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Tropical deforestation and its relation to internationally-traded commodities

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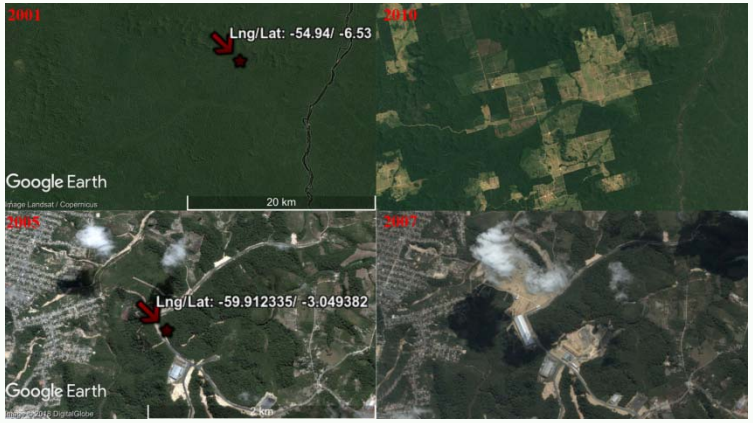
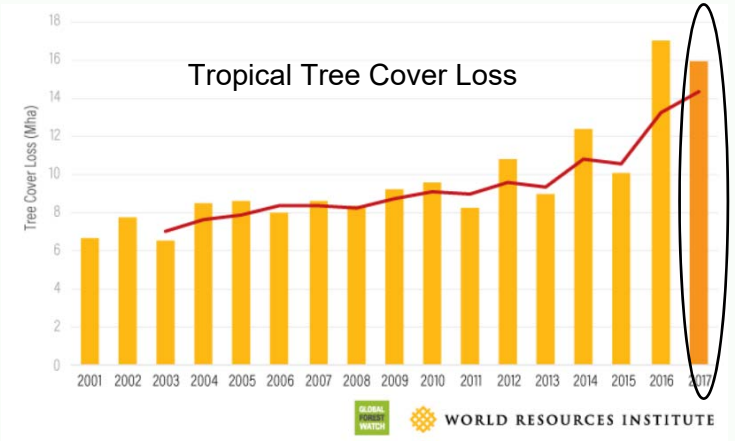
tess RESEARCH FOR LOW CARBON INITIATIVES

Introduction

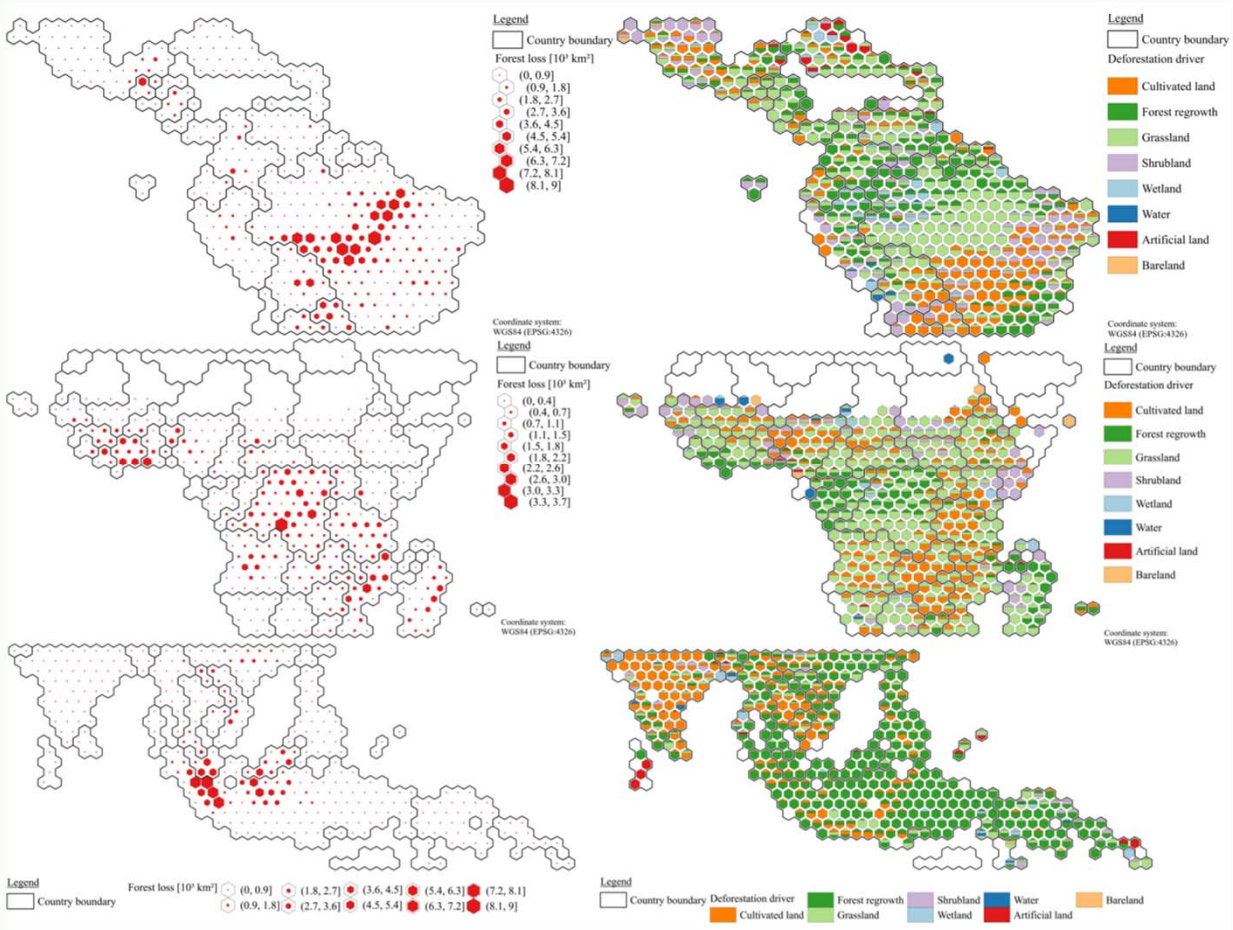
- **Globally, 25% of net anthropogenic GHG emissions** come from the agriculture, forestry, other land use **(AFOLU) sector** (IPCC, 2019)
- **Deforestation** amounts to **10-15% of total GHG emissions**
- **Land-use CO2 emissions** must **decrease** along a nonlinear trajectory and reach net 0 by 2050 (Rockström et al. 2017)
- Proximate/**direct** vs **underlying**/indirect **drivers of deforestation**
- **Underlying drivers: Urban population growth** and **agricultural trade** (DeFries, 2010)
- **Nature of deforestation**: From state-sponsored to **enterprise driven**

Size of > Greece





Direct drivers of deforestation



Seydewitz, T., D.M. Landholm, J.P. Kropp, A. Schultz, P. Pradhan (*In preparation*). Global assessment of proximate deforestation drivers across the tropics: impacts on carbon stocks and ecosystem services.

Underlying drivers of deforestation

- They focus on the **root causes** underpinning these land use change
- Typically grouped into a set of **broad categories** (Geist et al. 2001):
    - **Demographic**: population growth, migration, etc.
    - **Economic**: price of cash crops, market growth, poverty, etc.
    - **Technological**: labor, credit, wood fuel alternatives, etc.
    - **Institutional**: policy-related, land tenure, etc.
    - **Cultural**: public attitudes, tradition, etc.


LETTERS
PUBLISHED ONLINE: 7 FEBRUARY 2010 | DOI: 10.1038/NGEO756
nature geoscience

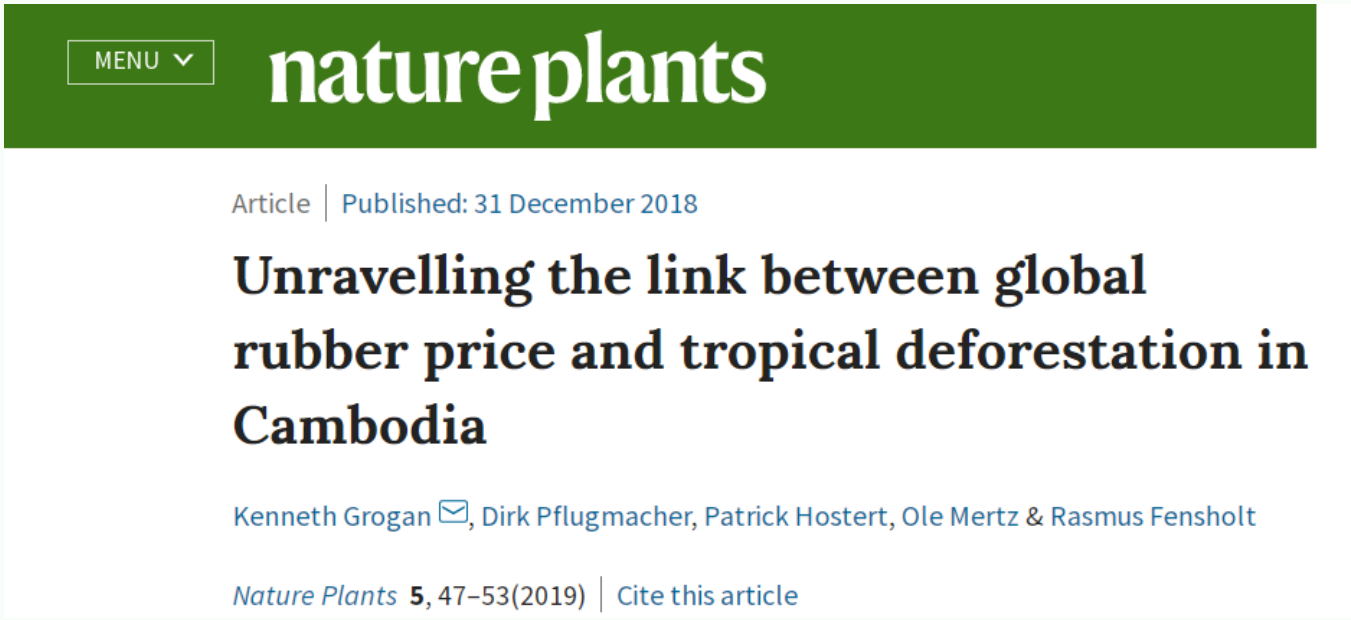
Deforestation driven by urban population growth and agricultural trade in the twenty-first century

