Deep learning-based earth mapping

Wetland ecosystem characterisation using CNN

Applied Machine Learning Final Exam - DecodeEarth Project

15th June 2022

Group members: Mate, Siyu, Yan, Maurice

“All group members have contributed equally to the project”

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PhD topic: Remote sensing in wetland studies, Supervisors: Rasmus Fensholt, Stephanie Horion
Part of the DeReEco project: Deep Learning and Remote Sensing for Unlocking Global Ecosystem Resource Dynamics

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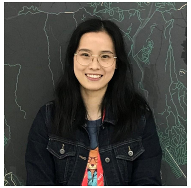
PhD topic: Canopy height retrieval at continental scale.
Supervisor: Martin Brandt, Rasmus Fensholt
Part of CTrees project: Mapping biomass in European forests.



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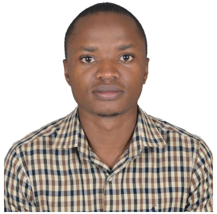
PhD topic: Remotely sensed forest health under intensified droughts
Supervisors: Stephanie Horion, Claus Beier
Part of DRYTIP project: Drought-induced tipping points in ecosystem functioning



Maurice Mugabowindekwe (mmu@ign.ku.dk) PhD Fellow @ KU IGN

PhD topic: Large-scale mapping and characterisation of individual forest and non-forest trees
Supervisors: Martin Brandt, Rasmus Fensholt
Part of DFF Sapere Aude project: Trees outside forests in African drylands

Outline

- Context
- Problem statement
- Dataset and features
- Data preprocessing
- Model selection, and hyperparameters
- Training and evaluation
- Results
- Discussion
- Conclusion

Context

[Credit: Yoda Adaman | Unsplash]

“It is indisputable that human activities are causing climate change, making extreme climate events, including heat waves, heavy rainfall, and droughts, more frequent and severe.

[Credit: Evgeny Nelmin | Unsplash]

“To limit global warming, strong, rapid, and sustained reductions in CO2, methane, and other greenhouse gases are necessary.

This would not only reduce the consequences of climate change but also improve air quality.

SDG 13 - Take urgent action to combat climate change and its impacts

Combatting climate change requires a comprehensive and multi-pronged strategic approach. Impacts of climate change are felt around the world, with an increase in climate-related disasters anticipated. Parties to the Ramsar Convention agreed in 2015 “wetlands in all parts of the world play an important role in disaster risk reduction if the wetlands are effectively managed and restored where necessary”[26].

Wetland soils contain over a third (35%) of the world’s organic carbon[27]. Coastal ecosystems and particularly mangroves, saltmarshes and seagrass beds sequester two to four times more carbon than terrestrial forests[28] and these “blue carbon ecosystems” play an important role in climate change mitigation. This carbon is stored for the long-term in wetland soils. Preventing further degradation, drainage and loss of wetlands ecosystems is critical to preventing further GHG emissions.

Given the scale of the climate change challenge, partnerships can mobilize expertise and funding more effectively. The International Partnership for Blue Carbon – announced during the Paris Climate Change conference in 2015 – aims to bring together diverse partners, from government to non-government and research organizations, to conserve coastal ecosystems. Already, 28 countries have included coastal blue carbon ecosystems in their nationally determined contributions (NDCs) under the United Nations Framework Convention on Climate Change (UNFCCC) while 59 countries have included these ecosystems in their adaptation strategies.

SDG 17 – PARTNERSHIPS FOR THE GOALS
The Ramsar Convention works in partnership with other MEAs to support governments in achieving the SDGs.

SDG 16 – PEACE, JUSTICE & STRONG INSTITUTIONS
Effective management of transboundary wetlands contributes to peace and security.

SDG 15 – LIFE ON LAND
40% of all the world's species live and breed in wetlands.

SDG 14 – LIFE BELOW WATER
Healthy and productive oceans rely on well functioning coastal and marine wetlands.

SDG 13 – CLIMATE ACTION
Peatlands cover only 3% of global land but store twice as much carbon as the entire world's forest biomass.

SDG 12 – RESPONSIBLE CONSUMPTION & PRODUCTION
Wetland areas properly managed can sustainably support increased demands for water in all sectors.

SDG 11 – SUSTAINABLE CITIES & COMMUNITIES
Urban wetlands play a vital role in making cities safe, resilient and sustainable.

SDG 10 – REDUCED INEQUALITY
Healthy wetlands mitigate the risk to an estimated 5 billion people living with poor access to water by 2050.

SDG 9 – INDUSTRY, INNOVATION & INFRASTRUCTURE
Healthy wetlands form a natural buffer against the increasing number of natural disasters.

SDG 1 – NO POVERTY
More than a billion people depend on wetlands for a living.

SDG 2 –ZERO HUNGER
Rice, grown in wetland paddies, is the staple diet of 3.5 billion people.

SDG 3 – GOOD HEALTH & WELL BEING
Half of international tourists seek relaxation in wetland areas, especially coastal zones.

SDG 4 – QUALITY EDUCATION
Safe water access enhances educational opportunities, especially for girls.

SDG 5 – GENDER EQUALITY
Women play a central role in the provision, management and safeguarding of water.

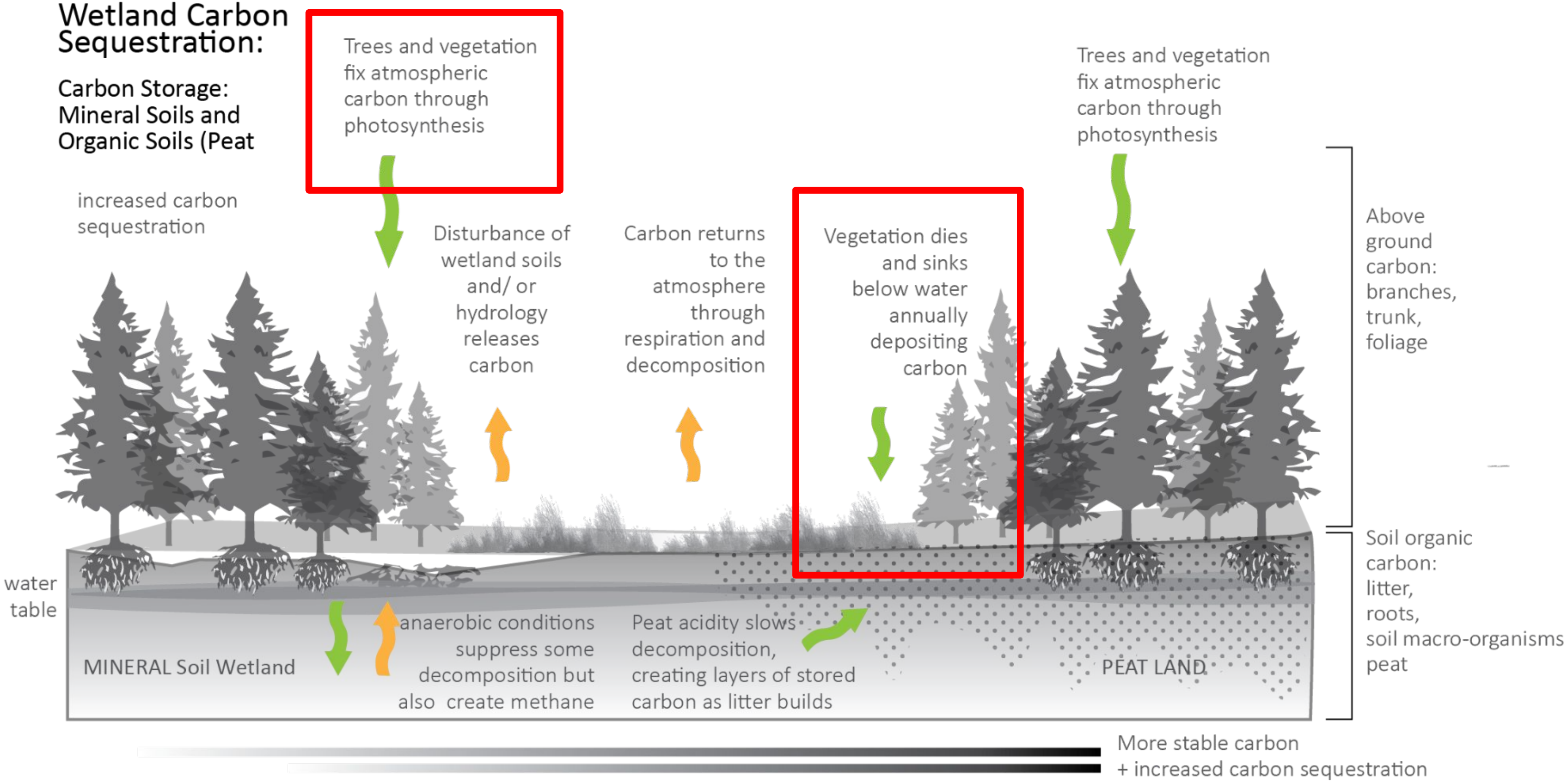
SDG 6 – CLEAN WATER & SANITATION
Almost all of the world's consumption of freshwater is drawn either directly or indirectly from wetlands.

SDG 7 – AFFORDABLE & CLEAN ENERGY
Sustainable upstream water management can provide affordable and clean energy.

SDG 8 – DECENT WORK & ECONOMIC GROWTH
Wetlands sustain 266 million jobs in wetland tourism and travel.

Wetland Carbon Sequestration:

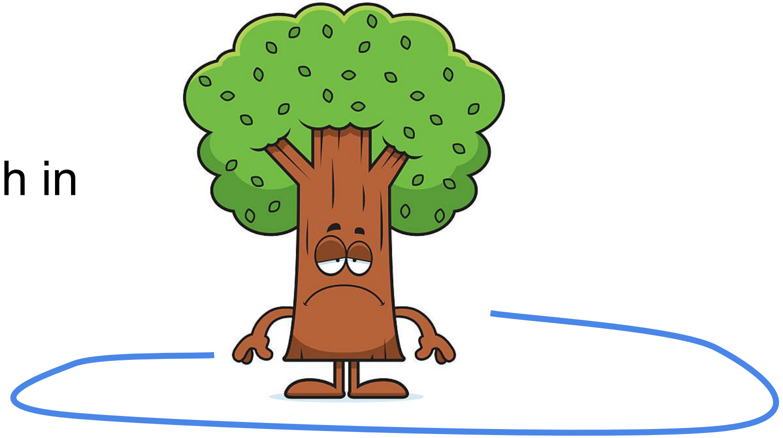
Carbon Storage: Mineral Soils and Organic Soils (Peat



Source: Minnesota Board of Water and Soil Resources

Wetland + Trees =

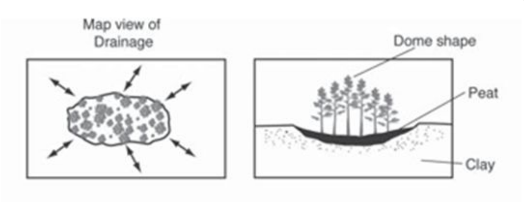
HOWEVER, very few trees flourish in standing water



