

# **ForestNet**: Classifying Drivers of Deforestation in Indonesia using Deep Learning on Satellite Imagery

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# Deforestation

- Preserving forests is critical.<sup>1,2</sup>
- Tropical deforestation:
  - 10% of annual GHG emissions<sup>3</sup>
  - Potential for climate tipping points<sup>4</sup>
- **Indonesia** is among the largest GHG emitters worldwide<sup>5</sup>



<sup>1</sup>Global consequences of land use. *Science* 2005.

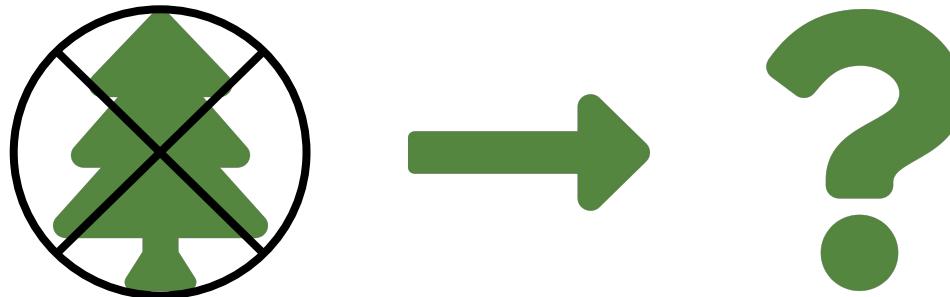
<sup>2</sup>Solutions for a cultivated planet. *Nature* 2011.

<sup>3</sup>IPCC special report on climate change. 2019.

<sup>4</sup>Climate tipping points—too risky to bet against. *Nature* 2019.

<sup>5</sup>A review of land-based greenhouse gas flux estimates in Indonesia. *Environmental Research Letters* 2018.

# Forest Loss Direct Drivers



- What causes tropical forest loss?
  - *Direct drivers*: land-use which replaces forest
- Why is determining forest loss drivers useful?
  - To help **companies** fulfill their zero-deforestation commitments<sup>6</sup>
  - To help **decision makers** design and implement targeted policy<sup>7</sup>

<sup>6</sup>Supply change: Tracking corporate commitments to deforestation-free supply chains. *Forest Trends* 2017.

<sup>7</sup>A policy-driven framework for conserving the best of earth's remaining moist tropical forests. *Nature Ecology & Evolution* 2020.

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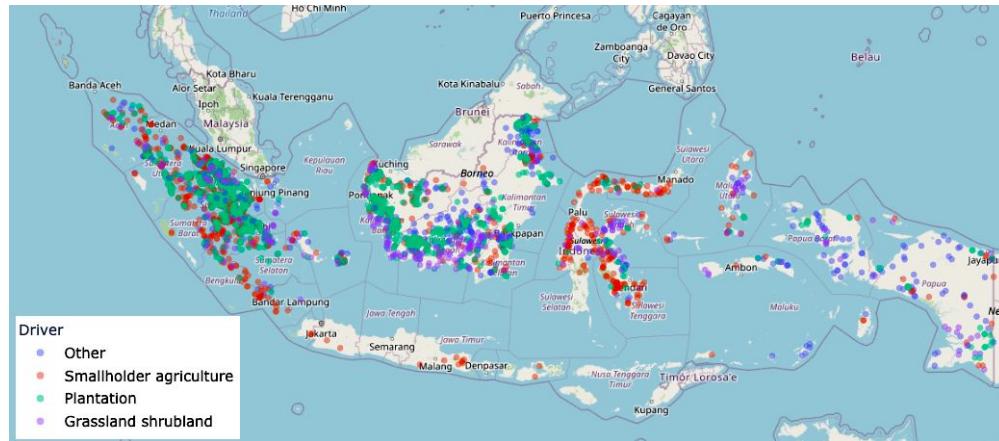
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# Data

# Forest Loss Events and Driver Annotations



Driver Class, N	Training	Validation	Test
Plantation	686	219	265
Smallholder Agriculture	556	138	207
Grassland/shrubland	143	47	85
Other	231	70	112
Overall	1,616	474	669

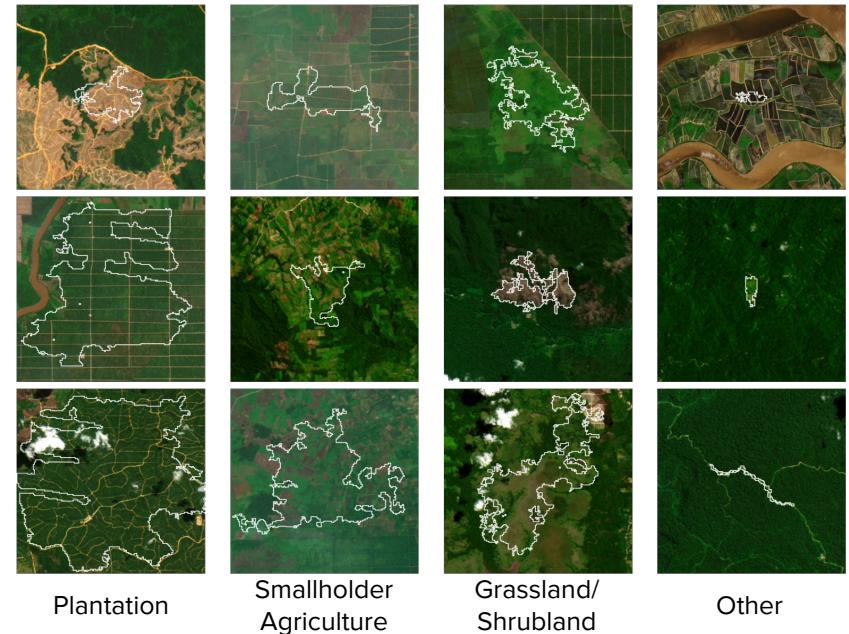
- Curated in Kemen et al.<sup>8</sup>
- Global Forest Change for forest loss regions from 2001 to 2016<sup>11</sup>
- Expert-annotated events using high res imagery in Google Earth

<sup>8</sup>What causes deforestation in Indonesia? *Environmental Research Letters* 2019.