Ruth S. DeFries[1]*, Thomas Rudel[2], Maria Uriarte[1] and Matthew Hansen[3]

Other factors of deforestation

- **Land Characteristics:**
  - Soil-related (e.g. good/bad soil quality)
  - Topography (e.g. slope)
  - Vegetation-related (e.g. vegetation density, fragmentation)
- **Biophysical drivers:**
  - Land degradation
  - Water-related (e.g. drought)
  - Vegetation-related (e.g. forest fires)
- **Social trigger events**
  - e.g. war and armed conflict
  - Health/economic crisis
  - Abrupt migrations
  - Policy failures

Now we focus on (economic) underlying drivers…



MENU

nature plants

Article | Published: 31 December 2018

Unravelling the link between global rubber price and tropical deforestation in Cambodia

Kenneth Grogan, Dirk Pflugmacher, Patrick Hostert, Ole Mertz & Rasmus Fensholt

Nature Plants **5**, 47–53(2019) | Cite this article

- **Global commodity prices (rubber)** to determine **deforestation**
- Include **time lag** (9 months), (Pearson's $r = 0.93$)

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Research gaps

- Impact of multiple commodities across different sectors on deforestation is not well understood
- **Comprehensive cross-country analyses missing**

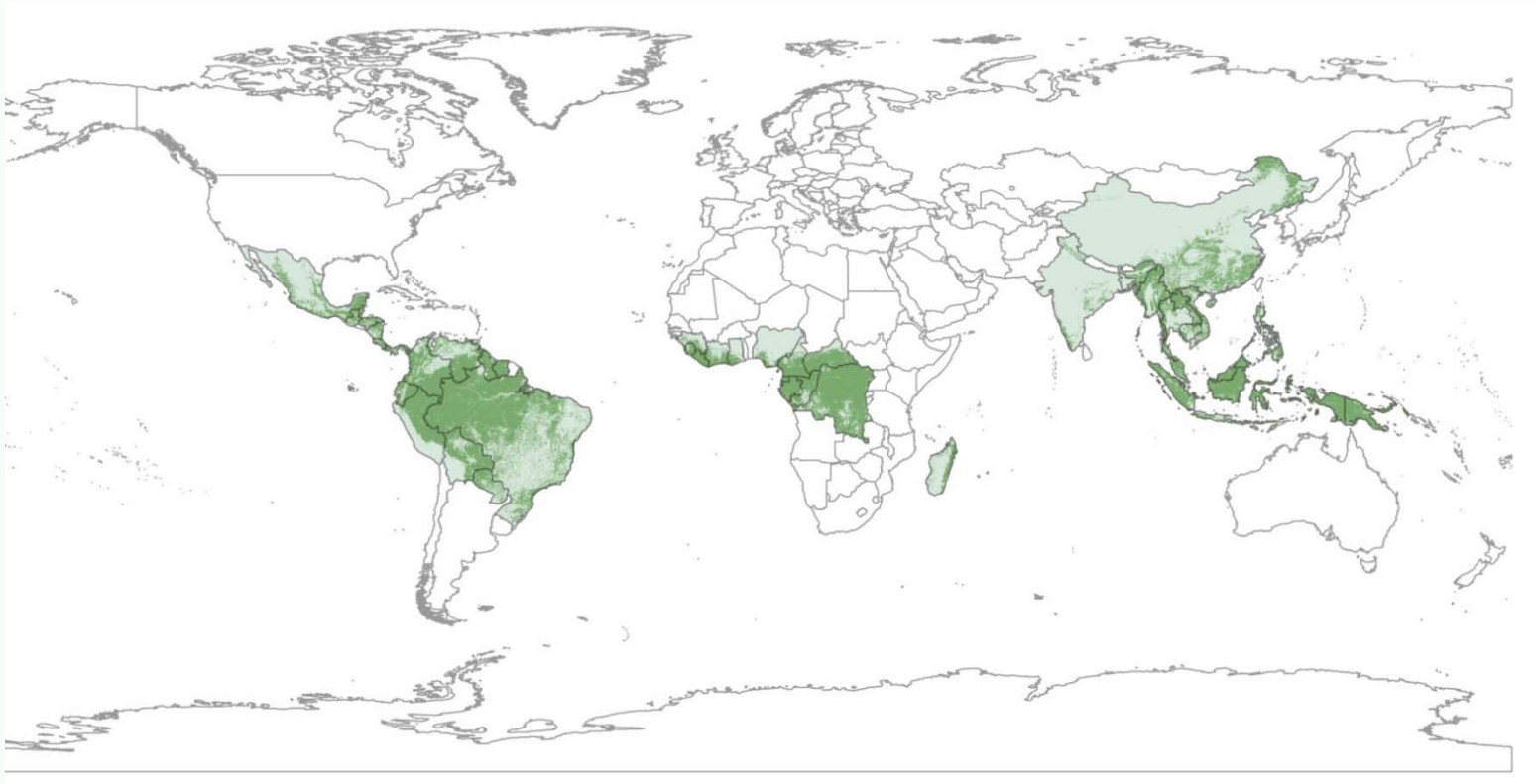
Objectives

1. Investigate the **impact of international markets** in driving **deforestation**
2. Cover **internationally-traded commodity products** across multiple sectors
3. Develop a modeling framework that is able to **identify tropical deforestation drivers across different spatial scales**

Landholm, D.M., D.D. Burra, M.K.B. Lüdeke, L. Reymondin, J.P. Kropp, G. Grosjean (Under review). Cross-country analysis of commodity-driven tropical deforestation, *Conservation Letters*.

Methods

- **Area under examination: 41 tropical countries, 2004-2016**
- **Monthly deforestation events from Terra-i dataset (Reymondin et al. 2012)**



Tree cover (2004) (Hansen, 2013)

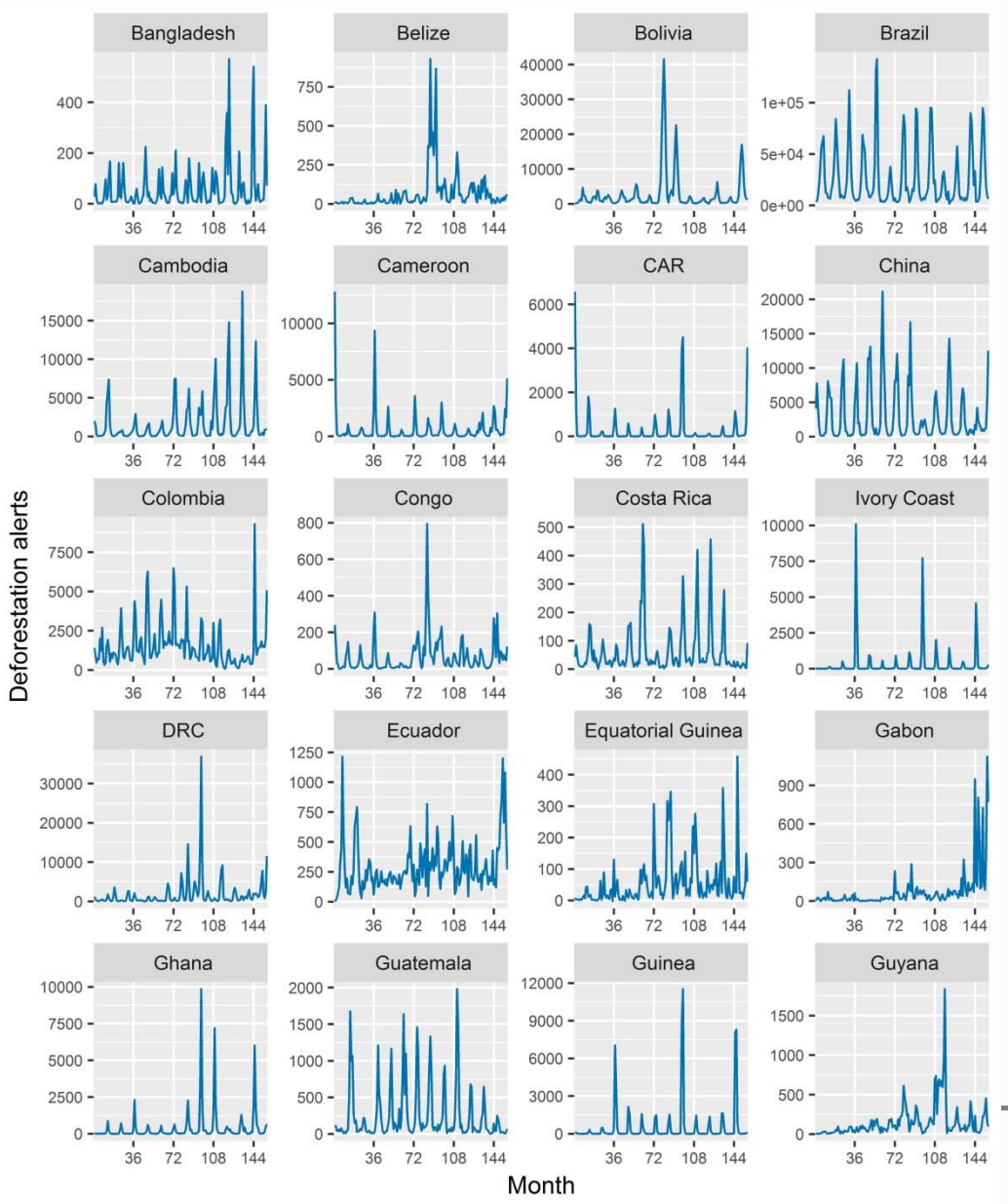
www.terra-i.org

- Deforestation alerts for the **entire tropics** from 2004 (vegetation loss)
- **16 day** deforestation resolution; **250 m**
- Deforestation alert is defined as **10-100% vegetation change** in pixel
- Alert system is based on the premise that **natural vegetation follows a predictable pattern of changes in greenness** from one date to the next brought about by site-specific **land and climatic conditions** over the same period.
- Terra-i used in **academia** (e.g. Leisher, 2013; Bax, 2016; McSweeney, 2014)
- Main use is for government monitoring:
  - **Used by** local and national governments of **Peru, Colombia, Honduras and Vietnam** as a near real time monitoring tool

