# Going Geospatial with Impact Evaluations

July 15, 2015

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**Dr. Mark Buntaine**, *University of California Santa Barbara*

# Dr. Ariel BenYishay

## *AidData*

Dr. Ariel BenYishay is Chief Economist at AidData and Assistant Professor of Economics at the College of William and Mary. Previously, he served as lecturer in Economics at the University of New South Wales in Sydney and was Associate Director of Economic Analysis and Evaluation at the Millennium Challenge Corporation. Ariel has been the principal investigator on a variety of large-scale experiments in developing countries, including Malawi, the Philippines, and the Solomon Islands. His work has been published in leading journals, including the Journal of Human Resources, the Journal of Comparative Economics, and Economic Development and Cultural Change. BenYishay earned a PhD in Economics from the University of Maryland.

## Dr. Daniel Runfola
### *AidData*

Dr. Dan Runfola is AidData's Geospatial Scientist at the College of William and Mary. Previously, he worked on research projects for the National Center for Atmospheric Research and the U.S. Army Corps of Engineers examining the use of Geographic Information Science (GIS) in climate-change related decision-making. Currently, he is working to integrate AidData's information into aid allocation decision-making. His work has been published widely and is included in the United Nations' Intergovernmental Panel on Climate Change Fifth Assessment Report. Runfola holds a PhD and MA in Geography from Clark University, and a BA in Geography from Georgia State University.

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# Dr. Mark Buntaine

***University of California Santa Barbara***

Dr. Mark Buntaine is an Assistant Professor at the University of California, Santa Barbara. His research investigates the sources of effective environmental policy in developing countries, with an emphasis on the targeting and impact of foreign aid. Buntaine leads a range of international projects that focus on the allocation practices of aid donors, the participation of citizens in environmental policy-making, the relationship between public and private financing of environmental technologies, the processes that lead to effective government reform, and the evaluation of environmental projects. His work has been published in leading journals including Global Environmental Change, World Development, and International Studies Quarterly. Buntaine received a PhD in Environmental Politics and Policy from Duke University.

# Geospatial Impact Evaluation

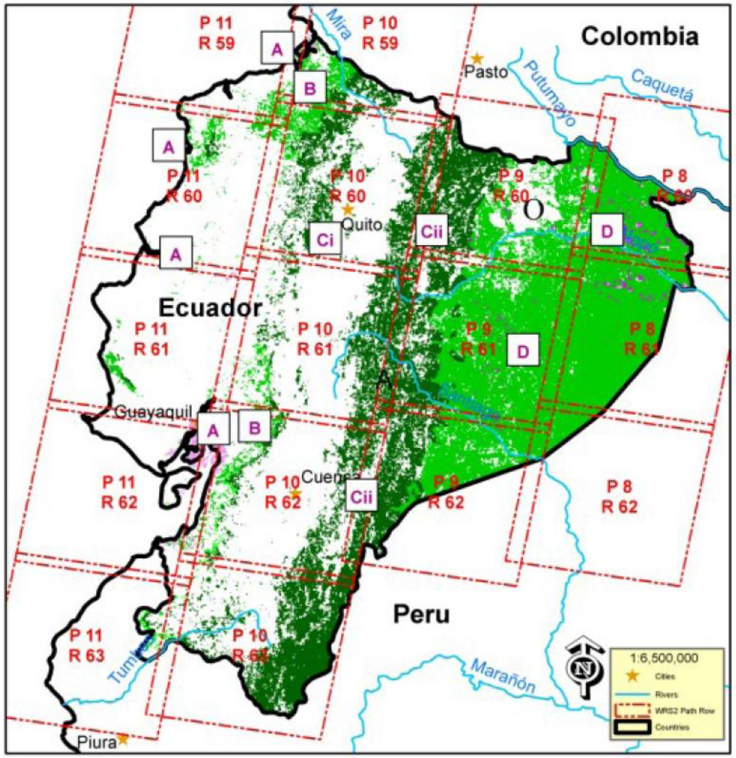
# Geospatial Impact Evaluation

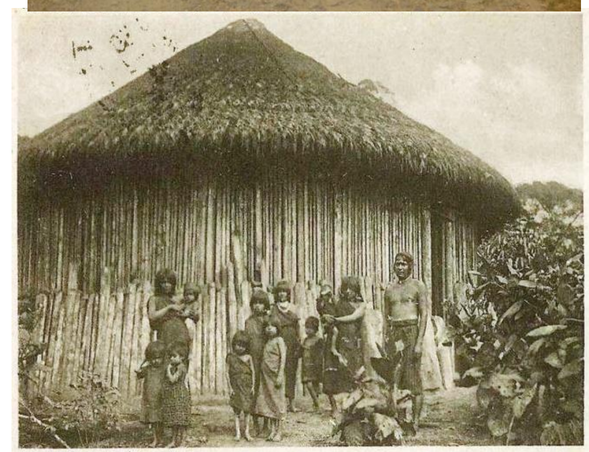
- Use spatial information on program activities
- Merged with high-resolution geo-referenced outcomes
  - Geo-referenced surveys
  - Remotely sensed (forest cover, nighttime lights)
- Causal attribution (identification) possible through *matching*, *fixed effects*, and *discontinuity* techniques

- Examples in growing number of fields/sectors
  - ***Land rights***
  - ***Health***
  - Governance
  - Post-conflict
  - Education

# Using Land Cover Change to Evaluate Program Impacts

## An Application to Forest Loss in Morona-Santiago, Ecuador



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# Titling community land to prevent deforestation: An evaluation of a best-case program in Morona-Santiago, Ecuador

Mark T. Buntaine[a], , Stuart E. Hamilton[b, 1], Marco Millones[c, 2]

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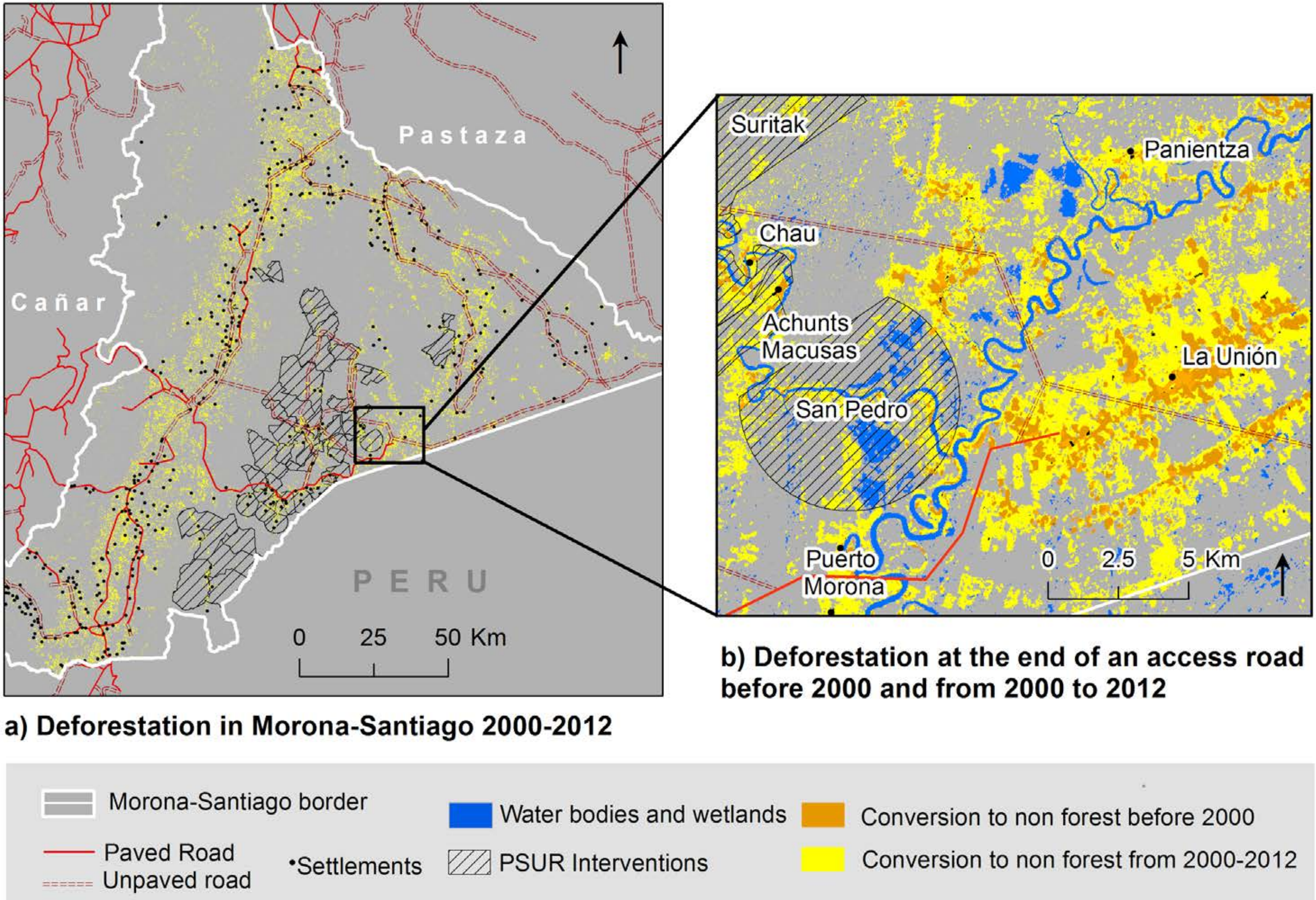
## Highlights

- Given their global reach, better evidence about land titling programs is critical.
- Land titling and community management programs did not reduce deforestation.
- Careful matching of program and non-program areas produces more reliable estimates of program impacts.
- Remote sensing data is a key tool for evaluating the impacts of globally relevant policies.

