Estimating the last disturbance year of forest stands in Coastal Georgia using all the available Landsat imagery with Google Earth Engine

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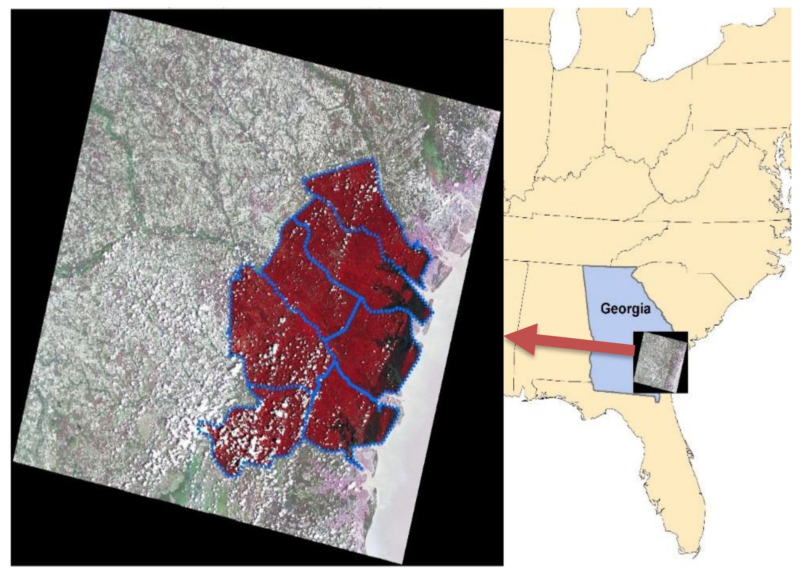
Forest in Coastal Georgia, US



Forest Cover %: 67 % , mainly plantation forest (*Pinus taeda, Pinus elliottii*).
Rotation age: 15-25 years.
Ownership: 90% privately owned forest.

Fig. 1: Area of Interest

=> Detecting stand level age structure is crucial to assess the resource sustainability.

Technical Background

Continuous Change Detection and Classification (CCDC): Zhu and Woodcock (2014) developed CCDC that use all the available Landsat imagery to detect and classify landuse change. Yuan et al. (2015) applied Hidden Markov Model to CCDC. CCDC can detect the land use change of all the season. CCDC can classify the type of landuse.
Google Earth Engine (GEE): GEE is the web API to access and use the Geospatial dataset in Google's archive. The analyst does not have to locally manage huge data. Also they can access the high-performing computing systems provided by Google (Gorelick et al. 2017) to deal with the computation using several hundred imagery.

Objective

In this research project, we are utilizing all the available Landsat imagery to provide information on forest disturbance, and to estimate an age of the current forest landscape at a stand-level basis in our area of interest. Landsat imagery is processed using Google Earth Engine.

Data Processing

Imagery: All the available Landsat 5 TM,7 ETM and 8 OLI imagery for R17/P38 between 1984-2018 in Collection 1 Tier 1 (604 imagery). Both TOA reflectance imagery and surface reflectance imagery are used.
Masking: Mask out cloud, shadow of cloud and snow using CFmask for each imagery.
Indices: 1.Integrated Forest Z-score (IFZ), Indicative of a pixel being forest. Computed based on Huang et al. (2010). 2. Tasseled Cap Brightness, Greenness and Wetness.