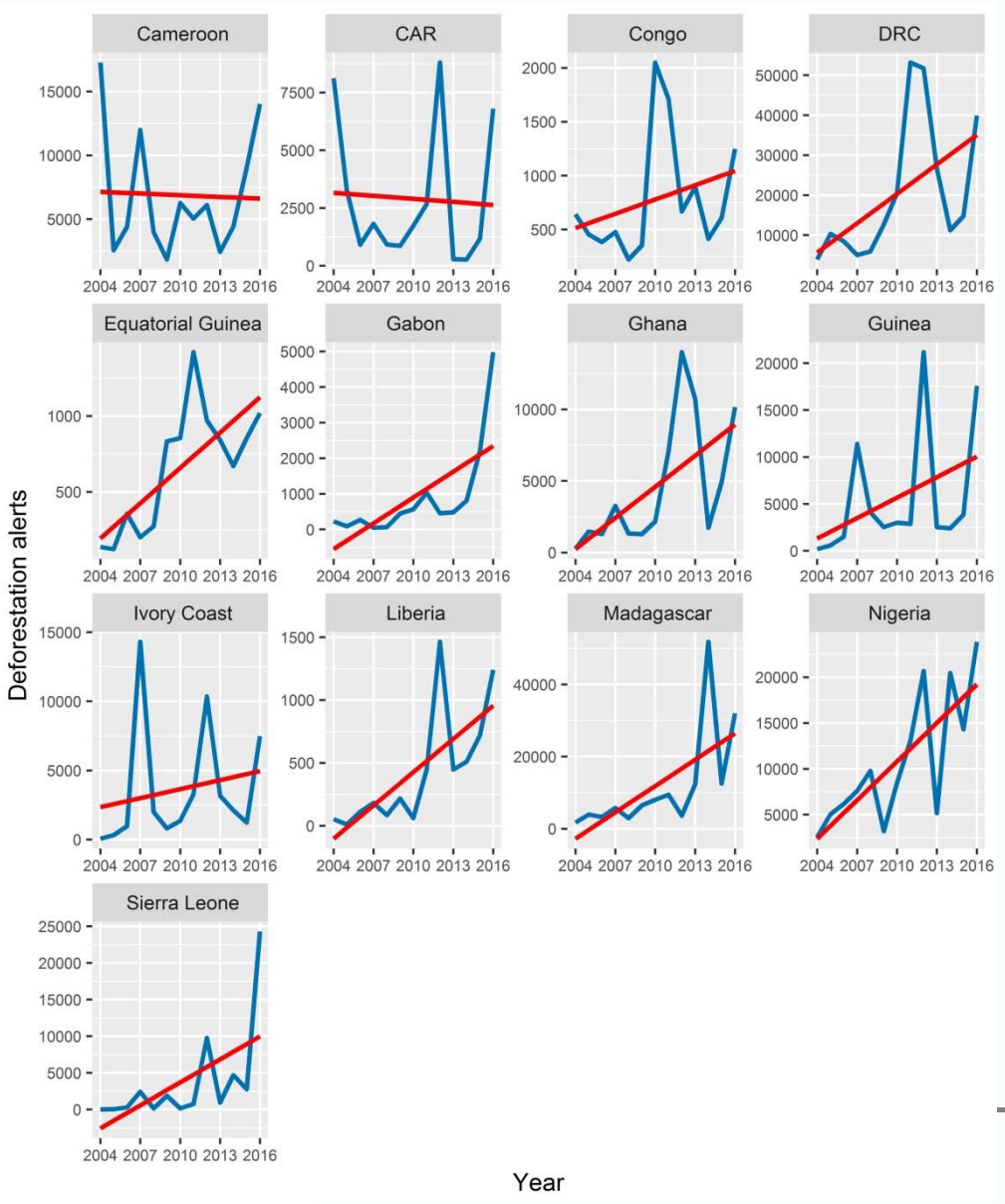
Methods

- **Given the strong seasonality observed, the deforestation variable is seasonally adjusted**

Dependent variable



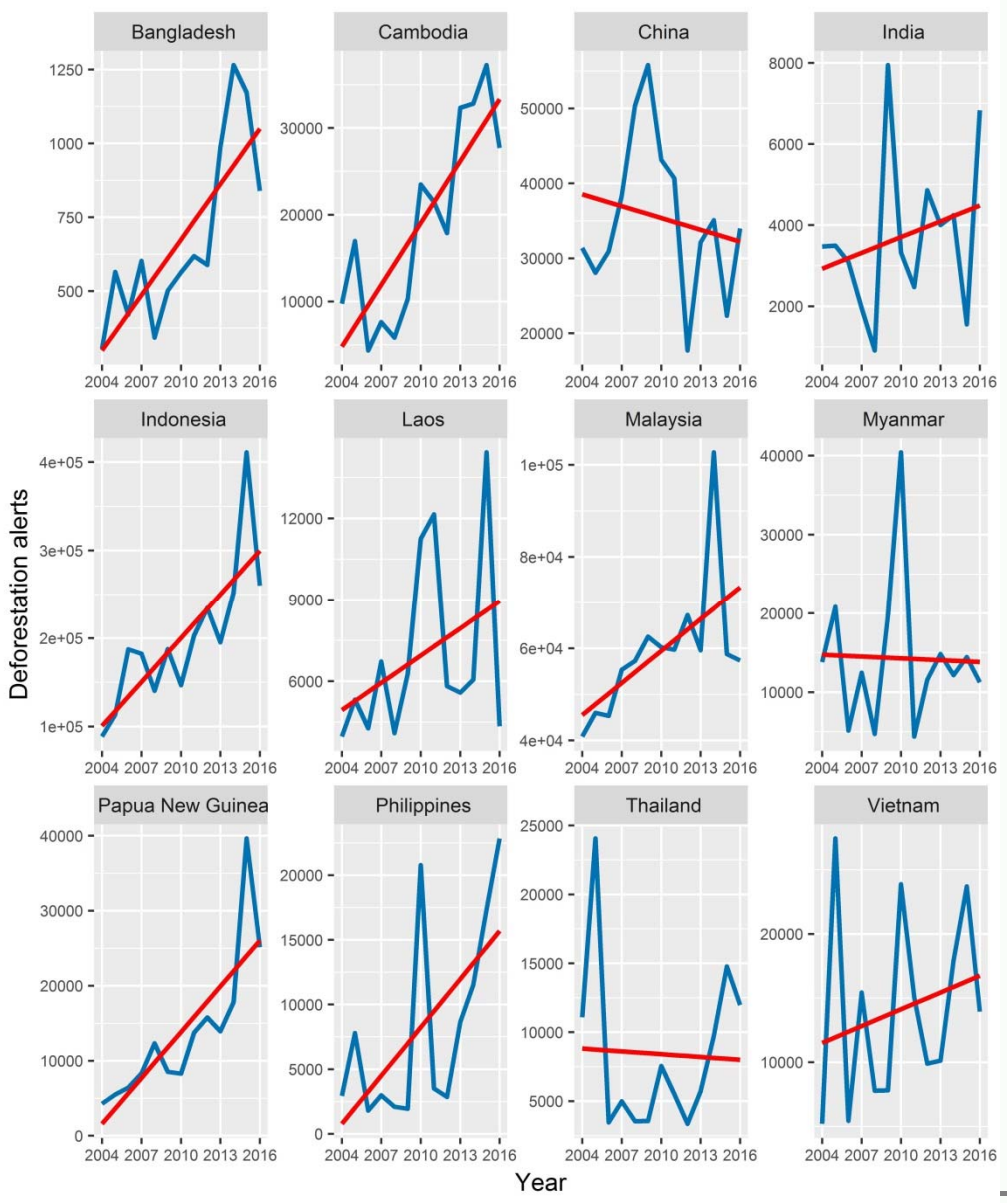
What is the deforestation status? (Africa)



- **11 out of 13 <u>African countries</u> presented increasing deforestation rates over time**

Deforestation in Asia

- **9 out of 12 Asian countries presented increasing deforestation rates over time**



