

# Multi-resolution quantification and driver assessment of hot spots of global forest disturbance

Alexandra Tyukavina (Project PI), Matthew C. Hansen (Co-PI), Peter Potapov (Co-PI), Jeffrey Pickering, Bernard Adusei, Andrew J. Poulson, Will Byrne, Aleksandra Mikus, Antoine Baggett, Andre Oktaviandra, Carolina Ortiz Dominguez, Steven Painter, Lauren Thomas, Arden Ireland, Hailey Papagjika, Xiao-Peng Song  
Department of Geographical Sciences, University of Maryland, College Park, MD, USA

## Project overview

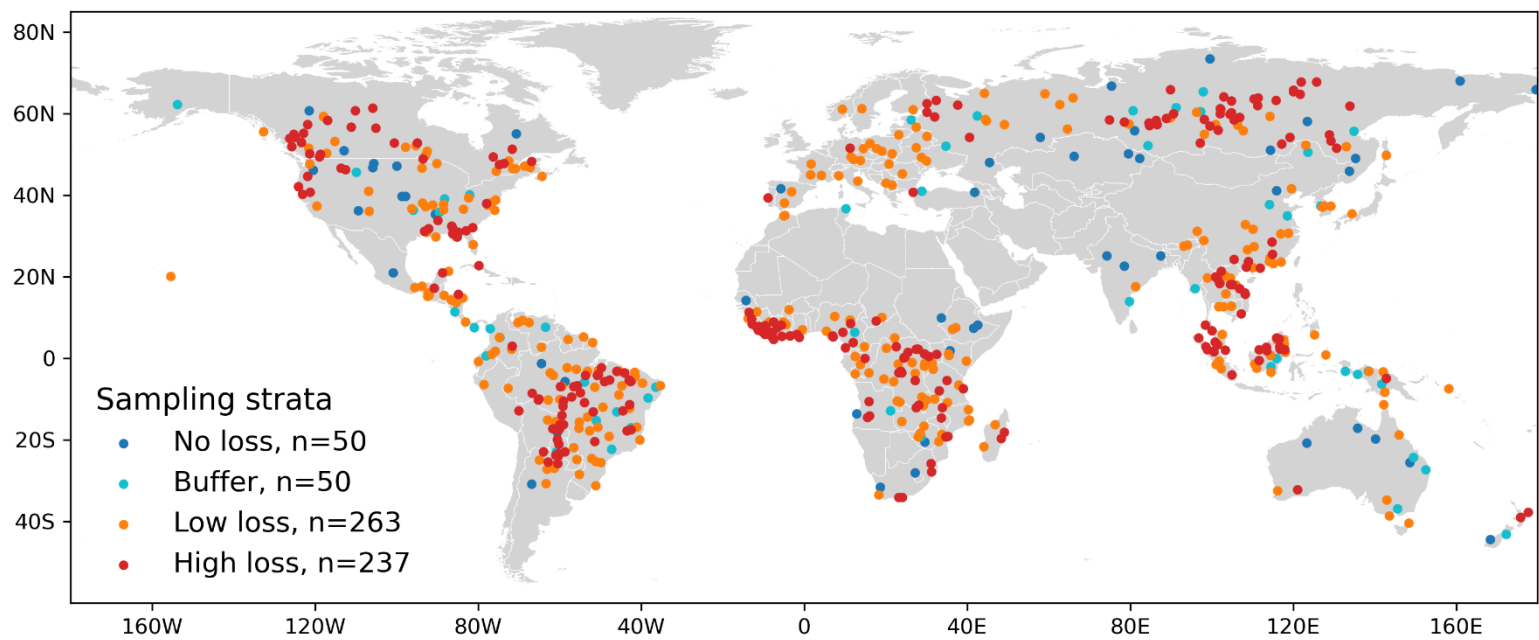
The goal of the project is to improve quantitative understanding of the global hotspots of forest loss, including deforestation, forest rotation and degradation using high resolution optical remote sensing data from PlanetScope and Sentinel-2 satellites (3 and 10 m spatial resolution, respectively).

