Making the Hidden Visible: Accelerated Land-Use Change Caused by Narco-Trafficking In and Around Central America’s Protected Areas

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Source: Daniele Volpe for The Washington Post

#80NSSC21K0297
Narco-Trafficking

• Before 2015, Narco-trafficking through the Central American corridor supplied over 80% of the cocaine consumed in North America (UNODC, 2010, 2012)

• Central America became the preferred transshipment location in the early to mid-2000s

• Response to interdiction

Numero de movimientos primarias (mar y aire) destinado por países indicadas. Source: Consolidated Counterdrug Data Base (CCDB), Office of National Drug Control Policy (ONDCP); extracted 1/31/2016.
Legend
- Maritime
- Air
- Limited U.S. Data Sharing

Source: US JIATF-S
Legend

- **Red**: Maritime
- **Yellow**: Air
- **Green**: Limited U.S. Data Sharing

Source: US JIATF-S
Three main pathways for narco-trafficking driven land-use change:

• Direct use (e.g., narco-pistas, territorial control)

• Money laundering (e.g., cattle ranching, palm oil)

• Indirect effects (e.g., informal markets, reinvestment of illicit capital)
Quantifying Narco-Land-Use Change

How much, when, and where is land-use change caused by narco-trafficking?

Challenges:

• Detailed time series needed for causal inference > LUC Mapping
• Data are fragmented, incomplete, and unreliable > Data Pedigree
• Quantifying causal effect of direct + indirect narco-trafficking activity > Counterfactual LUC Modeling
Quantifying Narco-Land-Use Change

Counterfactual land change modeling

How much, when, and where is land-use change caused by narco-trafficking?

Magliocca, Dhungana, Sink (2023). Review of spatially explicit land change modeling for counterfactual analysis in land system science, *J. Land Use Science*
LUC Mapping Results
Land Use Change Maps 1986-2020

Fagan et al. (in prep). Oil palm expansion threatens Costa Rica’s protected areas.
Data Pedigree

Need an approach to use as much data as possible

A data pedigree is a systematic grading system to assess the quality and appropriateness of a wide range of data – from precise and authoritative observations to informed guesses (Costanza et al. 1992).

**Data Pedigree: Infrastructure**

**Roads** are one of the first identifiable markers of Narco-activity.

**Airstrips:** possible markers of narco-activity

- 2km long, 20m wide
- 750m, 19m
- 850m, 25m

*Bing Imagery, 2022*
Data Pedigree: Infrastructure

Challenge: detection needs VHR data; time series to 2000
We labeled from 2022, blue = road, red = no road

Mukherjee et al. (*in prep*). Pixel-based informal infrastructure detection using RapidEye and PlanetScope imagery.
Magliocca/Tellman-Sullivan et al. (*in prep*). Land-use change causal inference with informal infrastructure detection.
Results will be more consistent after post processing:

- Removing cloudy, low quality grids
- Applying year-wise threshold instead of a blanket threshold
- Combining multiple years to improve grid data quality
Data Pedigree

Creates a standardized, comparable, and integrated database

<table>
<thead>
<tr>
<th>Study Region</th>
<th>Data Type (# obs)</th>
<th>Spatial Resolution</th>
<th>Temporal Extent &amp; Resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Osa Region, Costa Rica</td>
<td>Drug and asset seizures (n = 33)</td>
<td>Lat./Lon.</td>
<td>2015-2022, specific dates</td>
<td>Organismo Judicial Costarricenses (OJC)</td>
</tr>
<tr>
<td>RPBR Region, Honduras</td>
<td>Cocaine seizures and flow estimates (n = 95)</td>
<td>Department (admin. level 1)</td>
<td>2000-2018, annual</td>
<td>Consolidated Counterdrug Database (CCDB)</td>
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<tr>
<td>MBR Region, Guatemala</td>
<td>Coca cultivation areas (n = 17)</td>
<td>Lat./Lon.</td>
<td>2018 - 2022, year of event</td>
<td>Law enforcement reports</td>
</tr>
<tr>
<td>Settlements in protected areas (n = 50)</td>
<td>Lat./Lon.</td>
<td>1971-2004, year of event</td>
<td>Consejo Nacional de Areas Protegidas (CONAP)</td>
<td></td>
</tr>
<tr>
<td>Arrest records of individuals on protected area land (n = 50)</td>
<td>Lat./Lon.</td>
<td>2008-2014, year of event</td>
<td>Ministerio de Gobernacion</td>
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<td>Narco-trafficking hotspots (n = 41)</td>
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<td>Narco-roads (n = 13)</td>
<td>Road vector</td>
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<td>2017-2022, year of event</td>
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<td>Landing strips (n = 837)</td>
<td>Lat./Lon.</td>
<td>2010-2019, year of event</td>
<td>Various Honduran news outlets</td>
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<td>Seized cartel land holdings (n = 38)</td>
<td>Polygons</td>
<td>1990-2007, year of event</td>
<td>InSight Crime News media articles</td>
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<td>Reforestation incentive recipients linked to organized crime (n = 983)</td>
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<td>2000-2021, year of event</td>
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Data Pedigree