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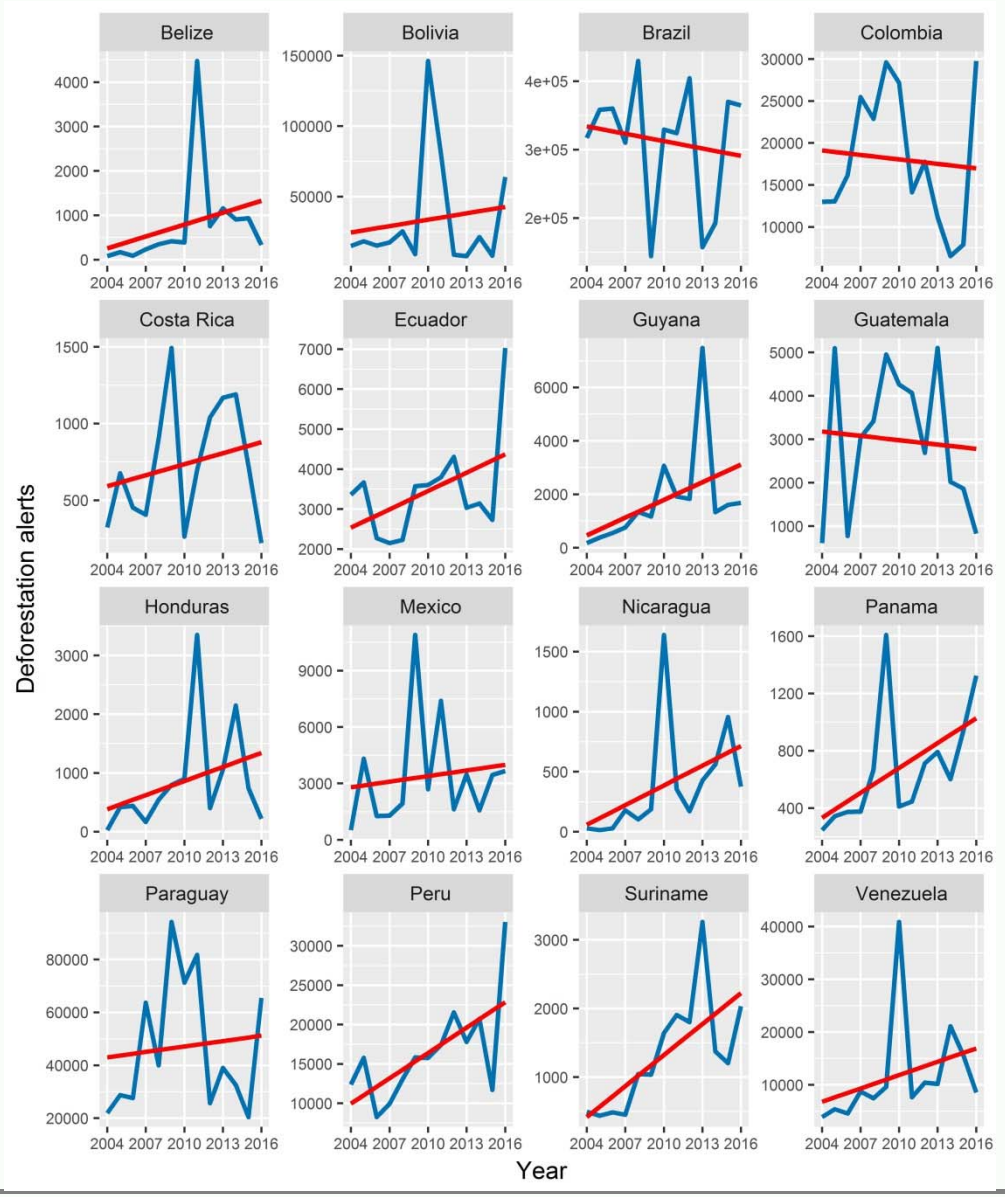
Deforestation in Latin America

- **13 out of 16 Latin American countries presented increasing deforestation rates over time**



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Methods

Covariates (2004-2016)

- **Monthly** resolution
- We use **spot prices** and **lagged prices**

Table 1. Summary of covariates used to explain deforestation events.

Covariates	Type	Unit	Source
GDP growth	Socioeconomic	%	World Bank,
Total population	Socioeconomic	Citizens	FAO
Urban population	Socioeconomic	Citizens	FAO
Banana	Agricultural commodity	US$/kg	World Bank
Beef	Agricultural commodity	US$/kg	World Bank
Cocoa	Agricultural commodity	US$/kg	World Bank
Coffee (Arabica)	Agricultural commodity	US$/kg	World Bank
Coffee (Robusta)	Agricultural commodity	US$/kg	World Bank
Groundnuts	Agricultural commodity	US$/mt	World Bank
Maize	Agricultural commodity	US$/mt	World Bank
Palm oil	Agricultural commodity	US$/mt	World Bank
Rice	Agricultural commodity	US$/mt	World Bank
Soybeans	Agricultural commodity	US$/mt	World Bank
Sugar	Agricultural commodity	US$/kg	World Bank
Tea	Agricultural commodity	US$/kg	World Bank
Copper	Mining commodity	US$/mt	World Bank
Gold	Mining commodity	US$/troy oz	World Bank
Nickel	Mining commodity	US$/mt	World Bank
Silver	Mining commodity	US$/troy oz	World Bank
Zinc	Mining commodity	US$/mt	World Bank
Coal	Mining commodity	US$/mt	World Bank
Logs (Malaysia)	Timber commodity	US$/$m^3$	World Bank
Logs (Cameroon)	Timber commodity	US$/$m^3$	World Bank
Plywood	Timber commodity	UScts./sheet	World Bank
Cotton	Raw material commodity	US$/kg	World Bank
Rubber	Raw material commodity	US$/kg	World Bank

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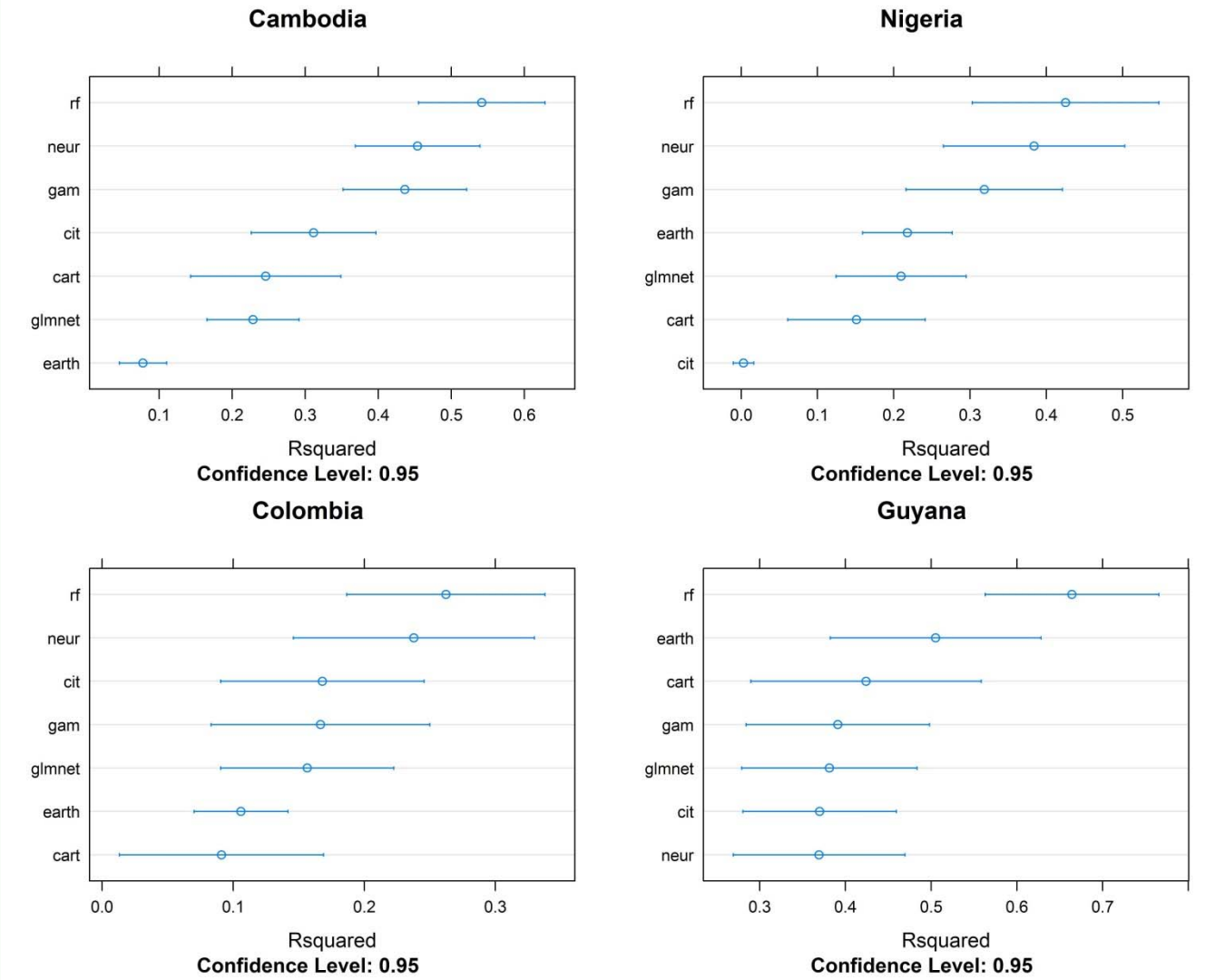
Methods: 41 country datasets

Month	Def (ha)	Price coffee ($/kg)	Price coffee (lag)	.	.
1	10,000	4.20	5.50		
.	.				
.	.				
156	14,500	3.90			

- 156 observations
- 49 covariates
(23 spot prices,
23 lagged prices,
3 socio-economic)
- Variables are centered and scaled