www.geoie.org

# Independent Evaluation Group, World Bank
# Field Evaluation of Forestry Projects in China

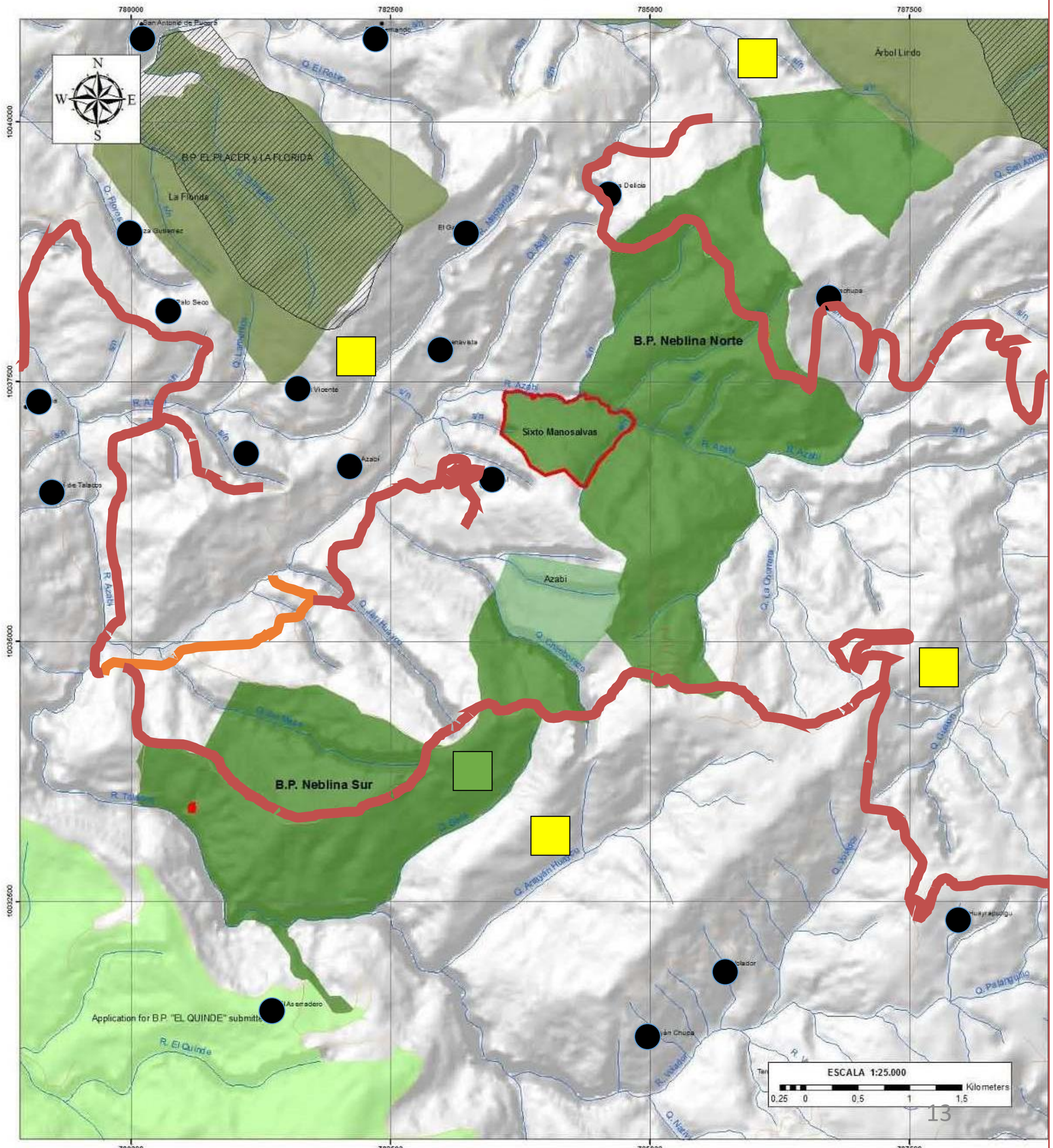



a) **Deforestation in Morona-Santiago 2000-2012**

b) **Deforestation at the end of an access road before 2000 and from 2000 to 2012**

Sources: a) based on GFC (Hansen et al. 2013) b) based on TNC (Geoplades 2010) and GFC.

