologically ordered violent events in Colombia, including date of occurrence, geographical location and the group, groups, or victims (Restrepo et al. 2003, 403). Prem et al. (2020) created a dummy for FARC presence if there was at least one event perpetrated by FARC.

Data

We use Prem et al. (2020)'s data to indicate the once FARC-controlled region at the municipality level. For coca cultivation information, we use data from satellite images originally collected as a part of the Integrated Illicit Crops Monitoring System (SIMCI) by the United Nations Office on Drugs and Crime (UNODC).

According to UNODC (2017), the dataset from coca monitoring in Colombia uses mid-resolution satellite image interpretation, and is validated with data obtained from aerial reconnaissance. More specifically, the data was collected from 274 Landsat 8 satellite images (LDCM). Sentinel-2 satellite images and 6 Worldview II were used for interpretation support. The acquired images cover the entire national territory (1, 142,000 km^2), except the islands of San Andres and Providencia. 70 percent of the study area was covered with satellite images obtained within the optimum range (two months before or two months after the cut-off date), according to established quality control parameters. This project uses the World Geodetic System (WGS 84) as a spatial reference framework, which was adopted in 1984. A mosaic was built for the whole country which is defined as the georeferencing base for each of the images.

Supervised learning needs 'ground truth' field data on crop types and land cover to train the model. Field data was collected by visual inspection from an aircraft on the territories affected by coca crops. A direct data collection system has been in place since 2014 for information obtained in the field, which relies on satellite images by way of a tablet synchronized with a wireless GPS antenna. The device creates a shapefile-type vector file, built by the expert during the overflight, and defines coca lot or zone, based on a list of previously defined attributes. Next section discusses how this data was produced by UNODC and the ways to improve data generation process.

Data Generation

Coca lot Identification

According to UNODC (2017), the preliminary visual interpretation included an analysis of the historical coca series and secondary information from various sources, such as geo-referenced photographs taken in overflights by the National Police, manual eradication data and information provided by different Government agencies and the United Nations System. Crop identification is not limited to verification in a single color composition, and the most widely used compositions on Landsat 8 are in RGB: 543, 547, 654, 562, and 743. Moreover, this data project had decision trees for interpretation support which have been developed by the University of Boku in several regions, which allows to reduce subjectivity and to document the process conducted by the interpreter to classify coca crop lots.

The information collected in the verification overflights was used to adjust the preliminary interpretation, taking into account the date of the images and the spraying or eradication operations. With the completion of this edition process, the coca crop interpretation file is obtained.

To improve the reliability and accuracy of data, several case studies were conducted from 2008. To obtain objective classes or spectral groupings present in scene, the average resolution image (Landsat 8) was taken as a base, and an unsupervised classification was applied with the Isodata method (Iterative Self-Organizing Data Analysis Technique). According to the input parameters established, this type of classification creates clusters or classes with sufficient spectral separability between them, and with as much inner homogeneity as possible. For "field truth", a Worldview II was obtained which provides high, 2 meters spatial resolution and medium spectral resolution with 6 bands in the visible spectrum and two in the infrared spectrum. Based on the this image and the objective interpretation of three experts, each of the sample points obtained was assigned to the corresponding class or coverage for their comparison with the map classified by each interpreter. Reliability was obtained based on the field truth sample, and class map obtained by each interpreter in the medium resolution image scene (Landsat 8). The results obtained report user accuracy above 80 percent and relative accuracy greater than 85 percent.

Increasing Traceability with Sentinel-2 data

Coca lot identification is based on the visual interpretation of satellite images supported by pictomorphological elements (tone, shape, texture, pattern), spectral behavior dynamics (traceability), geographic environment, specific characteristics of the area and the use of secondary information from various sources. Traceability of lots especially allows to follow the crop dynamics process through the use of satellite images in addition to those planned during the cutoff period, and enhances the reliability in interpretation. Moreover, images of the Sentinel-2 program were used to improve traceability of coca crops and to reduce the percentage of areas without information due to cloud covers.

The Sentinel-2A (launched in June 2015) and 2B (launched in March 2017) satellites have a combined revisit period of 5 days, making them suitable for drug monitoring. Sentinel-2's MultiSpectral Instrument (PSI) covers 13 spectral bands, including visible (red, green, blue), near-infrared, short-wave infrared bands, and bands used for the correction of atmospheric effects (e.g. coastal aerosol, water vapor, cirrus). Each band has different spatial resolution: four bands at 10 meters, six bands at 20 meters and three bands at 60 meters. Among these, four bands at 10 meters (bands 2-3-4 and 8) were mainly used for support. The Sentinel-2 images were used exclusively as support even though its generally better spatial resolution, revisit interval, and 6 additional multi-spectrum B-bands compared to Landsat 8. It is because the color compositions that can be obtained through Sentinel-2 provide spectral information with a spatial resolution of 20 meters, which is lower than that reached by Landsat 8. Moreover, Sentinel-2 does not have a panchromatic band.