The first portion of the analysis consists of the sample-based estimation of forest loss area with known uncertainty for the baseline year of 2018. The method was prototyped by our team for mapping tree cover loss in Peru and wheat extent in Punjab, Pakistan (Pickering et al., 2021). The reference area of forest loss derived from automated classification of a sample of high resolution data will be used to assess the accuracy of the Landsat-based (30m resolution) global forest loss map (Hansen et al., 2013). The second portion consists of forest loss type (initial disturbance type and proximate driver) and pre-disturbance forest type attribution for the mapped reference forest loss. Both are probability-based assessments, with the loss mapping performed using machine learning mapping algorithms, and the from-to forest type, disturbance driver and land use outcome attribution performed using expert visual interpretation.

## Methods: sampling design and reference imagery

The reference stratified random sample of 600 5x5km blocks was selected from a global grid of equal-area blocks with non-zero percent tree cover in the year 2000, subdivided into the following strata based on the global tree cover loss map for the year 2018 (Hansen et al., 2013): high loss (> 3.3% of forest loss per block), low loss (0 - 3.3%), no loss – one block buffer around loss blocks (to target omission errors), no loss – outside of buffer (see figure below for sample block locations).

For each sample block we have acquired at least one minimally clouded PlanetScope image closest to the beginning of each month of the year 2018, December 2017 and January-February 2019, to ensure the clear anniversary-date (beginning and end of year) images. We have also downloaded all available Sentinel-2 imagery for the same time period, resampled to the 3m PlanetScope grid, forming a single data stack.



## Types and drivers of forest loss

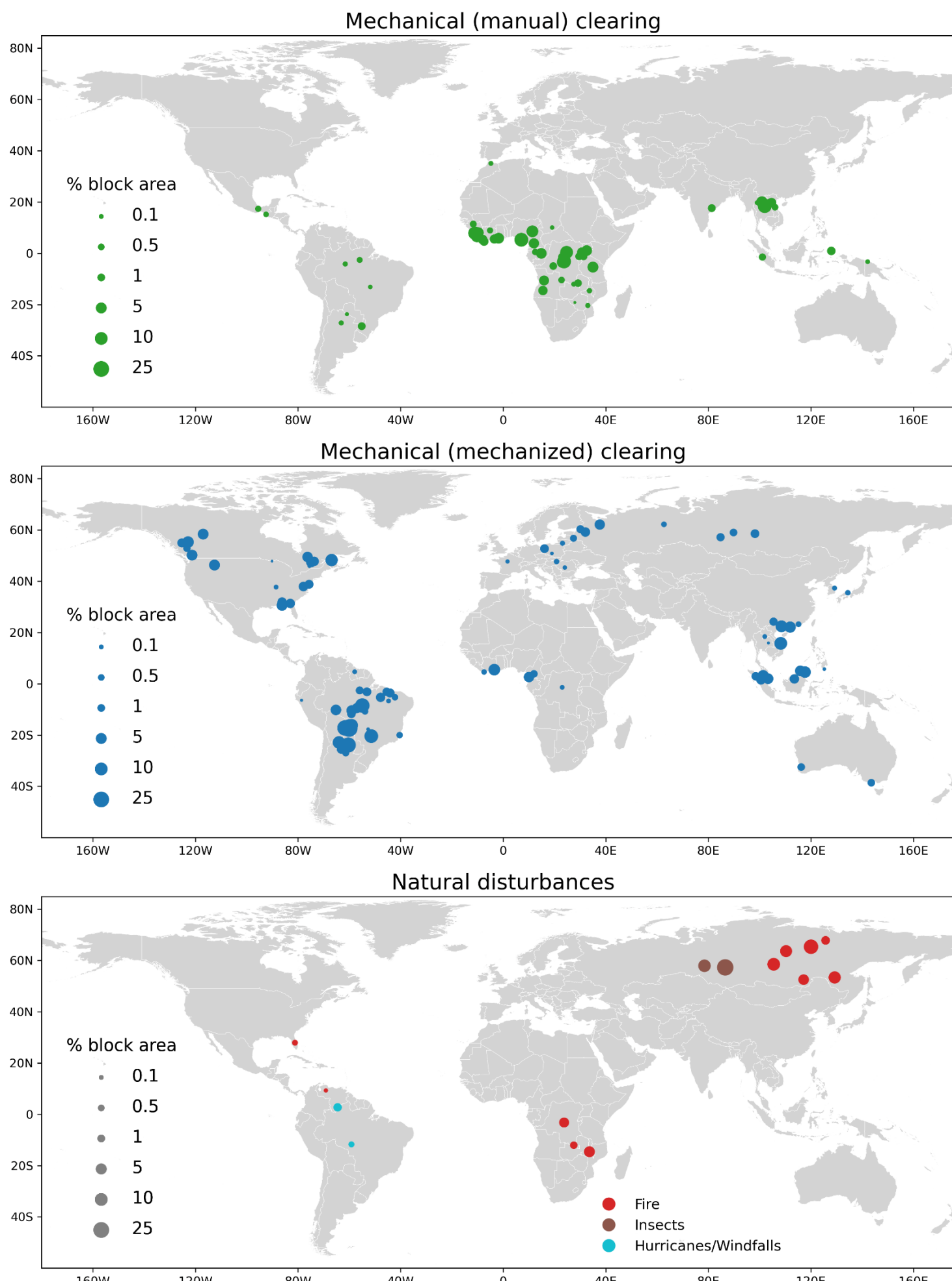
For each mapped pixel of year 2018 forest loss in each of the reference sample blocks we have assigned the following categories: pre-disturbance forest type, initial type of disturbance, and proximate cause (driver) of forest loss (based on land use 3 years post-disturbance).