- Town
- Slope
- Road
- Treated Plot
- Control Plot



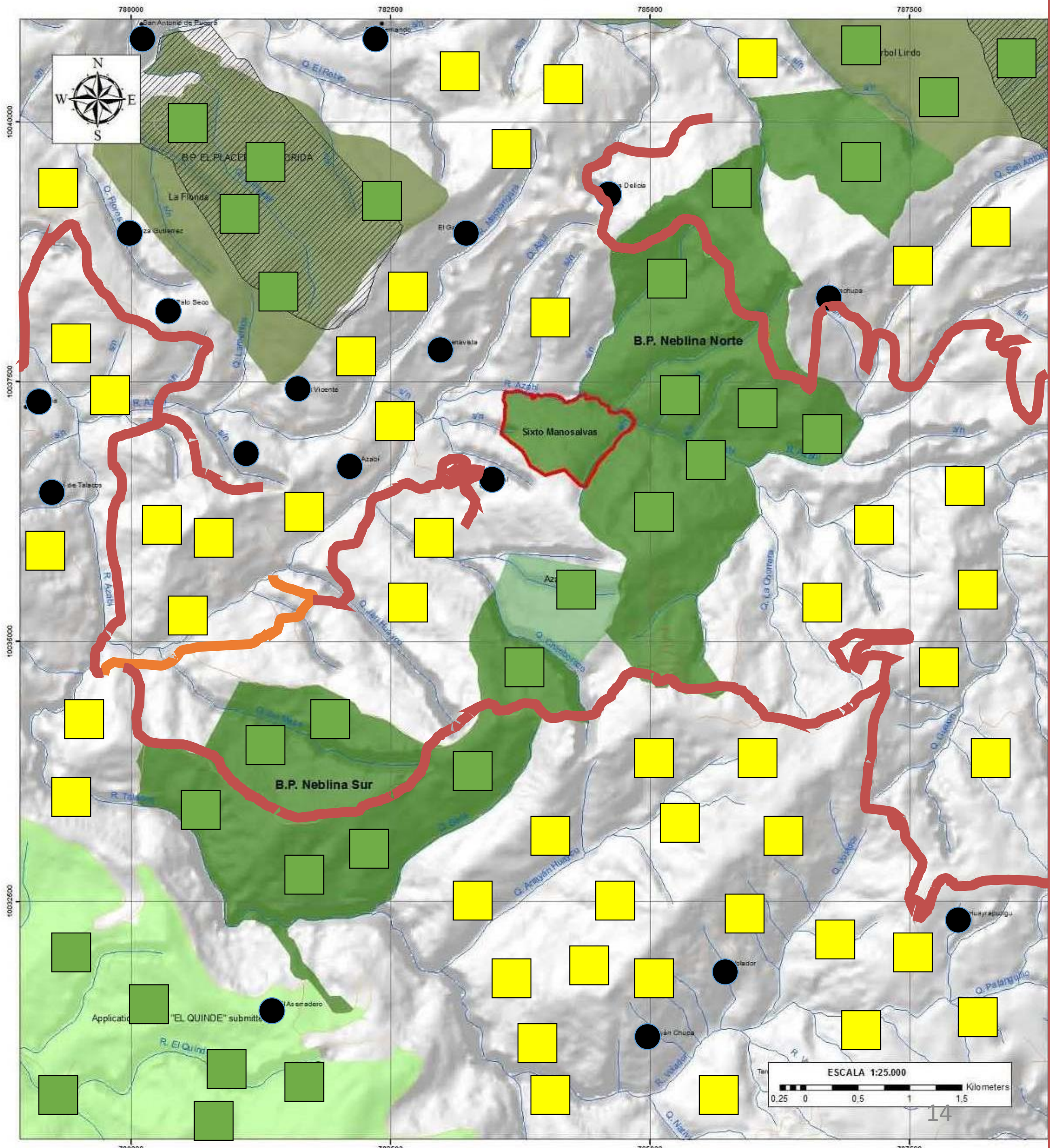
Town

Slope

Road

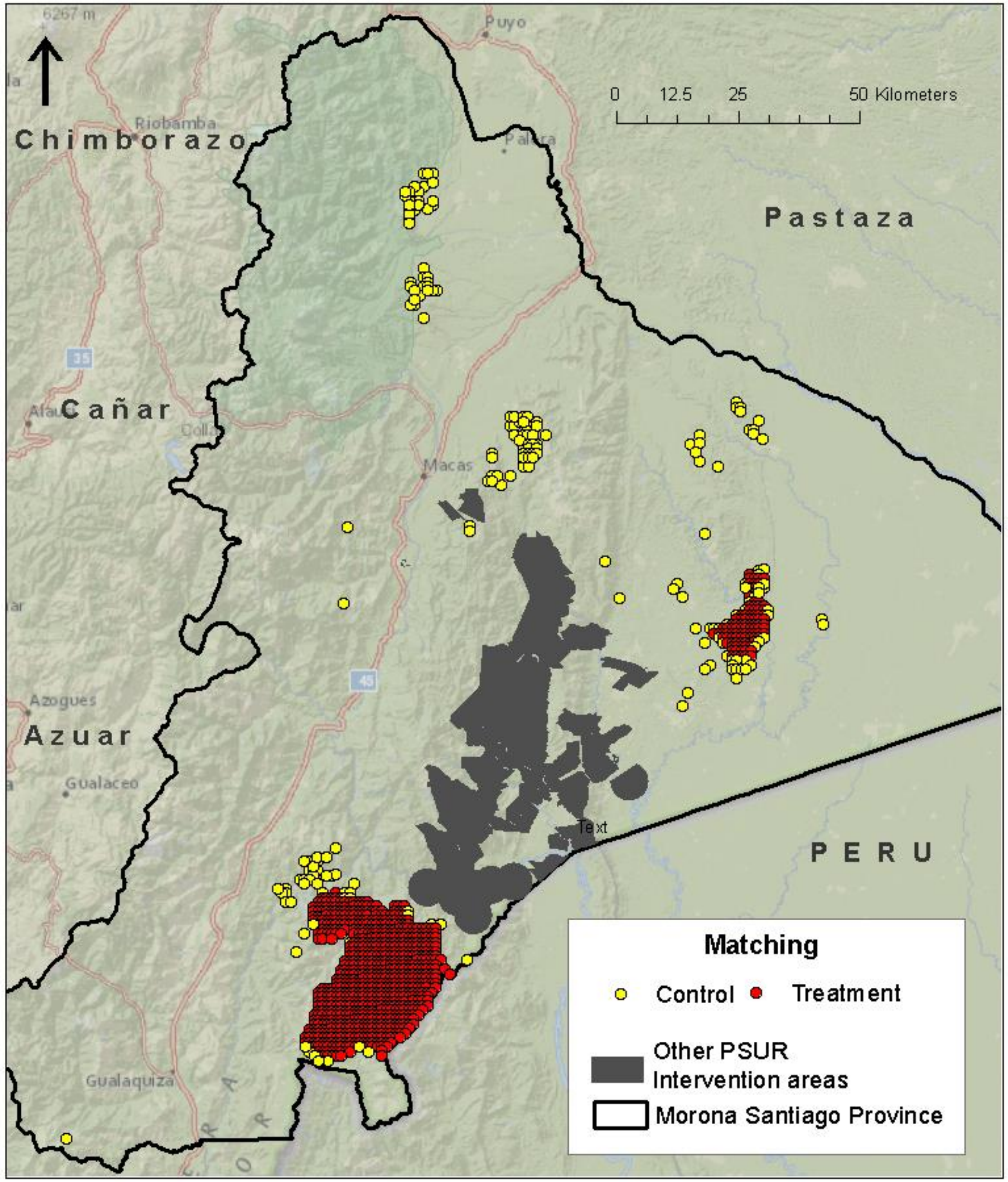
Treated Plot

Control Plot

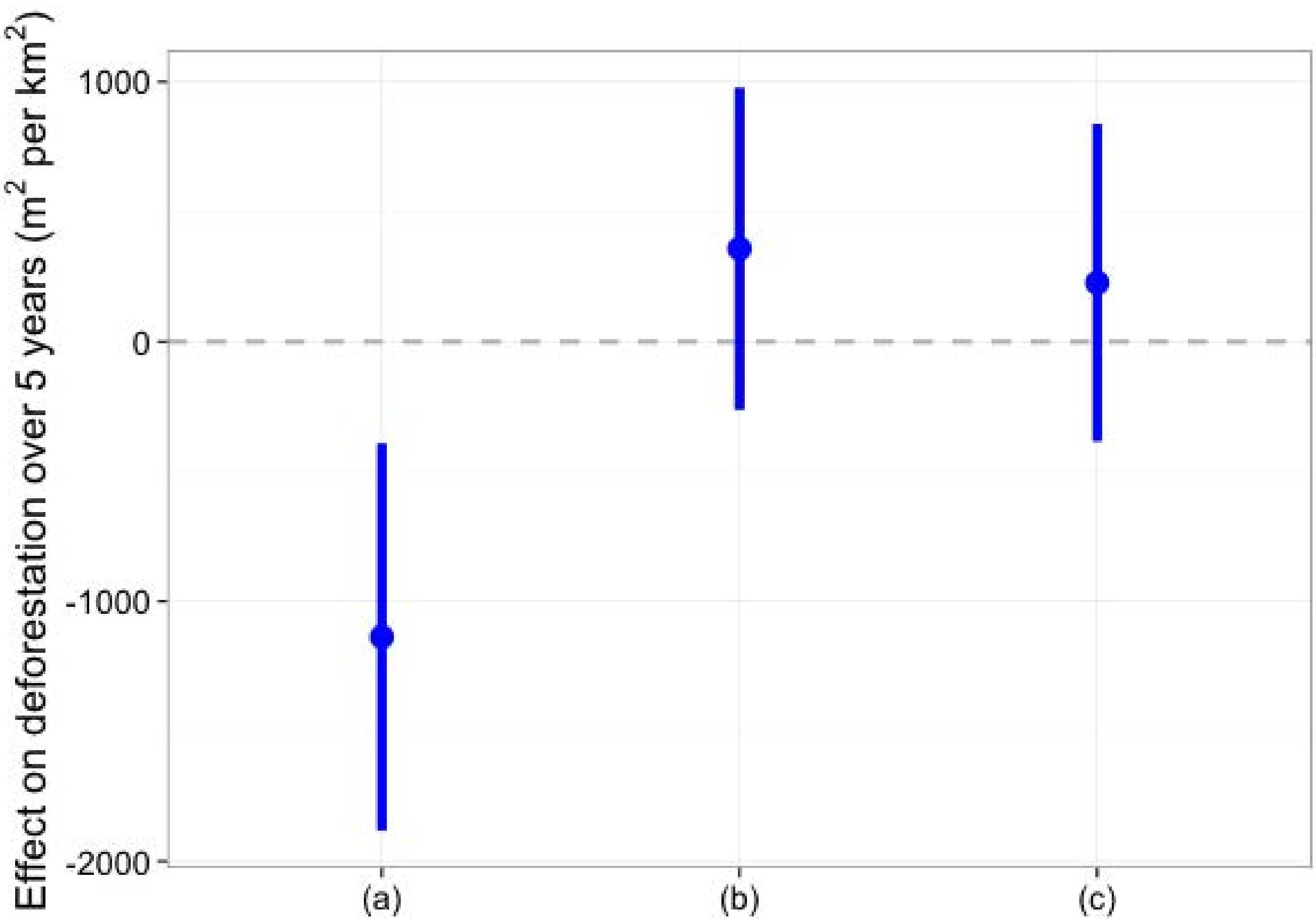


# Matching Variables

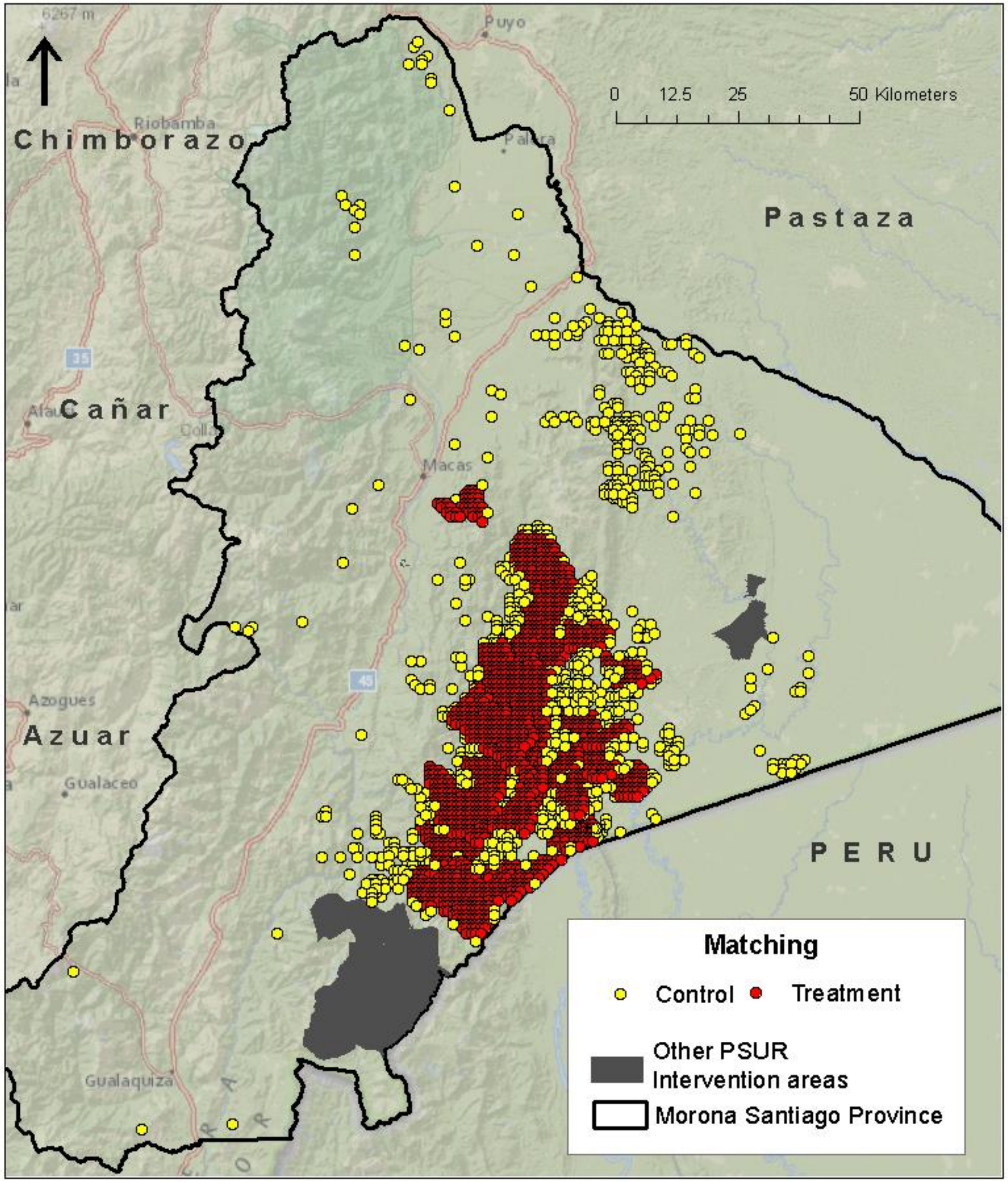
| | **Source** | **Temporal Granularity** | **Native Resolution** |
|---|---|---|---|
| **Forest Loss** | Hansen et al. 2013 | annual | 30m |
| Forest Loss within 5 $km^2$ (*t-1*) | Hansen et al. 2013 | annual | 30m |
| Forest Cover Percent (*t-1*) | Hansen et al. 2013 | annual | 30m |
| Distance to Major Roads | OSM, VMAP1, MAE | various, 1993, 2012 | vector |
| Distance to Electric Grid | VMAP1, MAE | 1993, 2012 | vector |
| Distance to River | VMAP1, MAE | 2012 | vector |
| Distance to Disturbed Land Classification | MOD12Q1 | annual | .5 km |
| Indigenous Shuar Land | TNC | 2012 | vector |
| Protected Area Status | WDPA, MAE, TNC | annual | vector |
| Elevation / Slope | Souris, IRB | 2001 | 30m |
| Population Density within 5 $km^2$ (*t-1*) | Landscan | annual | 1 km |


0 12.5 25 50 Kilometers
Chimborazo
Pastaza
Cañar
Azuar
PERU
Puyo
Riobamba
Macas
Azogues
Gualaceo
Gualaquiza
Text
Matching
Control
Treatment
Other PSUR Intervention areas
Morona Santiago Province

# Treatment Effect of Legalization Only

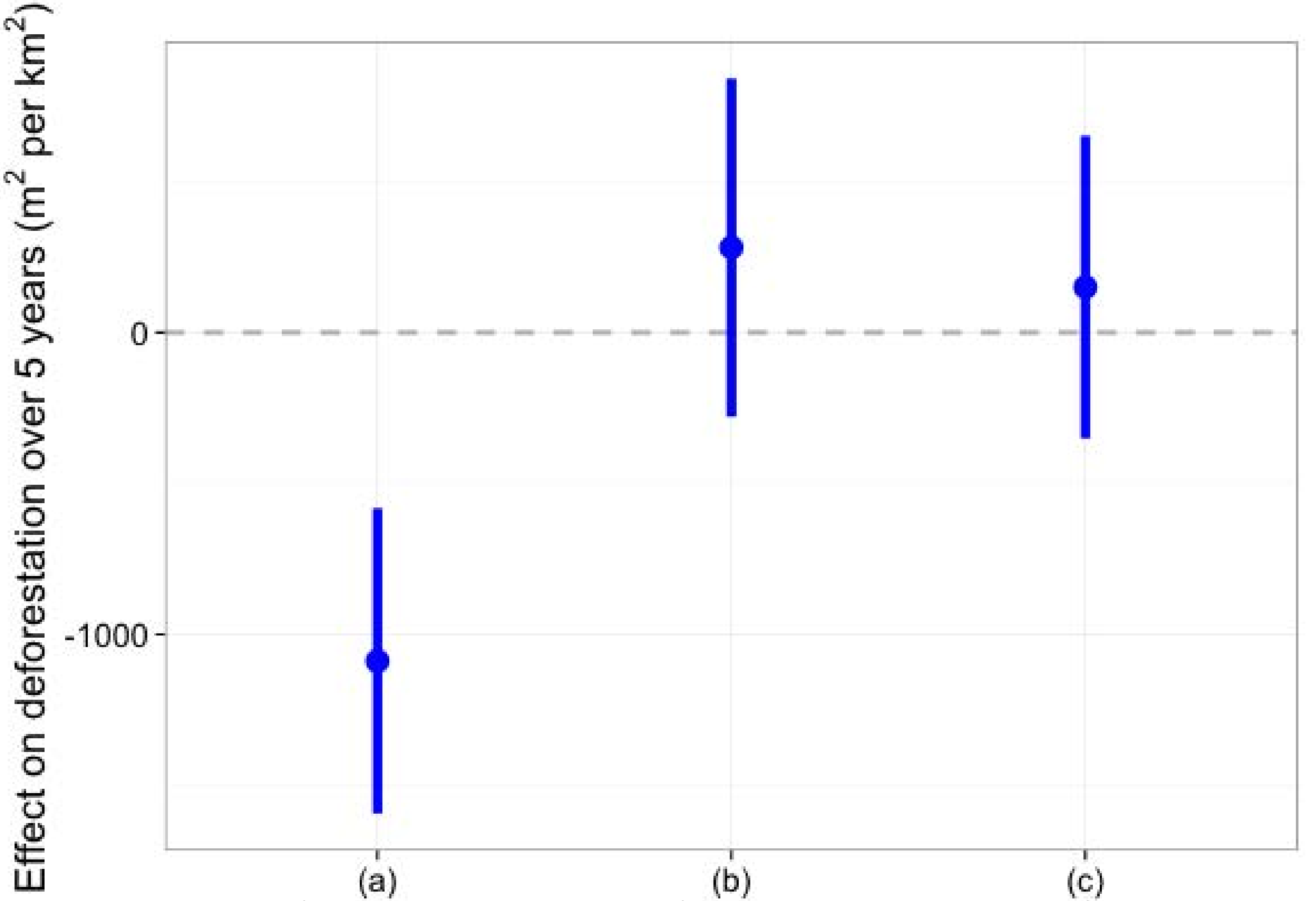



**No pre-matching, covariates** **Pre-matching, no covariates** **Pre-matching, covariates**



Chimborazo
Riobamba
Puyo
Palora
0 12.5 25 50 Kilometers
Pastaza
Cañar
Macas
Azogues
Azuar
Gualaceo
Gualaquiza
P E R U
Matching
Control
Treatment
Other PSUR Intervention areas
Morona Santiago Province

# Treatment Effect of Legalization and Community Management Plan




No pre-matching, covariates    Pre-matching, no covariates    Pre-matching, covariates

# Future Directions

1. Develop tools for geospatial impact evaluation across project types and sectors

2. Use geospatial evaluation to understand mid- to long-term impacts of programs

3. Combine geospatial impact evaluation with traditional evaluations methods to better understand mechanisms

Thank you:

USAID Ecuador Mission
ECOLEX
The Nature Conservancy Ecuador Office
Al Tropico
Costas y Bosques (USAID)
CARE Ecuador

www.geoie.org

# Evaluating Indigenous Land Right Projects in the Amazon

AidData and KfW

# Does Demarcating Indigenous Lands Reduce Deforestation?

- Land tenure security not widely shown to reduce deforestation
- Indigenous control / stewardship shown in several recent studies to be associated with lower deforestation rates (Nelson et al 2001, Nelson and Chomitz 2012, Nolte et al 2013, Vergara-Aseno and Potvin 2014)
- Most studies compare indigenous to other governance/rights
    - Don’t consider time variation in protection status
- Given low rates of deforestation observed on indigenous lands, is demarcation likely to influence deforestation?