Big Cypress National Preserve, Florida, USA

Bald cypress (Taxodium distichum)

Cypress domes



distribution

Big Cypress National Preserve, Florida, USA

- Most common vegetation class: Cypress Forest, Cypress Scrub, Pine Woodlands, and Mixed Graminoid Freshwater Marshes and Prairies



Photo from Vegetation Mapping Inventory

Biogeosciences, 12, 2285–2300, 2015
www.biogeosciences.net/12/2285/2015/
doi:10.5194/bg-12-2285-2015

Biogeosciences Open Access

Carbon exchange between the atmosphere and subtropical forested cypress and pine wetlands

W. B. Shoemaker[1], F. Anderson[2], J. G. Barr[3], S. L. Graham[4], and D. B. Botkin[5]

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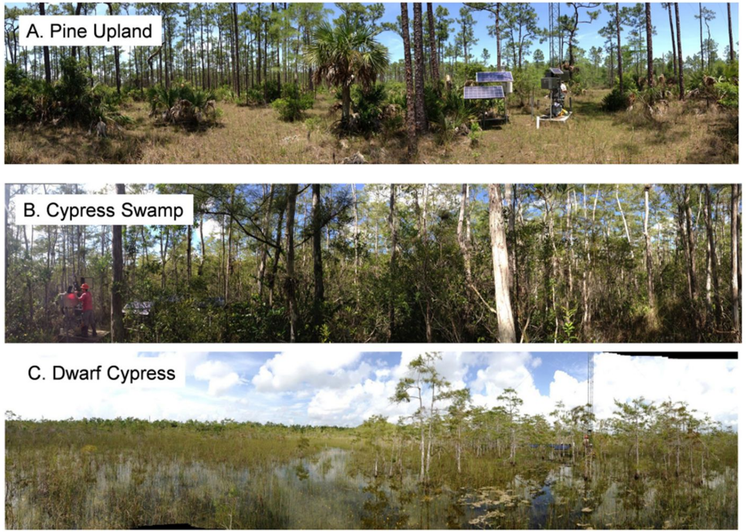
[4]National Institute of Water and Atmospheric Research (NIWA), Christchurch, New Zealand
[5]Department of Biology, University of Miami, Coral Gables, FL, USA

Correspondence to: W. B. Shoemaker (bshoemak@usgs.gov) and F. Anderson (fanders@usgs.gov)

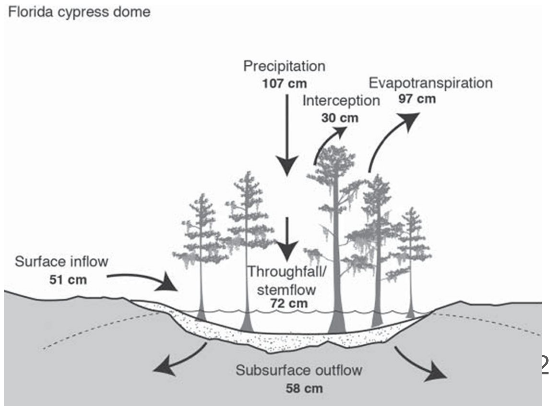
Received: 30 September 2014 – Published in Biogeosciences Discuss.: 14 November 2014
Revised: 19 March 2015 – Accepted: 24 March 2015 – Published: 16 April 2015



Panoramic photos of the **(a)** Pine Upland, **(b)** Cypress Swamp and **(c)** Dwarf Cypress plant communities.

They found: the bigger the trees -> the higher the C sink

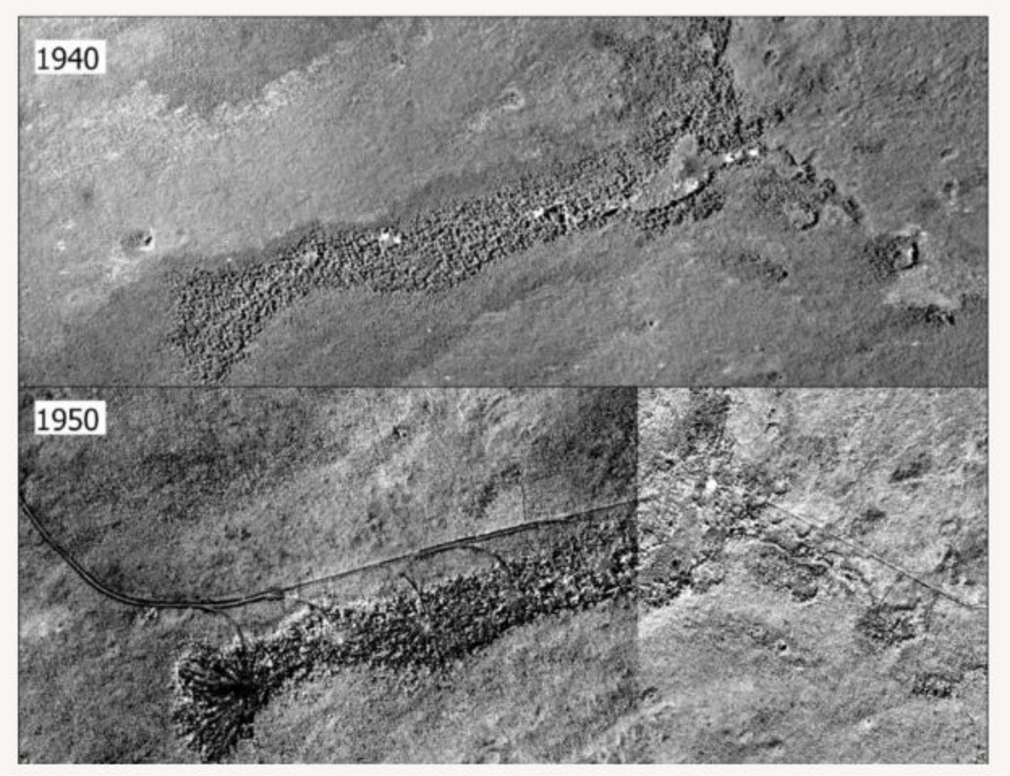
(makes sense!)



BUT!

Cypress timber was historically harvested for valuable heartwood until the late 1950s (300 million board feet annually)

Today threatened by climate change (fires, drought, etc.)



Source: Florida International University

Monitoring systems and maps are needed!

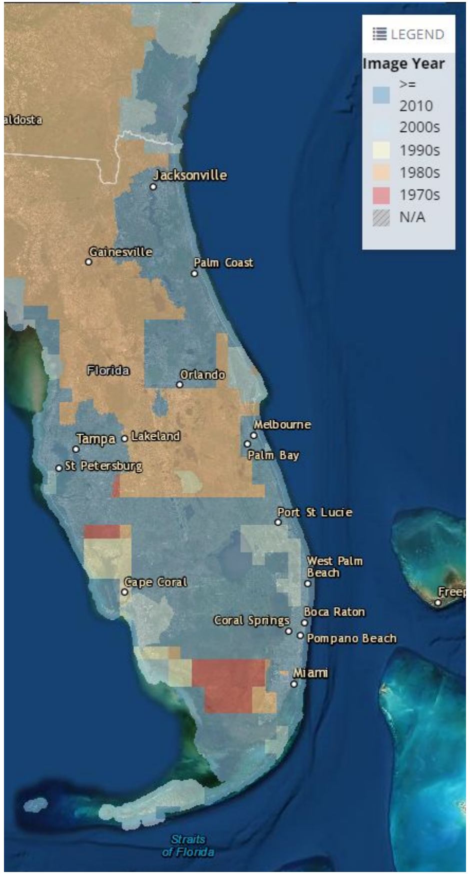
Problem statement

Why deep learning?

- Outperformance in image analysis
- Machines are cheaper than humans :), i.e., photo-interpretation (laborious and time-consuming)
- Predictions are faster than tree-based algorithms, which enables large-scale and frequent updates

U.S. Fish & Wildlife Service

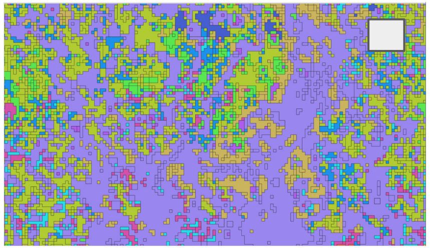
National Wetlands Inventory

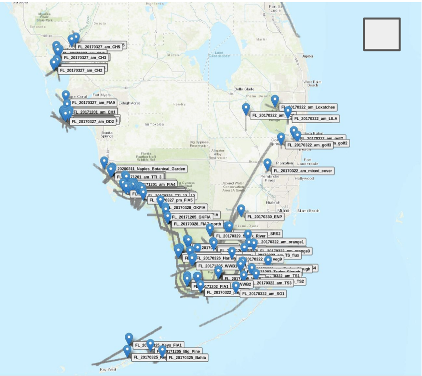


- Produced by manual delineation of aerial photos
- Outdated, some areas not updated since the 1970s!
- Most recent iteration more than 10 years ago