Method

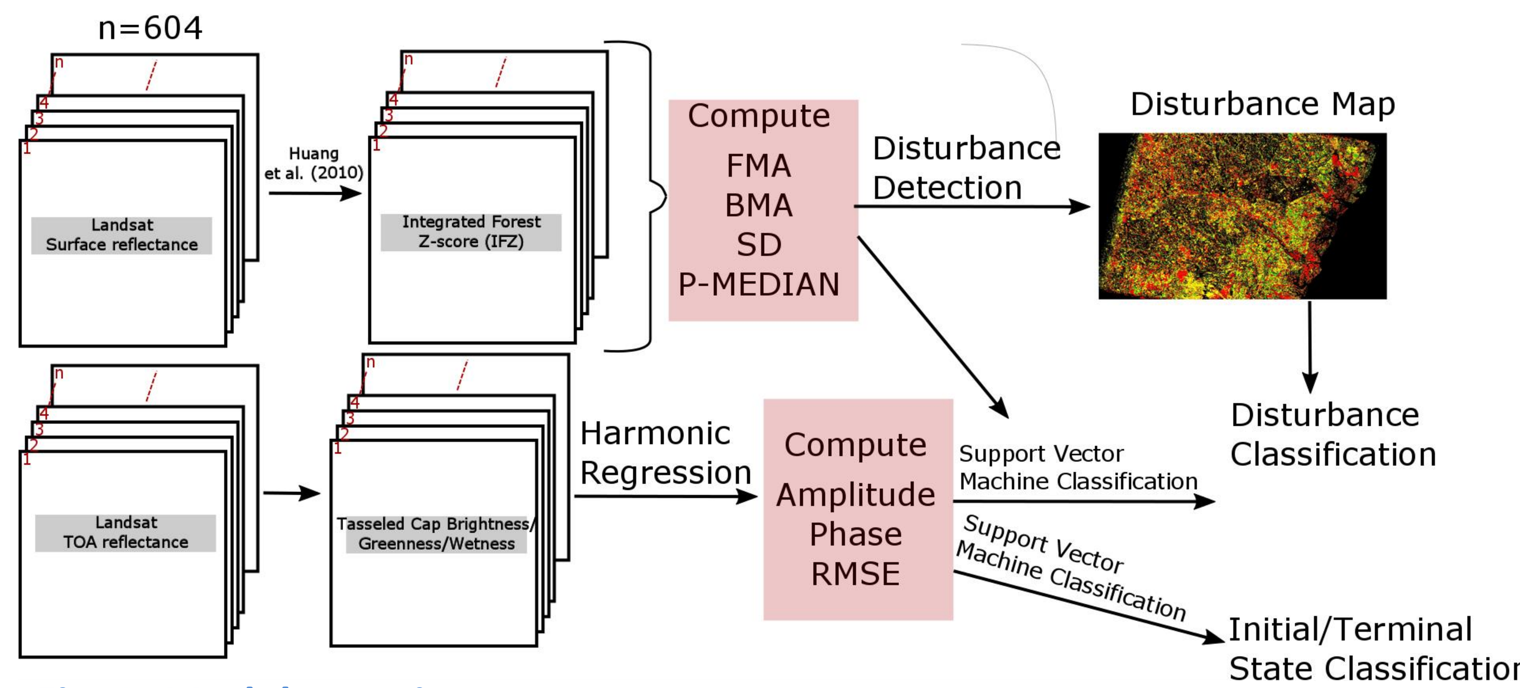


Fig. 2: Model overview

Metrics used for disturbance detection:
Backward/Forward Moving Average (BMA/FMA):
Moving average of IFZ for the last/next 3 years for each scene.
Standard deviation (SD):
Last 3 years is also computed.

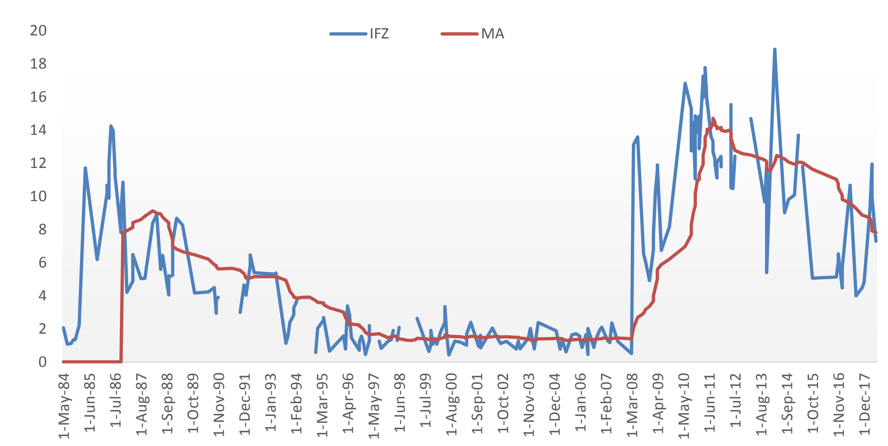


Fig. 3: Time series IFZ and moving average of IFZ at Lat. 31.545/Lon. -81.701

Decision rule for disturbance detection:
for scene *i*, only if following 3 conditions are met, the pixel is regarded as disturbed between scene *i-1* and *i.*
1. BMA is smaller than 3.
2. FMA is larger than 3.
3. Median IFZ between scene *i+1* and scene is larger than BMA+3SD.

Disturbance classification:
Set 5 types of disturbance (major disturbance for hardwood, major disturbance for softwood, partial disturbance and wet vegetation). For each class, 10 region is selected. For the region, Support Vector Machine classification is conducted to classify the types of disturbances over our area of interest.