Qualitative decision-trees to score all data sources

Is the department (or more precise geometry) of the event provided?

Yes

Is the municipality (or more precise geometry) of the event provided?

No

Geographic Clarity

National data
Score = 1

Mapped to department boundary
Score = 2

Is the event appropriately represented by a point/polygon at the given lat/lon coordinates (e.g., property, address, town)?

No

Does the largest administrative area approximate the area influenced by the event (i.e., administrative area smaller than level 2)?

Yes

Mapped as a point/polygon
Score = 4

No

Mapped to large sub-national geometry (e.g., rural district)
Score = 2

Mapped to small sub-national geometry (e.g., populated municipality)
Score = 3

Magliocca et al. (in prep). Overcoming poor data availability with a data pedigree to study illicit economic activities.
Data Pedigree

Creates a standardized, comparable, and integrated database

Narco-activity in locations > 3.35
Data Pedigree

Creates a standardized, comparable, and integrated database

Rio Platano Biosphere Reserve

Narco-activity in locations > 3.0
Data Pedigree
Creates a standardized, comparable, and integrated database

Maya Biosphere Reserve

Narco-activity in locations > 2.8
Land Change Modeling: Dyna-CLUE

Data Pedigree: Location & Time

Calibrate $t_1-t_2$ Predict $t_3$
Validate $t_3$
Calibrate $t_2-t_3$ Predict $t_4$
Validate $t_4$
Calibrate $t_1-t_3$ Predict $t_4$
Validate $t_4$
Ensemble Calibration with All Combinations $t_1-t_4$

Obs. Map 1986
Obs. Map 1989
Obs. Map 1992
Obs. Map 1995
Obs. Map 2004
Obs. Map ...
Obs. Map 2020

Predicted
Obs. + Counter

Counterfactual Comparison

Data by Matt Fagan, Felipe Saad

Magliocca, Dhungana, Sink (2023). Review of spatially explicit land change modeling for counterfactual analysis in land system science, *J. Land Use Science*
Counterfactual Land Change Modeling

Effect size (%) of narco-trafficking presence

Data Pedigree:
Location & Time

Observed
Predicted

Magliocca et al. (in prep). Narco-trafficking caused land-use change in and around Central America’s protected areas.

Magliocca et al. (in prep). Comparative performance of quasi-experimental matching and counterfactual modeling for causal inference in land-use change research.
Next Steps

Infrastructure detection and classification
• Validation of Landsat gridded model (May fieldwork)
• Gridded Landsat model of MBR, RPBR AOIs
• Pixel-based road segmentation, adding RapidEye to 2009

Land change mapping
• MBR and RPBR AOIs, validation

Counterfactual land change modeling
• Implementation and scalability at 30m resolution
• Compare with quasi-experimental matching
Research Plan

How much, when, and where is land-use change caused by narco-trafficking?