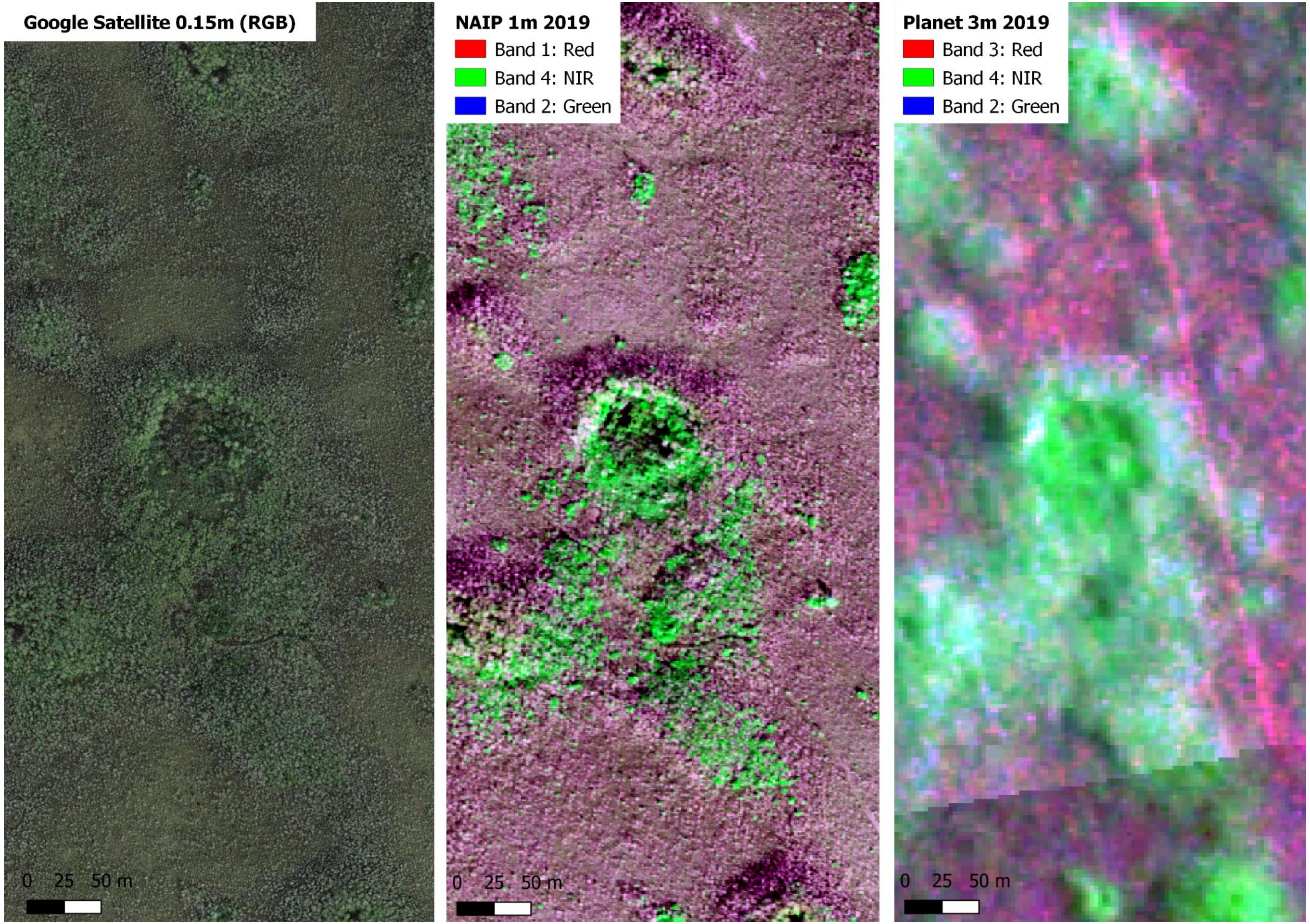
Datasets

- NAIP 2019 The National Agriculture Imagery Program (NAIP)
    - 1-meter (resampled from 60cm for 2019)
    - RGB + NIR
- PlanetScope mosaic 2019
    - 3-meter spatial resolution
    - RGB + NIR
- GEDI from Google Earth Engine
    - Sparse 25m rasterized data
    - Spaceborne LiDAR
- Aerial LiDAR Canopy Height Model Data
    - 1m rasterized height map
- Vegetation Mapping Inventory
    - Vegetation map (50m)
    - Field measurements

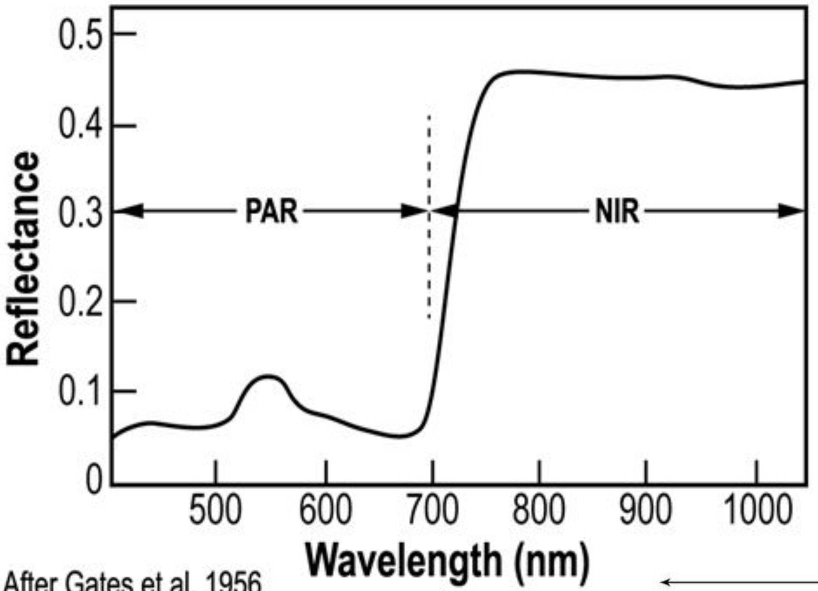




Dataset comparison

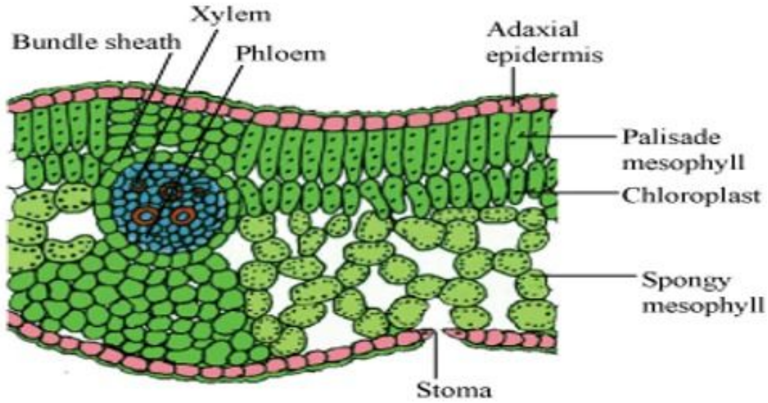


Reflectance of a typical plant leaf in the visible and near infrared



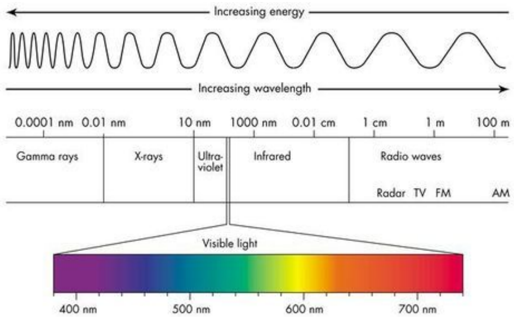
After Gates et al, 1956

Cross section of a typical leaf



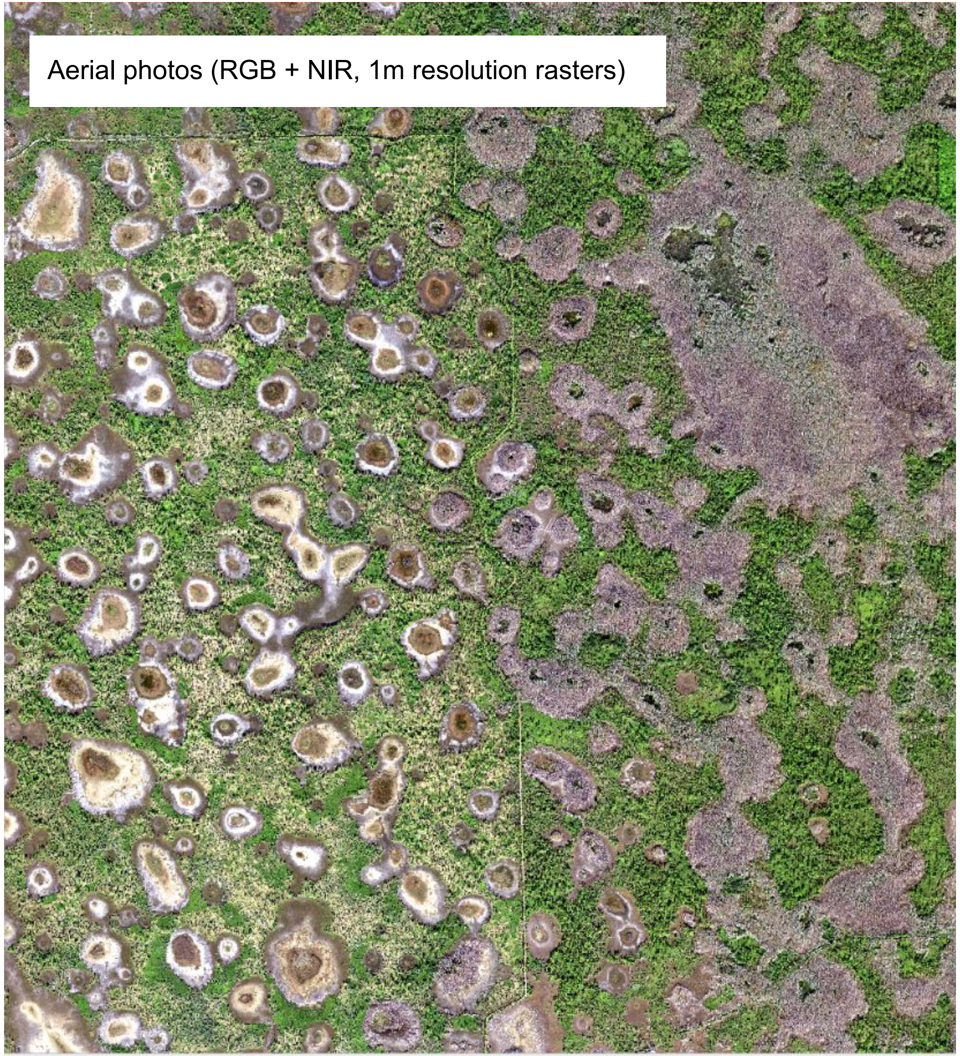
- high degree of scattering of NIR in the spongy mesopyll tissue
- evolved to help reduce the leaf temperature

PAR: Photosynthetically Active Radiation
NIR: near-infrared region of the EM spectrum



Land cover/species mapping from aerial imagery


Aerial photos (RGB + NIR, 1m resolution rasters)