Estimation of Annual Production and Permanence

The methodology for estimating the annual production of coca relies on existing information on hectares, yields per hectare, conversion factors of extraction and refining processes, etc. A new methodology of spatial analysis was developed that allows the estimation of the permanence of coca cultivation through the construction of a factor that allows to systematically incorporate the dynamics of the area and the available information on variables that directly affect stability, such as forced eradication, aerial spraying and plant coverages. These were not taken into consideration in traditional methodology.

The methodology of the permanence factor included spatial information (georeferencing) such as polygons of areas eradicated manually by mobile eradication groups, polygons of areas sprayed by the National Government's glyphosate aspersion program, data on coca crop censuses for each cut-off date since 2001, land coverage interpreted by satellite images since 2000, areas with no information because of clouds. The permanence factor ranges from 0 to 1, where 1 implies a productive batch throughout the year, while 0 implies a nonproductive lot.

In addition, given the increase in the sale of coca leaf, it's necessary to incorporate a differentiated conversion factor of the transformation with coca base. The conversion factor was estimated from the results obtained from 33 coca base processes. In sum, the estimation of the production of coca is as follows:

1. **Production of fresh coca leaf (PHC)** = Production area during $year_n$ X Annual yield of coca leaf $year_n$ (RAH)

2. **Production of coca base** = $PB_1 + PB_2 + PB_3$

where,

- **PB1** (Production of basic paste made at the UPAC (the agricultural units with coca) = PHC X Percentage of farmers processing basic paste X Basic paste yield per ton of coca leaf in UPAC (RPB) X Ratio/base coefficient (RBC/RPB)
- **PB2** (Production of coca base at the UPAC) = PHC X Percentage of growers who process coca base X Coca base yield per ton of coca leaf at UPAC (RB1)
- **PB3** (Production of coca base outside the UPAC) = PHC X Percentage of growers selling coca leaf X coca base yield per ton of coca leaf outside UPAC (RBe)
- **Production of pure cocaine hydrochloride** = PBC X Purity of caca base (P) X Conversion factor Base kg / Hydrochloride kg (RHCL)

How to Do Better: Image Classification using CNN

Although UNODC used traditional machine learning method (decision tree) to identify coca field, most studies now use Convolutional Neural Network (CNN) for crop type classification. Studies used CNN showed 94 to 99 percent accuracy, which is better than UNODC's 80 to 85 percent. This section discusses the way to improve accuracy using CNN.

A CNN is trained with images with known labels, and its accuracy is validated with another set of images with labels (Williams et al. 2020). In case of Kpienbaareh et al. (2021), seventy percent of ground truth data were used as training samples, and the remaining thirty percent were used for validation. Crop type is an attribute of images that CNN is trained to predict.

Various types of the Convolutional Neural Network and library can be used for crop type classification. Naushad et al. (2021) reviewed recent studies on land cover and crop classification with Sentinel-2 (EuroSAT) data. It showed that Geometry Group (VGG16, VGG19), Wide Residual Networks-50 (ResNet-50), and GoogleNet were widely used, although some built their models like the Deep Discriminative Representation Learning with Attention Map (Li and Chen 2020). Most models achieved 94 percent to 99 percent accuracy.

Thus, many studies used transfer learning (or fine-tuning). In Naushad et al. (2021), the final classification layers were replaced with fully connected and dropout layers. Several studies used Adam as the model optimizer instead of using the stochastic gradient descent, with categorical cross-entropy loss for loss calculation. ReLU and log-softmax activation functions were also widely used. In order to enhance performance, researchers often used data augmentation techniques such as horizontal flip, vertical flip, rotation, zoom, resizing, and Gaussian blurring. (However, they were often not very useful due to the uniformity of the Sentinel-2 dataset.) Early stopping and learning rate optimization techniques such as ReduceLROnPlateau were also widely used to prevent over-fitting. The batch size and epoch were much different among studies.

Grest (2019) showed the detailed method of the transfer learning with ResNet50 and fatasi library. He created *SegmentationPklList* and *classesSegmentationPklLabelList* to implement functionality to load file images to patches. He used this loss function to score the model:

$$CrossEntropyFlat(axis = 1, weight = inv\_prop, ignore\_index = 0)$$

The initial layers from training were frozen, and the modified layer was fine-tuned with data, allowing the encoder weights to be updated. The 'fit_one_cycle' function was used for this. He also utilized many performance-enhancing techniques, including weighting the loss function in proportion with the inverse frequency of each crop type (using 'weight' parameter).

