Using AI/deep learning and remote sensing images to detect and track land use following deforestation at the pantropical scale

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The 3 ingredients

1. Remote sensing

    -Looking the earth from above

2. Land use following deforestation/Deforestation drivers

    -Human activities

3. Deep learning

    -Automatic image understanding

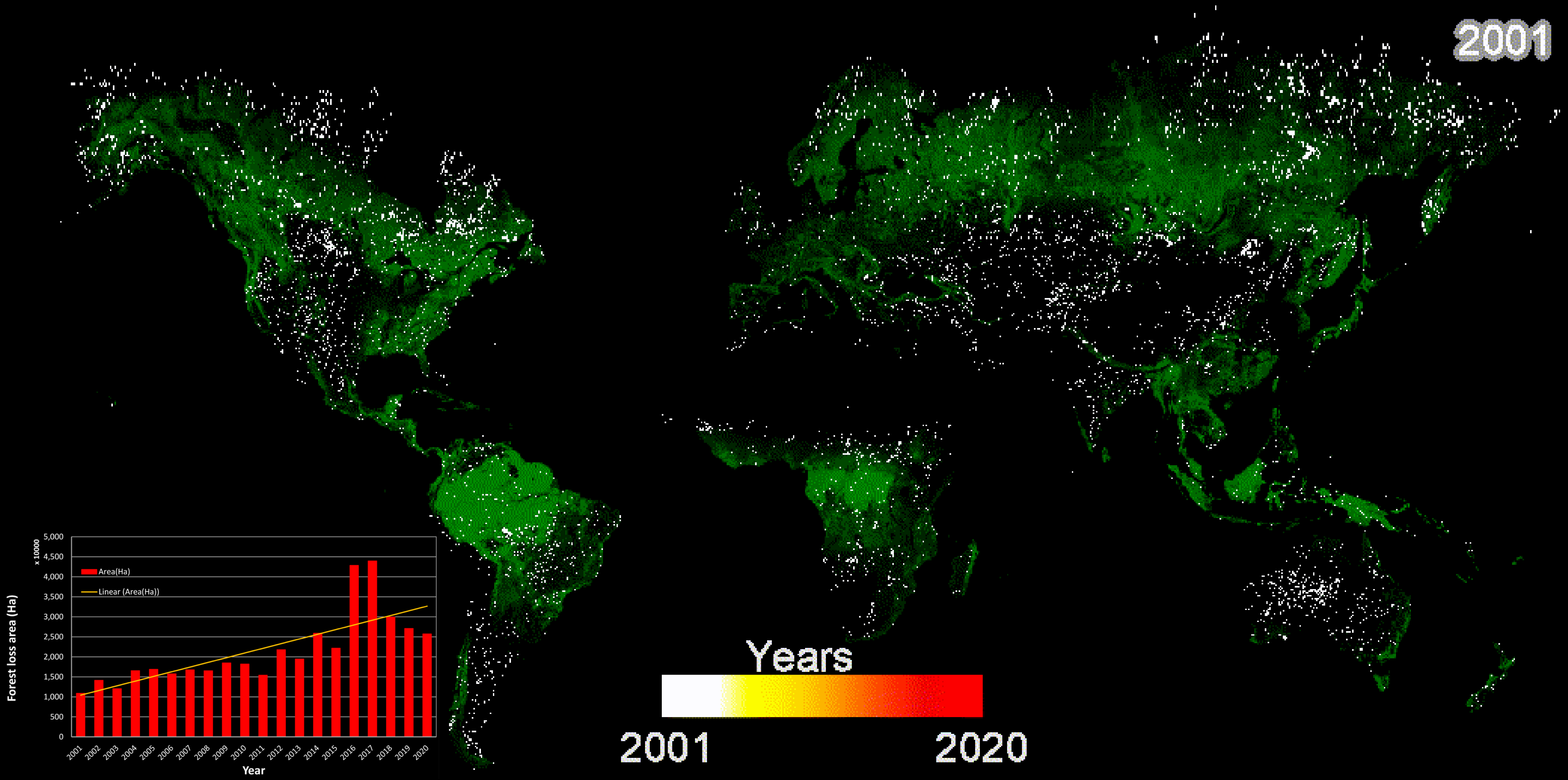
Large scale cropland

Importance of forests






Trend of deforestation



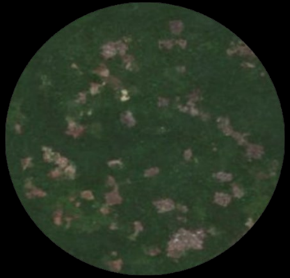
Land activities causing deforestation

- Large scale cropland

- Oil palm

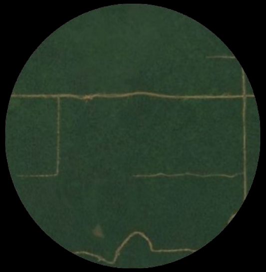
- Pasture

- Small scale cropland



- Rubber

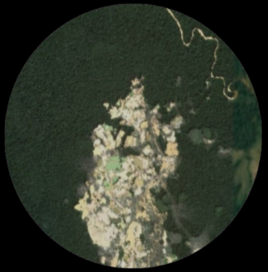
- Roads



- Cacao

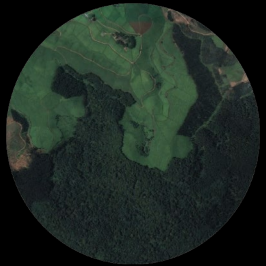
- Coffee

- Mining



- Cashew

- Tea plantation



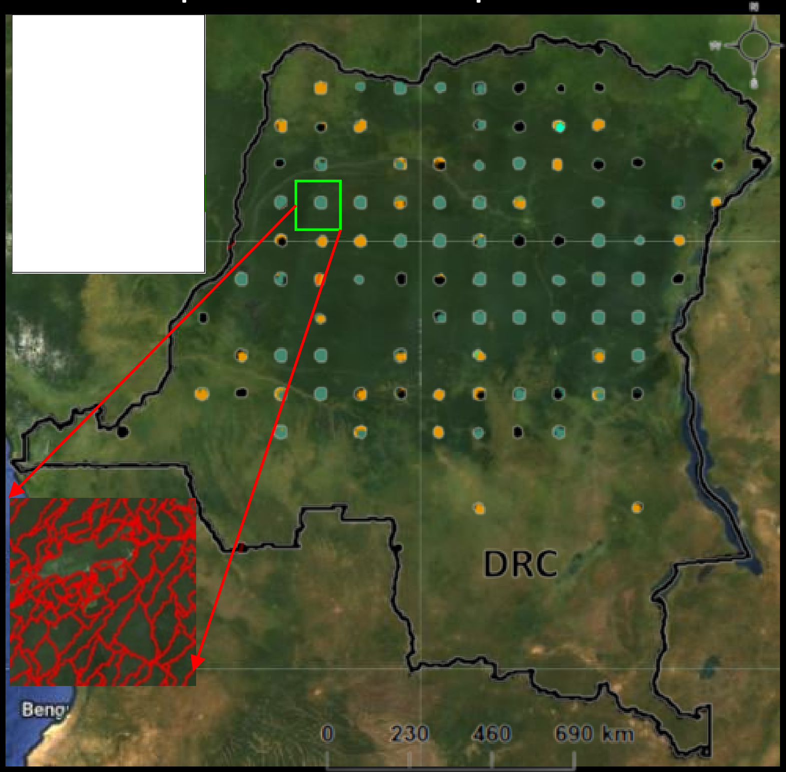
Deforestation free Initiatives

- National Reporting – Supporting post-Paris land use sector mitigation
- EU's Deforestation-Free Supply Chain Regulation
- EU's US Fostering Overseas Rule of Law and Environmentally Sound Trade (FOREST) Act
- UK Environment Act: Use of Forest Risk Commodities in Commercial Activity (Schedule 17)
- California Climate Corporate Accountability Act
- New York Deforestation-Free Procurement Act