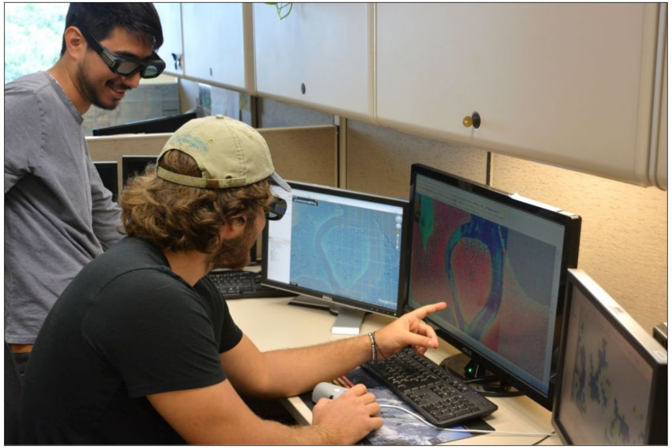
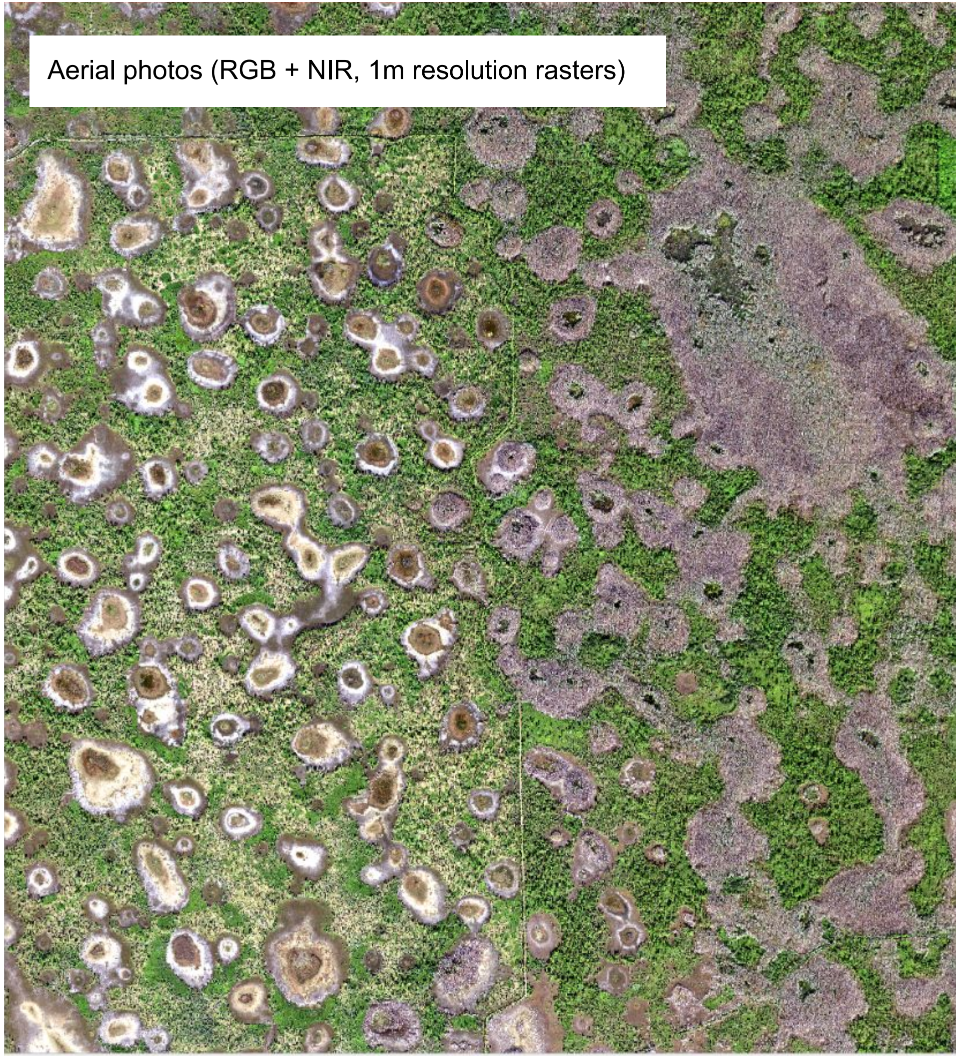
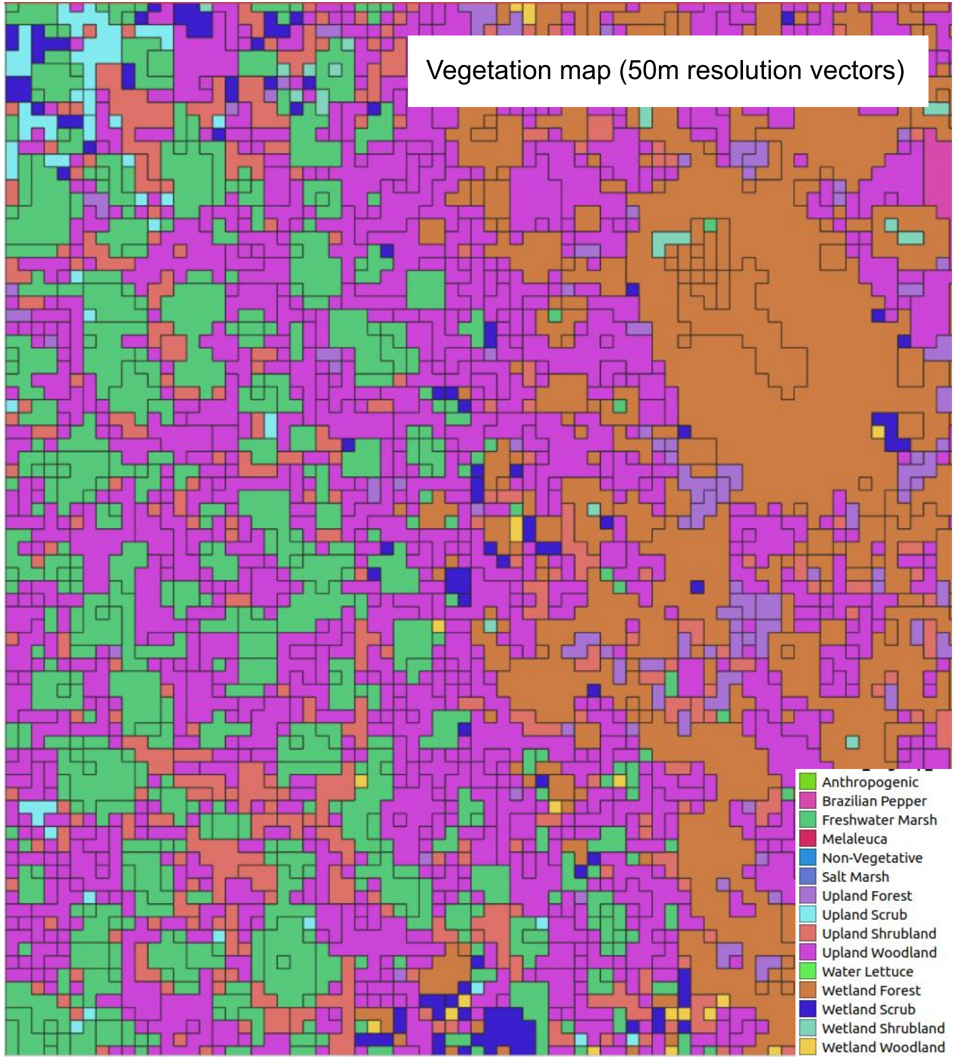


Photo 1. Photo-interpreters (Michael Foguer, left, and Alejandro Arteaga Garcia, right) working on a photogrammetric workstation running Summit Evolution v7.4.

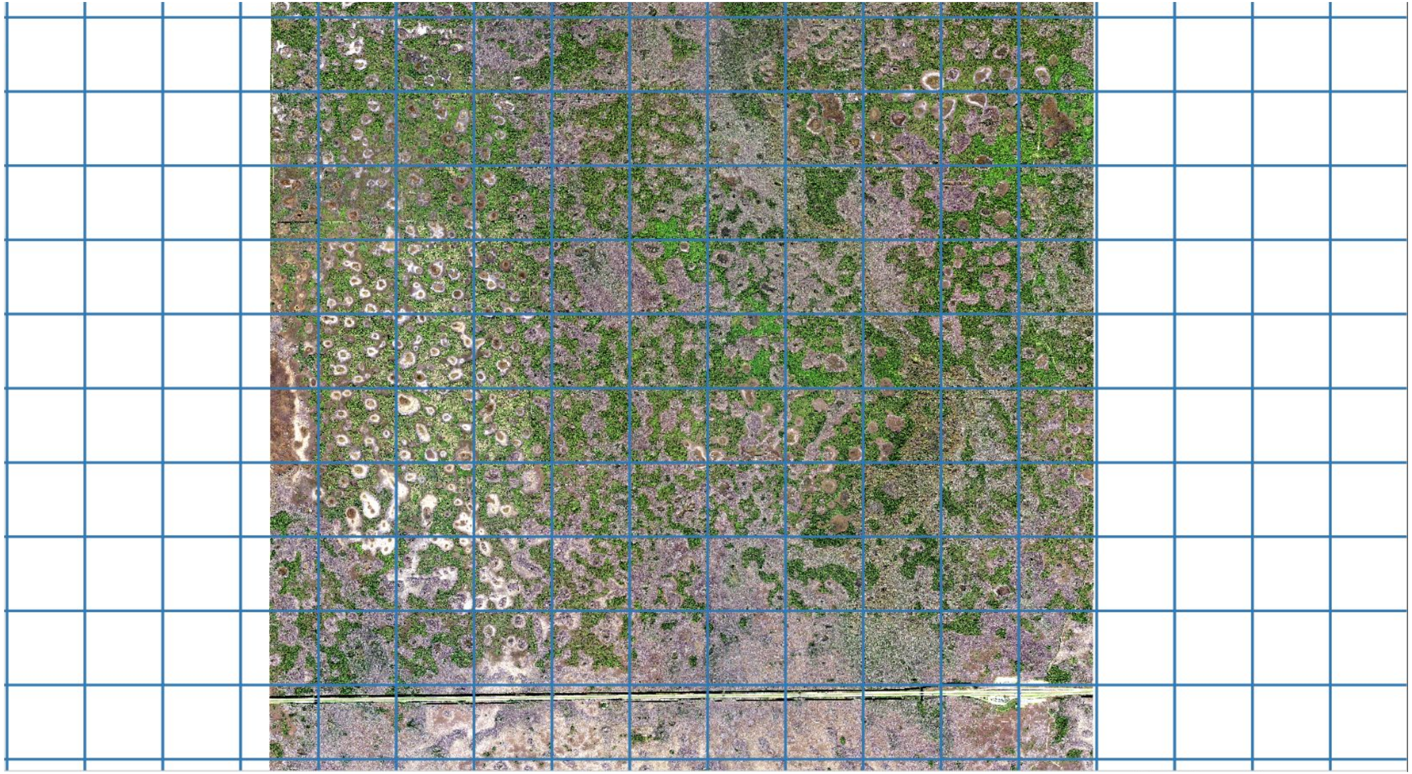


Aerial photos (RGB + NIR, 1m resolution rasters)