Forest types included natural forests (including primary and secondary), timber plantations, and non-timber plantations (including palm).

Initial disturbance type was identified from year 2018 reference imagery, and included mechanical forest clearing (manual vs. mechanized) and natural disturbances (fire, insects, floods, hurricanes, windfalls). Disaggregation of mechanical clearing into manual vs. mechanized was based on clearing size and presence of access roads.

Proximate cause (driver) of forest loss (Geist and Lambin 2002) was identified based on the reference imagery 3 years after disturbance (PlanetScope and Google Earth). This was done to differentiate conversion of forests to various land uses (cropland vs. pasture vs. plantations), separate forest rotation in shifting cultivation cycle from semi-permanent conversion to cropland, and planted clearcuts from clearcuts with natural regeneration.

## Initial disturbance type



## Examples of mapped sample blocks

**Urbanization and palm plantation rotation in Malaysia**

**Shifting cultivation in the Democratic Republic of the Congo**

**Natural forest clearing for pasture in Argentina**

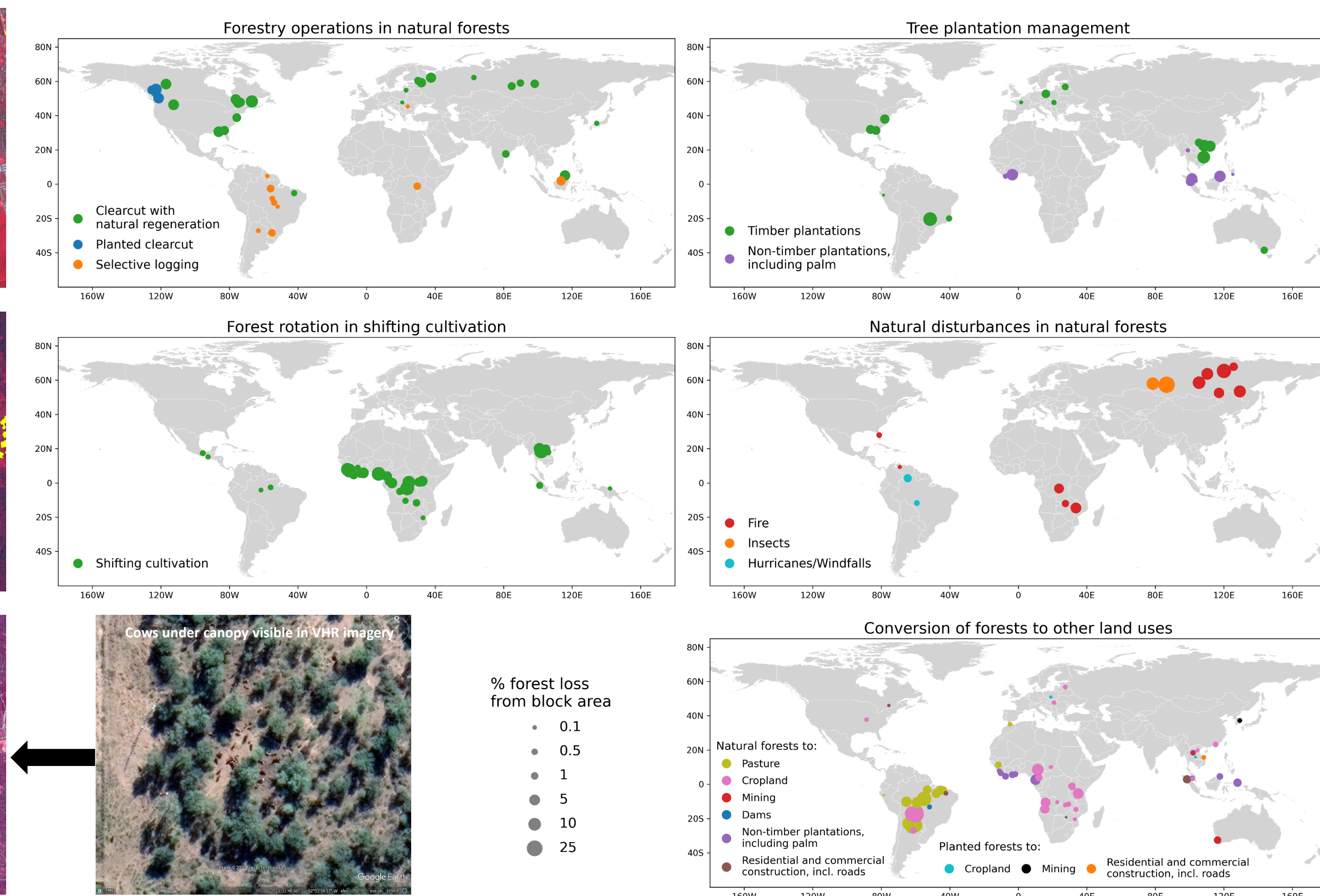
**Timber plantation management (thinning) in Brazil**