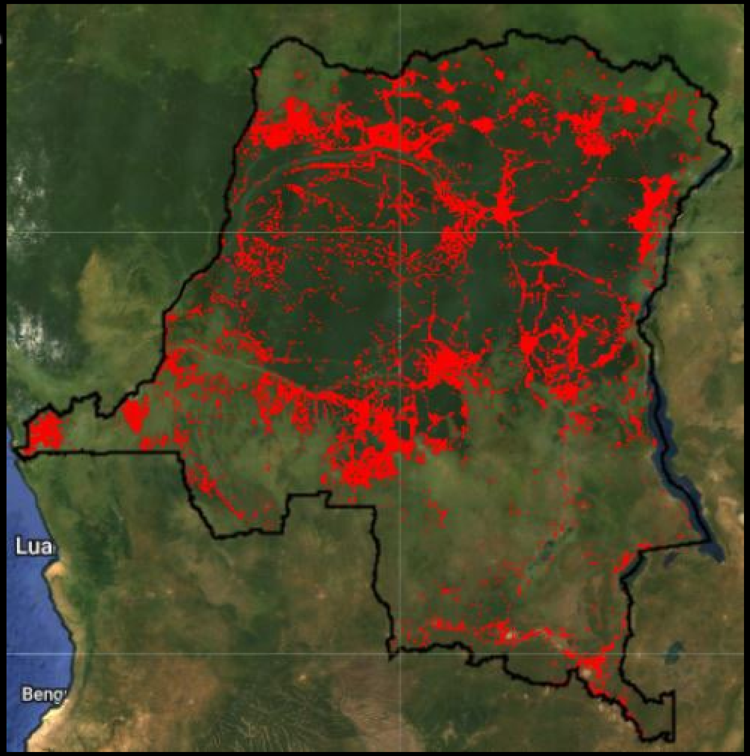
https://www.aim-progress.com/storage/resources/Ropes%20&%20Gray_AIM-Porgress_Corporate%20Social%20Responsibility%20Legislation%20Summary%20(February%202022).pdf

Need for automated large scale land use monitoring

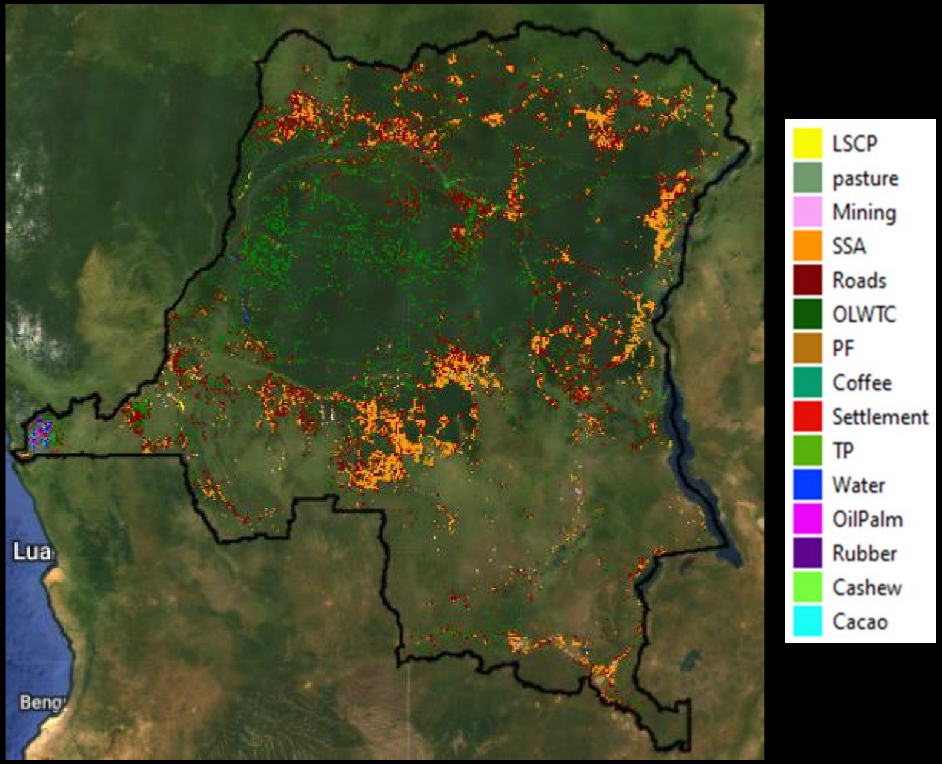
Sample-based interpretation



Forest loss



Large area prediction

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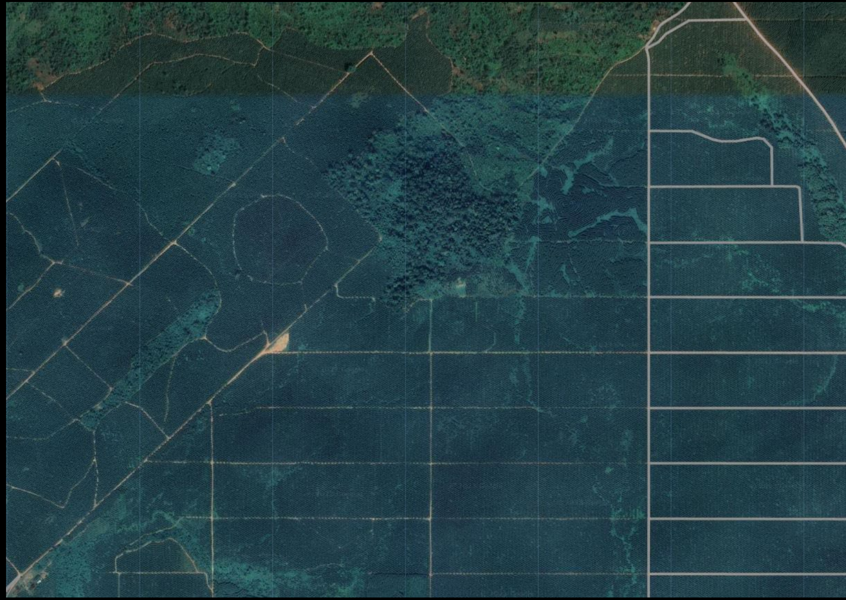