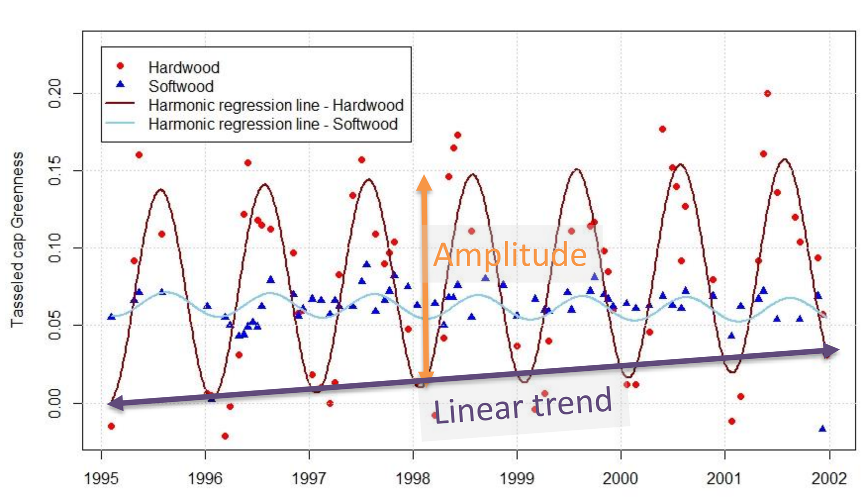


Fig. 4: Harmonic regression for Tasseled Cap Greenness for hardwood and softwood

Initial/Terminal state specification:
First/Last 3 years of disturbance can not be detected.
Landuse trend of each pixels are classified using Support Vector Machine classification.

Result

Fig. 5: Landsat 8 imagery in a part of our AOI (Aug 27, 2014)