Finally, applying preprocessing to satellite data can further improve accuracy. Preprocessing can include atmospheric correction, topographic correction, resampling, band stacking, seamless mosaicking, and image sub-setting (Kpienbaareh et al. 2021). For Sentinel-2 data, we can use Eo-learn Python library. For instance, the library has pretrained pixel-level cloud detector model for atmospheric correction. This functionality is available through the S2PixelCloudDetector and theAddCloudMaskTask classes. Cloud detector uses all 13 bands, and is based on a single-scene pixel-based classification. After cutting out clouds, we can fill the gap caused by it using LinearInterpolation EOTask. We can interpolate between preceding and subsequent time slices and find an interval to resample on.

Results

We analyze the data primarily using visualization via maps, graphs and charts as opposed to utilizing statistical inference models due to certain deficiencies in the data as we have created it, such as a lack of sufficient covariates within the dataset for analysis or the much shorter timeline of available data after the peace agreement. However, visual analysis should be satisfactory in that we are attempting to ascertain the changes in coca production in municipalities in Colombia which may or may not have been under FARC control or influence.[1]

[1] Note that there are two dummy variables for FARC; while these denote different categorization for FARC within the original datset, the differences are negligible in analysis.

Figure 1: Cultivation of Coca plants by Hectares 2002-2019

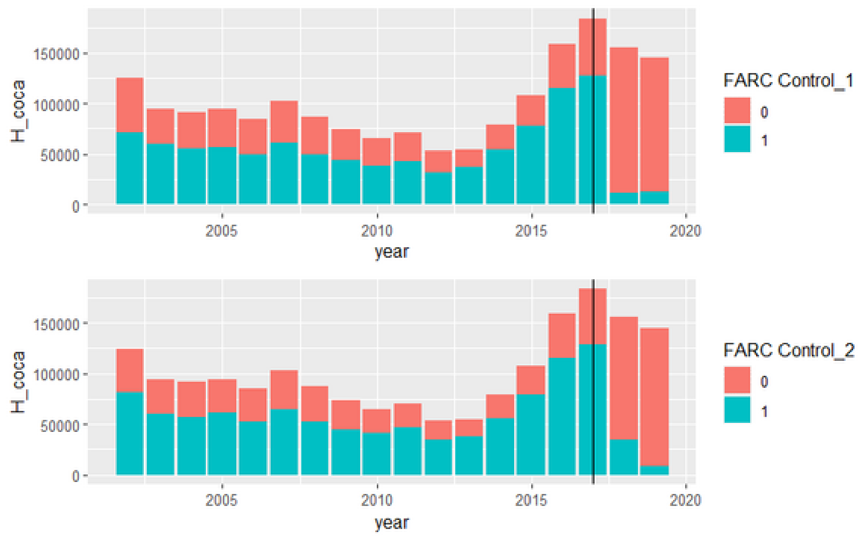


Figure 1 tells an interesting story easily verified by qualitative reports on the ground. Coca production has fallen slightly, but coca production in previously FARC-controlled territories has dropped off significantly. We can observe a huge drop in the percentage of FARC-controlled coca crop cultivation after the agreement takes force. According to reports from Colombia, this is consistent with actual trends as FARC attempts to honor a major point of the peace agreement concerning divestment from coca farming and the drug trade. The problem, however, is that while FARC coca production has sharply decreased, their share of the trade has been snapped up by rival gangs, cartels from both within and without Colombia.

Figure 2 depicts the changes in coca production by hectare in Colombian municipalities where data is available. Due to the very high variation in production levels, we use a logarithm for simplicity of viewing. We do not see any significant drop in coca production at any time; rather, we see an increase in the mid 2010s consistent with qualitative reports that in anticipation of the peace agreement and subsequent "buy outs" to discourage coca farming, many coca farmers were encouraged to increase production and the amount of land used in cultivation (Ladino et al. 2021). Indeed, we can observe a trend in increased production after peace negotiations began in 2012, peaking the year after the agreement was signed.