Methods

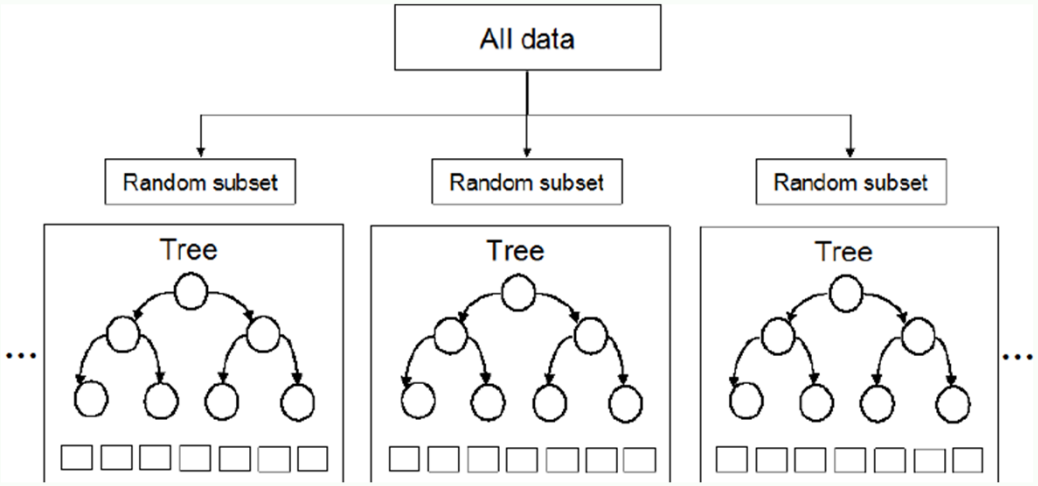
- **Preliminary testing of different modelling options**



Random Forests (RF) ranked 1st for 22 countries and second for 14 in our study and was never amongst the 3 poorest performing models

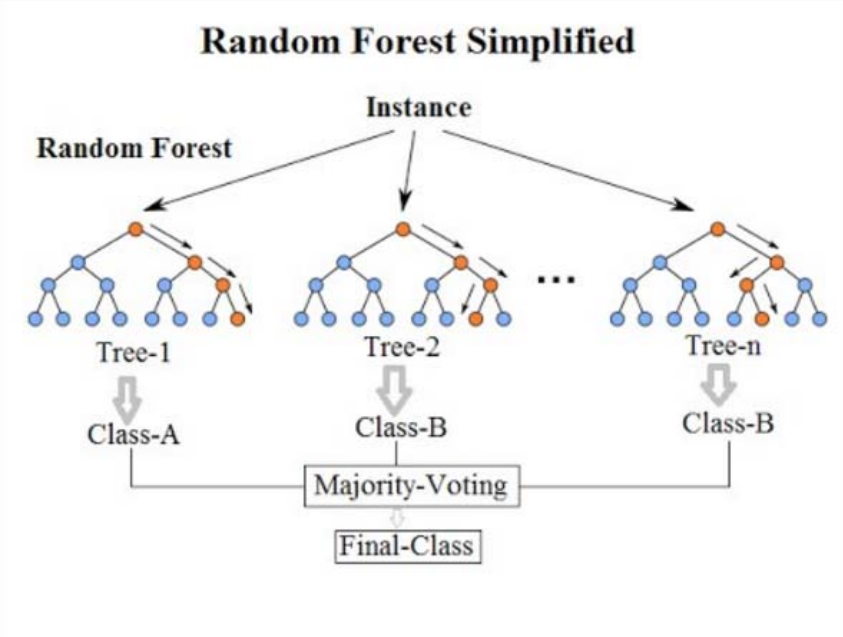
Methods

- We apply **Random Forests model** (Breiman, 2001) (50,000 citations)
- **Ensemble model** built on hundreds/thousands of **individual decision trees**
- Particularly **useful** for problems with **high number of covariates** (n)
- **Randomly subsets a reduced number of features** (n/3)
- Good performance with **highly correlated variables**
- **RFs correct** for decision trees' **habit of overfitting** to their training set
- **Interactions of covariates, non-linear relationships**
- Very **little pre-processing** of data required (centering, scaling)

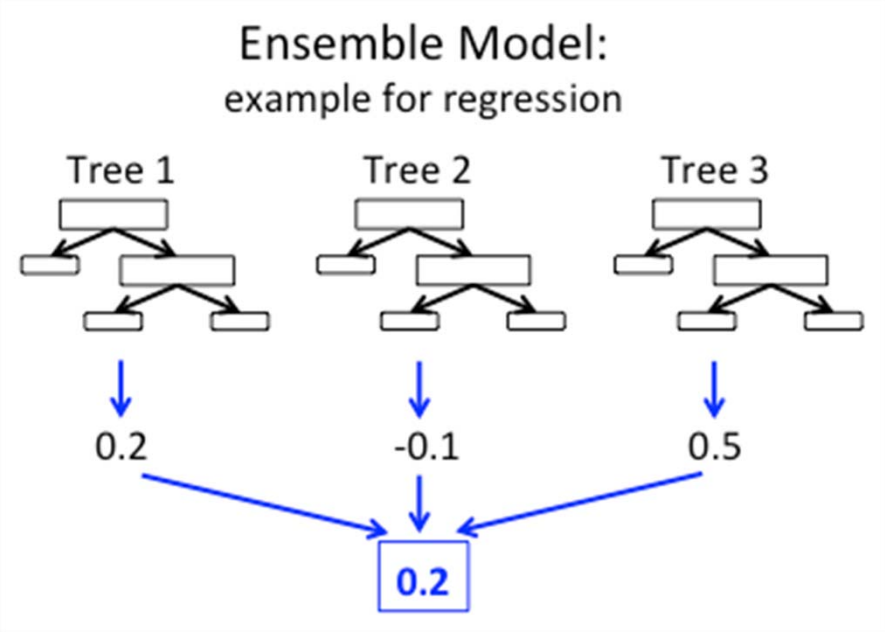


Methods

Classification



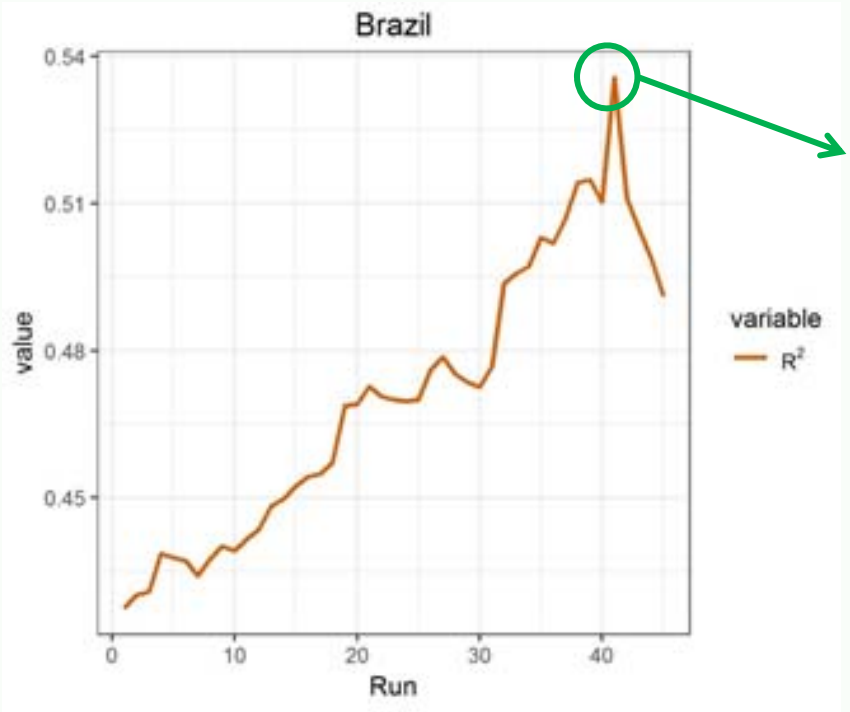
Regression



- Each **tree represents** a different **subset of observations**
- Each **tree** selects a **different subset of covariates**/features (n/3)
- We select a **large number of trees** (here 4000)
- **10-fold cross validation**, 2 repetitions

Methods: interpretation of Random Forest

- **Output of RFs** algorithm is **importance** ranking of all 49 covariates
- **Importance** is determined by how much the model's **RMSE increases when leaving out a given covariate**



	Overall	commodity
Trend_Plywood	100.00000	Trend_Plywood
Trend_Maize	98.44136	Trend_Maize
Trend_Rice	97.94086	Trend_Rice
GDP_growth_int	80.97683	GDP_growth_int
Trend_Beef	67.02791	Trend_Beef
price_Rubber	52.93944	price_Rubber
Trend_Soybeans	45.79904	Trend_Soybeans
Trend_Banana	42.97326	Trend_Banana
price_Tea	0.00000	price_Tea