<sup>11</sup>High-resolution global maps of 21st-century forest cover change. *Science* 2013.

# Satellite Imagery

- Landsat 8
  - Publicly available
  - 15m spatial resolution
  - Visible (RGB) + infrared bands
- Cloud-minimized using custom procedure leveraging cloud and cirrus bands



# Scene Data Augmentation (SDA)



# Models

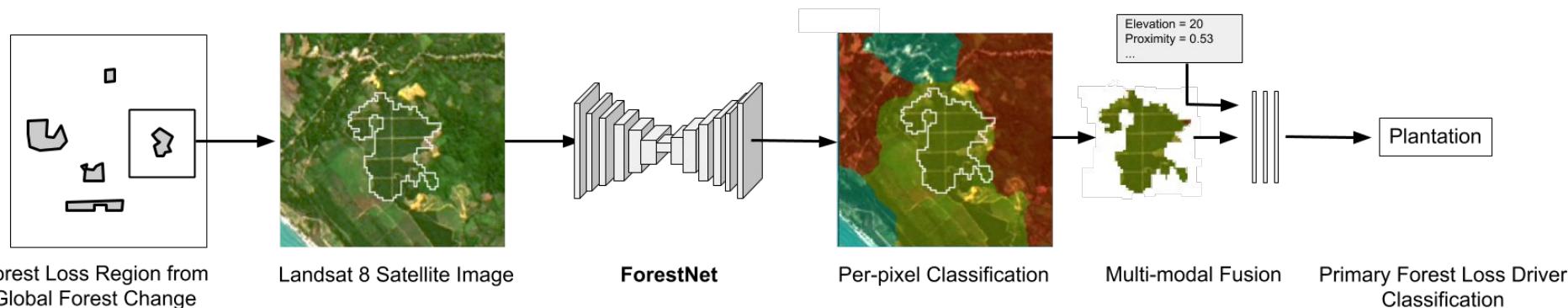
# Baseline Models and Auxiliary Predictors

- Random Forest models
- Input variety of predictors
- Inputs and outputs data w.r.t forest loss region

Predictor Group	Predictor (units)	Spatial Resolution	Temporal Resolution	Source
Topographic	Elevation (m) Slope (0.01°) Aspect (0.01°)	30m	N/A	USGS (SRTM)
Climatic	Surface-Level Albedo (0.01%) Clear-Sky Longwave Flux (W/m <sup>2</sup> ) Clear-Sky Solar Flux (W/m <sup>2</sup> ) Direct Evaporation from Bare Soil (W/m <sup>2</sup> ) Longwave Radiation Flux (W/m <sup>2</sup> ) Ground Heat Net Flux (W/m <sup>2</sup> ) Latent Heat Net Flux (W/m <sup>2</sup> ) Specific Humidity (10 <sup>-4</sup> kg/kg) Potential Evaporation Rate (W/m <sup>2</sup> ) Ground-Level Precipitation (0.1 mm) Sensible Heat Net Flux (W/m <sup>2</sup> ) Volumetric Soil Moisture Content (0.01%) Air Pressure at Surface Level (10 Pa) Wind Components 10m above Ground (0.01 m/s) Water Runoff at Surface Level (0.01 kg/m <sup>2</sup> )	56km	1 day	NCEP (CFSv2)
Soil	Presence of Peat	N/A	N/A	GFW (MoA)
Accessibility	Euclidean Distance to Road (km)	N/A	N/A	Open Street Map
Proximity	Euclidean Distance to City (km)	N/A	N/A	Open Street Map
Imaging	Landsat 8 Visible Landsat 8 IR Landsat 8 NDVI	15m 30m 30m	16 days	USGS (Landsat 8)

# ForestNet

- **Semantic segmentation**
- Three key technical developments:
  1. Scene Data Augmentation (SDA)
  2. Multi-modal fusion
  3. Pre-trained (PT)



# Results

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Model	Predictors	Val		Test	
		Acc	F1	Acc	F1
RF	Visible	0.60	0.52	0.52	0.44
RF	Visible + Aux	0.71	0.67	0.69	0.64
CNN	Visible	0.79	0.76	0.76	0.72
CNN + SDA	Visible	0.83	0.79	0.77	0.72
CNN + SDA + PT	Visible	0.84	0.81	0.79	0.74
CNN + SDA + PT	Visible + Aux	<b>0.85</b>	<b>0.82</b>	<b>0.80</b>	<b>0.76</b>

**Best CNN:** FPN + EfficientNet-B2 Backbone

# Limitations and Future Work

1. Inputs a single satellite image during prediction
  - a. Different drivers demonstrate different evolution of landscape over time
2. Can't differentiate species of plantations and types of smallholder agriculture development

Future work should explore use of **multiple high resolution images** to improve prediction accuracy and granularity.

# Conclusion

- ForestNet accurately identifies the direct driver of forest loss in satellite imagery
- Potential to generate accurate maps of forest loss drivers over all of Indonesia
- This new data could aid companies and policymakers to **reduce deforestation and mitigate climate change**



Thank you!