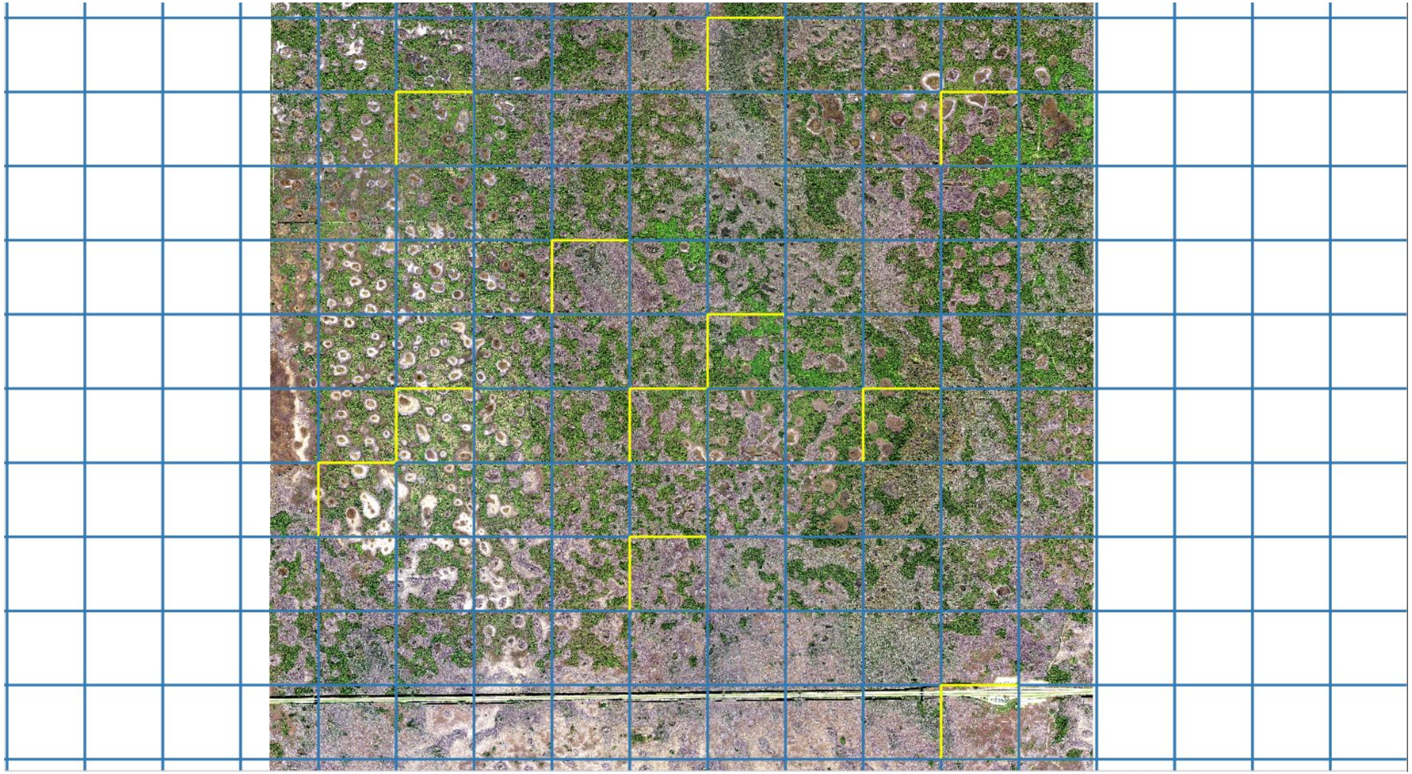


Vegetation map (50m resolution vectors)
Anthropogenic
Brazilian Pepper
Freshwater Marsh
Melaleuca
Non-Vegetative
Salt Marsh
Upland Forest
Upland Scrub
Upland Shrubland
Upland Woodland
Water Lettuce
Wetland Forest
Wetland Scrub
Wetland Shrubland
Wetland Woodland

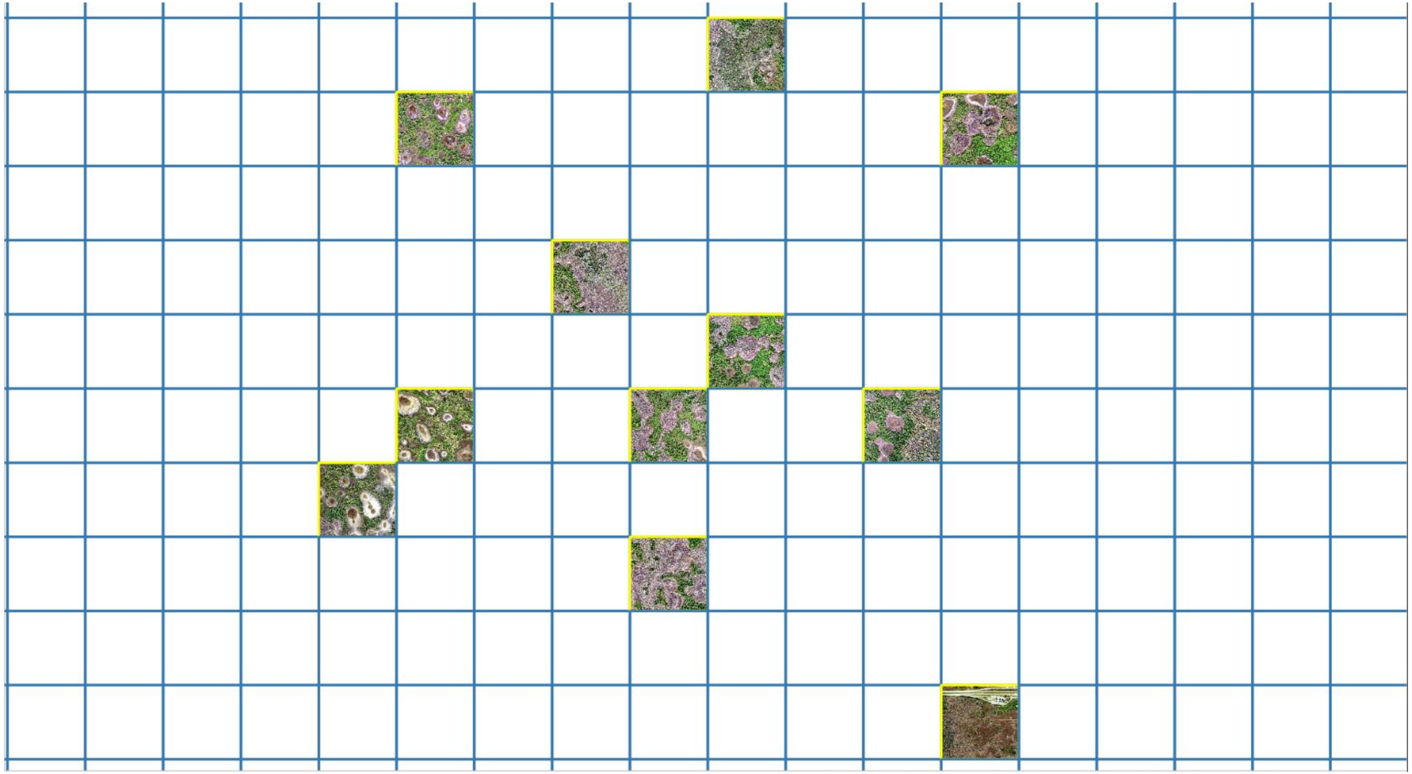
Data preprocessing - create grids



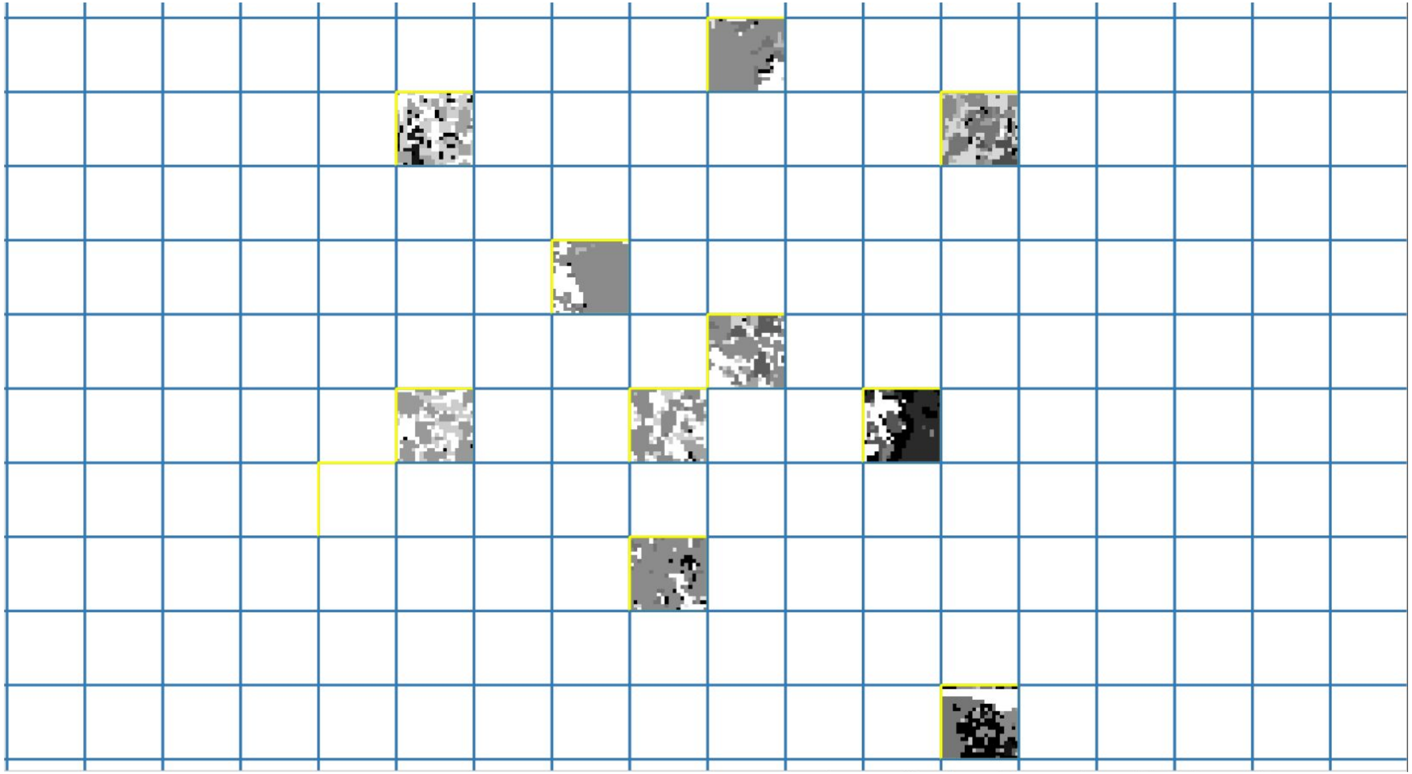
Data preprocessing - select aois



Data preprocessing - clip aerial images (input features)



Data preprocessing - clip vegetation maps (labels)

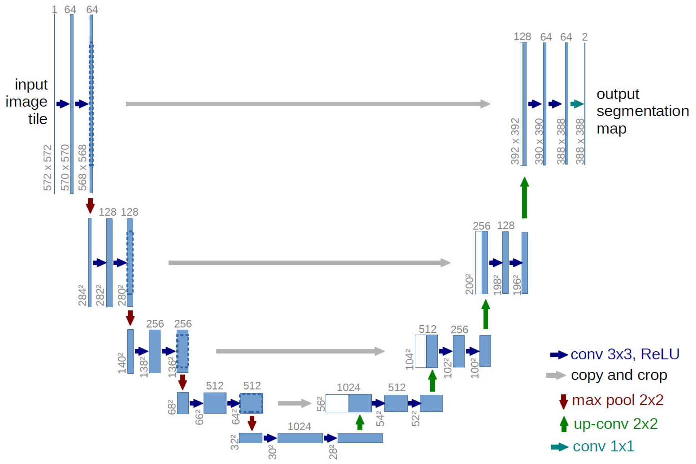


UNet-based multiclass land cover classification

Model architecture

- Input: Aerial photos, RGB and NIR bands, 1-meter resolution, float
- Labels: Mask layer, 1 channel, 1-meter resolution, integer
- **Number of classes: 15**
- Validation percentage: 10%
- Learning rate: 1e-4
- **Loss function: Weighted Cross Entropy**

$$\mathrm{loss}(x, class) = weight[class]\left(-x[class] + \log\left(\sum_j \exp(x[j])\right)\right)$$