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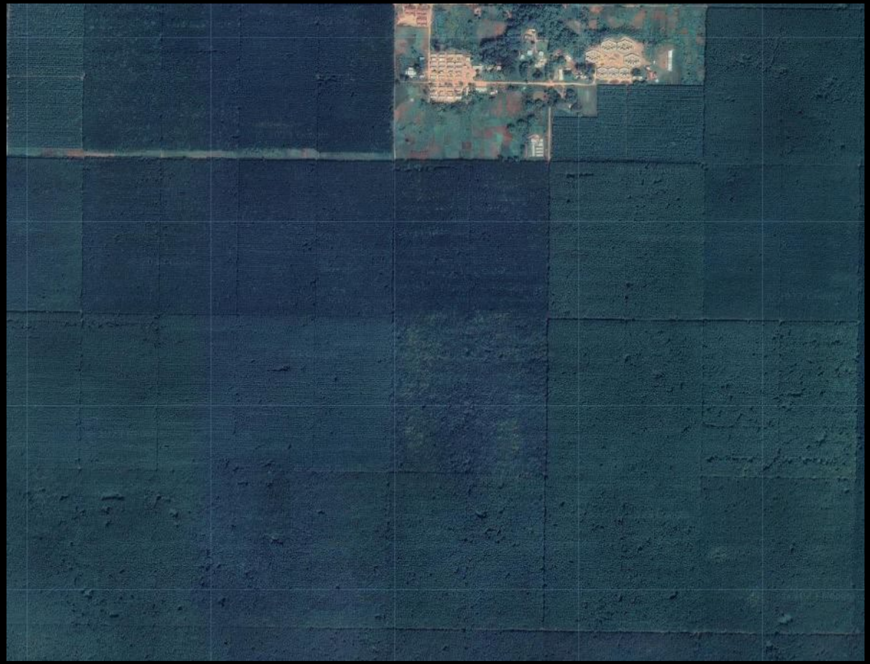
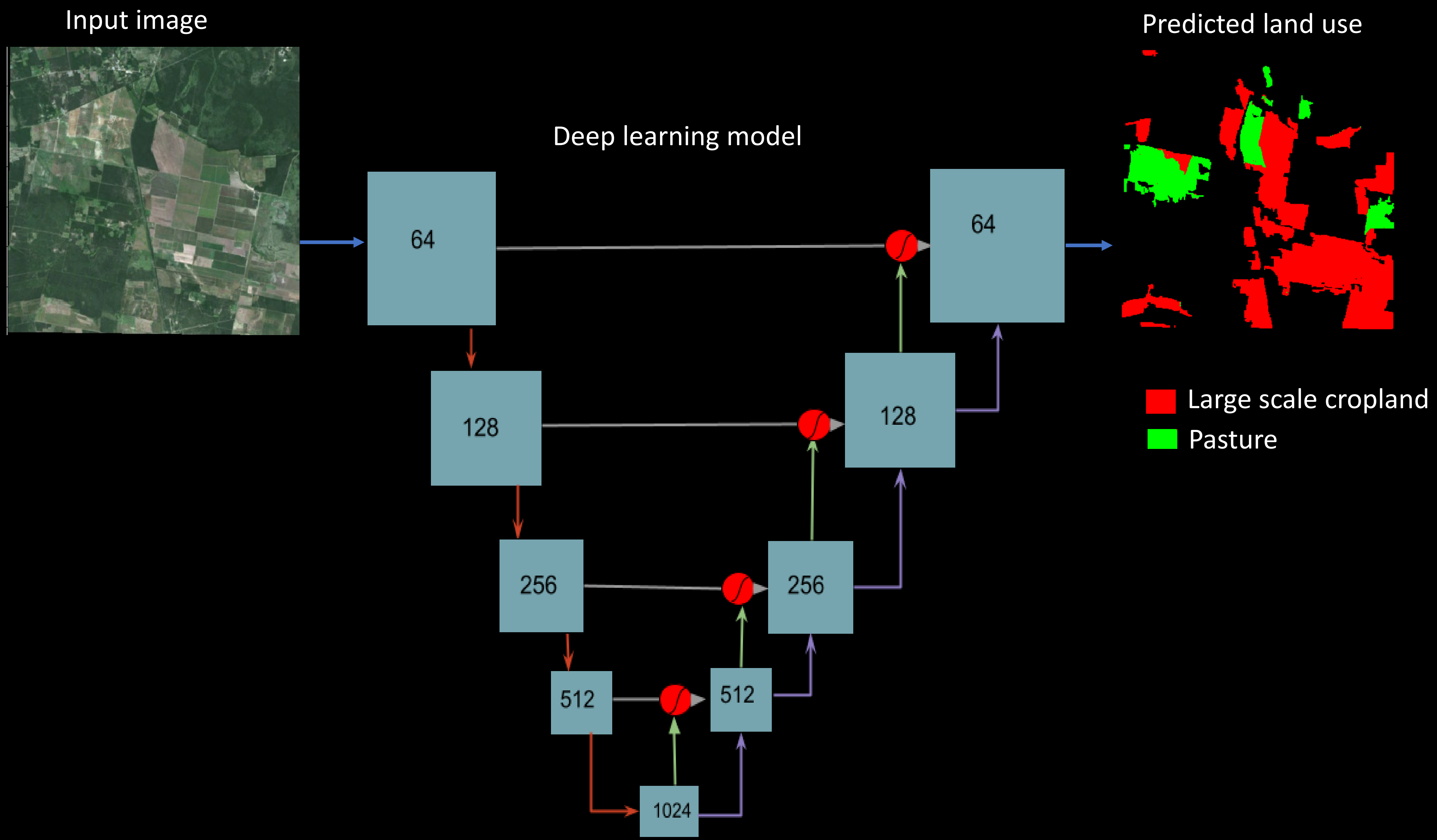
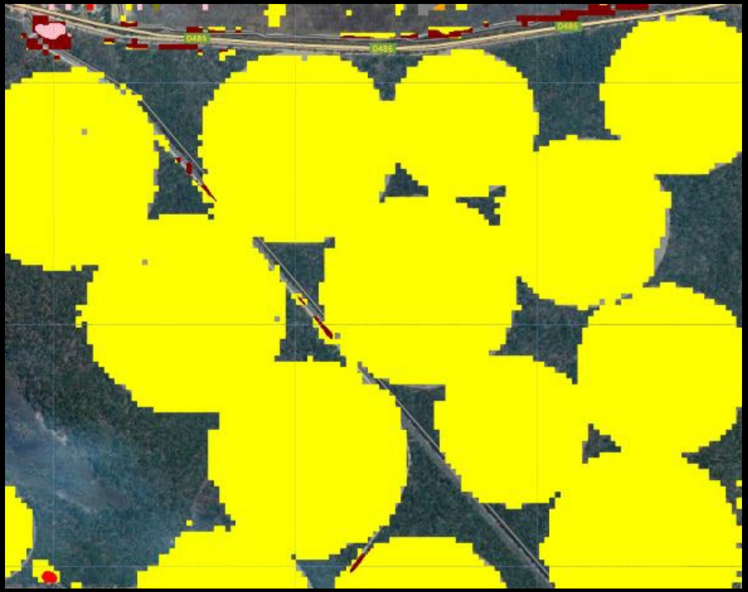


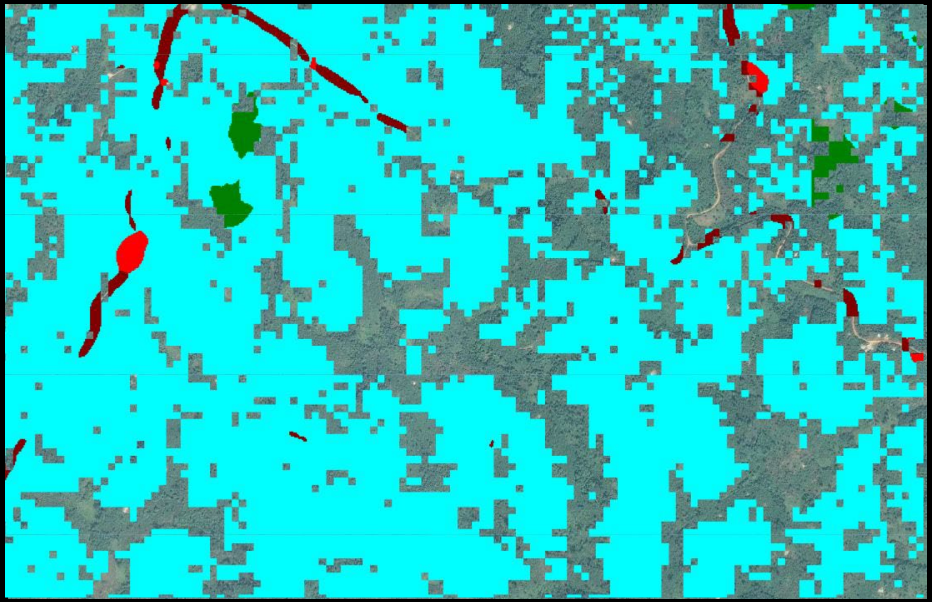
Input image
Deep learning model
Predicted land use
64
128
256
512
1024
512
256
128
64
Large scale cropland
Pasture