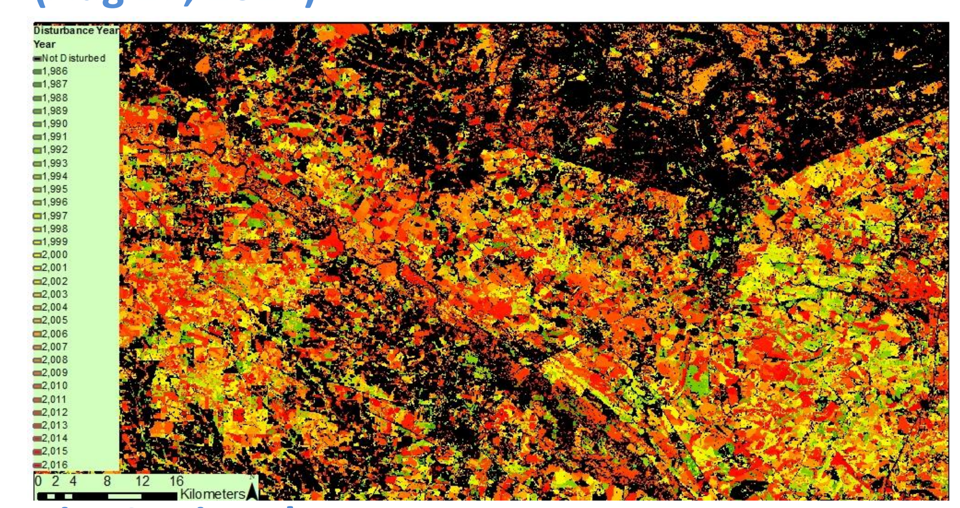


Fig. 6: Disturbance year map

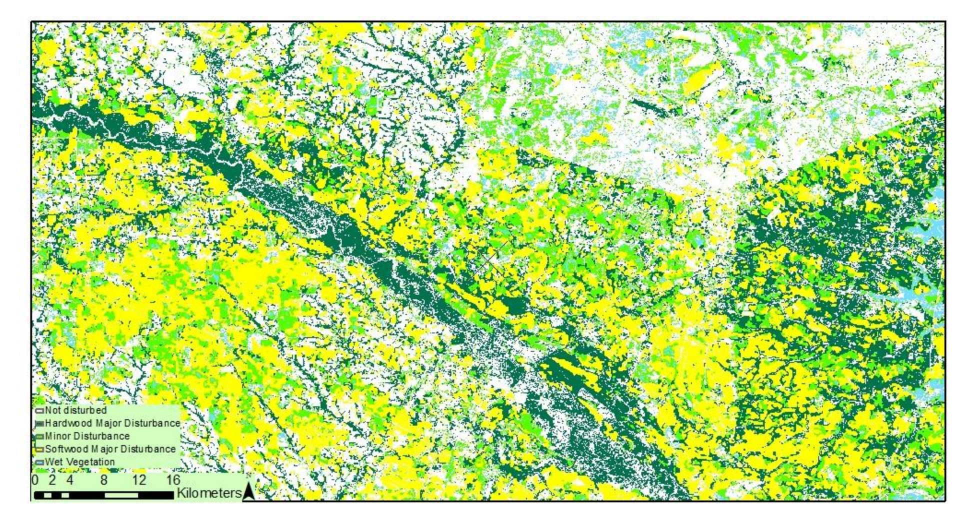


Fig. 7: Disturbance type classification

Accuracy assessment for disturbance detection:
- 1306 sample points selected through stratified sampling are visually detected the disturbance year.
- If +/- 1 year of error is allowed, overall accuracy is **80%**.
- An application created by GEE was used to make annual mosaic imagery in leaf-on season.

Accuracy assessment for disturbance type classification:
- Pixels in 10 regions for each class are split into training class or validation class. Validation class is used to evaluate the accuracy of the SVM classification. Overall accuracy was 97.7%

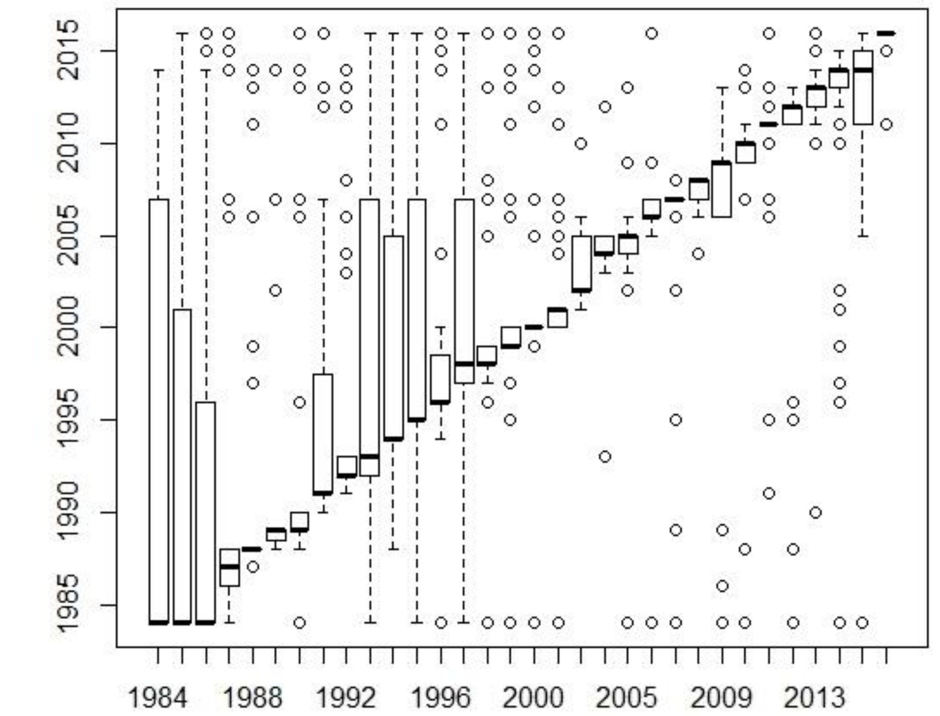


Fig. 8: Boxplots for Accuracy assessment

Table 1: Confusion matrix For disturbance type classification

	MaD-HW	MiD	MaD-SW	WetV	Total	User's Accuracy
MaD-HW	270	2	1	0	273	98.9%
MiD	0	156	5	33	194	80.4%
MaD-SW	4	11	255	0	270	94.4%
WetV	0	0	0	1707	1707	100.0%
Total	274	169	261	1740	2444	
Producer's accuracy	98.5%	92.3%	97.7%	98.1%	Overall Acc.= 97.7%	

Discussion

- **+/- 1 year of error from reference data:** As we use the annual leaf-on season (Jun-Aug) imagery as reference data, disturbance after leaf-on season is classified as the disturbance in the next year.
- **Low accuracy in some years:** Minor disturbance before 2005 is not visible in Landsat imagery. Therefore it is overlooked in accuracy assessment.
- **Multiple detection of disturbance:** Disturbance is detected several times for 1 disturbance.
- **Computation time:** Current code cannot display the result on the GEE API. To export the data, it takes 8 hours.
- **In-situ data required:** IFZ is computed from sampled forest pixels. This may

Ongoing works

- Accuracy assessment for initial/terminal state classification.
- Detecting regeneration within the model.
- Reconstructing the age structure of forest stands.
- Segmentation of the pixels to acquire the boundaries of the forest stand.

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References

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