**Industrial logging of natural forests in Malaysia**

**Forestry/clearcuts in natural forests in Novgorod region, Russia**

**Fire in sparse larch forests in Sakha region, Russia**

## Proximate cause (driver) of forest loss, based on land use 3 years post-disturbance



## Methods: block mapping

Each sample block was classified into regions of 'tree cover loss' and 'no loss' using a supervised bagged classification tree algorithm. Training and classification was performed using the combined time series of Sentinel-2 and PlanetScope imagery. Training data was collected via identifying target regions with noticeable tree cover loss, as well as non-target regions that remained unchanged (see figure below). The fine resolution of PlanetScope imagery helped capture the precise spatial extent of tree cover loss events while the temporal resolution of Sentinel-2 images allowed pinpointing the date of onset for each identified loss event. The temporal dimension was especially important around the start and end dates of the time series because any tree cover loss occurring before January 1, 2018 and after December 31, 2018 was disregarded. The block mapping method was iterative: training inputs were modified following the results of each classification run until a satisfactory tree cover loss map was created for each block.

Each mapped block went through the quality assessment (QA) by the entire mapping team during the group QA sessions. The following checks were performed for each block during QA: commission error check 1 (make sure all the areas mapped as tree cover loss had trees at the beginning of 2018), commission error check 2 (make sure all areas mapped as tree cover loss experienced loss by the end of 2018), omission error check (make sure there are no areas with tree cover loss that were not mapped as loss). If problematic areas were found, more mapping iterations were performed, or block maps were manually edited until a satisfactory map was produced. Quantitative validation of the resulting maps will be performed at the end of the project, once all sample block maps are finalized.

## Acknowledgements

The authors would like to acknowledge NASA's Commercial Smallsat Data Acquisition program for providing access to PlanetScope imagery, and NASA's Land-Cover and Land-Use Change program grant #80NSSC21K0308 for funding this research.

## References

Geist, H.J. and Lambin, E.F., 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience*, 52(2), pp.143-150.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R. and Kommareddy, A., 2013. High-resolution global maps of 21st-century forest cover change. *science*, 342(6160), pp.850-853.

Pickering, J., Tyukavina, A., Khan, A., Potapov, P., Adusei, B., Hansen, M.C. and Lima, A., 2021. Using multi-resolution satellite data to quantify land dynamics: applications of PlanetScope imagery for cropland and tree-cover loss area estimation. *Remote Sensing*, 13(11), p.2191.

Background imagery is PlanetScope, RGB band combination NIR – Red – Green spectral bands