Going back to our previous example

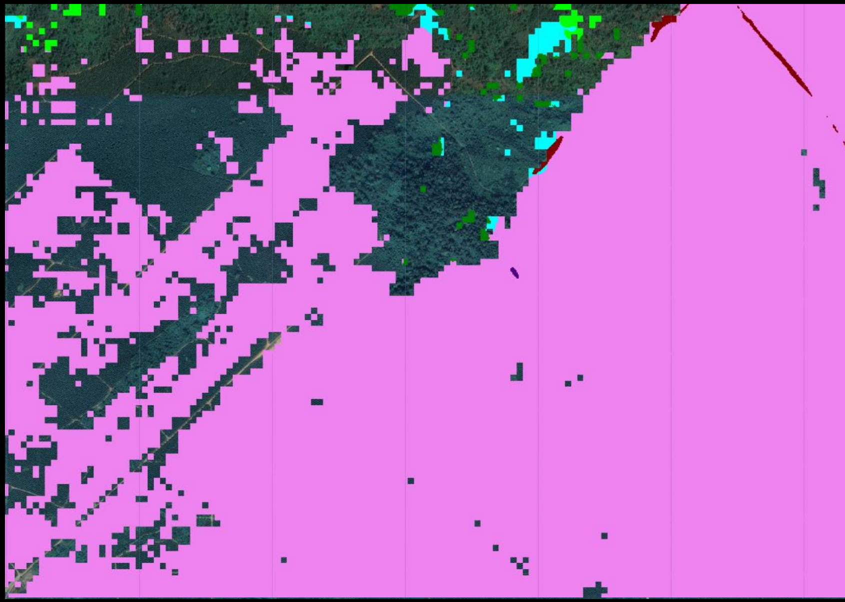
Large scale cropland



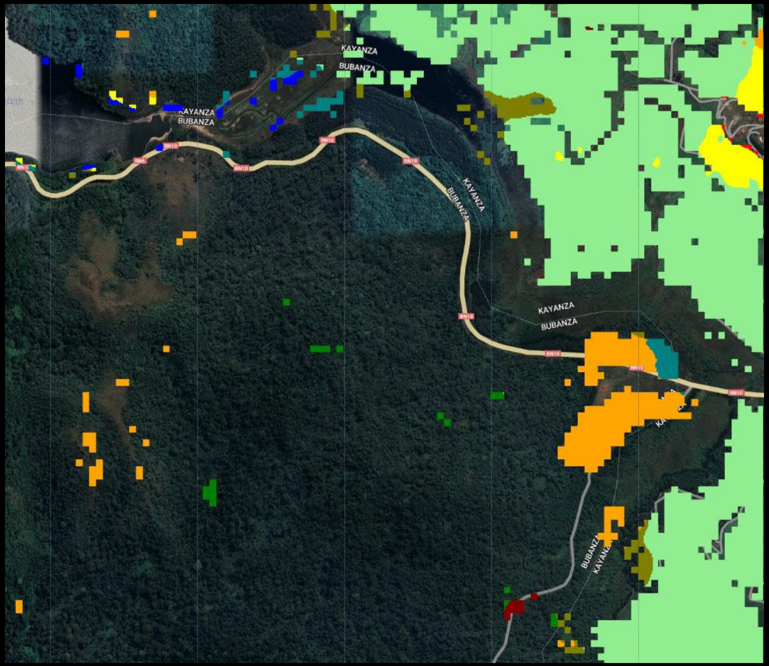
Cacao



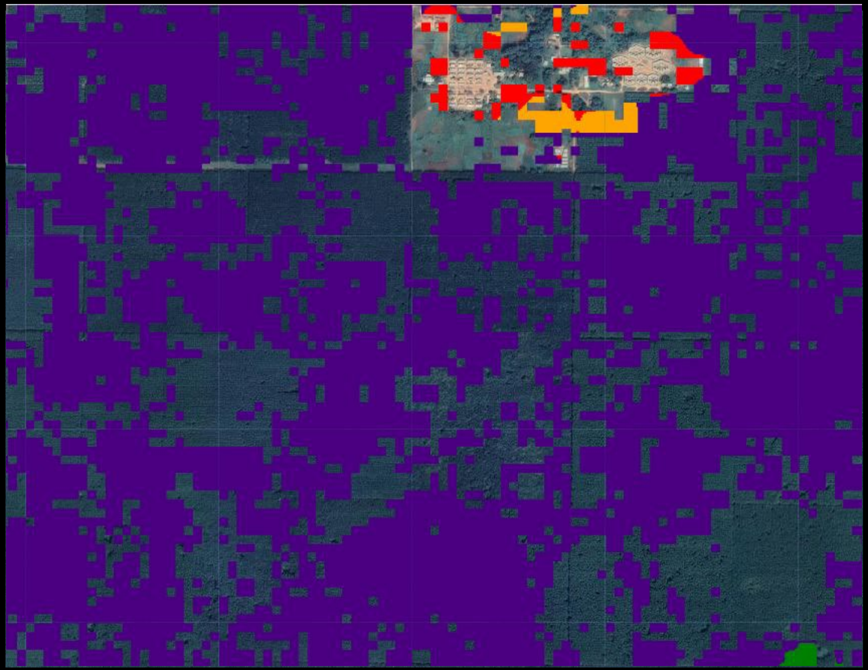
Oil palm



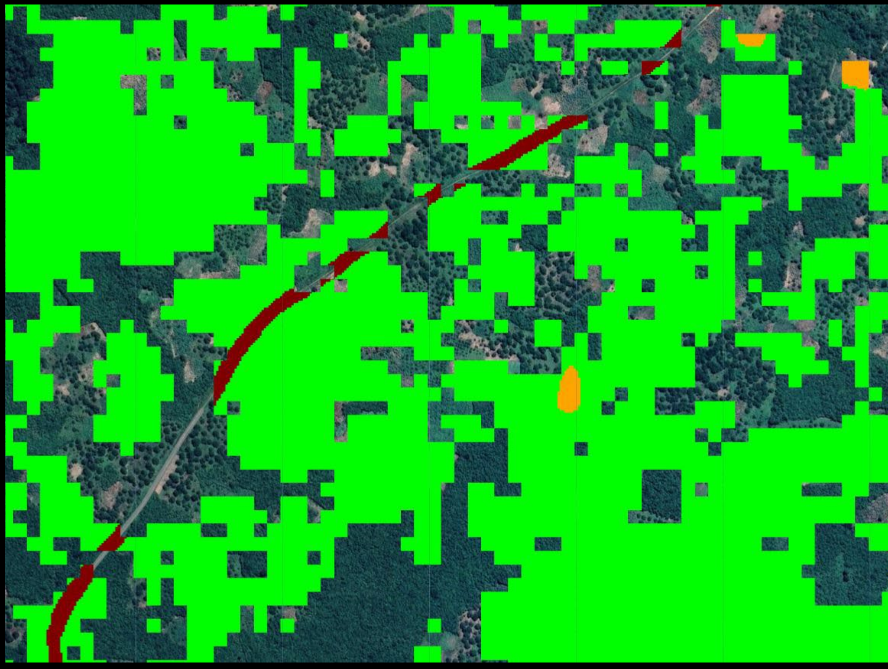
Tea plantation



Rubber



Cashew



Important questions

1. How can we use deep learning for assessing land-use following deforestation using remote sensing data?

2. How can these methods be applied to analyse land-use following deforestation in different national/regional context?

3. How can we leverage heterogeneous reference data to increase the thematic detail of land-use following deforestation mapping? What are the challenges and future opportunities?

Qn1: Spatial and temporal aspect of the land use following deforestation

Qn1: How can we use deep learning for assessing land-use following deforestation using remote sensing data?

Background

- Pantropical case study
- AI/deep learning models using spatial and temporal information from dense Landsat time-series to predict land use activities driving deforestation
- Open source platform in SEPAL and GEE

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Spatial and temporal deep learning methods for deriving land-use following deforestation: A pan-tropical case study using Landsat time series

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ABSTRACT

Assessing land-use following deforestation is vital for reducing emissions from deforestation and forest degradation. In this paper, for the first time, we assess the potential of spatial, temporal and spatio-temporal deep learning methods for large-scale classification of land-use following tropical deforestation using dense satellite time series over six years on the pan-tropical scale (incl. Latin America, Africa, and Asia). Based on an extensive reference database of six forest to land-use conversion types, we find that the spatio-temporal models achieved a substantially higher F1-score accuracies than models that account only for spatial or temporal patterns. Although all models performed better when the scope of the problem was limited to a single continent, the spatial models were more competitive than the temporal ones in this setting. These results suggest that the spatial patterns of land-use within a continent share more commonalities than the temporal patterns and the spatial patterns across continents. This work explores the feasibility of extending and complementing previous efforts for characterizing follow-up land-use after deforestation at a small-scale via human visual interpretation of high resolution RGB imagery. It supports the usage of fast and automated large-scale land-use classification and showcases the value of deep learning methods combined with spatio-temporal satellite data to effectively address the complex tasks of identifying land-use following deforestation in a scalable and cost effective manner.

1. Introduction

Land-use change is the second-largest contributor to greenhouse gas (GHG) emissions globally (IPCC, 2013), and in total, 24% of global greenhouse gas emissions come from deforestation activities(FAO, 2014). In response, the United Nations Framework Convention on Climate Change (UNFCCC) established a framework to reduce emissions from deforestation and forest degradation and enhance carbon stocks (REDD+) by result-based payments (UNFCCC, 2017). Before payments are made countries are required to show that emissions were reduced through a clear methodological and well-documented Measuring, Reporting, and Verification system (MRV) (IPCC, 2013; UNFCCC, 2018). A robust deforestation monitoring system can also support more informative and effective land-use policies and measures (UNFCCC, 2018) by monitoring what land-use activities drive deforestation. These land-use activities, i.e., proximate or direct drivers of deforestation (Geist and Lambin, 2001), can be assessed using Earth Observation Technologies (EOT) to help provide spatially explicit and temporal information on land-use (Curtis et al., 2018; De Sy et al., 2015, 2019). However, these studies detect land-use following deforestation at coarse thematic, spatial and temporal scales or use time-consuming methods (i.e., visual interpretation of satellite imagery) which makes these approaches less suited for national level operational monitoring. Recent advances in Earth Observation (EO), computing technology and deep learning methods provide opportunities for automated large-scale assessment of land-use following tropical deforestation at more detailed spatial and temporal scales.