# Project Description

- In 1988 constitution, Gov of Brazil committed to demarcating indigenous people's territories
- Between 1995-2008, with funding and tech support from KfW and the World Bank, the PPTAL project identified, recognized, and studied 181 community lands
- By 2008, 106 community lands demarcated, covering 38 million hectares (~35% of all indigenous lands in Amazon)

# Project Description

- *Demarcation*: recognition by the Min of Justice

- Followed by regularization (entry into municipal, state and federal registries)

- Varied by community between 1995 and 2008
  - Median year is 2001

- Support for Boundary Enforcement

# Data

- Treatment status
  - Boundaries of community lands
  - Administrative data on demarcation dates
- Merged with satellite-based greenness measure
  - NASA Land Long Term Data Record (LTDR), 1982-2010
  - Processed to Normalized Difference Vegetation Index (NDVI)
  - Range is [0, 1] (0 = rocky, barren; 1 = dense forest)
  - Annual NDVI max and mean measures
- Covariates
  - Climate (precip., temp.); topology (elevation, slope); distance to rivers; gridded, interpolated population

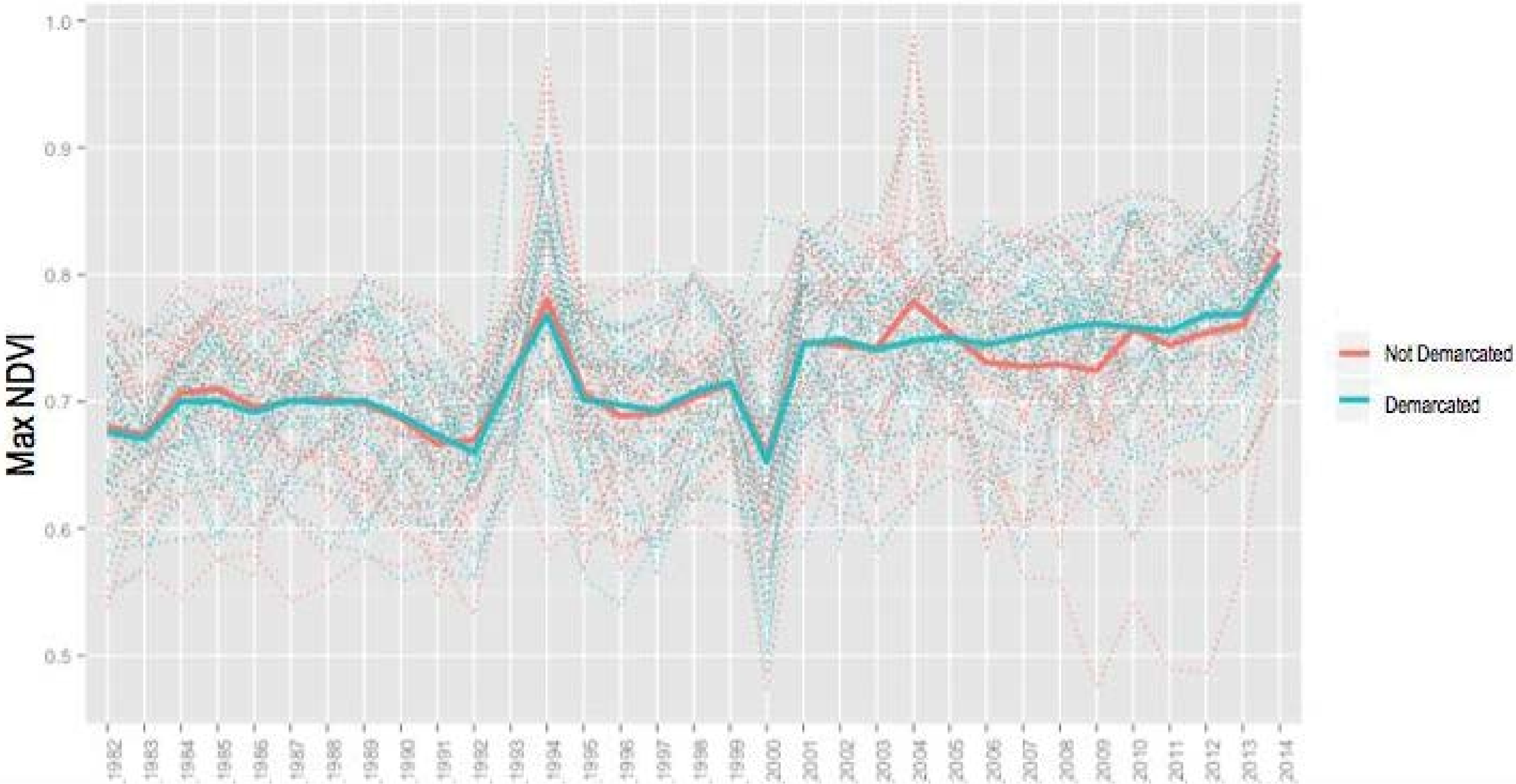
# Empirical Methodology

- Propensity Score Matching
  - Differences over time across matched treated/comparison communities
  - Match on baseline levels, pre-trends, & covariates
  - Demarcated vs. not;  "Early" ('95-'01) vs "Late" ('01-'08)

- Fixed effects
  - Control for time-invariant community unobservables
  - Treatment status at finer time intervals

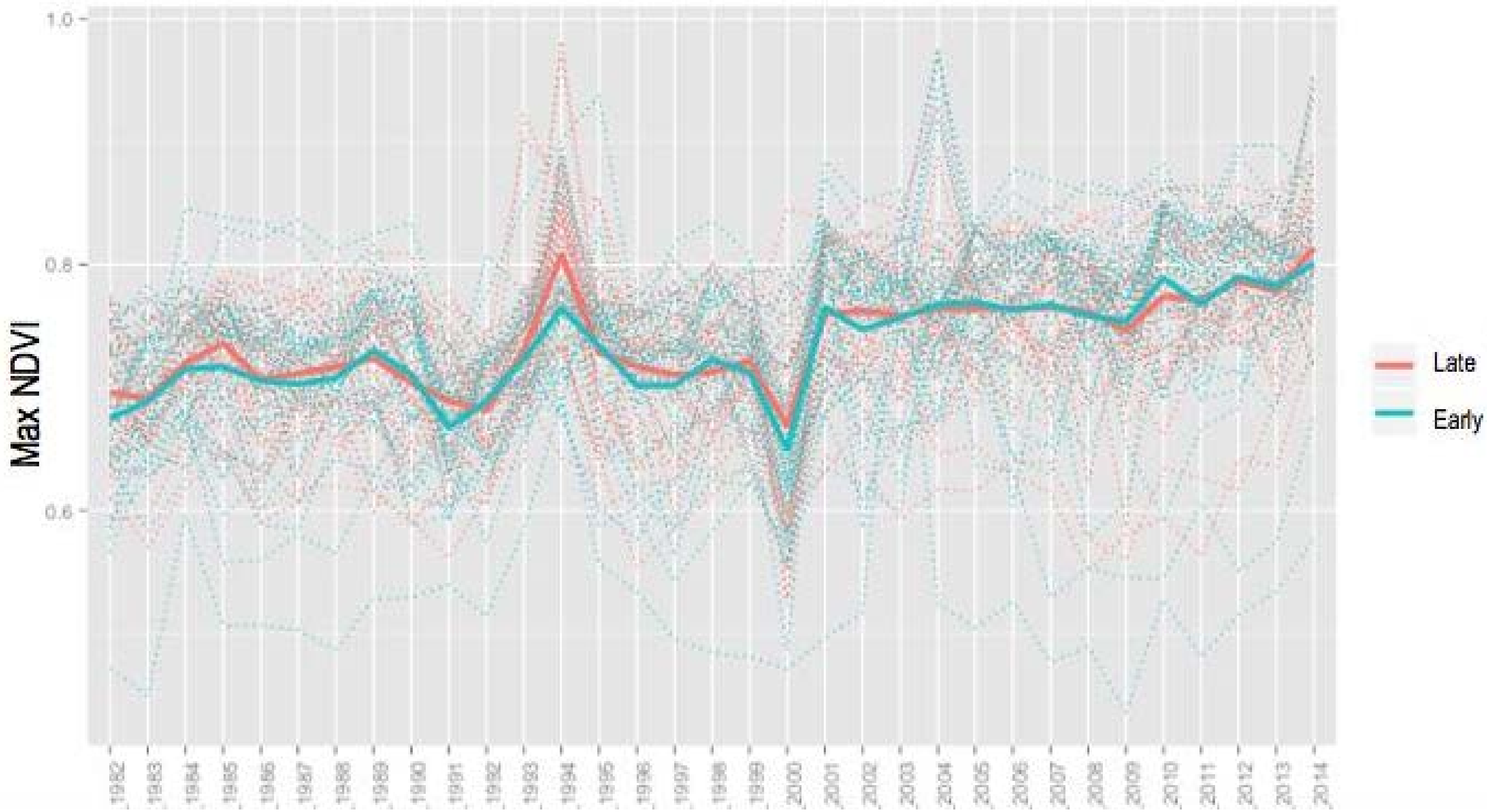
# Sample Communities

# NDVI Trends



Max NDVI
1.0
0.9
0.8
0.7
0.6
0.5
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
Not Demarcated
Demarcated

# NDVI Trends



1.0
0.8
0.6
Max NDVI
1982
1983
1984
1985
1986
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1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
Late
Early