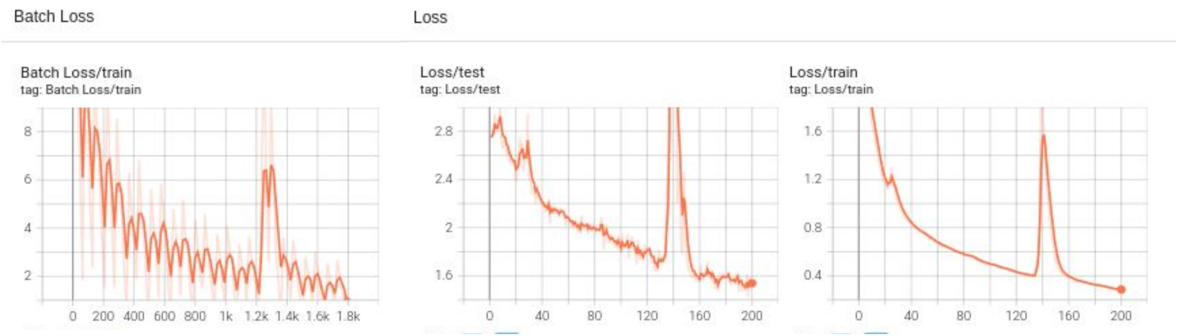
The last layer of the architecture performs an 1x1 convolution used to reduce the 64 components to the desired number of classes

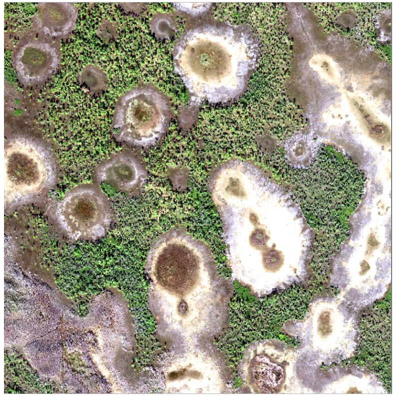
In practice

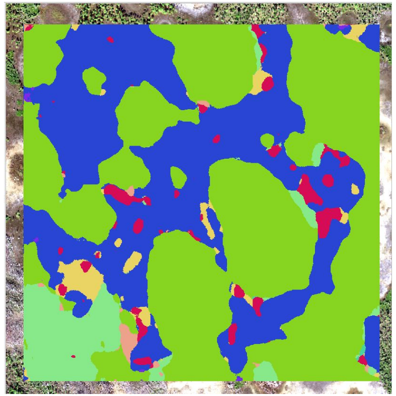
- 9 (training dataset) + 1 (validation dataset)
- 1 (testing dataset) (1x1km2 per image chip)
- 200 epochs

Acknowledgement: Inspired by and adapted from the github repository developed by Srimannarayana Baratam and Georgios Apostolides

Results





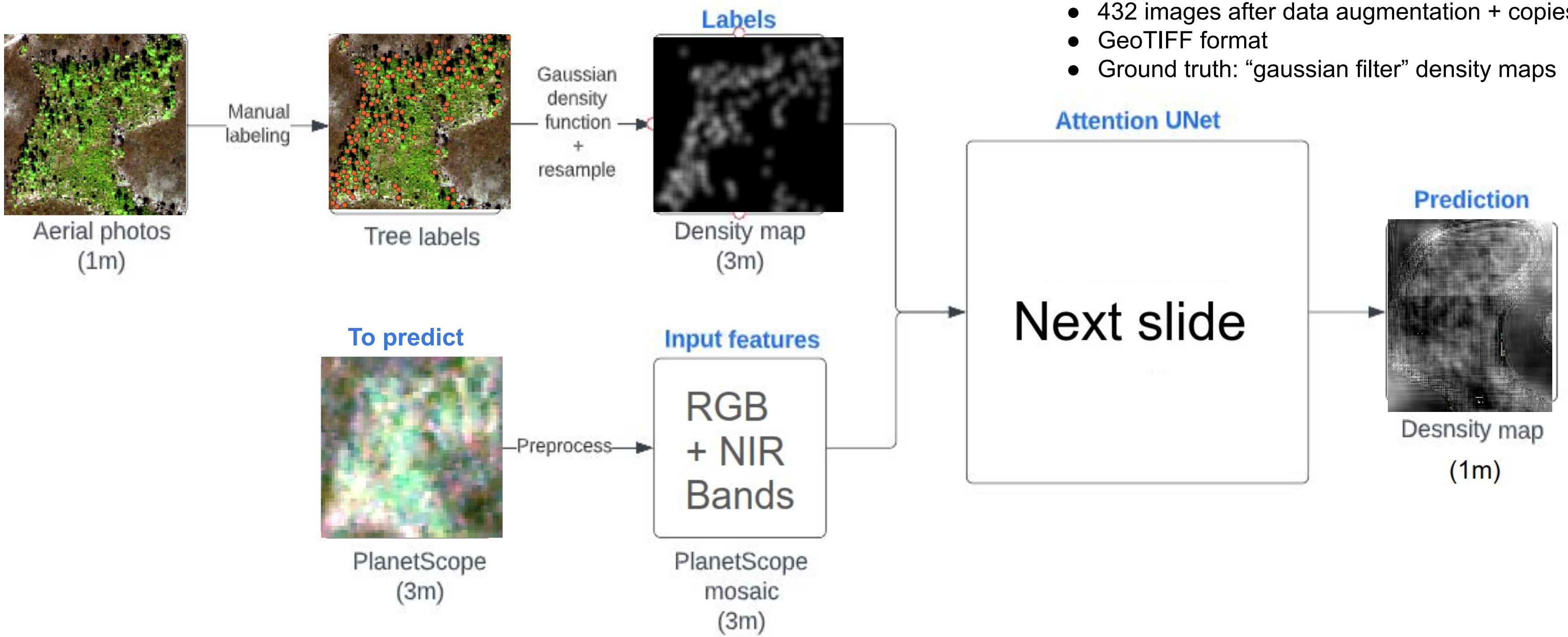


Challenges and future work

- Different resolutions between input imagery and labels
- Test over larger areas and more detailed classes

Methods - tree density mapping

- 72 (256x256 px) Planet images resampled to 1 m resolution
- **47,651 manual labels (tree crown centroids)!!!**
- 432 images after data augmentation + copies
- GeoTIFF format
- Ground truth: “gaussian filter” density maps

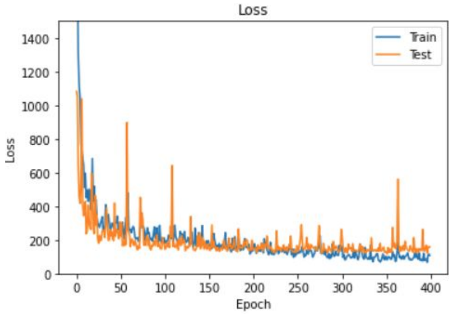


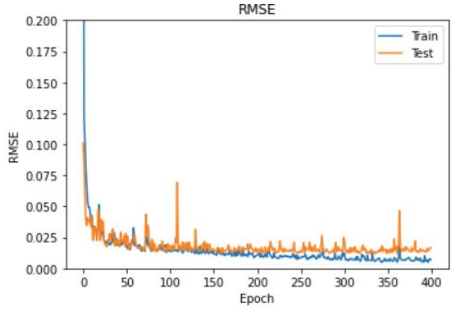
Tree density mapping through a regression task, using CNN (UNet architecture[1] with modifications as recommended by [2]) with “linear” activate at the last layer (for regression task)

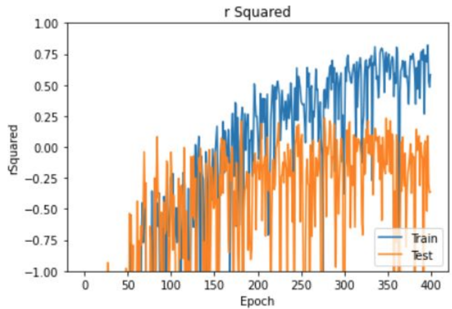
1. Ronneberger, O., Fischer P. & Brox, T. U-net: convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (eds. Navab, N. et al.) 234–241, (Springer, 2015).
2. Koch, T., Perslev, M., Igel, C. & Brandt, S. Accurate segmentation of dental panoramic radiographs with U-nets. In Proc. IEEE International Symposium on Biomedical Imaging (ISBI) (eds Davis, L. et al.) 15–19 (IEEE Computer Society, 2019).

Methods - Model, hyperparameters and training

Tree density mapping!



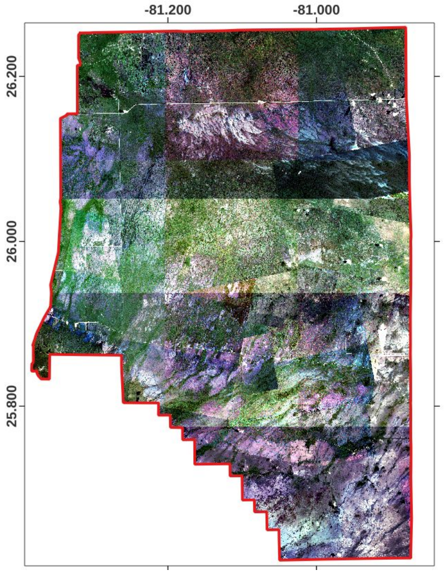




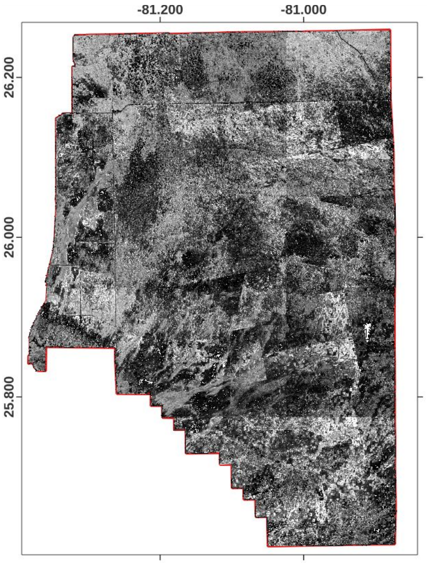
- UNet architecture model with “linear” activation at the last layer (for the regression task)
- Optimizer - Adam(lr=1e-04, 1e-05, **5.0e-05**, 5.0e-06, decay= 0.0, beta_1= 0.9, beta_2=0.999, epsilon= 1.0e-8)
- Loss : mse, (rmse / y_pred.mean()) * 100, **combined_loss ((rmse / y_pred.mean()) * 100 + count_loss**
- Metrics: MSE, RMSE, **(rmse / y_pred.mean()) * 100**, RSE, MAE, count_loss!
- Epochs:30, 50, 80, 100, 150, 200, **400**
- Training steps: 50, 60, 80, **100**, 150
- Validation steps: 10, 20, 25, **40**