The latest advances and investments in Earth Observation Programmes (EOP) for global environmental data acquisitions, such as the European Copernicus EOP (Sentinel-1, Sentinel-2A, —2B) and joint

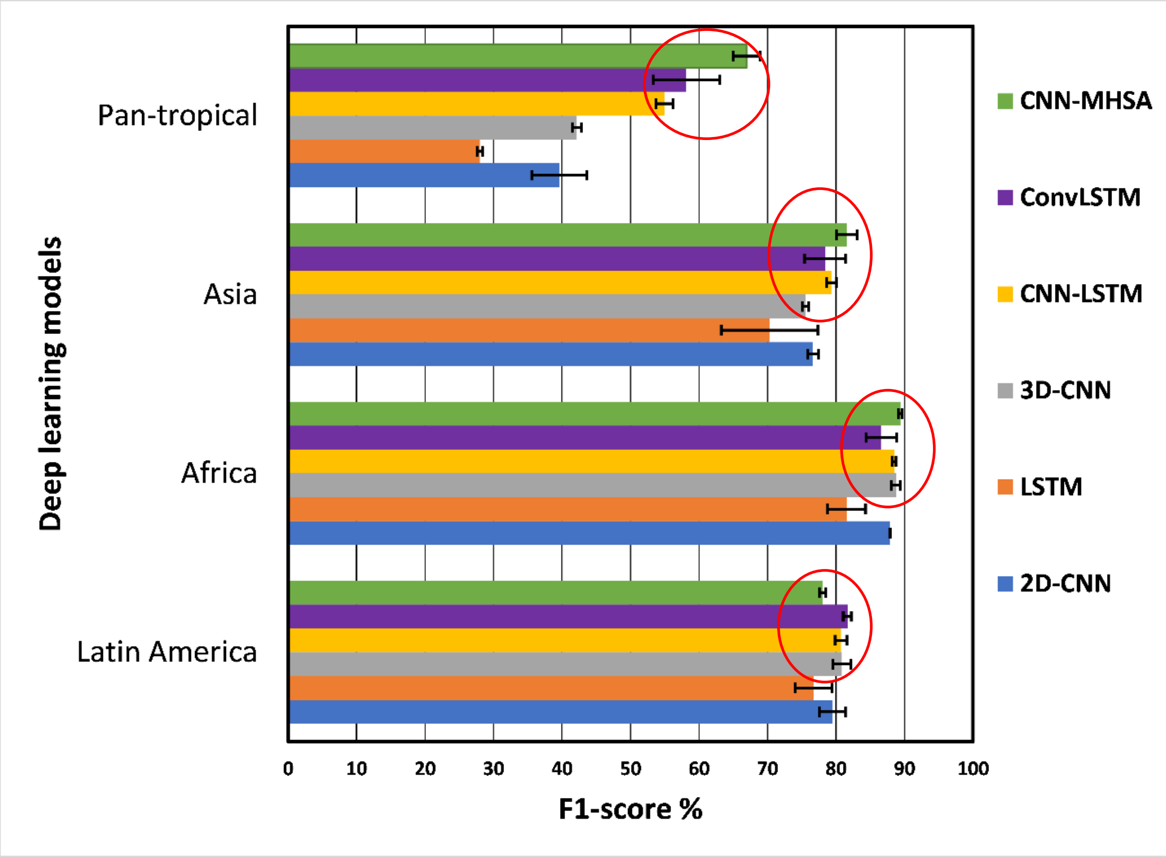
Qn1: How can we use deep learning for assessing land-use following deforestation using remote sensing data?

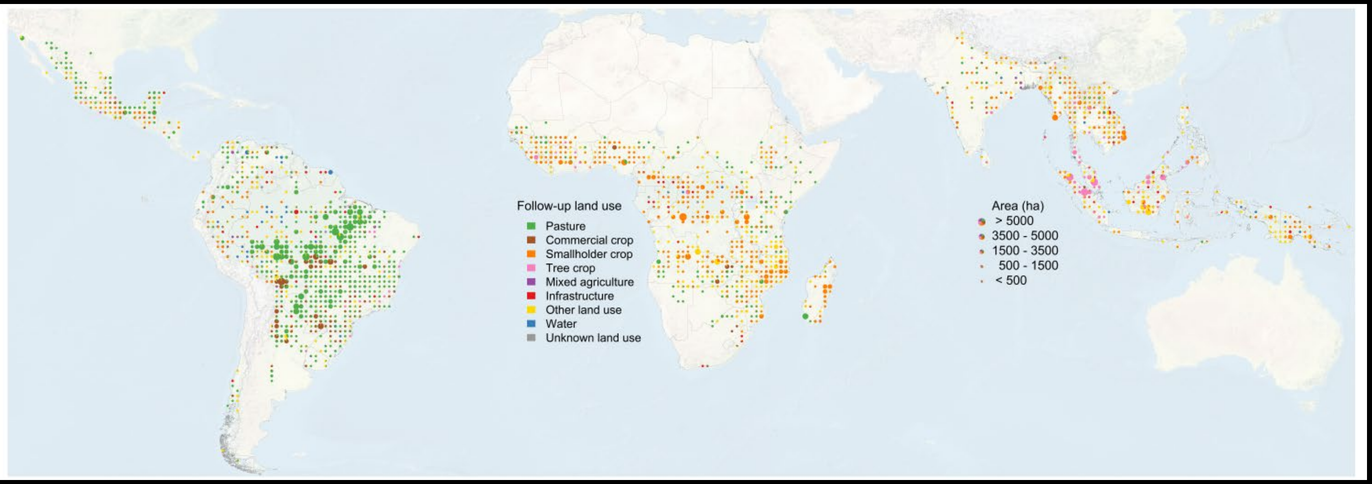
1. CNN-MHSA
2. ConvLSTM
3. CNN-LSTM
4. 3D-CNN

Spatial-temporal models

5. LSTM → Temporal models

6. 2D-CNN → Spatial models





FAO, (2000)

Spatial-temporal models (>=80%)
- CNN-MHSA
- ConvLSTM
- CNN-LSTM
- 3D-CNN

Temporal models <80%
- LSTM

Spatial models=<80%
- 2D-CNN

Qn2: Applying deep learning to analyse land-use following deforestation at national scale (Ethiopia)