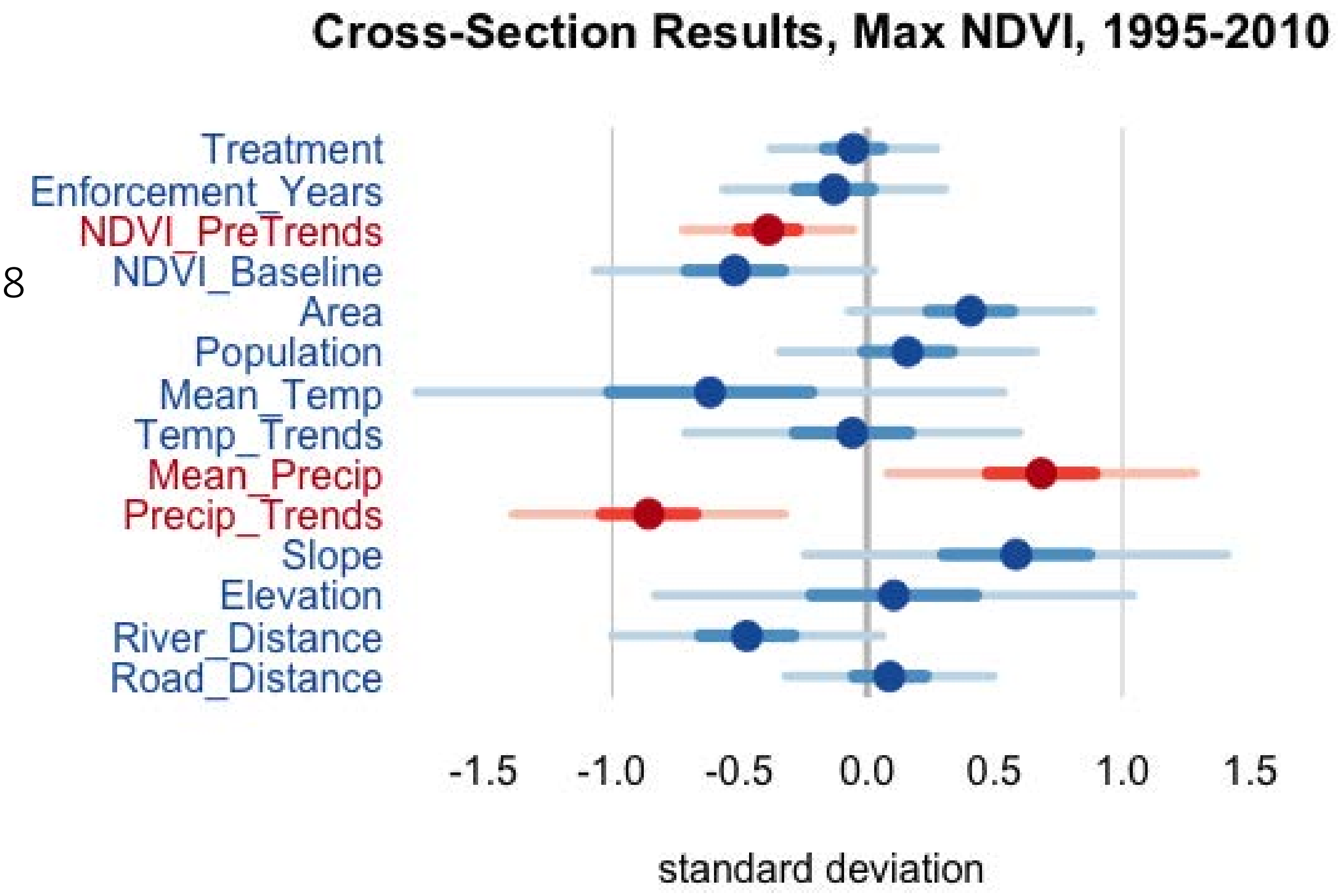
*Differences-in-differences:*

Demarcated vs. non-demarcated

Treatment = demarcated begins '95 and ends in '08

Outcome = Change in mean NDVI between '95 and '10

Sample: 30 community pairs, matched on covariates



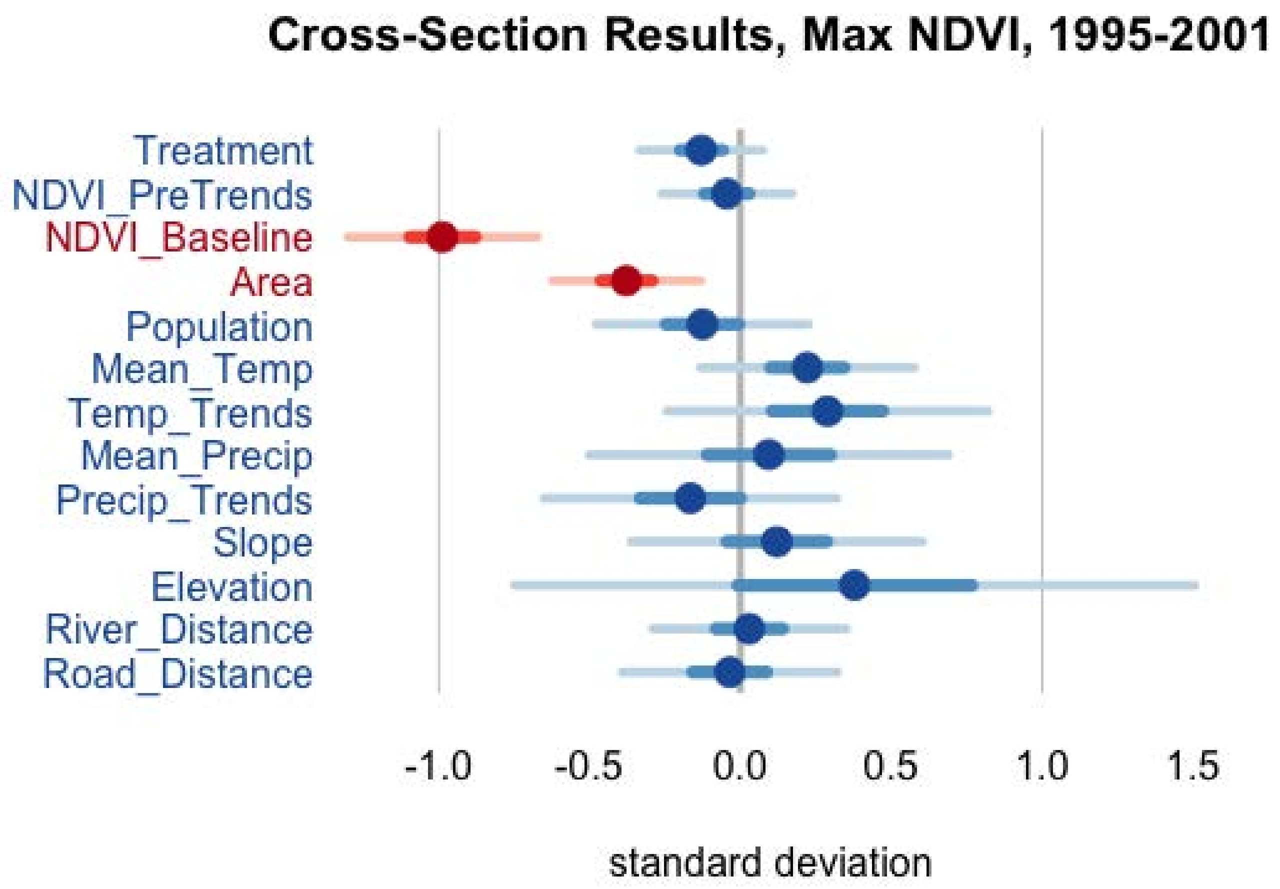
*Differences-in-differences:*

“Early” vs. “Late”

Treatment = “Early” demarcation (‘95-’01)

Outcome = Change in mean NDVI between ‘95 and ’10

Sample: 40 community pairs, matched on covariates



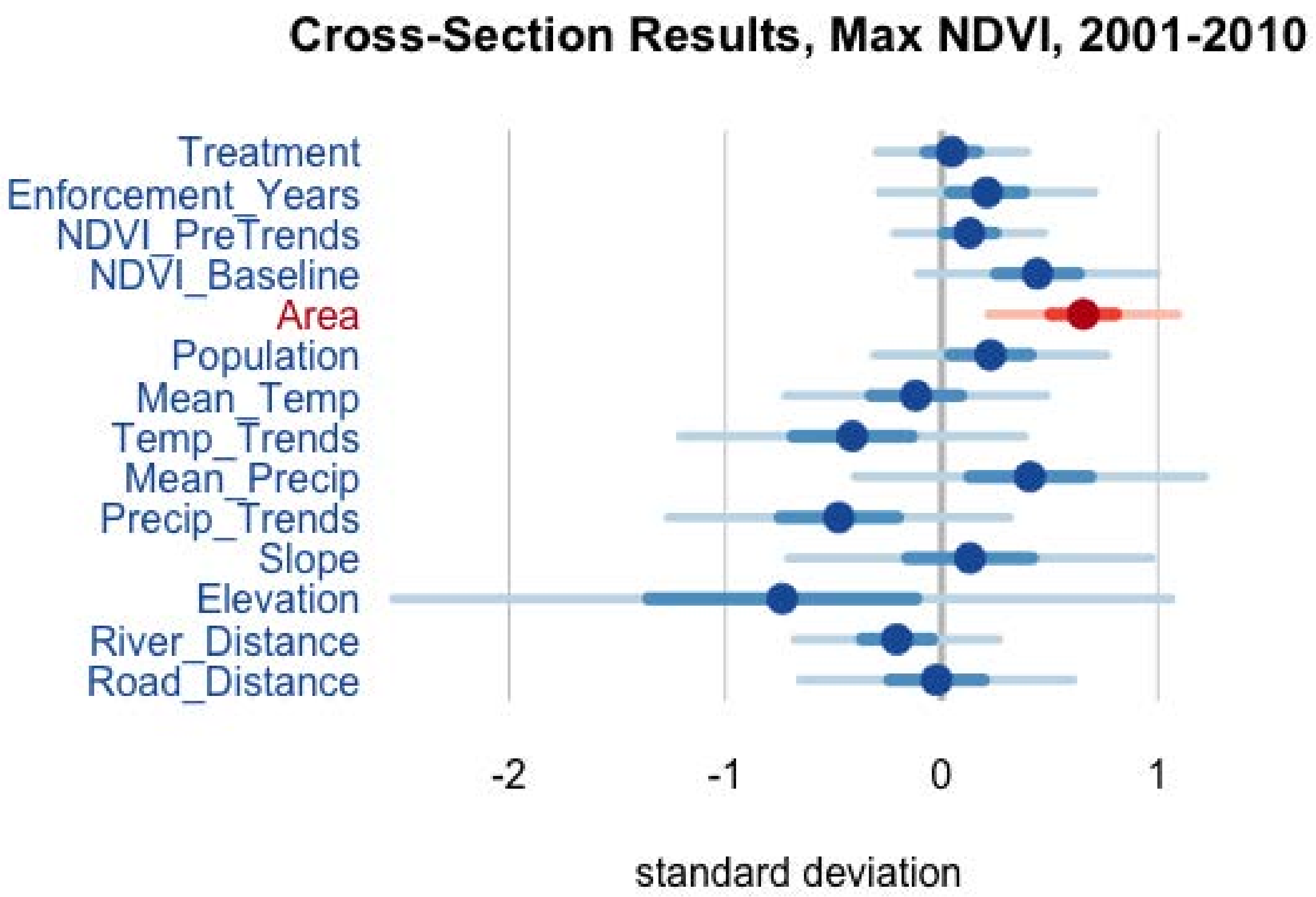
*Differences-in-differences:*

“Early” vs. “Late”

Treatment = “Early” demarcation (‘95-’01)

Outcome = Change in mean NDVI between ‘95 and ’10

Sample: 40 community pairs, matched on covariates



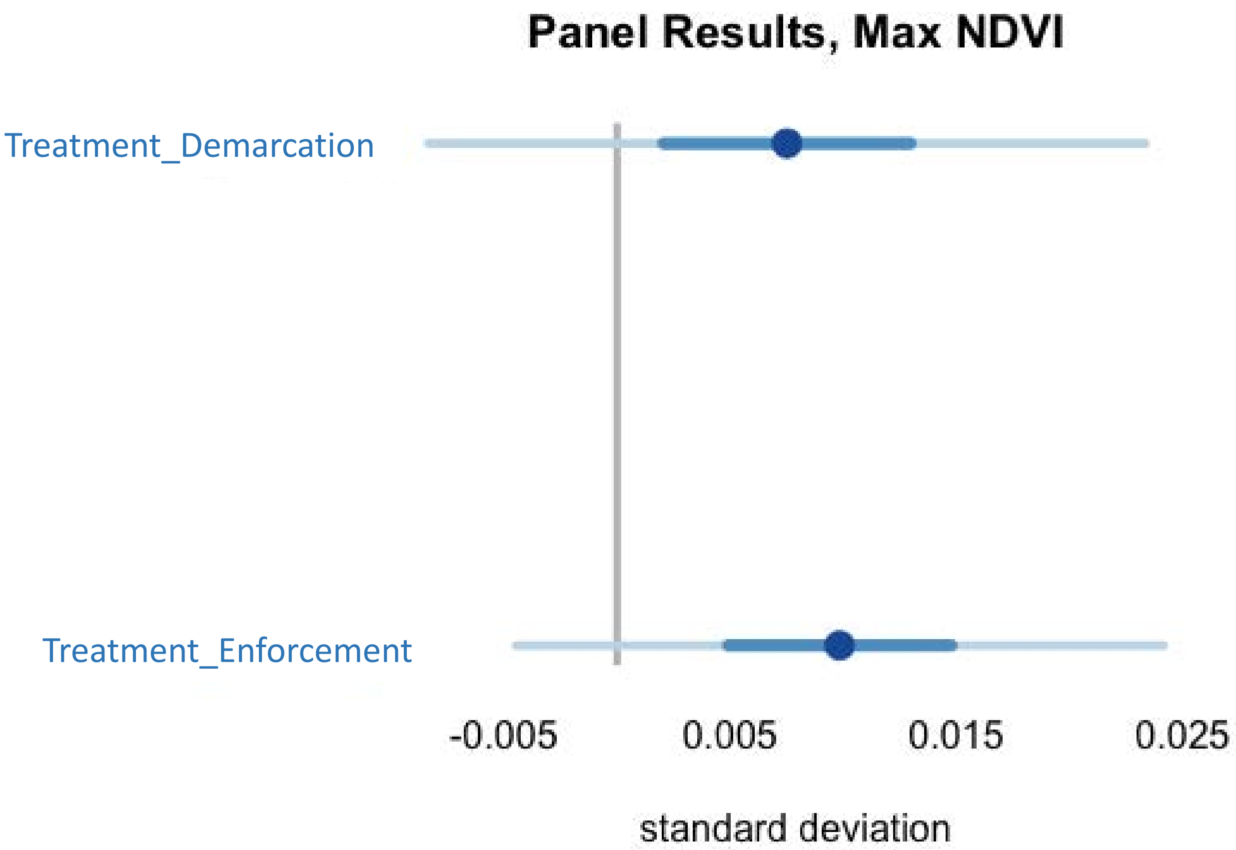
*Panel model*

Outcome = Level of max NDVI in year

Covariates include community fixed effects and year trends

Sample: 2128 annual observations for demarcated communities

Standard errors clustered by community & year



# Preliminary Conclusions

- No clear, robust evidence of differences in deforestation attributable to the PPTAL project