Tree density mapping

PlanetScope image



Predicted tree density

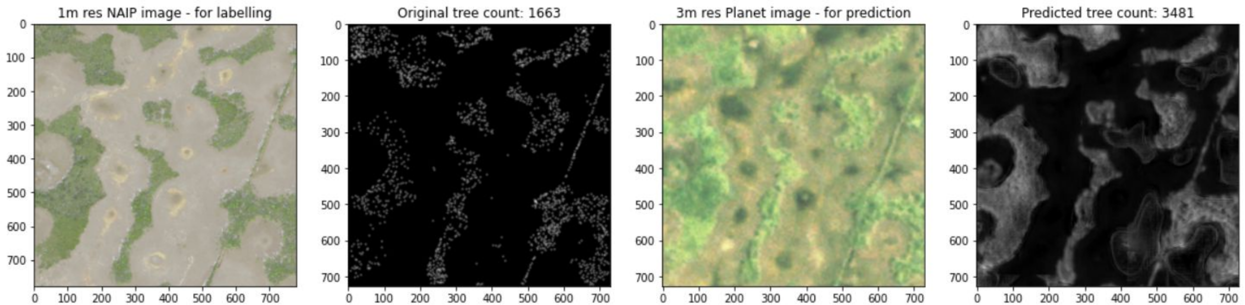


Results

- Total number of predicted trees = 34,277,644
- Predicted mean tree density = 121.3 trees ha^{-1}
- Train R2 = 0.30, Val R2 = 0.21
- Train MAE =0.006, Val MAE = 0.008
- Train Avg Err %= 140.1, Val Avg Err = 117.7
- Train RSE =2.65 , Val RSE= -
- Train RMSE = 0.009 , Val RMSE = 0.013
- Total labels = 47,651, Predicted=57,841 (21.3% overestimation)

Discussion

- Tree counts informs about biodiversity
- Support plan for restoration and fighting climate change (planning guidance)



Challenges and future work

- “Unharmonised” images
- Artefacts from Planet images
- Did not work well at overall count (about 2x overererestimation)
- Edge effect!!!!!!
- Biomass + C stocks map…

Height retrieval from Planet Imagery: Datasets

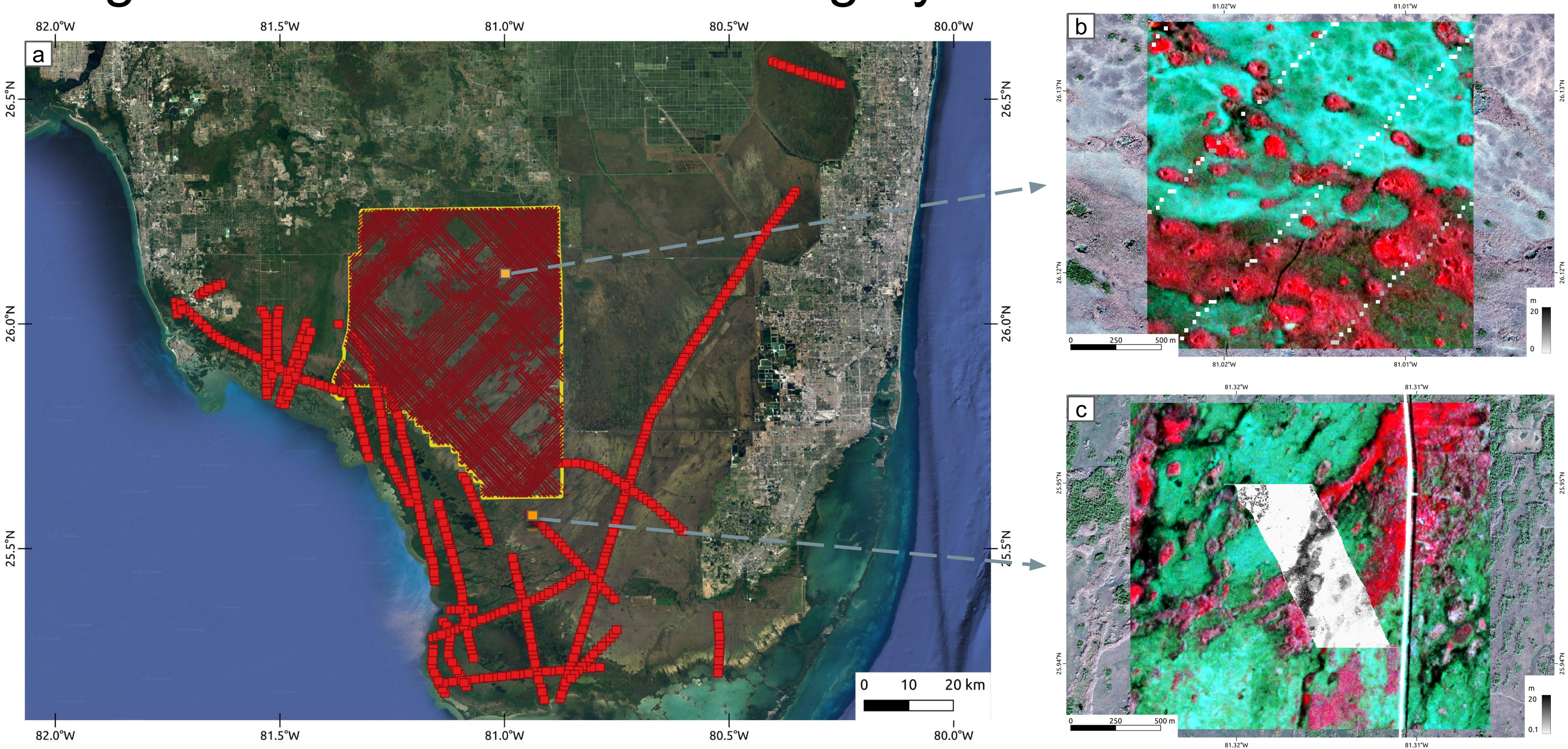


Fig: Data overview for training height model. **a,** Spatial coverage and position of aerial LiDAR CHM and GEDI data. **b,** GEDI data distribution in one of 699 training patches. **c,** Aerial LiDAR CHM data spatial coverage in one of 627 training patches. Each batch is 600x600 pixels at 3m resolution, enlarged from the center of aerial CHM center. (Background: false color planet imagery NRG).

Methods: Sparse supervision with Gaussian NLL loss

$$\mathcal{L}_{NLL} = \frac{1}{N}\sum_{i=1}^{N}\frac{(\hat{\mu}(x_i) - y_i)^2}{2\hat{\sigma}^2(x_i)} + \frac{1}{2}\log\hat{\sigma}^2(x_i).$$

If σ is a constant then loss function becomes equivalent to MSE*const.
σ is a variable in this case, and hence the network gives higher weight to data with lower variance.

Pytorch NLL :

```
variance = torch.exp(log_variance) + self.eps
return torch.mean(weights * 0.5 / variance * (prediction - target)**2 + 0.5 * torch.log(variance))
```

Learning Process :

```
elif base_cfg.num_classes == 2:
    score = model(img)
    means, vars = score[:,0,...], score[:,1,...]
    loss = criterion(means[:,None,...][~mask], vars[:,None,...][~mask], gt[~mask])
```

Fig: Training and validation curves with different input and ground truth data. CNN model: UNet backbone, Efficientnet-b4 encoder.

Weights in the loss function can be the inverse distribution of the height.

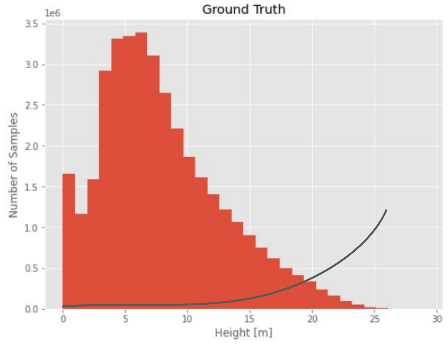


Fig: Ground truth height histogram and weight curve

Results: wall-to-wall height mapping

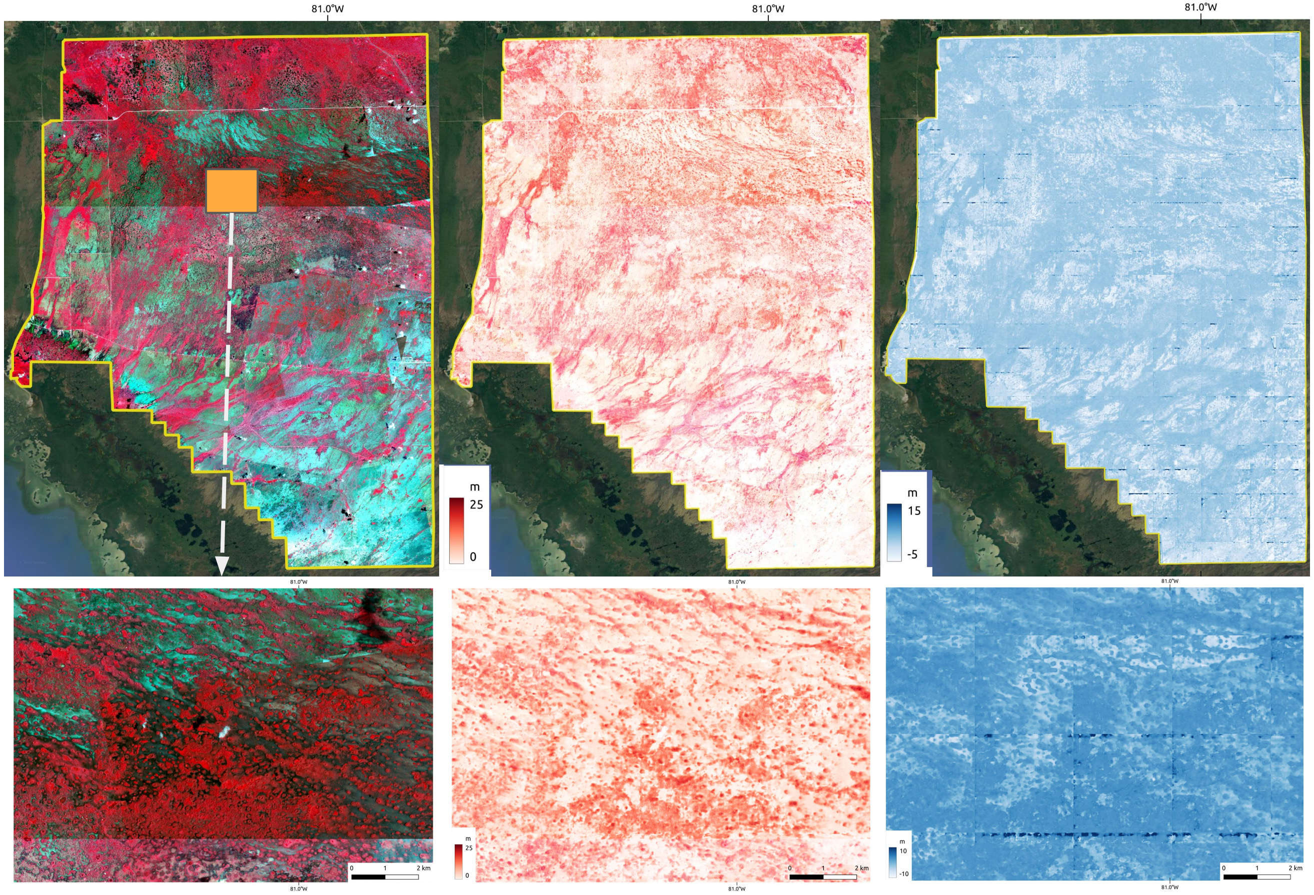


Fig: Height and uncertainty map for the research area and zoom in visualization. Planet Imagery with false color (NRG)

- Mapping with both mean height and variance.
- Boundary area have very high uncertainty. (TTA?)
- The pattern with low height also show relatively low variance.
- Model tend to saturate with the increase of height.
- r2:0.23; mae:4.57.
- Future: drop out and deep ensemble for model uncertainty.