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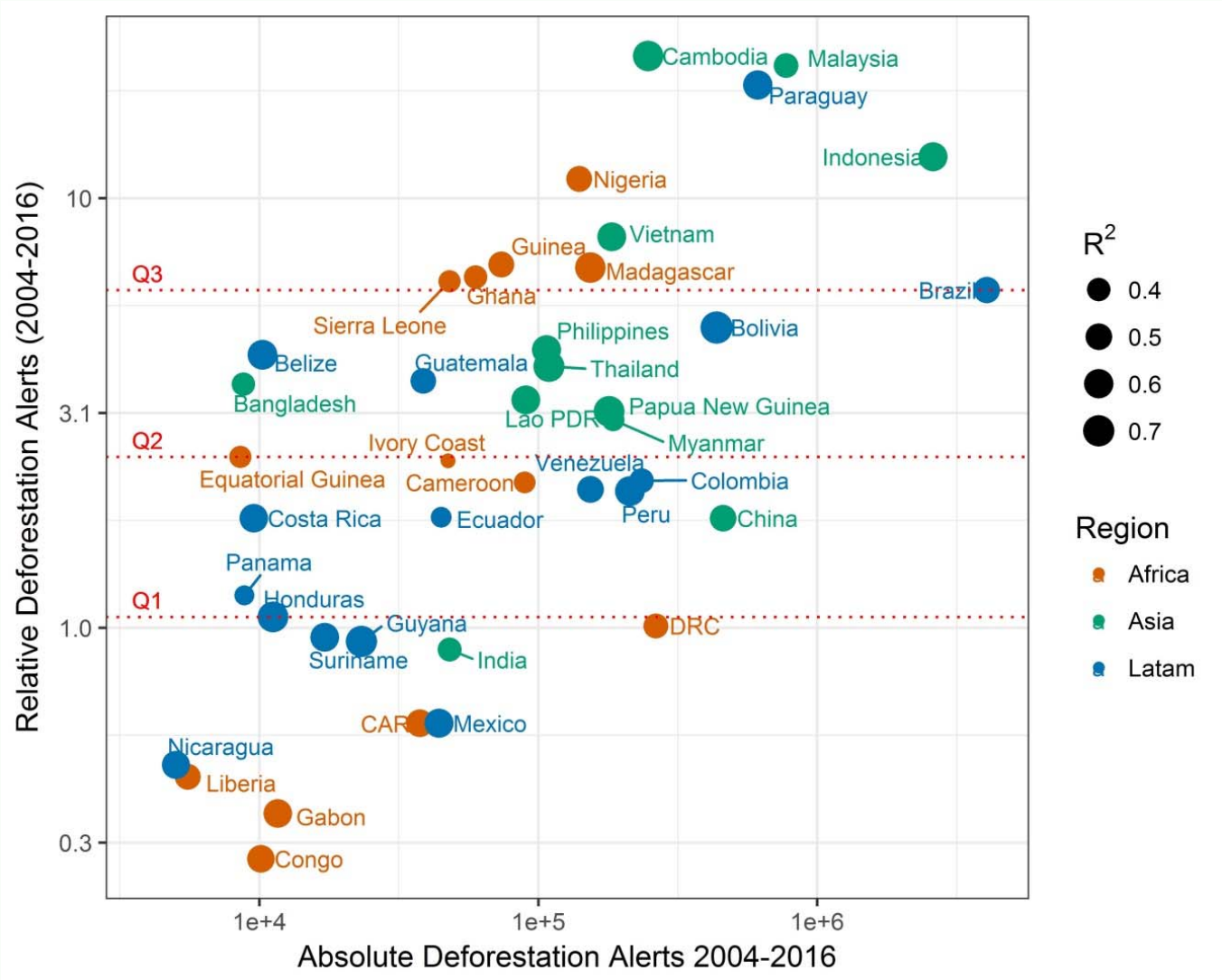
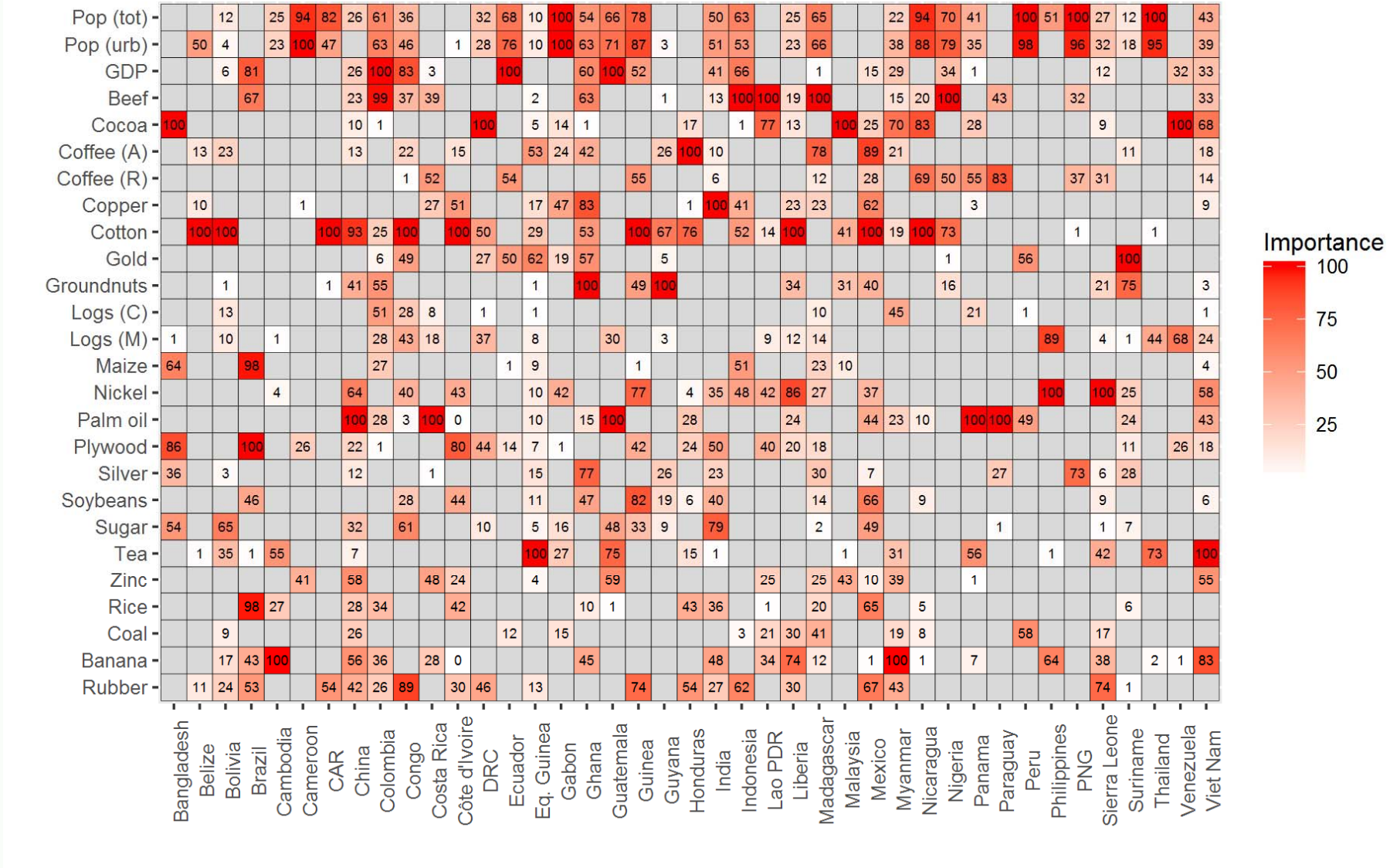
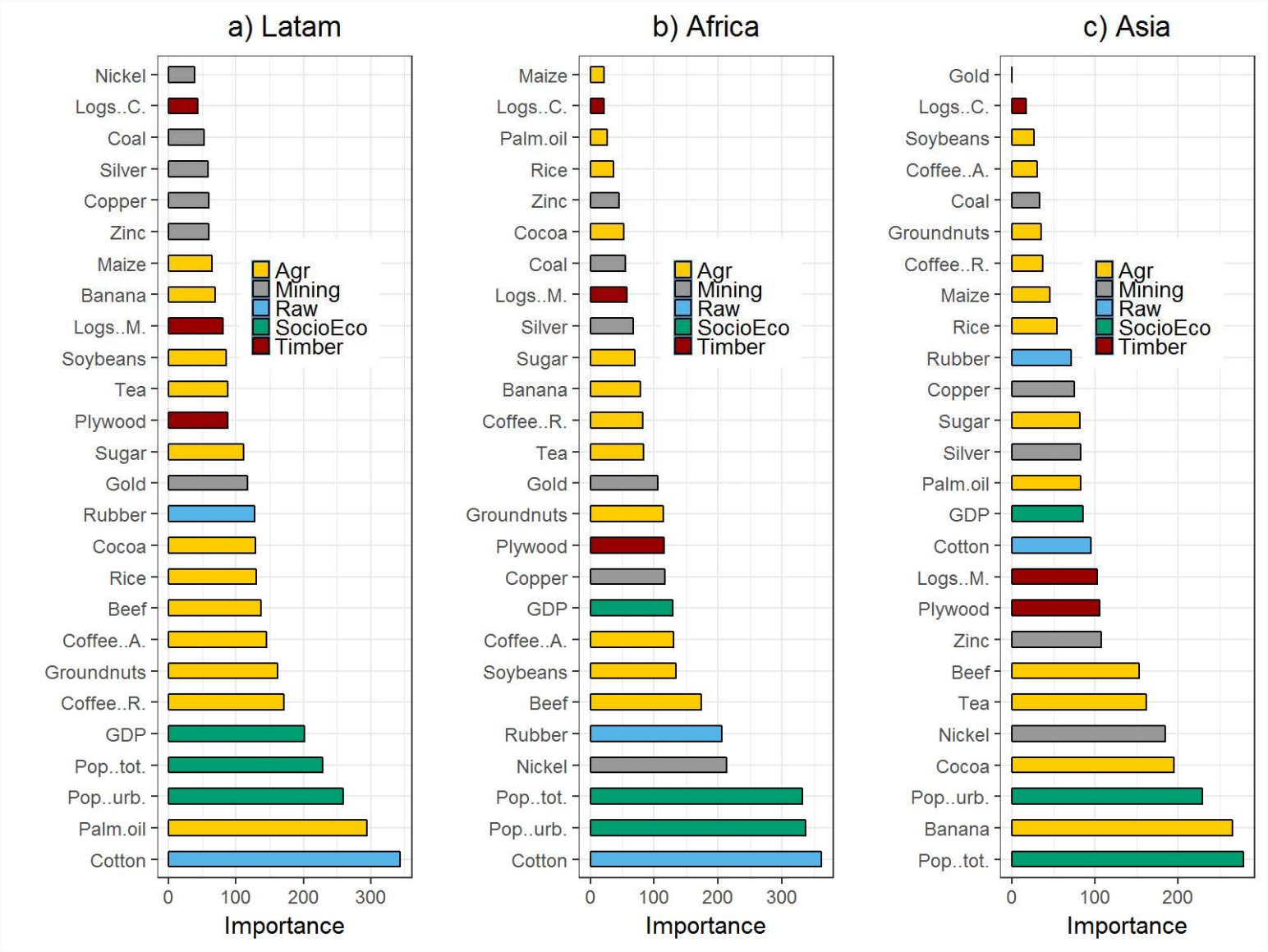
Results: deforestation-international markets