- Much lower rates of deforestation on indigenous lands in cross-section may not be related to land tenure status of these lands (or may be mediated through multiple, complex channels)

# Next Steps / Future Research

- Identifying “high pressure” communities (both T and C) where treatment effects may be larger
- Disaggregating to smaller units of analysis, adding precision from finer covariates
- Using admin data on criteria for timing of community demarcation to control for remaining selection concerns
- Expanding the control groups by including communities that never entered PPTAL

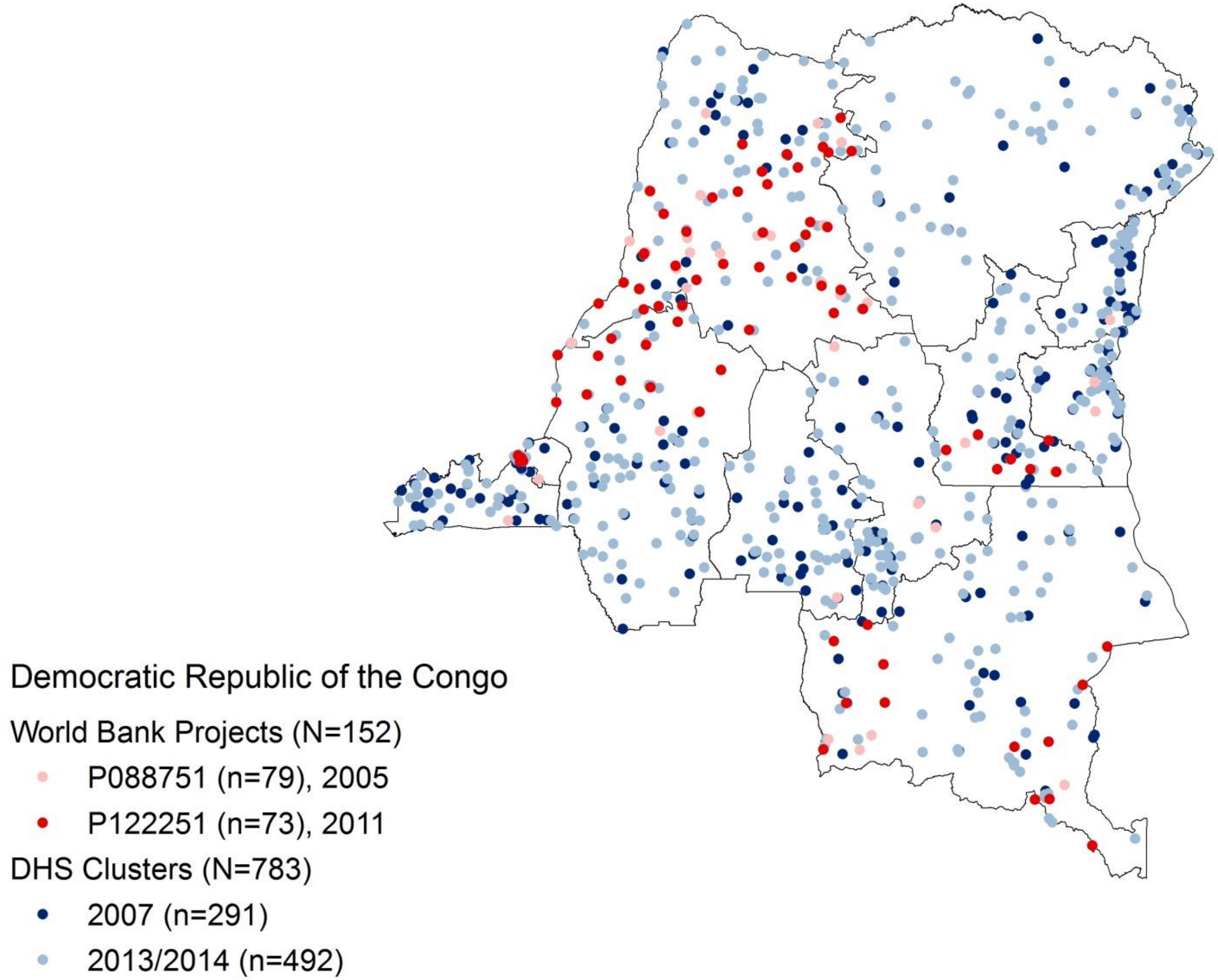
# Evaluating Malaria Aid

*Ariel BenYishay (W&M), Carrie Dolan (VCU), Karen Grepin (NYU), Gordon McCord (UCSD)*

# Effectiveness of Malaria Aid

- In 2005-2014, World Bank projects invested $230M in health sector in Democratic Republic of Congo, much of it fighting malaria
  - Intermittent preventative treatment (IPT) for pregnant women
  - ACT for first-line treatment for malaria
  - Provision of malaria-related preventive, diagnostic and treatment services in HSRSP target health zones
  - Scaling up coverage of LLINs, including via a government-led mass distribution campaign

# Project and Survey Locations




AidData
Open Data for International Development

# Empirical Approach

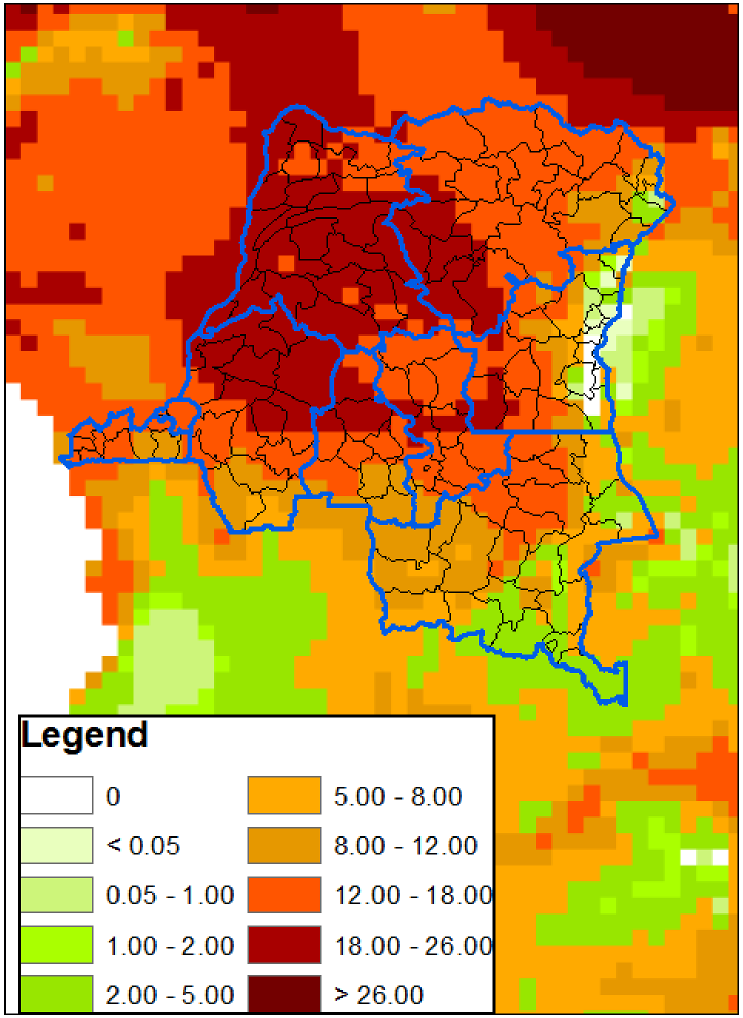
- Does child mortality decrease after a project is active differentially for children closer to a project site?
- Survival analysis with differences-in-differences and district-level fixed effects and trends

$$Survival_{idbt} = f\begin{pmatrix} \beta_1 Dist2005_{id} + \beta_2 Dist2005_{id} * Post2005_t \\ +\beta_3 Dist2011_{id} + \beta_4 Dist2011_{id} * Post2011_t \\ +\beta_5 female_{id} + DAge_{idbt} + D_d + D_d * t \end{pmatrix}$$

# Variation in Malaria Ecology

- Is this effect larger in locations where underlying malaria risks are higher due to ecological conditions?

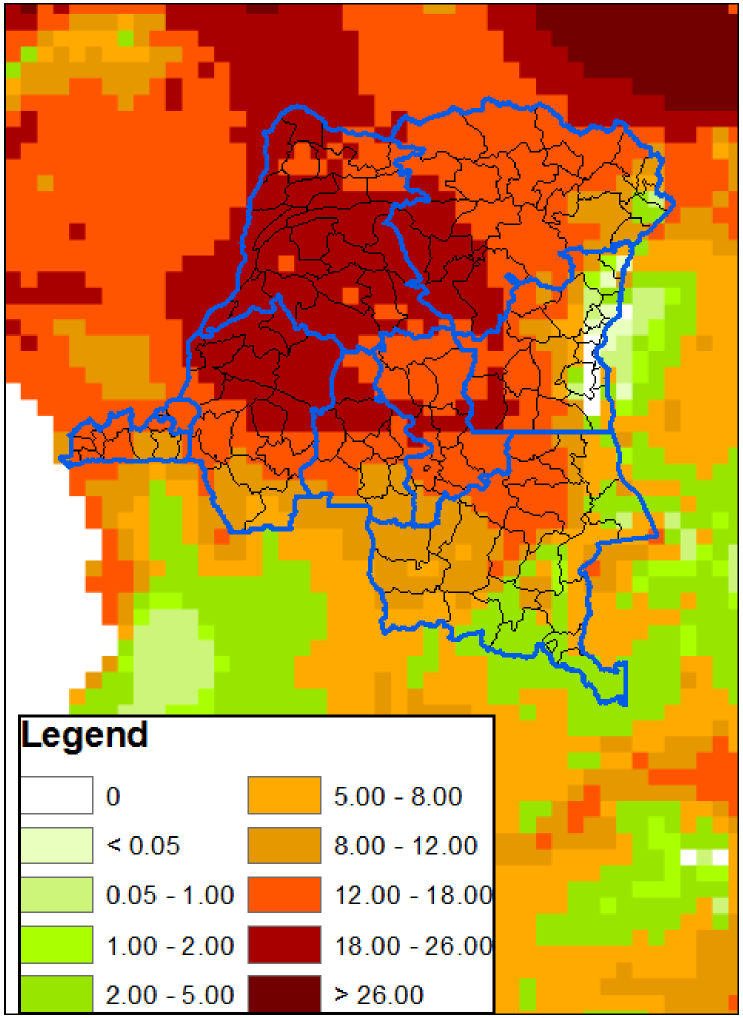
- Even more granular (time-varying) data on climate conditions



# Variation in Malaria Ecology

- In addition to more plausibly random variation…

- Big remaining question:
  - What share of community needs to be treated?
  - Are there thresholds or disproportionate gains?