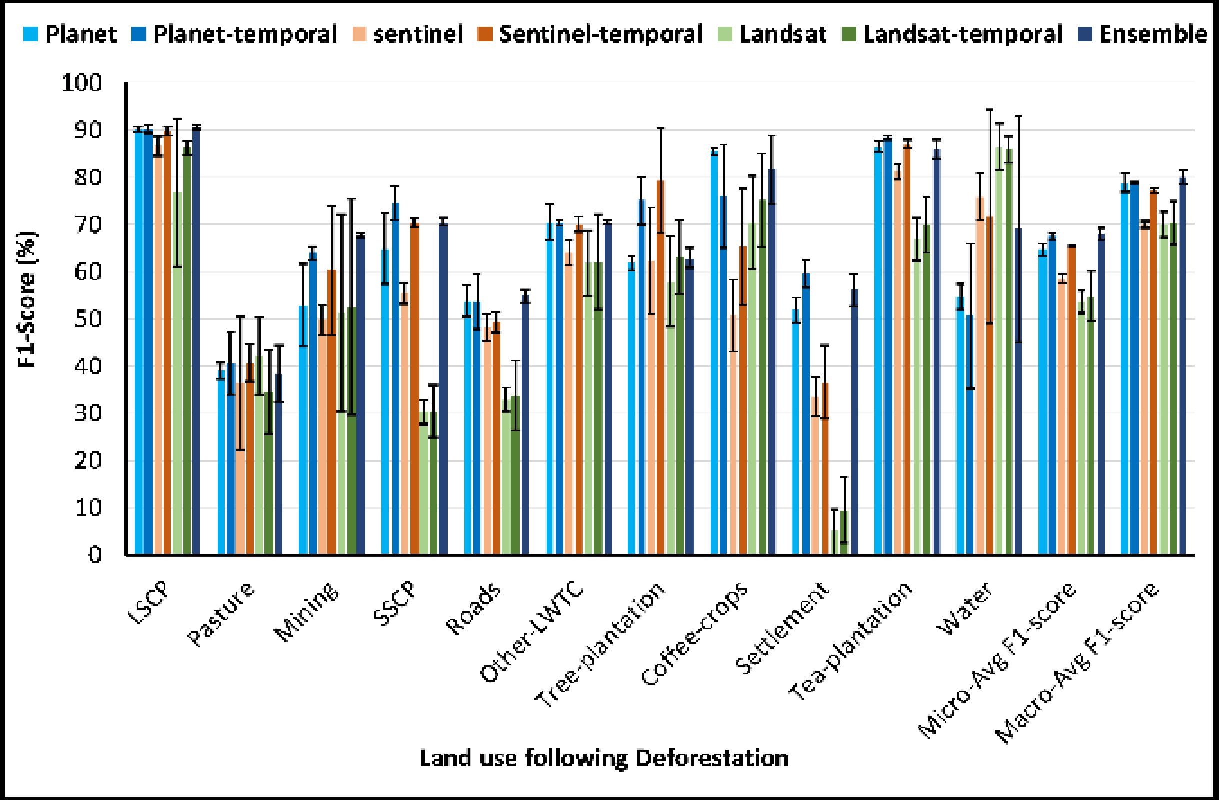
NEXT

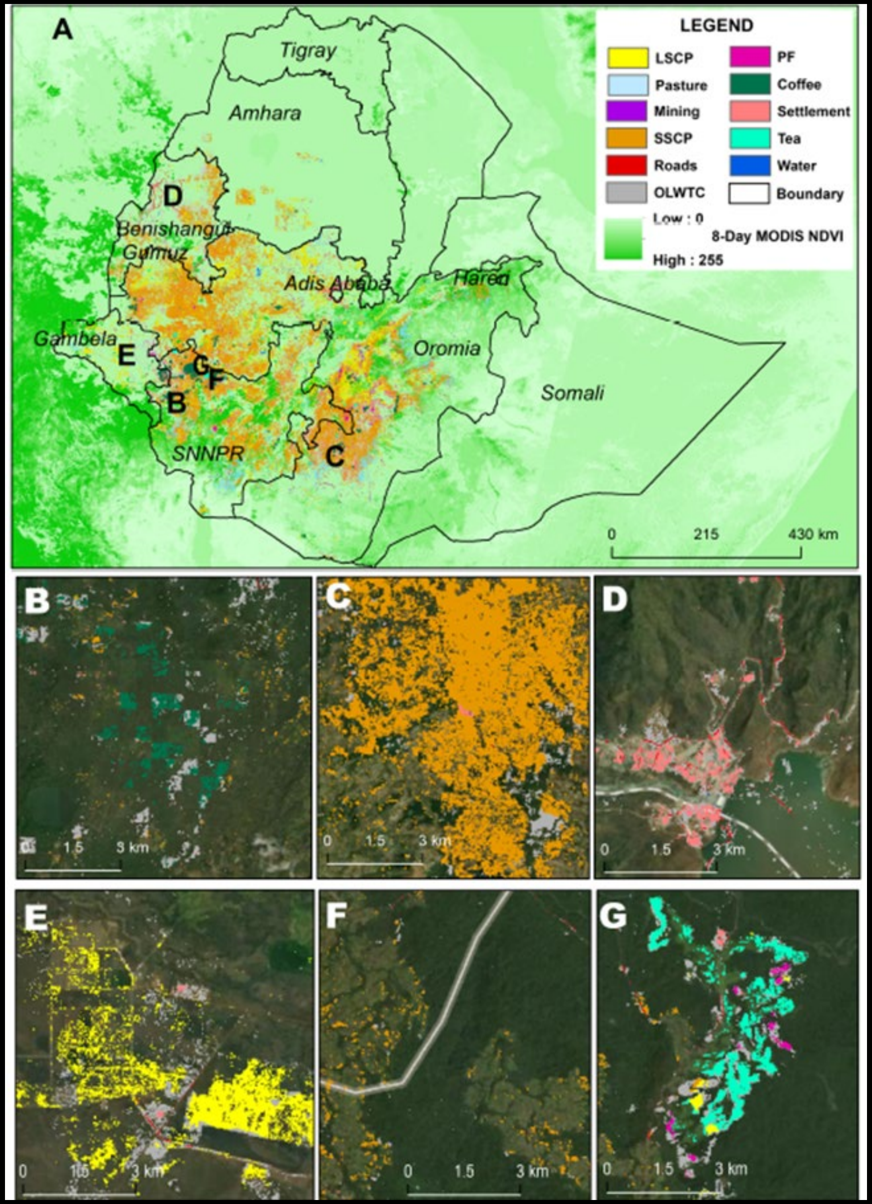
- Adapt deep learning model to Ethiopian context
- Land use classes
- Method
  - SEPAL
  - Forest loss 2010 – 2014
  - Land use following deforestation 2016
  - Planet data, Landsat & Sentinel 2
  - Other open-source data for calibration and validation

Follow-up land use classes

Agriculture	Large-scale croplands
	Small-scale cropland
	Pasture/free grazing
	Coffee crops
	Tea plantation
Mining	
Water	
Infrastructure	Roads
	Buildings and/settlement
Plantation forest	
Other land with tree cover	

Qn2: Applying deep learning to analyse land-use following deforestation at national scale (Ethiopia)