1. Data Pedigree
   - Location & timing of narco-trafficking activity

2. CNN inference

3. LUC Mapping
   - Observed LUC
   - Counterfactual LUC

4. LUC Modeling

Objectives
- Obj. 1: Timing of increased narco-trafficking activity
  - Task 1.1: Database of existing & acquired data
  - Task 1.2: Annual infrastructure maps 2000-2020
- Obj. 2: Hotspots of LUC
  - Task 2.1: Annual LUC maps 1985-2020
  - Task 2.2: Counterfactual LUC maps 1985-2020
- Obj. 3: Quantify LUC directly and indirectly attributable to narco-trafficking
  - Treatment Locations
  - LUC Controls
  - Task 3.1: LUC effect sizes

Tasks & Outcomes

Analytical Elements
- 1. Data Pedigree
- 2. CNN inference
- 3. LUC Mapping
- 4. LUC Modeling

Key:
- 1. Data Pedigree
- 2. CNN inference
- 3. LUC Mapping
- 4. LUC Modeling
Land cover maps: methodology

- Osa receives 5+ meters of rain a year; very cloudy, especially in the 1990s.
- Google Earth Engine was used to create 3-year composites of Landsat data from 1986 to 2020.
- Landsat clouds were masked using the CFMask algorithm and custom cloud masks.
- Using GEE, additional SAR (Sentinel-1, ALOS Palsar) and spectral (Sentinel-2) data were added for available years, as well as texture variables.
- Extensive training data set (n=\sim120,000 pixels); Random Forest models were developed for each year to produce 30 m resolution maps.
- Rules-based land cover map compositing was used to further minimize the effects of clouds and cloud shadows.
Model Training Accuracies

**ALOS PALSAR**, 30m, only 2 bands (HH, HV) = Overall 81.5%, no road correctly detected = 79.8%, road correctly detected = 82.8%

**PlanetScope NICFI**, 5m, 4 bands = Overall 90.1%, no road correctly detected = 87%, road correctly detected = 92.5%

**Landsat 8**, 30m, 6 bands = Overall 88.75%, no road correctly detected = 86.7%, road correctly detected = 90%

**Landsat 7**, 30m, 6 bands = Overall 87.54%, no road correctly detected = 81.1%, road correctly detected = 91%
Data Pedigree

Creates a standardized, comparable, and integrated database

Criteria:
- Geospatial Clarity – does the data represent the event?
- Geospatial Interpretation – bias introduced by analyst?
- Authorial Provenance – knowledge/authority of data provider?
- Narco-Trafficking Certainty – reporting on targeted phenomenon?
- Temporal Accuracy – when (exactly) did it happen?
Geographic Clarity

Is the department (or more precise geometry) of the event provided?

No

Is the municipality (or more precise geometry) of the event provided?

Yes

Is the event appropriately represented by a point/polygon at the given lat/lon coordinates (e.g., property, address, town)?

No

Does the largest administrative area approximate the area influenced by the event (i.e., administrative area smaller than level 2)?

No

Mapped to large sub-national geometry (e.g., rural district) Score = 2

No

Mapped to department boundary Score = 2

Yes

Mapped as a point/polygon Score = 4

National data Score = 1

Mapped to small sub-national geometry (e.g., populated municipality) Score = 3
Narco-Trafficking Certainty

Does the event refer an illegal or informal economic activity (e.g., legal activity in prohibited area)?

- No
  - Reported event cannot be differentiated from legal activities.
    - Score = 0

- Yes
  - Is the event related to organized crime?
    - No
      - Relationship of the actor or activity cannot be linked to drug trafficking
        - Score = 2
    - Yes
      - Does the event refer specifically to drug trafficking (i.e., not just a drug arrest)?*
        - No
          - Reported event is an organized criminal activity but not reportedly linked directly to drug trafficking (e.g., money laundering)
            - Score = 3
        - Yes
          - Event references activities and/or law enforcement actions involving narco-traffickers
            - Score = 4

* Does the event refer specifically to drug trafficking (i.e., not just a drug arrest)?
Discussion

Rate of oil palm expansion:
• Sumatra and West Malaysia: 2.26% from 2000-2015 (Wagner et al., 2022)
• Osa study region: 15.1% from 2007-2019
• Narco-trafficking areas: 40.37% from 2007-2019
  • Counterfactual rates highest 2013, 2016

Insights from field interviews:
• Oil palm sector vulnerable to infiltration in all supply chain phases
• Rapid infrastructure development in ag and tourism sectors
• Costa Ricans serving as ‘logistics contractors’
• Illicit capital from trade visible in poor communities

Wagner, Wentz, Stuhlmacher (2022). Quantifying oil palm expansion in Southeast Asia from 2000 to 2015: A data fusion approach. JLUS