Commodity-driven tropical deforestation

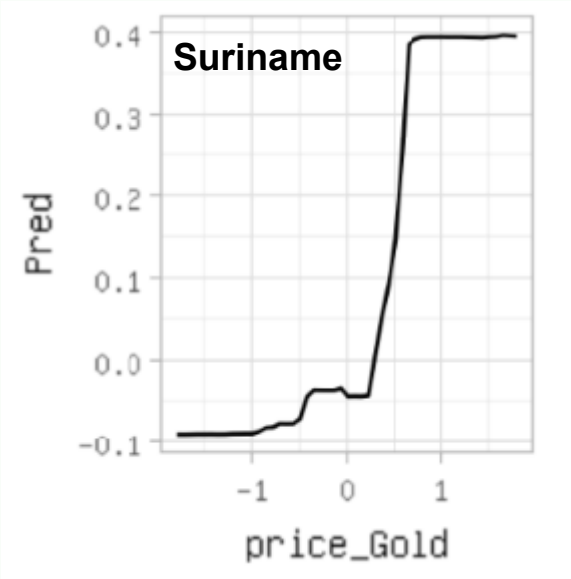


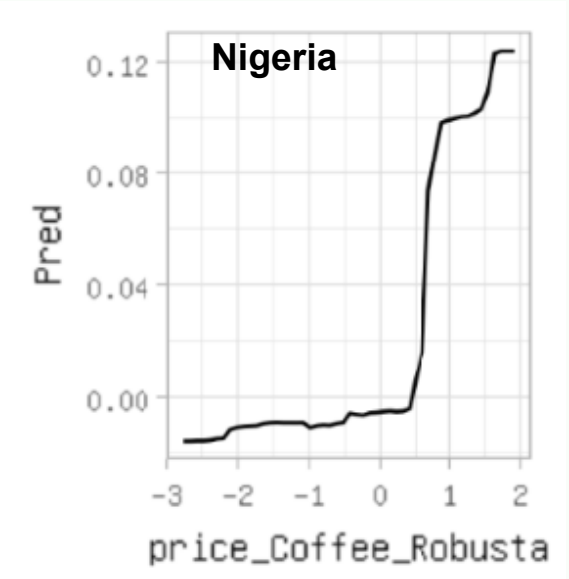
Results: variable importance across regions



Results: How to interpret the mechanisms?

- **Random Forests** algorithms can be **difficult to interpret**
- One option is to use **Partial Dependence Plots** (PDPs)
- **PDPs** can show the **effect a given feature has on the predicted outcome** of a machine learning model (Hastie et al. 2008)





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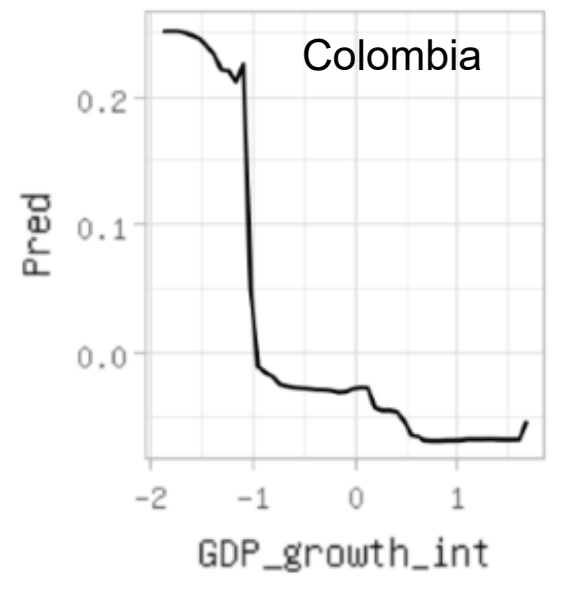
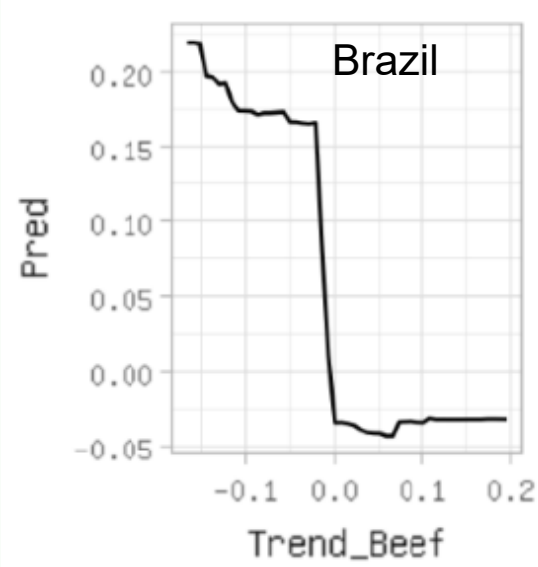
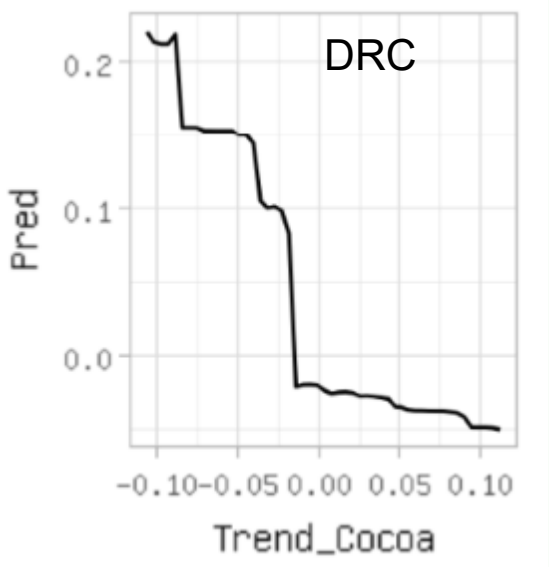
Results: What are the mechanisms?

- We observe a **majority of positive correlations** between price and deforestation
    - Higher demand for products (or lower supply) drive deforestation
- Relationships tend to be **non-linear**: price extremes!
- However, there are several exceptions of negative correlation (e.g. GDP, beef)







Summary

- Provide **evidence** of the **relationship between tropical deforestation** and international **markets**
- We **identify what commodities** are driving **deforestation where**
- **Latin America and Asia** appear more linked to international prices
- **Demographic variables** important across regions
- **Agricultural commodities** are key drivers of forest loss
- PDPs show **a majority of non-linear positive correlations**, with exceptions
- Hypothesis: **large-scale deforestation** more likely to respond to **high prices**; **small-scale deforestation** more likely to react to **low prices**

vs

Limitations / Further work

- Random Forests can be **difficult to interpret** -> PDPs
- RFs may be more useful for **predictive-oriented studies**
- Combine with **other methods?**
- Dozens of **other underlying drivers** affect deforestation
  - Related to economics, e.g. **labor costs, land value**, etc.
- **Commodity-specific lagged price**? (e.g. palm oil vs soybean)
- **Terra-i** (>10% change of resolution pixel) -> **overestimate deforestation**
- **Large opportunities** in the use of **monthly deforestation data**