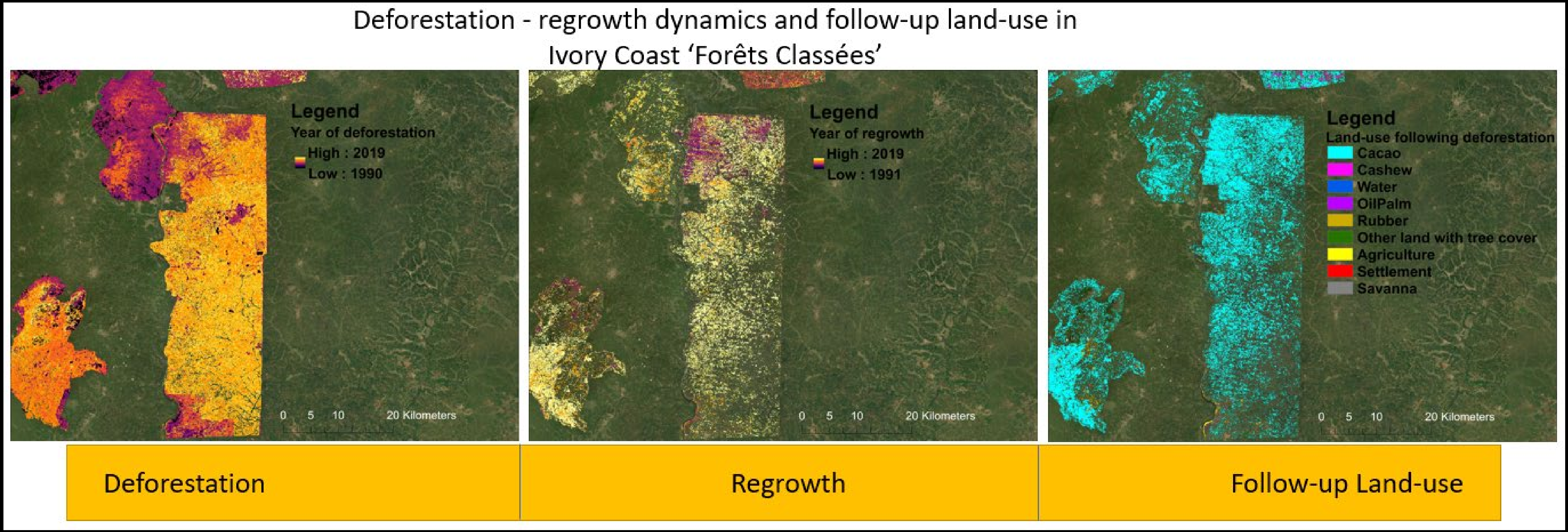




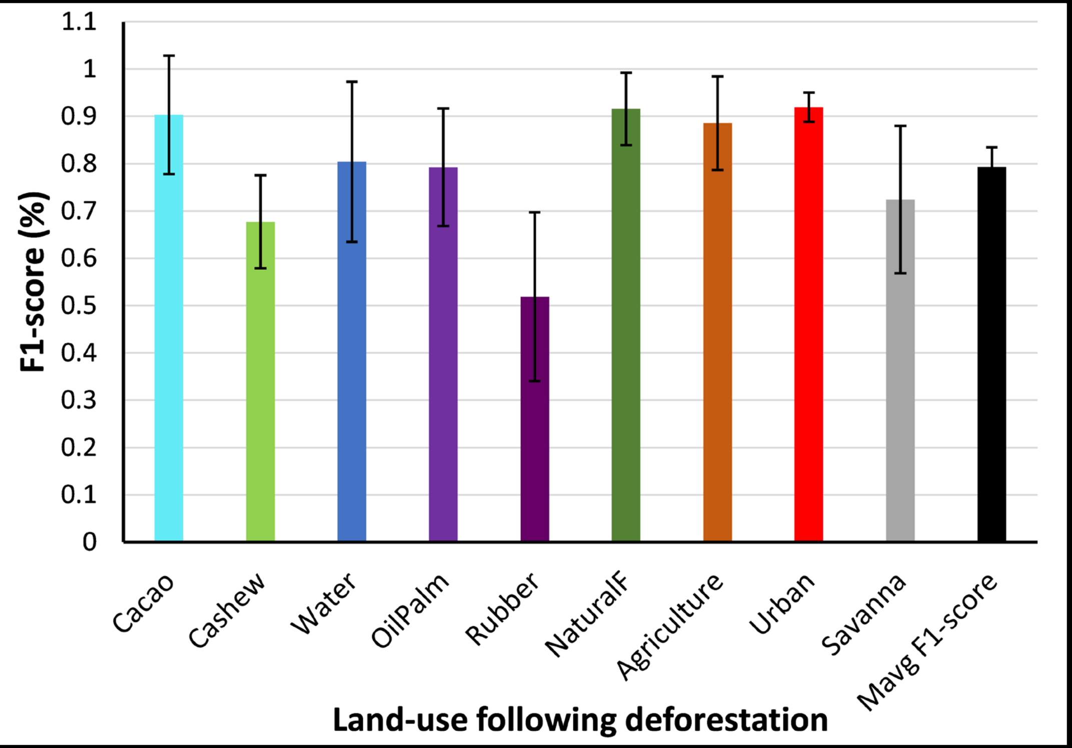
Masolele et al., (2022)

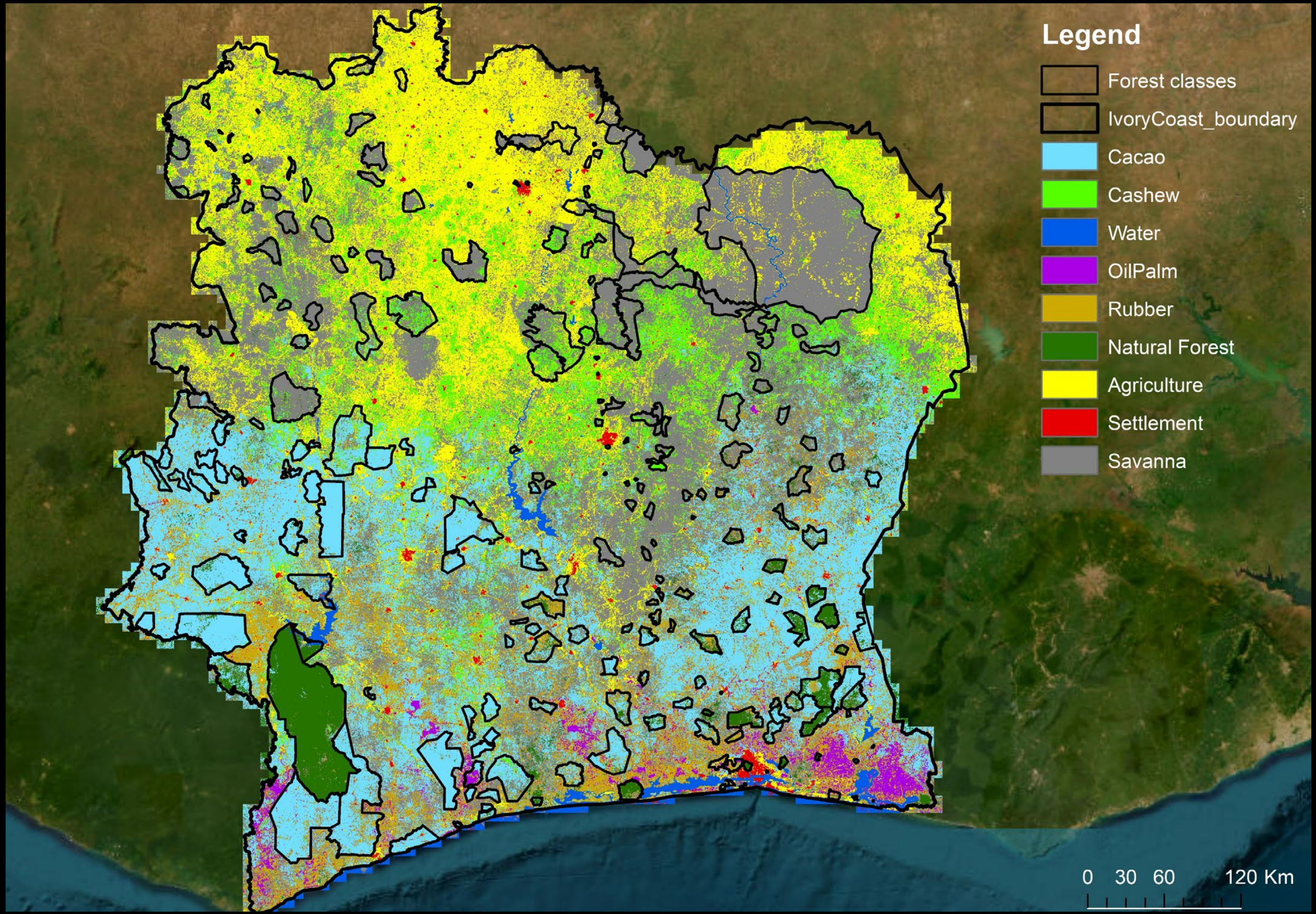
Link to GEE app: https://robertnag82.users.earthengine.app/view/deforestationdriverethiopia

Qn2: Applying deep learning to analyse land-use following deforestation at national scale (Ivory Coast)



RQ2: Country scale land use change monitoring (Ivory Coast)

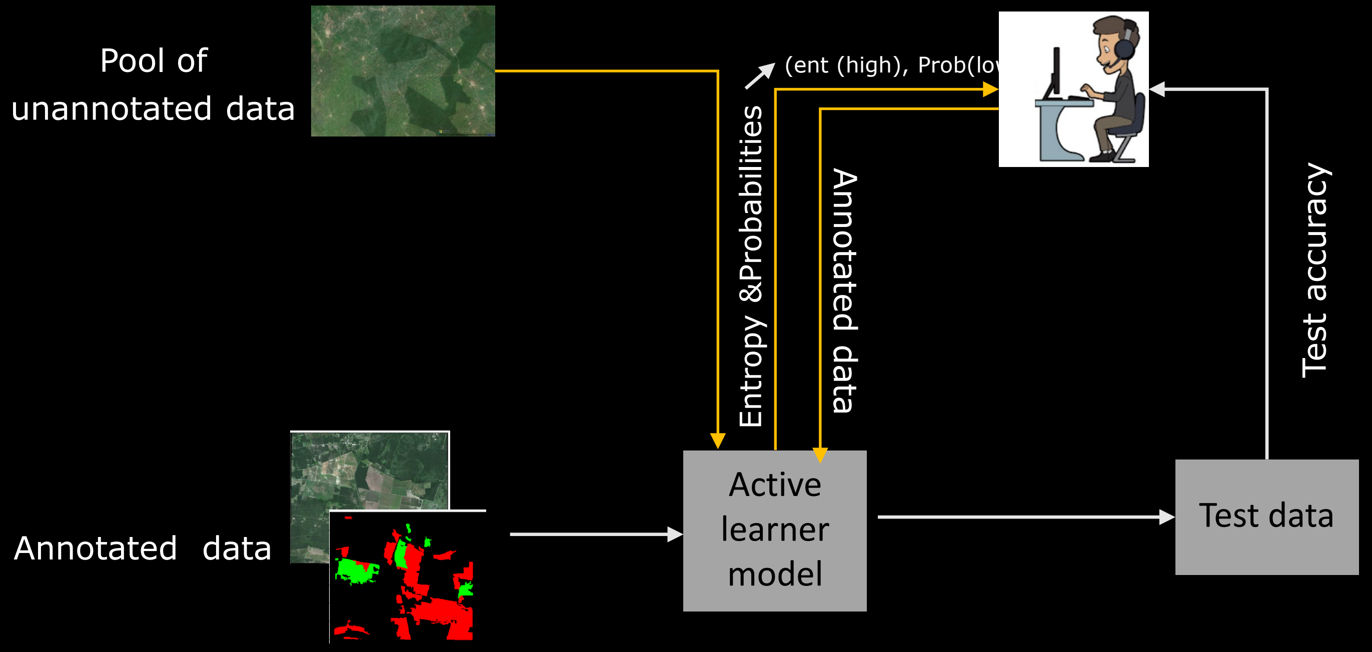




Qn3: Leveraging heterogeneous reference data to map land use following deforestation at continental scale