# Ready for a Geospatial Impact Evaluation?

# Advantages and Needs

- Can sometimes “recover” baselines using existing geo-referenced data
- Can often be accomplished relatively quickly, less expensively
- Need spatial variation: many locations/sites at which project carried out

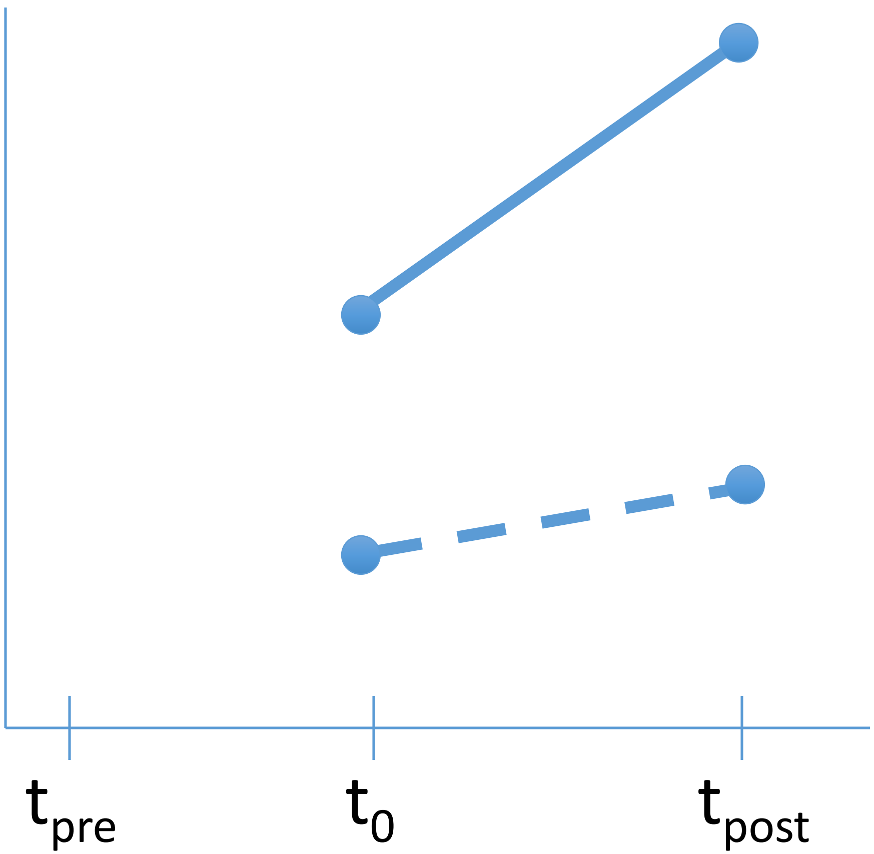
# Ready?

- Contact Kristina Kempkey (kkempkey@usaid.gov) or Brian Bingham (bbingham@usaid.gov)

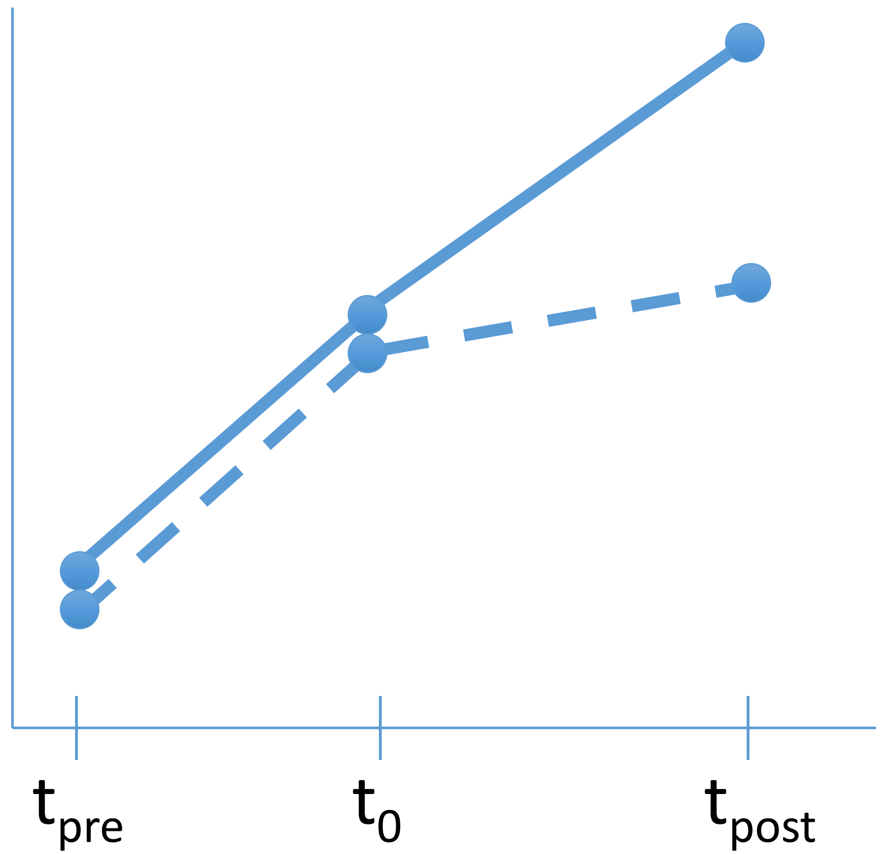
- First set of questions:
  1. How precisely are locations/sites known?
  2. How was/is roll-out across these sites planned?
  3. What are the outcomes of interest?