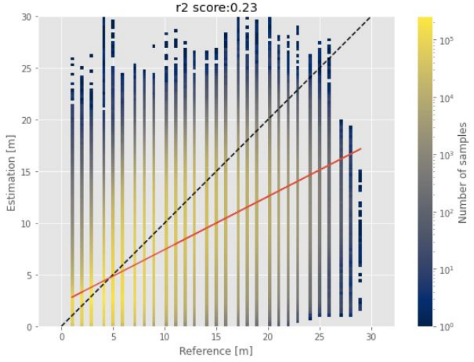
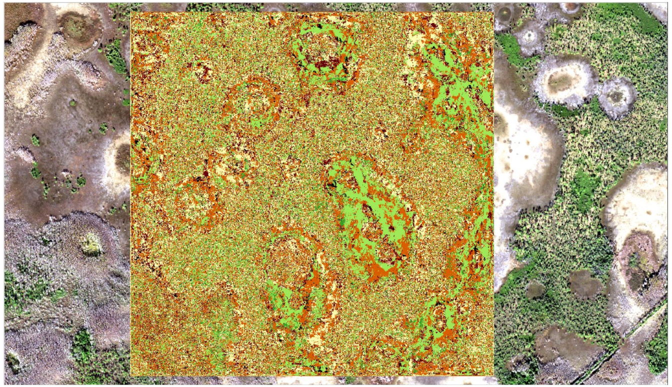
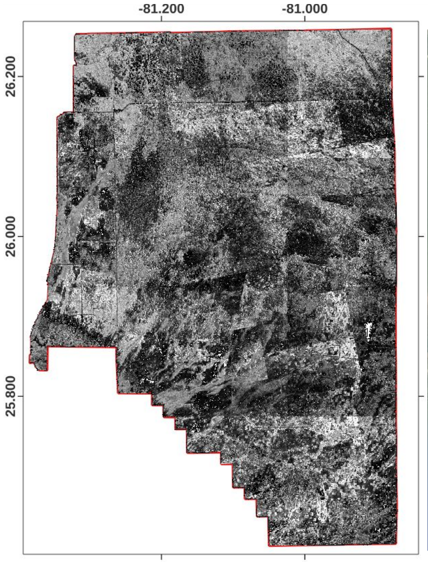


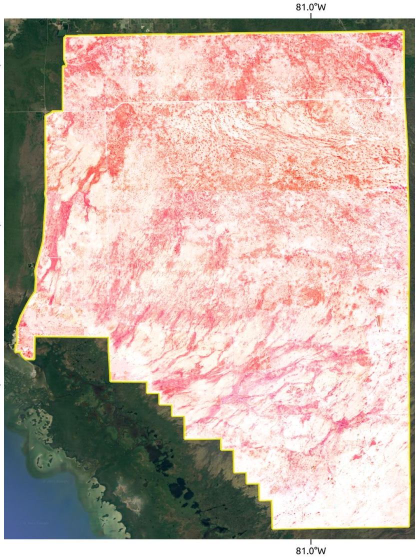
Fig: Confusion plot between prediction and reference height.

Results

- 1m Land cover classification
- Tree density map
- Tree height map

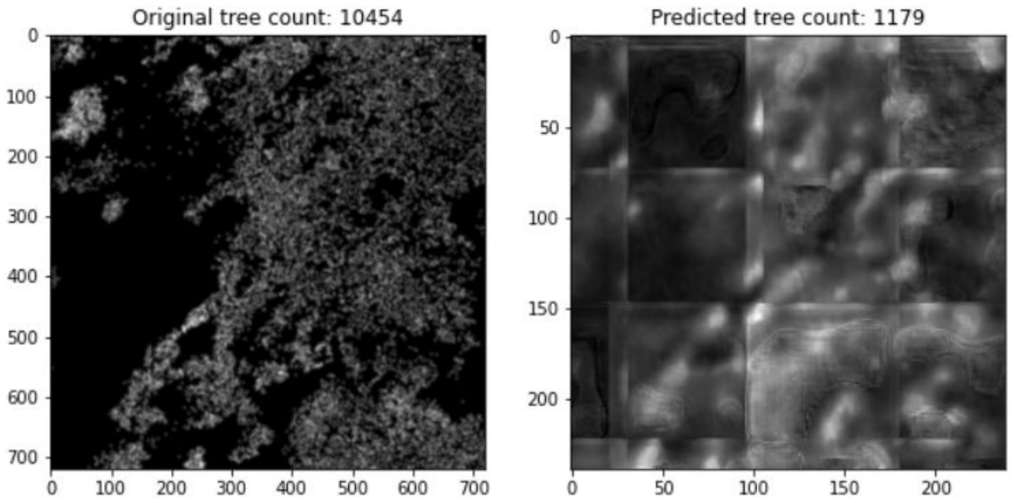


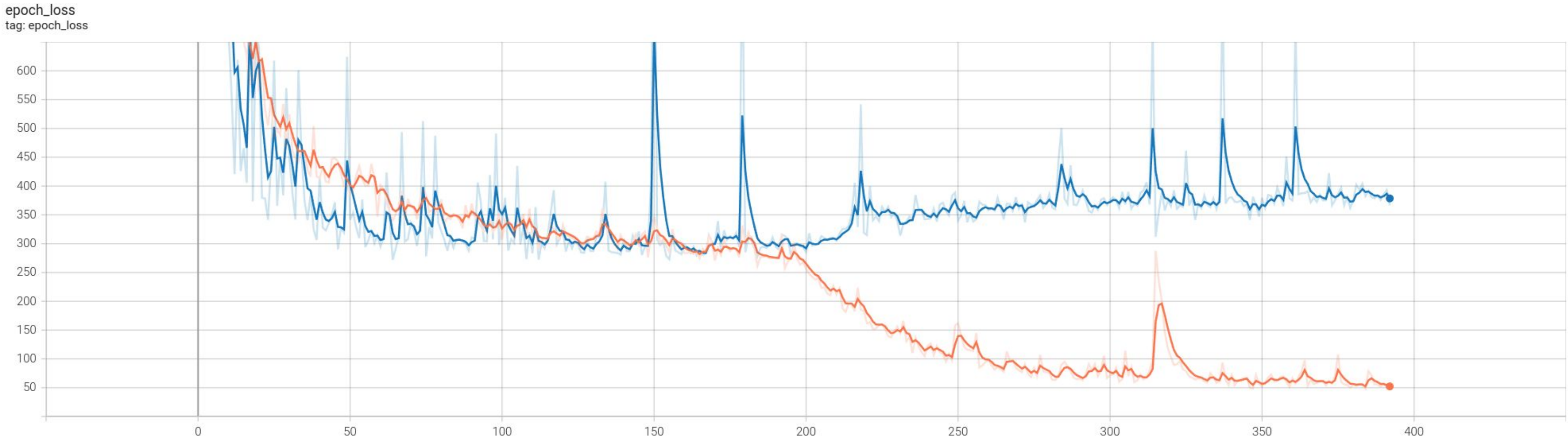




Appendix

- Edge effect for tree density mapping at "unresampled scale - 3m"!!! (fig. right)
- About 10x underestimation of total tree count in some areas (the DL-based regression did not work well here!!!), and ~4x underestimation overall..
- Some changes in learning rate and no. epochs lead the model either to overtraining or lack of convergence (fig. below)

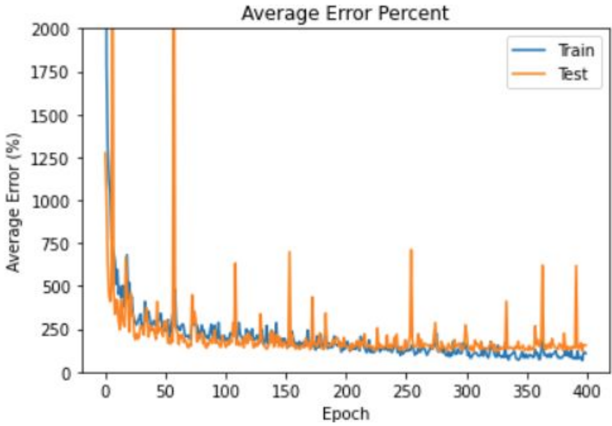


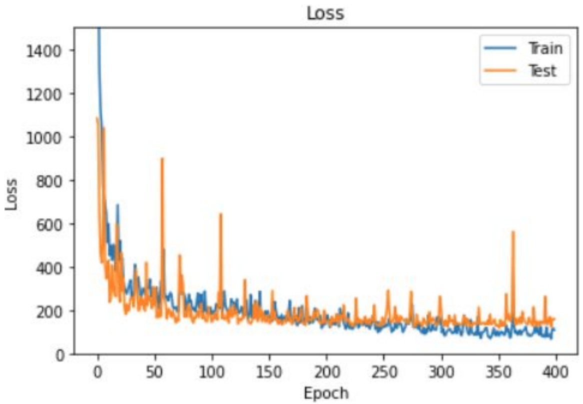


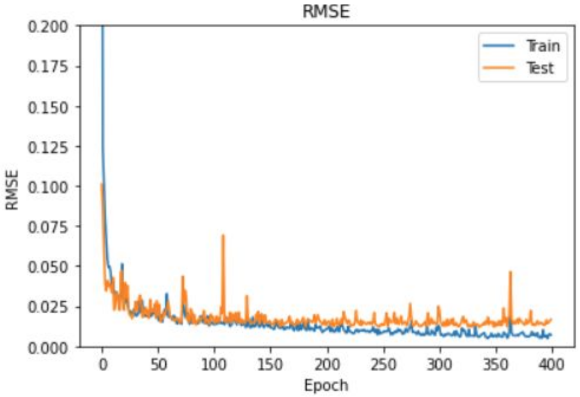
Data pre-processing and training - tree density mapping

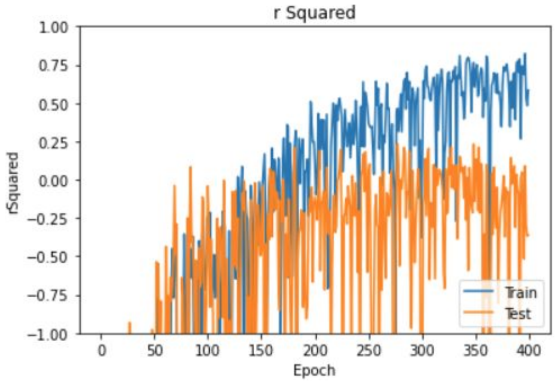
- Gaussian filter generation around every tree centroid (kernel_size=15, sigma=4.0)
- Offline data augmentation(using imgaug library)
- Image upsampling to 1 m res + normalisation
- 80% training, 20% validation

(rmse/y_pred.mean())*100









Data pre-processing for unet-based landcover mapping