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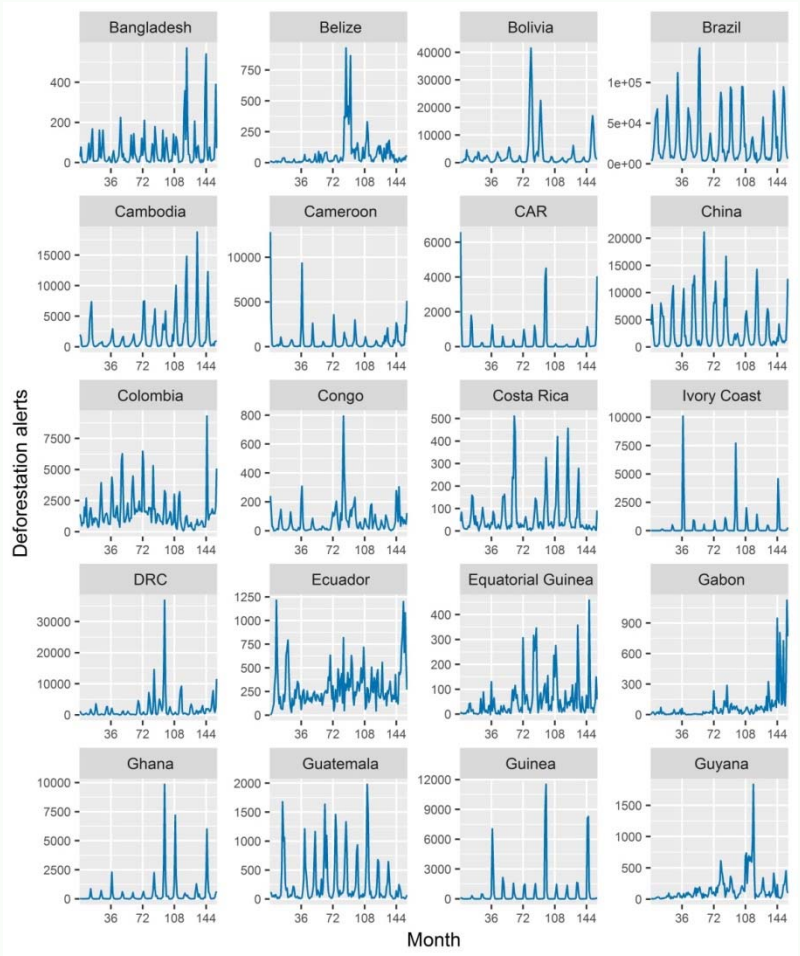
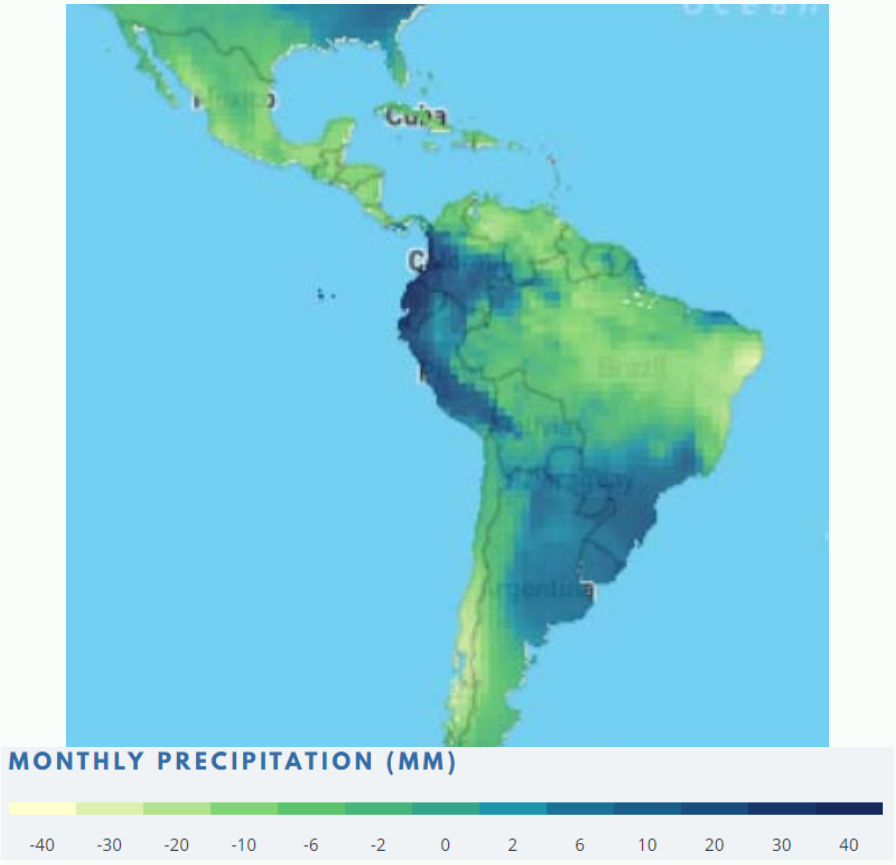
Future opportunities

Terra-i data

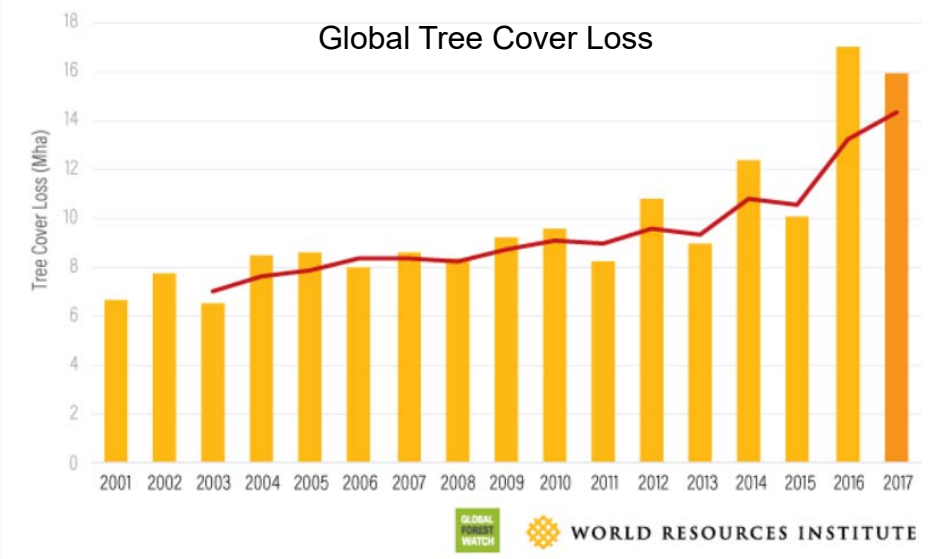


CMIP precipitation projections



Biophysical drivers, water-related (length of dry season)

Concluding remarks



?

"CO2 emissions from land-use must decrease along a nonlinear trajectory to 0 by 2050" (Rockström et al. 2017)

Demand-side measures:

- Dietary change
- Food loss reduction
- Price-premiums for responsible producers
- Market access restrictions

Supply-side measures:

- Sustainable LU options (e.g. agroforestry)
- Alternative income opportunities
- Improve land tenure
- Establishment of protective areas

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Thank you!

David M. Landholm (PhD student)

Supervisors: Prof. Klaus Eisenack, Prof. Jürgen P. Kropp

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Past projects: SUSA, TESS

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Underlying drivers (Gueist, 2001)

Table 2: List of variables (underlying causes) - II

Underlying causes (I)		
Economic factors (economic growth, change or development, commercialisation)	Market growth & commercialisation	Unspecified: rapid market growth (especially of the export-oriented sector), rise of cash economy, increasing commercialisation, incorporation into (world) economy
		Increased market accessibility (esp. of semi-urban and urban markets)
		Growth of sectoral industries (wood-related, agriculture-related, mineral-related, others)
		Lucrative foreign exchange earnings
		Growth of demand for consumer goods and services procured with cash due to a rise in well-being (unspecified, wood-related, agriculture-related, housing & transport)
	Specific economic structures	Unspecified
		Large individual (mostly) speculative gains
		Poverty & related factors (lack of income opportunities, joblessness, resource poverty, low living standard, etc.)
		Economic downturn, crisis conditions
		Indebtedness, heavy foreign debt
	Urbanization & industrialization	Urbanization: growth of urban markets
		Industrialization: rapid built-up of new basic, heavy and forest-based or –related industries
	Special economic parameters	Comparative advantages due to cheap, abundant production factors in resource extraction & use
		Special, mainly artificially low kept production conditions
		Price (value) increases (of fuel, land, cash crops)
		Price decreases (of cash crops)
Policy and institutional factors (change of political economy institutions)	Formal policies	On taxation, charges, tariffs, prices
		On credits, subsidies, licenses, concessions, (logging) bans
		On economic development (agriculture, infrastructure)
		On finance, legislation, investment, trade
		On population (migration)
		On land
		Other pro-deforestation policy (unspecified)
	Informal policies (policy climate)	Corruption, lawlessness
		Growth or development coalitions at work
		Poor performance, mismanagement
		Clientelism, vested (private) interests
		Redefinition of (forestry) policy goals
	Property rights regimes	Insecure ownership, land tenure insecurity (unspec.)
		Land race, race for property rights
		Titling, legalization, consolidation (of individual titles)
		Malfunct customary rights
		Low empowerment, deprivation, marginality
		Open access conditions

Table 3 : List of variables (underlying causes) – III

Underlying causes (II)		
Technological factors (technological change or progress)	Agro-technological change	Land-use intensification
		Land-use extensification
		Agricultural involution
		Other changes (landholding, production orientation, etc.)
	Technological applications in the wood sector	Damage & wastage due to poor logging performance
		Wastage in wood processing, poor industry performance
		Lack of cheap, technological alternatives to woodfuel; poor domestic & industrial furnace performance
	Other production factors in agriculture	Low level of technological inputs (unspecified)
		Land-related factors (landlessness, land scarcity)
		Labour –related factors (limited labour availability)
		Capital-related factors (no credits, limited irrigation)
Cultural (or socio-political) factors	Public attitudes, values, beliefs	Public unconcern or lack of (public, political) support for forest protection and sustainable use: low morale or education, frontier mentality, and dominance of other public attitudes (modernization, development, nation-building, etc.)
		Unconcern about the welfare of others and future generations, or disregard of the "sacredness of nature"
		Beliefs about how environmental conditions affect those things which individual values
	Individual and household behaviour	Unconcern by individuals about the environment as reflected in increasing levels of demands, aspirations, materials and energy consumption, commonly associated with commercialisation and increased income
		Situation-specific behaviour of actors: rent-seeking, non-profit orientation, tradition/imitation/continuation of inherited modes of resource use
Demographic factors (human population dynamics)	"Population pressure" (unspecified)	
	Population growth (unspecified)	
	Natural increment (fertility, mortality)	
	In-migration	
	Population density	
	(uneven) spatial population distribution	
	Life cycle features	

Other drivers of deforestation (Gueist, 2001)

Table 4: List of variables (other factors) – IV

Other factors		
Land characteristics (biophysical environment)	Soil-related	Good/bad soil quality
	Slope & topography-related	Flat areas
		Gently sloping areas
		Lowlying areas
	Water-related	Location next to water resources
	Vegetation-related	Forest size & fragmentation
		Vegetation density (high, of marketable woods)
Biophysical drivers (triggers)	Soil-related	Soil compaction
		Soil fertility decline
		Land degradation (unspecified)
	Water-related	Drought conditions (aridity)
		Wet conditions (high humidity)
		Floods
	Vegetation-related	Weed intrusion
		Forest fires
Social trigger events	(Civil) war, rebellion, revolution, social unrest & disorder	
	Health & economic crisis conditions (e.g., epidemics, economic collapse)	
	Abrupt (& violent) population displacements (refugee movements)	
	Government policy failures (e.g., abrupt shifts in macro-policies)	