Figure 2: Production of Coca by Hectare (2012-2019)

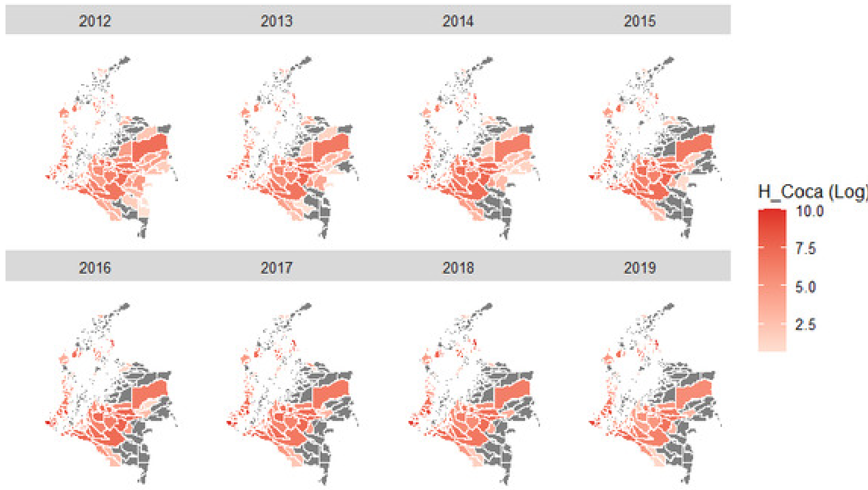
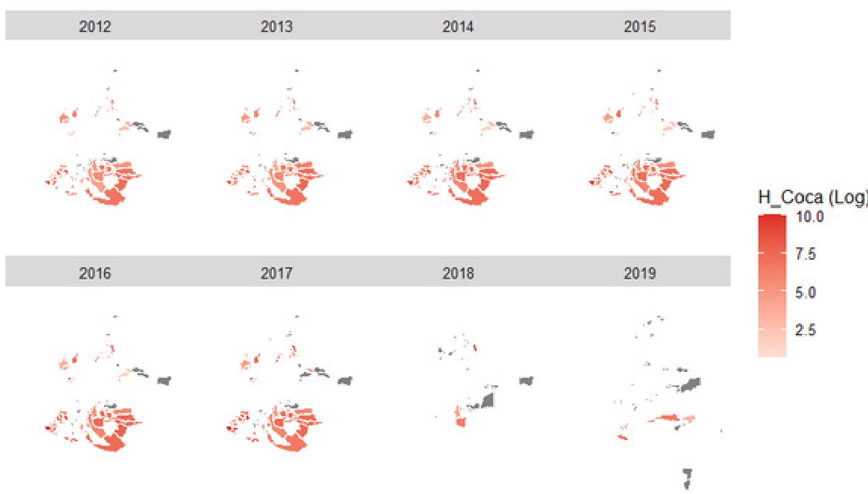


Figure 3: Coca Production by Hectare in FARC-Controlled Areas (2012-2019)



Limitations

Based on Figure 3, we can observe the changes in coca production in FARC-controlled areas. One large caveat, however, is a flaw of the research design born of necessity: since there is, technically, no more FARC in its original form after the peace agreement, in order to compare coca production before and after the agreement we coded any area which was considered FARC-controlled for the last year of the original data (2017) as FARC-controlled in subsequent years; however, due to a larger number of missing values in 2017, we elected to code 2018 and 2019 according to data from 2016.

Still, even without distinguishing between FARC-control or not, we do see a small decrease overall, and more recent data will be necessary to see how compliant former FARC territories are with the peace agreement's stipulations on drug production. Requiring further explanation is the relationship between FARC high-ranking members, the peace negotiation process, the coca producers and the middle managers: stating in simplistic terms that coca production went up or down may hide more complex processes which are, unfortunately, undetectable by satellites orbiting the Earth, but rather require deep-dive, qualitative inquiry.

Conclusion

In this paper, we tested our hypothesis on illicit coca production in Colombia using the panel data derived from satellite images. The result shows that the overall amount of coca production in Colombia have increased after the Colombia-FARC peace agreement. However, the coca production in ex-FARC controlled regions have dramatically reduced after the agreement. Such findings suggest that while the peace agreement was successful in making the FARC to shrink its coca production, it led other actors to replace the FARC in coca production who can hence play as other threat to peace.

Theoretically, this paper shows that civil wars are indeed intractable when rebel groups have wide illicit-drug economy. A sustainable peace in Colombia will only be achieved when the government succeeds in fighting its war against illicit drug. Methodologically, we have provided an outline for the potential for utilizing satellite imagery as a means of detecting illicit drug cultivation and territorial changes among groups in contested areas, among other uses.

Through better object identification algorithms and techniques, it should be possible to achieve greater accuracy in ascertaining information on illegal activities in regions too dangerous for on the ground research, or generally overly-difficult or resource-intensive to conduct fieldwork. Interesting future applications could include utilizing satellite imagery and analysis in order to cross-validate self-reported statistics on crime or drugs; for example, in more mountainous and difficult-to-reach areas of Colombia such as the Amazonian regions, sophisticated satellite image analysis could enable monitoring agencies and international organizations to easily "double-check" supposed increases or decreases in the cultivation of illicit drugs, and thereby detect corruption by bypassing the "human element."

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