Data	LSCP	Pasture	Mining	SSCP	Roads	OLWTC	PF	Coffee	Settlement	TP	Water	OilPalm	Rubber	Cashew	Cacao
FAO 2010 global Remote Sensing Survey	X	X	X	X		X			X		X				
Crowdsourced deforestation drivers (IIASA) (Bayasa et al., 2022) http://pure.iiasa.ac.at/id/eprint/17539/)	X	X	X	X	X		X		X			X			
Masolele et al,. 2022 (Ethiopia)	x	x	x	x	x	x	x	x	x	x	x				
ICRAF, Econometric	x			x		x			x		x	x	x	x	x
NAFORMA (Tanzania)	x		x	x			x							x	
Large-scale farms and small holder (Jann et al,. 2018) (Zambia)	x			x											
Global Map of Oil Palm Plantations (Descale et al., 2021)												x			
Kenya GIS data (World Resources Institute - https://www.wri.org/data/kenya-gis-data)	x			x			x	x		x					
Namibia (Visual interpretation)	X			X											
Ghana (Visual interpretation/online)	x			x								x	x	x	x
Google research open-buildings dataset (https://sites.research.google/open-buildings/)									x						
https://ipisresearch.be/home/maps-data/open-data/ (Mining)			x												
Landuse data Nigeria (https://grid3.gov.ng/datasets)	x			x					x			x		x	x

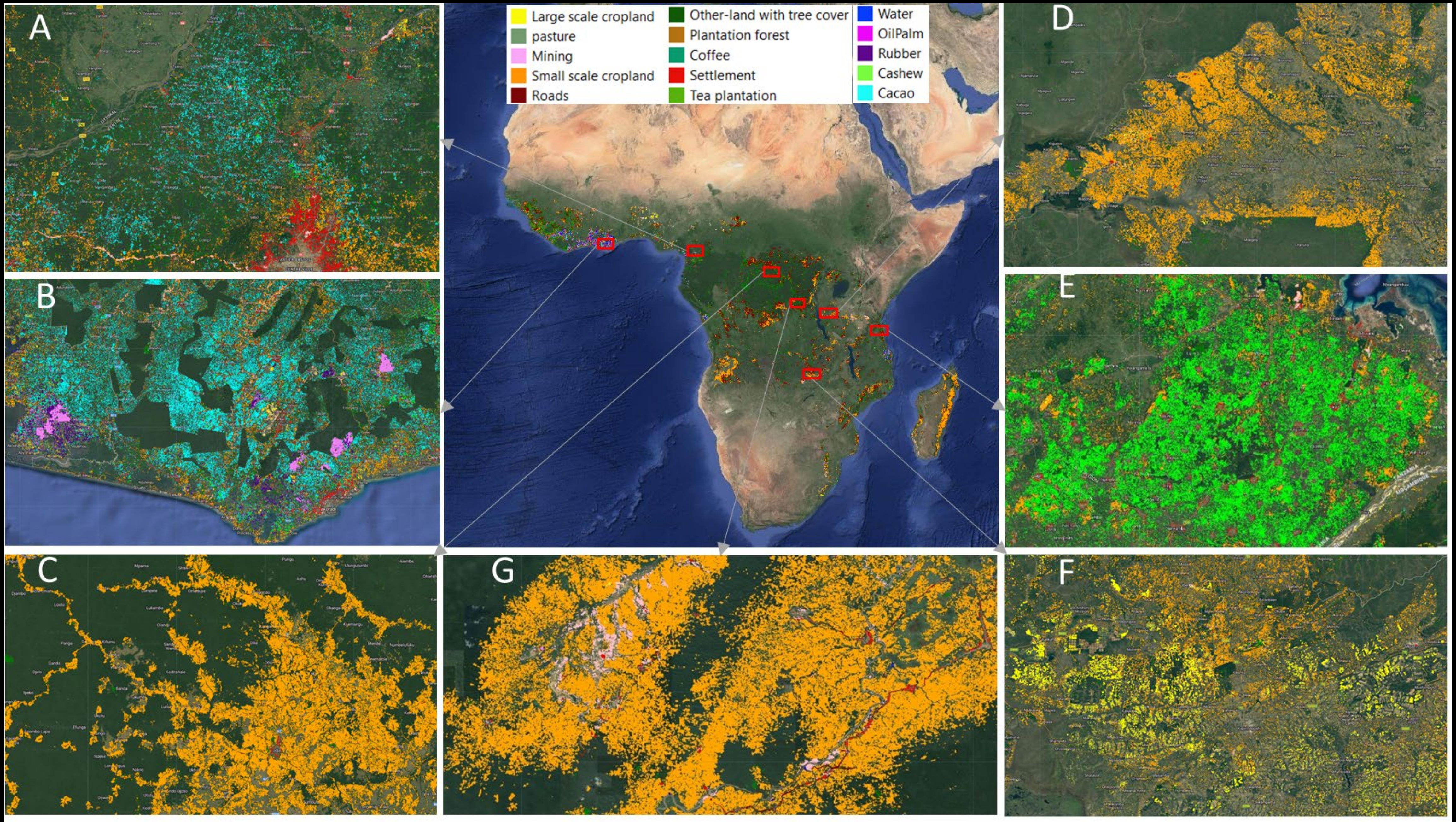
Qn3: Leveraging heterogeneous reference data to map land use following deforestation at continental scale



Improvement of accuracies with active learning

43% → 50% → 84%

Qn3: Continental scale land use change monitoring (Africa)



Qn3: Continental scale land use change monitoring (Africa)

https://robertnag82.users.earthengine.app/view/africalu

Conclusion: Challenges & future opportunities

- We can use deep learning for mapping land-use following deforestation at a large scale with good accuracy.
- Continental models performs better compared to the pan-tropical model.
- Increased spatial and thematic detail in monitoring land-use following deforestation – (deep learning, Africa).
- Increased availability of cloud computing infrastructure provides an opportunity for monitoring natural resources at global scale.
- We need to address the gap in availability of data related to land use change/drivers of deforestation (annotated data specific for AI application).
- Pantropical near real-time tracking of deforestation and its corresponding direct drivers.

Thank you

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Qn2: Applying deep learning to analyse land-use following deforestation at national scale (Ivory Coast)

- Change detection (loss & regrowth) & follow-up land-use
  - Use avocado algorithm to detect changes (Decuyper et al,. 2022)
  - With deep learning we can attribute changes to different land-use
    - Cacao, Cashew, water, Oil Palm, Rubber, Natural forest, Agriculture, Settlements, and Savanna
- Methodology
  - Fine tune a DL model (Ethiopia) to attribute forest changes to different land-use (Ivorycoast) using Use planet-NICFI images (2020-2022)
  - Assess model accuracy based on independent test data
  - Produce a wall-to-wall map of land-use after forest loss and regrowth based on forest classes in Ivory coast
  - Assess map accuracy based on reference data from stratified random sampling

Data & Method- Continental scale

Satellite data

- Planet-NICFI mosaics data ≈ 5m

Forest loss

- Hansen forest loss 2001 – 2020

Reference land-use data

- 15 land use classes for 2001-2020

Method

- Attention U-Net & Active learning

Output

- Wall-to-wall map (2001-2020)
- Land-use hotspots