# Extra Slides

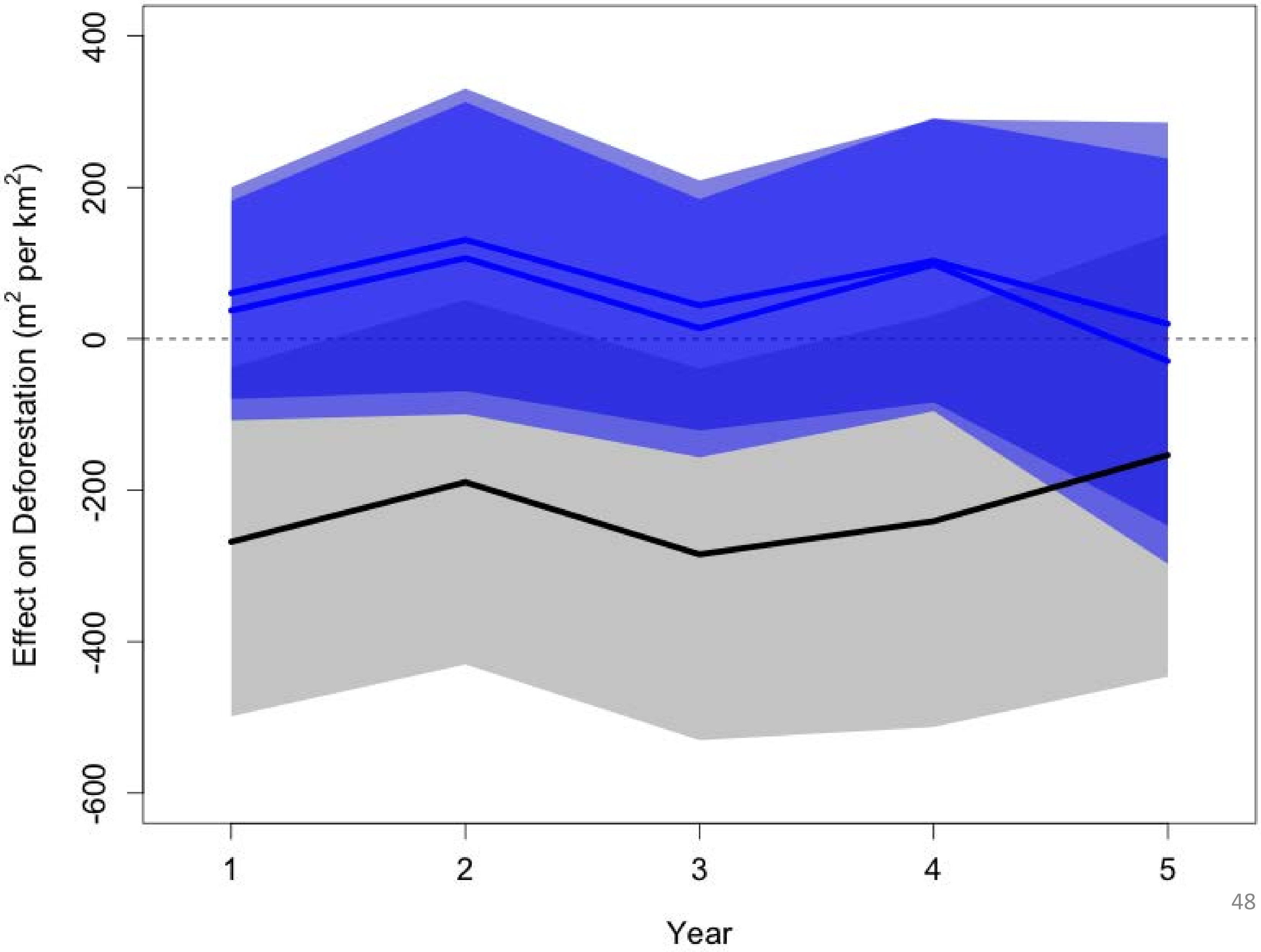
## Difference in Differences



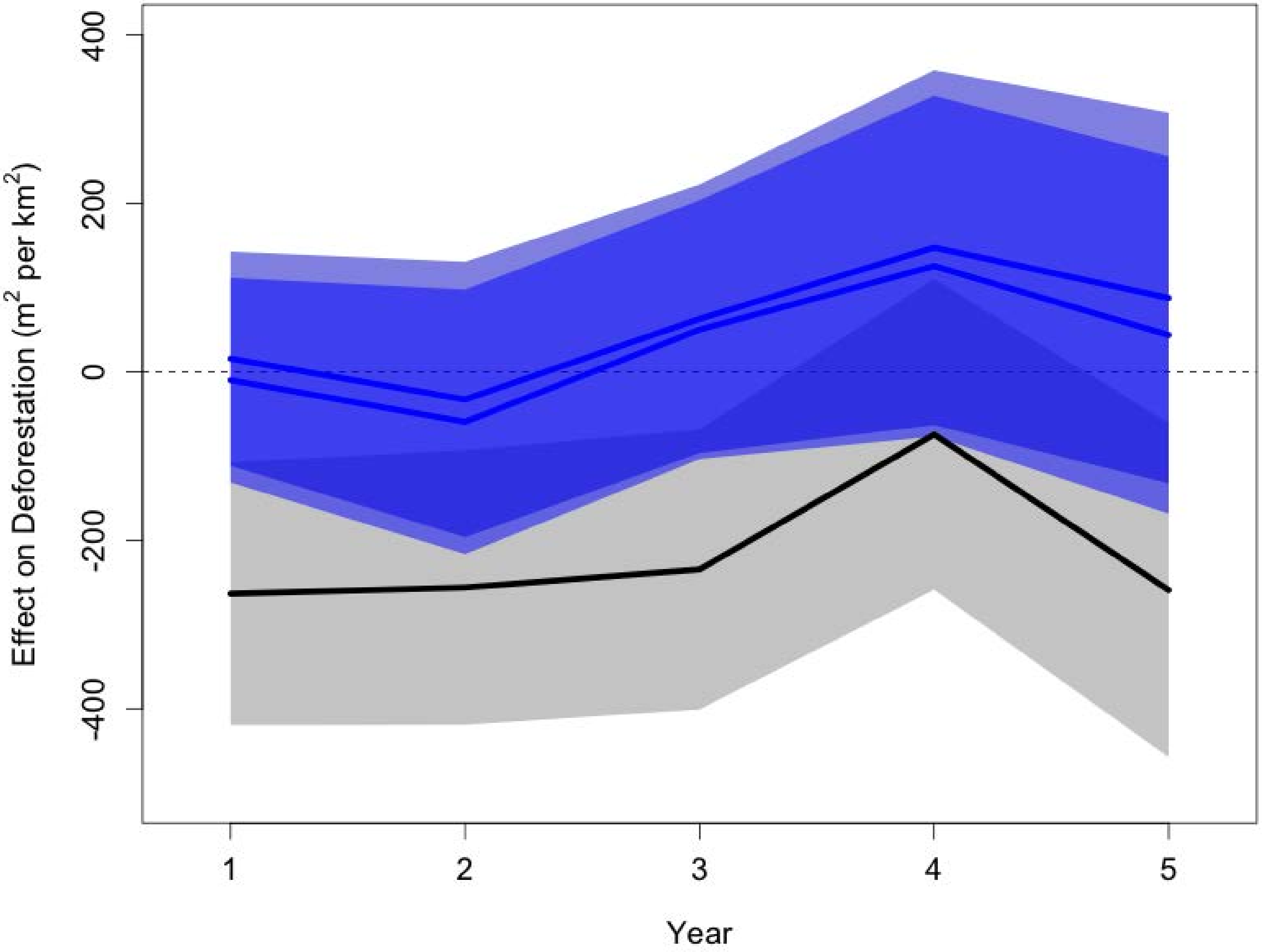

## Trajectory and Pretreatment Outcome Matching



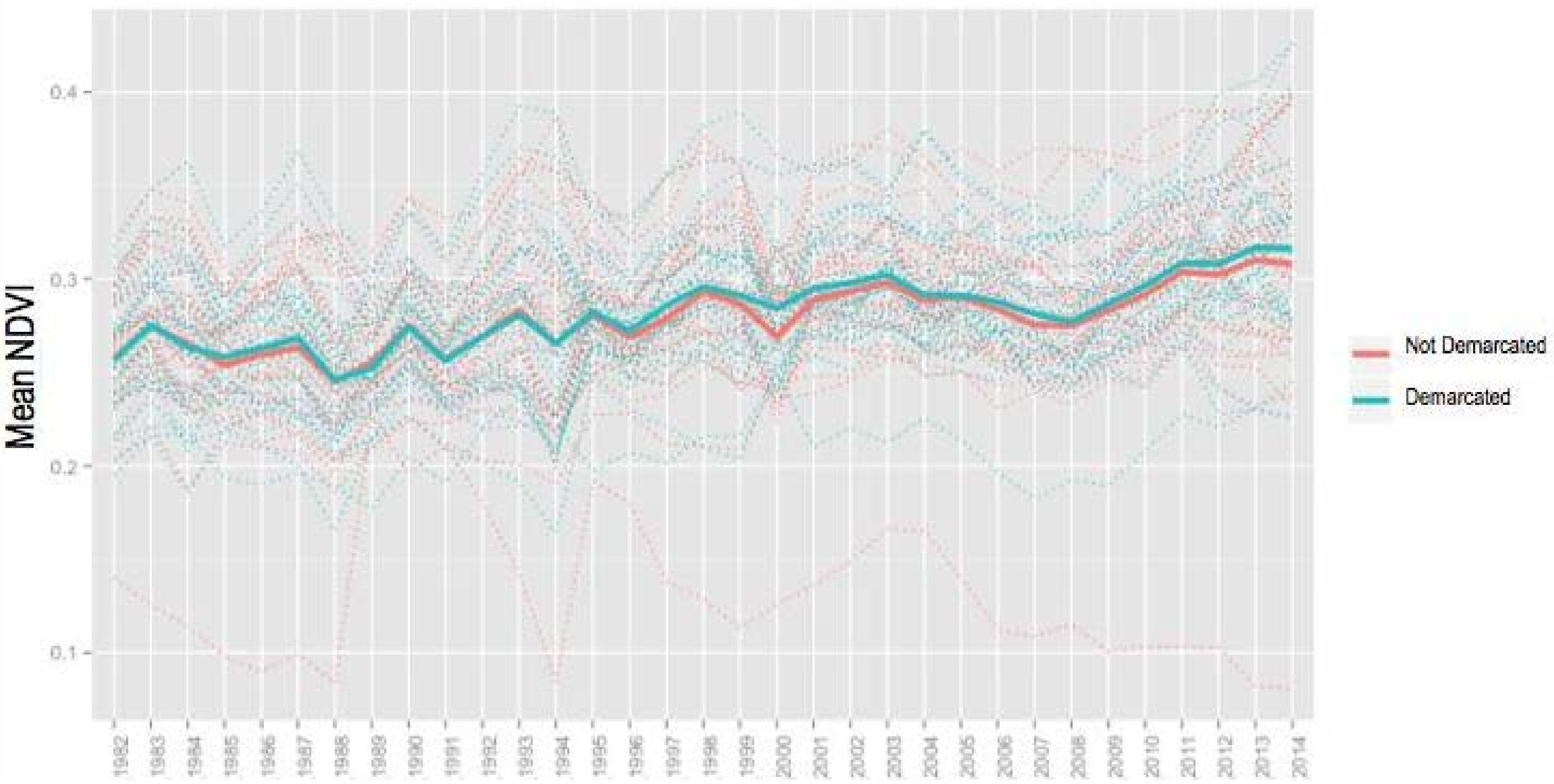
# Treatment Effect of Legalization Only



# Treatment Effect of Legalization and Community Management Plan



# NDVI Trends


Mean NDVI
0.4
0.3
0.2
0.1
1982
1983
1984
1985
1986
1987
1988
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1990
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1992
1993
1994
1995
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2005
2006
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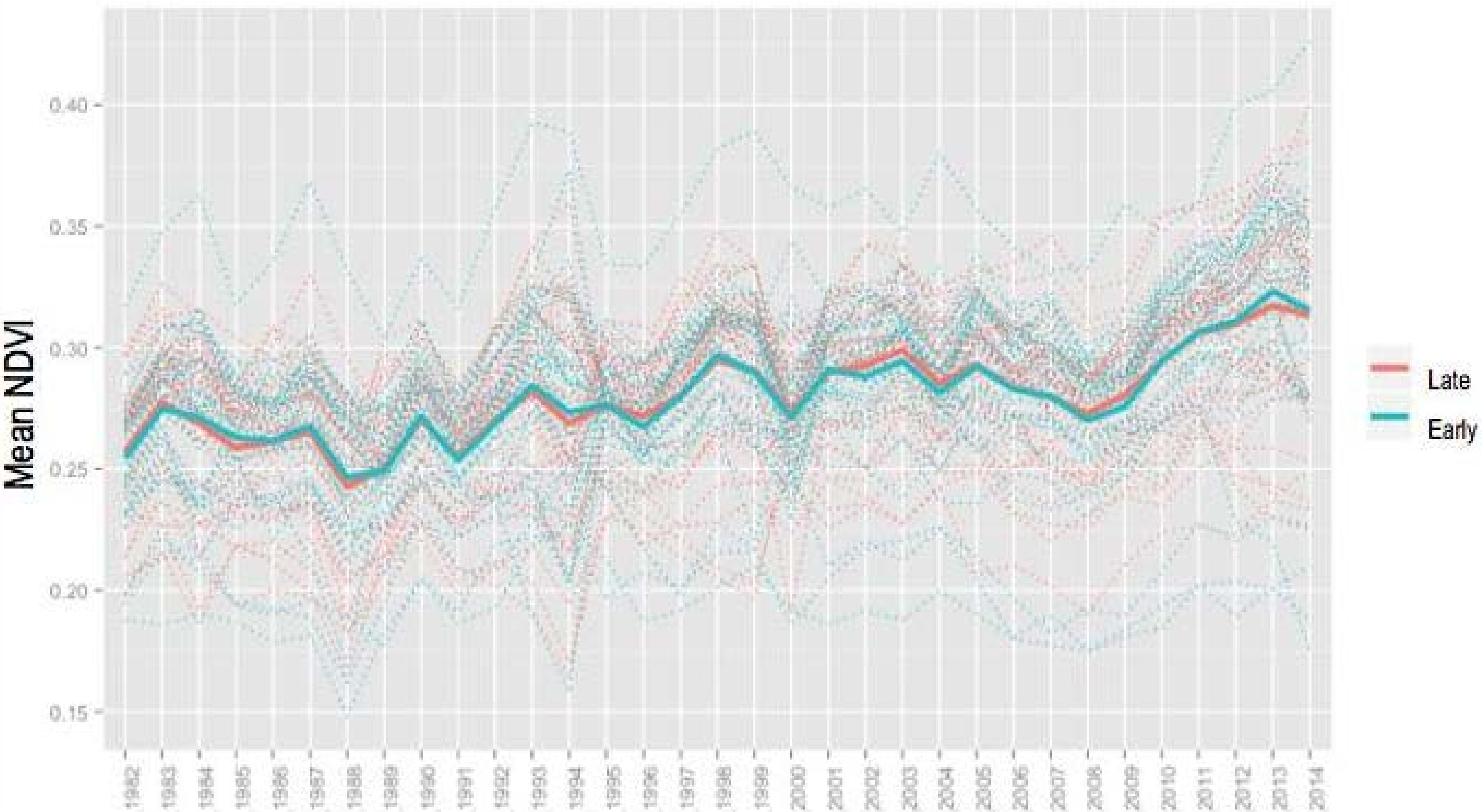
2008
2009
2010
2011
2012
2013
2014
Not Demarcated
Demarcated

# NDVI Trends



Mean NDVI
0.40
0.35
0.30
0.25
0.20
0.15
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
Late
Early

**PSM First Stage Results**

| | *Dependent variable:* | |
|---|---|---|
| | Early vs. Late Ever Demarcated | |
| | (1) | (2) |
| Area (hectacres) | 1.239 | 0.972* |
| | (0.968) | (0.563) |
| Population Baseline | 0.017 | 0.005 |
| | (0.399) | (0.256) |
| Pre-trend Mean Precipitation | 0.600 | 0.206 |
| | (0.680) | (0.566) |
| Pre-trend Max Precipitation | -0.633 | -0.470 |
| | (0.553) | (0.427) |
| Pre-trend Min Precipitation | -0.576 | 0.429 |
| | (0.388) | (0.360) |
| Pre-trend Mean Temperature | -0.673 | 0.291 |
| | (1.137) | (0.805) |
| Pre-trend Max Temperature | -0.504 | -0.866 |
| | (1.019) | (0.757) |
| Pre-trend Min Temperature | -0.775 | -0.471 |
| | (0.523) | (0.413) |
| Pre-trend NDVI Mean | -0.037 | 0.210 |
| | (0.329) | (0.246) |
| Pre-trend NDVI Max | 0.216 | 0.068 |
| | (0.330) | (0.261) |
| Slope | -0.814 | 0.048 |
| | (0.562) | (0.310) |
| Elevation | 0.678 | -0.420 |
| | (0.869) | (0.364) |
| Mean Precipitation Baseline | -1.000 | -0.256 |
| | (0.662) | (0.514) |
| Mean Temperature Baseline | 1.634** | 0.111 |
| | (0.661) | (0.417) |
| Max NDVI Baseline | 0.015 | 0.778** |
| | (0.364) | (0.325) |
| Mean NDVI Baseline | 0.008 | -0.632** |
| | (0.416) | (0.322) |
| Distance to Rivers | -0.111 | 0.072 |
| | (0.243) | (0.203) |
| Distance to Roads | -0.415 | 0.512 |
| | (0.500) | (0.367) |
| Constant | -0.263 | 1.140*** |
| | (0.293) | (0.230) |
| Observations | 106 | 151 |
| Log Likelihood | -51.660 | -72.324 |
| Akaike Inf. Crit. | 141.320 | 182.648 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |