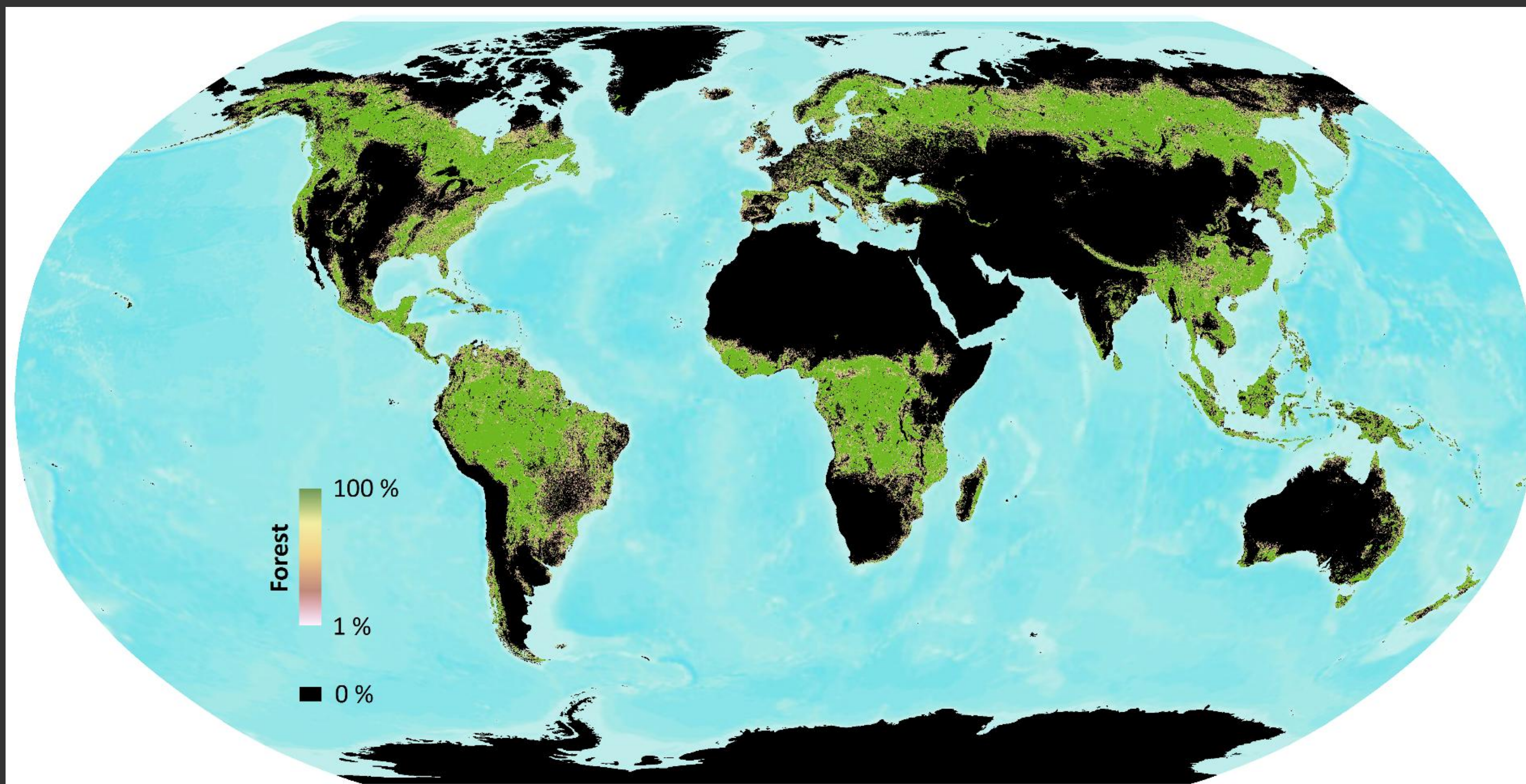
NASA/GLCF tree-canopy and surface-water data products: support and synergy for GlobBiomass aboveground biomass estimates

Joseph O. Sexton

Global Land Cover Facility
Department of Geographical Sciences
University of Maryland

GlobBiomass 1st User Workshop
Institute for Applied Systems Analysis (IIASA)
Laxenburg, Austria
February 3, 2016

Global forest cover

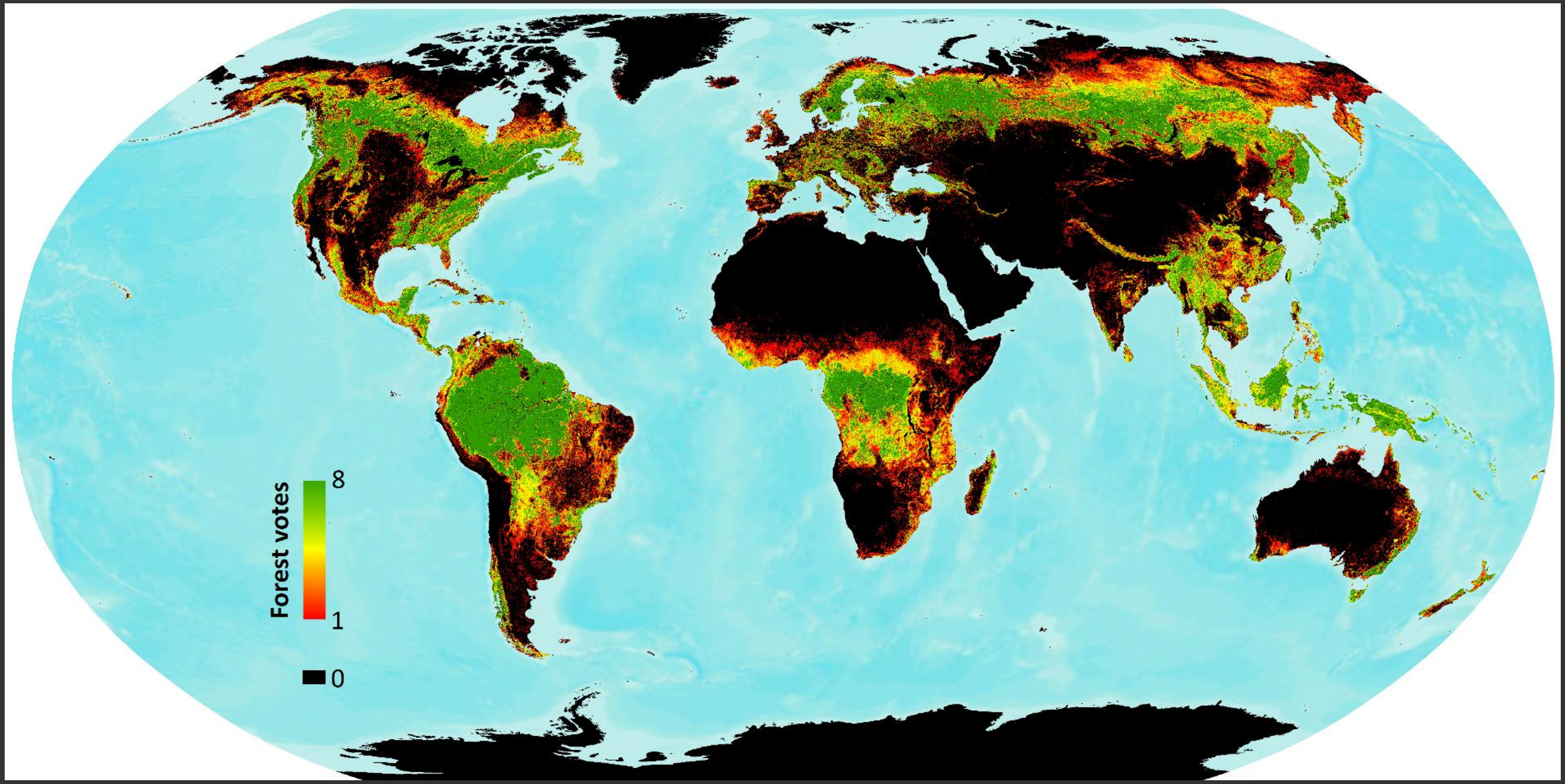


Global forest cover from Landsat-based, 30-m resolution percent-tree cover (Sexton et al. 2013).

Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth 6:* 427-448.

Global forest cover?

8 datasets…. 8 estimates.



Loveland et al. (2000)
Hansen et al. (2000)

Bartholomé & Belward (2005)
Hansen et al. (2003, 2005)

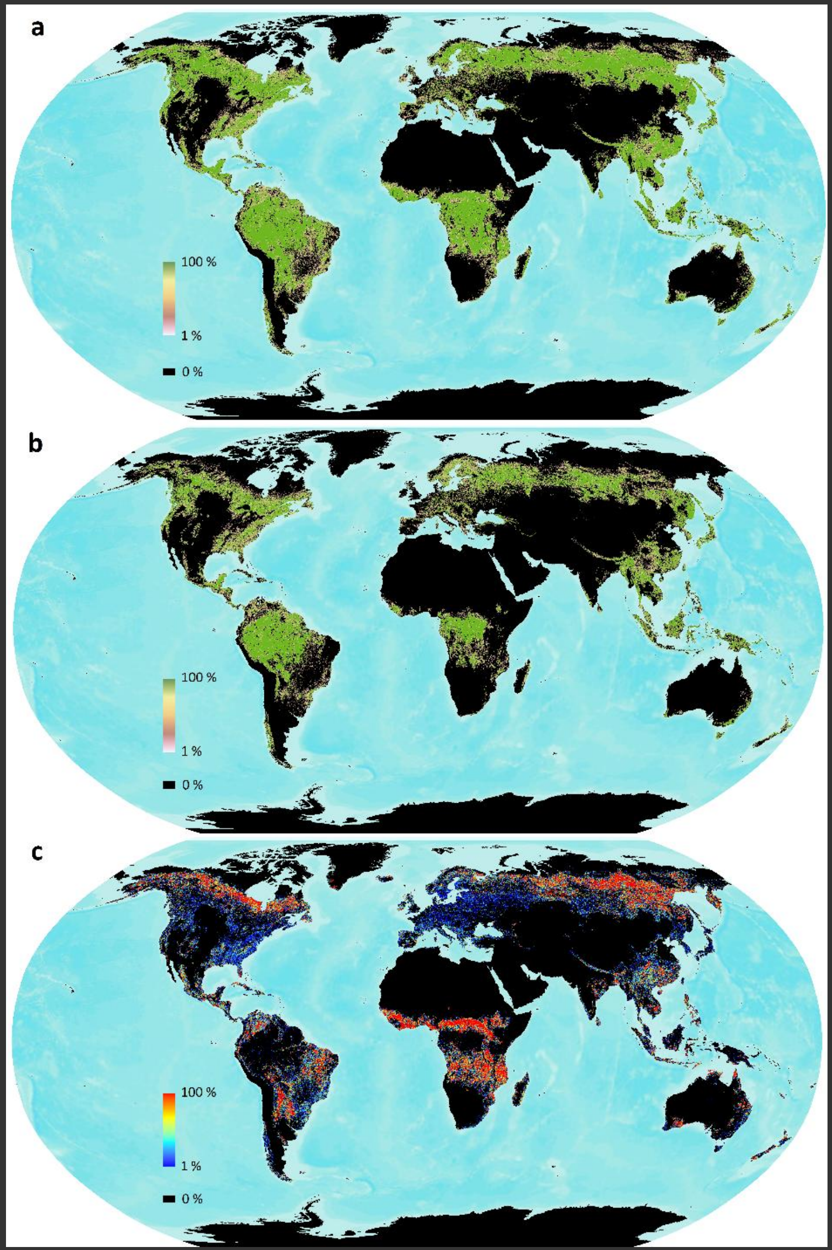
Bicheron et al. (2008)
Friedl et al. (2002)

Hansen et al. (2013)
Sexton et al. (2013)

Sexton, J.O., et al. 2015. Conservation policy and the measurement of forests. *Nature Climate Change* (2015)

How much forest is there?

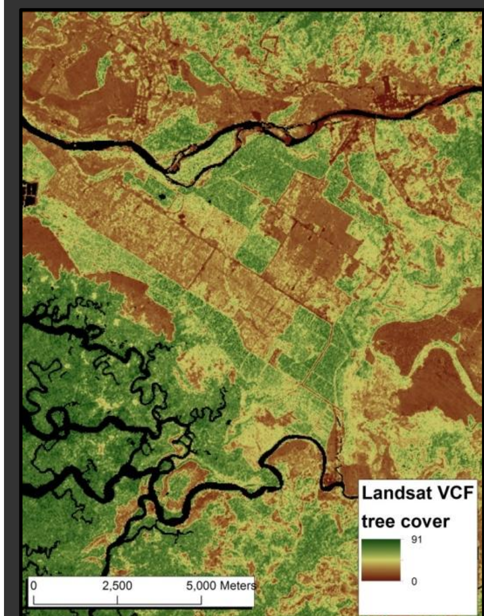
- UNFCCC allows countries to define "forest" based on a criterion of tree cover, from >10 to >30% cover.
  - Defined as 10% cover -> 51.5 x 10^6 km^2
  - Defined as 30% cover -> 32.2 x 10^6 km^2
- Difference = 17.9 x10^6 km^2 ≈ 12% of Earth's land area.
- Greatest uncertainty in tropical savannahs & boreal forests.
- The discrepancy within the tropics alone involves a difference of 43.5 Gt C of biomass valued at >US$ 1 trillion.

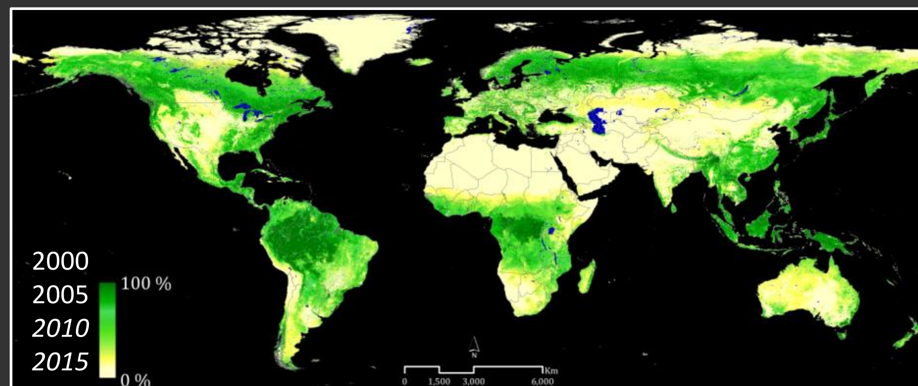


Sexton, J.O., et al. 2015. Conservation policy and the measurement of forests. *Nature Climate Change* (2015)

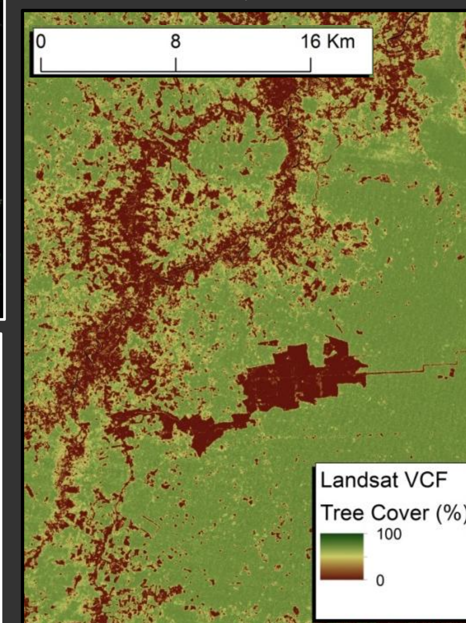
Long-term, globally consistent forest monitoring

Costa Rica, 2000





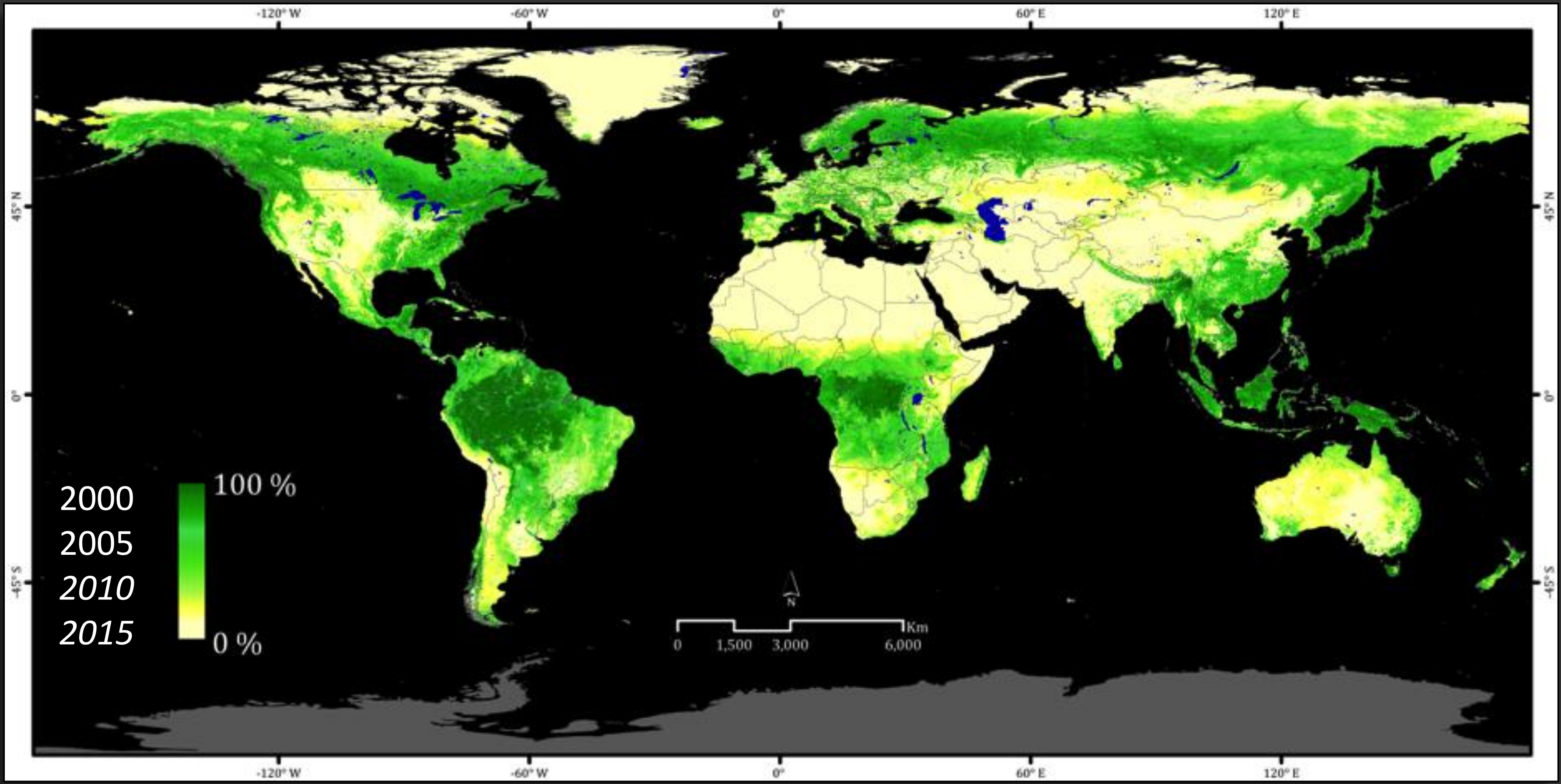
Peru, 2006



- Carbon & Biomass
- Habitat & Biodiversity
- Forestry Products
- Watershed Health
- Land-use change
- REDD+

Sexton et al. 2013. *International Journal of Digital Earth* 6: 427-448; Sexton et al. 2015. *Remote Sensing of Environment*; Kim et al. 2014. *Remote Sensing of Environment; 2015 GRL*

Global, 30-m percent tree canopy cover (“Landsat VCF”)



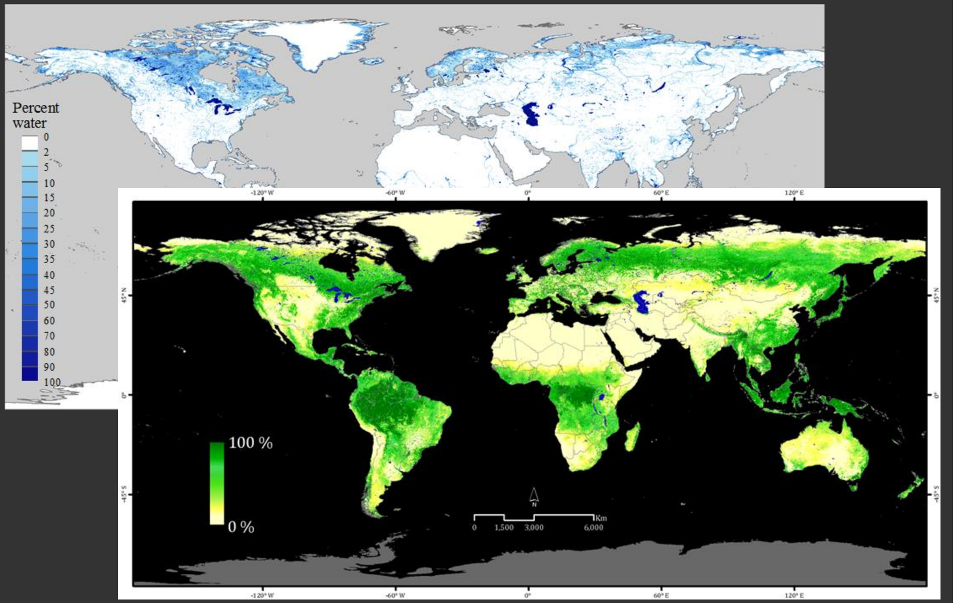
Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth 6:* 427-448.

Requirements

- Long term, high resolution
- Historically consistent
  - 1975, 1990, 2000, 2005, 2010-2015
- Semantically flexible
  - Tree canopy -> forest cover -> forest change
- Peer-reviewed methods
  - Tree-cover estimation
  - Forest-cover classification
  - Forest-change detection
  - Time-series analysis
- Sensor-agnostic
  - Landsat, Sentinel 1
  - PALSAR, Sentinel 2
  - Lidar
  - Visual (human)
- Quantified uncertainty
  - Global
  - Biome
  - Pixel (mapped)

Products

Product	Epochal	Annual	Uncertainty layer?
Tree cover (%)			
Continental		X	Y
Global	X		Y
Water Cover (binary)			
Continental		X	Y
Global	X		Y



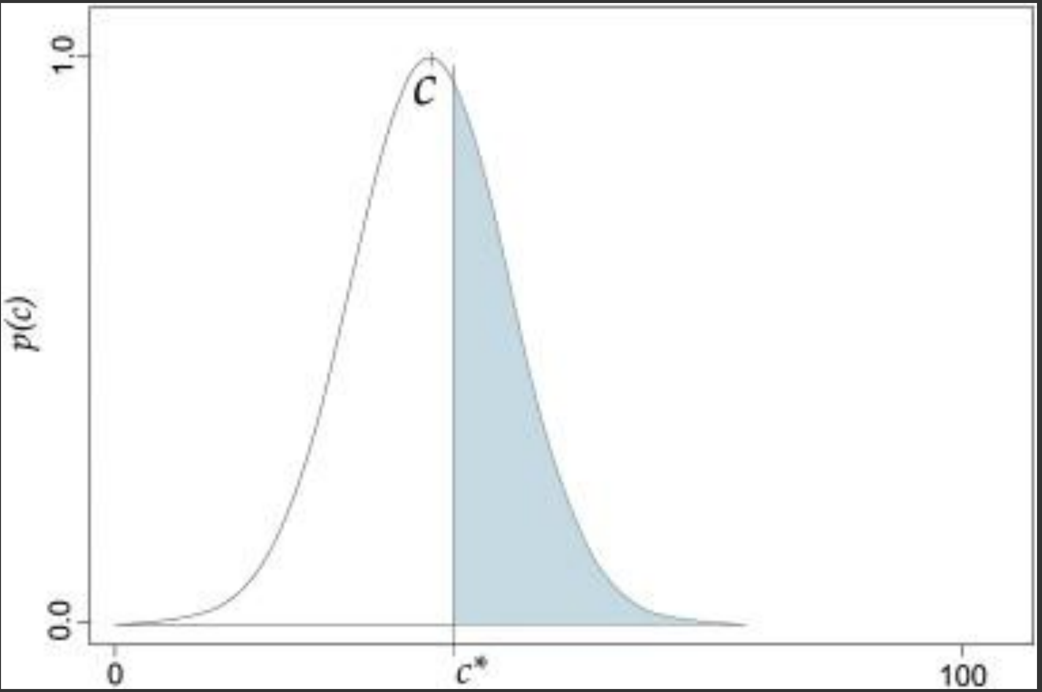
A simple probability model of tree cover

$$\hat{c} = f\left(X; \widehat{\beta}\right) + \varepsilon;$$

$$\hat{c} = c + \varepsilon;$$

$$\sigma_{\varepsilon} = \sqrt{\frac{\sum_i (c_i - \hat{c})^2}{n-1}};$$

$$p(c) \stackrel{\text{def}}{=} N(\hat{c}, \sigma^2).$$



In each pixel, tree cover is estimated as a Normal distribution of possible values, with estimate $\hat{c}$ and root-mean-square error (RMSE) σ.

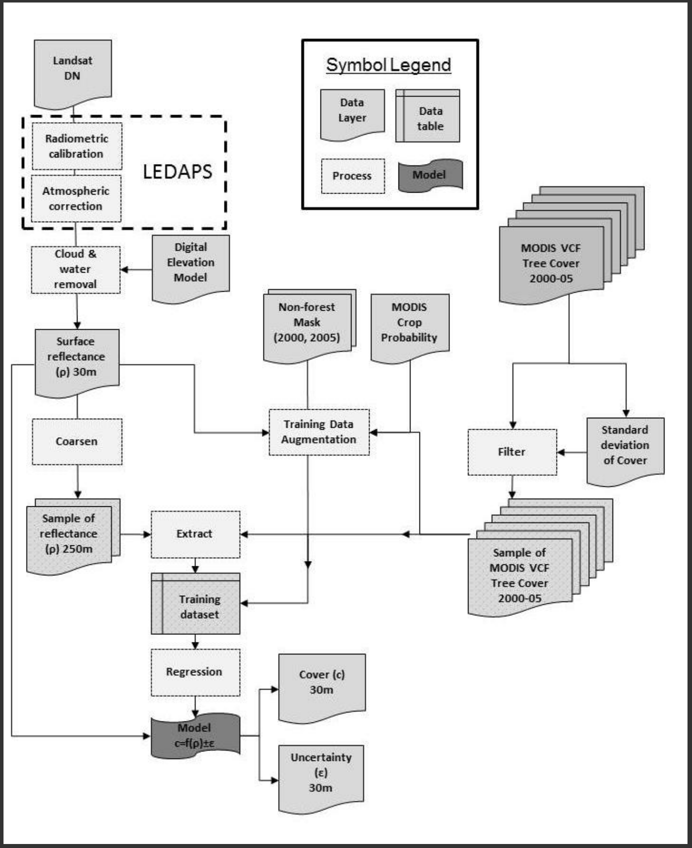
Algorithm: *model-based estimation & data fusion*

- Algorithm
  1. Aggregate 30-m (Landsat) reflectance to 250-m (MODIS) resolution
  2. Sample 250-m layers

     Landsat reflectance

     MODIS Tree Cover and Cropland Probability
  3. Parameterize model:

     cover ~ reflectance
  4. Apply model to original Landsat reflectance image (30-m)
- Product: tree-cover at 30-m resolution
  - Tree cover (%)
  - Uncertainty (RMSE)



Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth.* DOI: 10.1080/17538947.2013.786146

Response variable: percent tree (canopy) cover

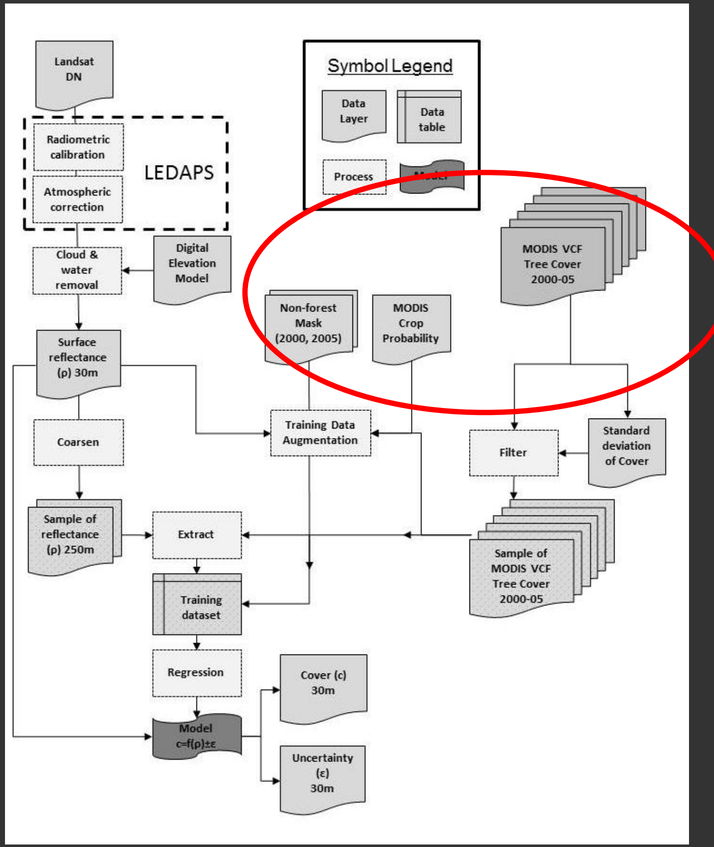
Collection of "ground truth" training data is the most expensive & time-consuming part of remote sensing.

So, instead:

- Train on readily available, independent datasets
- Save the best, most reliable truth for validation

How?

- Decompose each input dataset into a probability distribution
- Combine these "soft truth" datasets into an ensemble for training



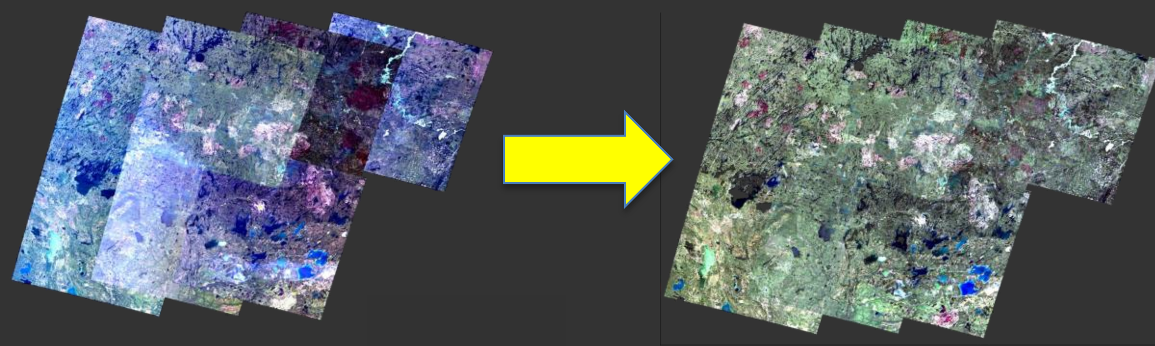
Then, use LiDAR, high-res, and in situ data for *post hoc* calibration and validation.

Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth.* DOI: 10.1080/17538947.2013.786146

Landsat Surface Reflectance

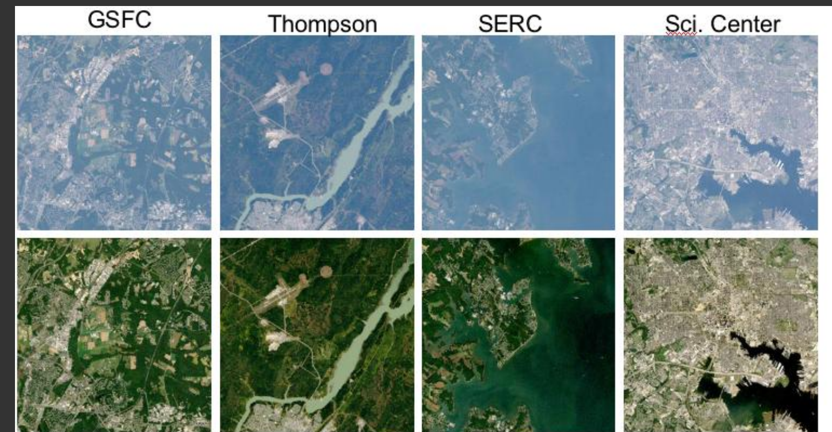
Landsat images

- Five "epochs"
  - 1975
  - 1990
  - 2000
  - 2005
  - *2010*
- ~Global coverage
- Optimally selected
  - Minimal cloud, snow
  - Growing season
- Orthorectified
- *Public*

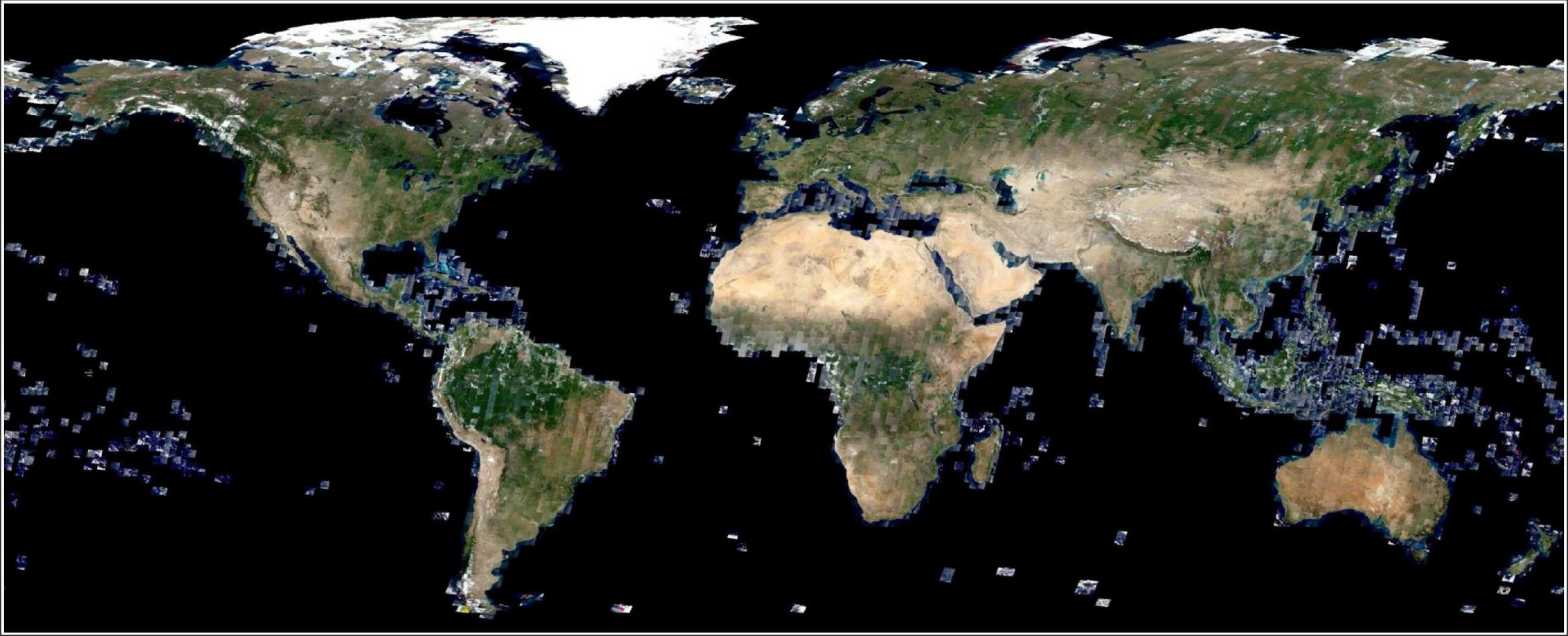


Top-of-atmosphere

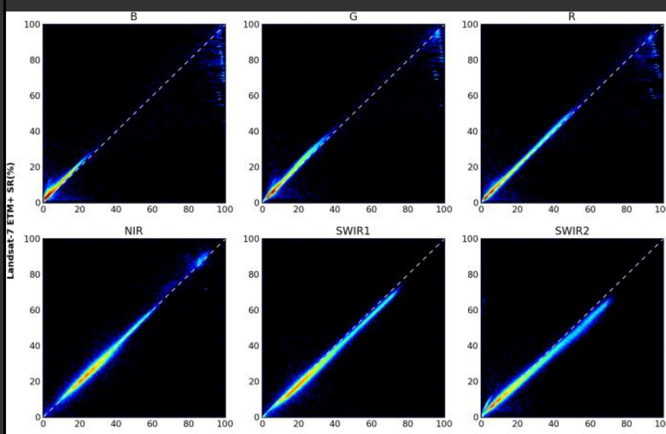
Surface



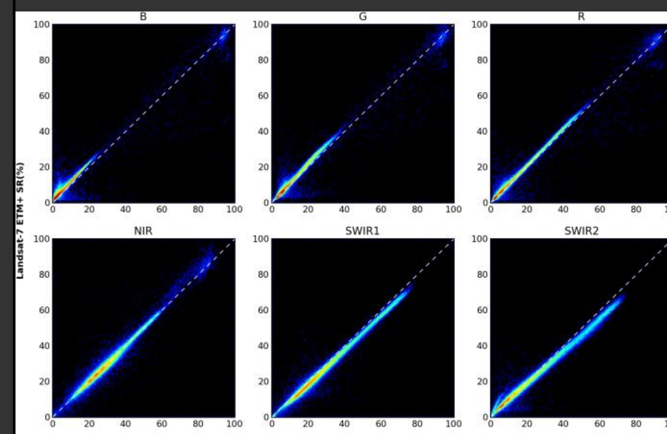
Feng, M., **J.O. Sexton**, C. Huang, J.G. Masek, E.F. Vermote, F. Gao, R. Narasimhan, S. Channan, R.E. Wolfe, J.R. Townshend. 2013. Global, long-term surface reflectance records from Landsat: a comparison of the Global Land Survey and MODIS surface reflectance datasets. *Remote Sensing of Environment* 134:276-293



Landsat-5 TM vs. MODIS SR (2000)



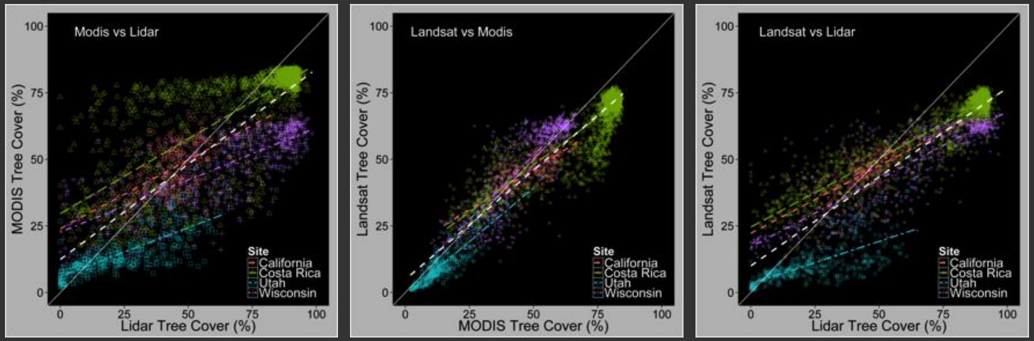
Landsat-7 ETM+ vs. MODIS SR (2005)



Feng, M., **J.O. Sexton**, C. Huang, J.G. Masek, E.F. Vermote, F. Gao, R. Narasimhan, S. Channan, R.E. Wolfe, J.R. Townshend. 2013. Global, long-term surface reflectance records from Landsat: a comparison of the Global Land Survey and MODIS surface reflectance datasets. *Remote Sensing of Environment* 134:276-293

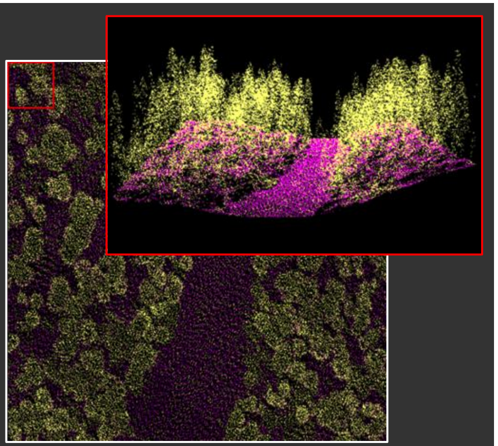
Lidar-based calibration & validation

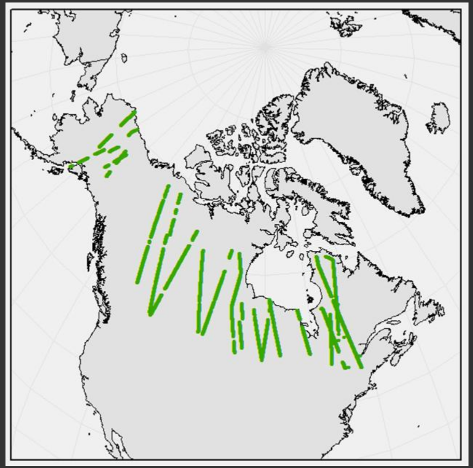
- Improved precision over MODIS VCF
  - comparable to visual interpretation
- Strong potential for calibration to lidar
- *Per-pixel estimates of certainty*

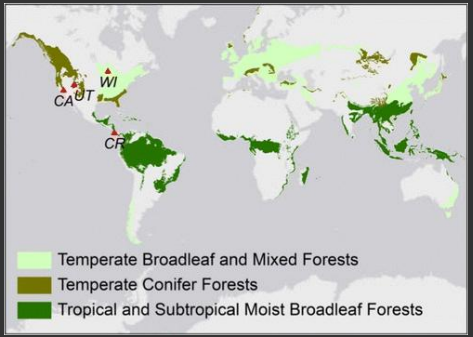


Intercept *(S.E)*	12.429 *(0.549)*	4.530 *(0.323)*	10.016 *(0.384)*
Slope *(S.E.)*	0.714 *(0.008)*	0.825 *(0.005)*	0.668 *(0.006)*
R^2	0.705	0.882	0.811
RMSE	16.83	10.28	17.40
$RMSE_s$	*10.097*	*7.063*	*14.637*
$RMSE_u$	*13.462*	*7.473*	*9.406*

$RMSE_s$ = systematic error; $RMSE_u$= unsystematic error; $RMSE^2 = RMSE_u^2 + RMSE_s^2$

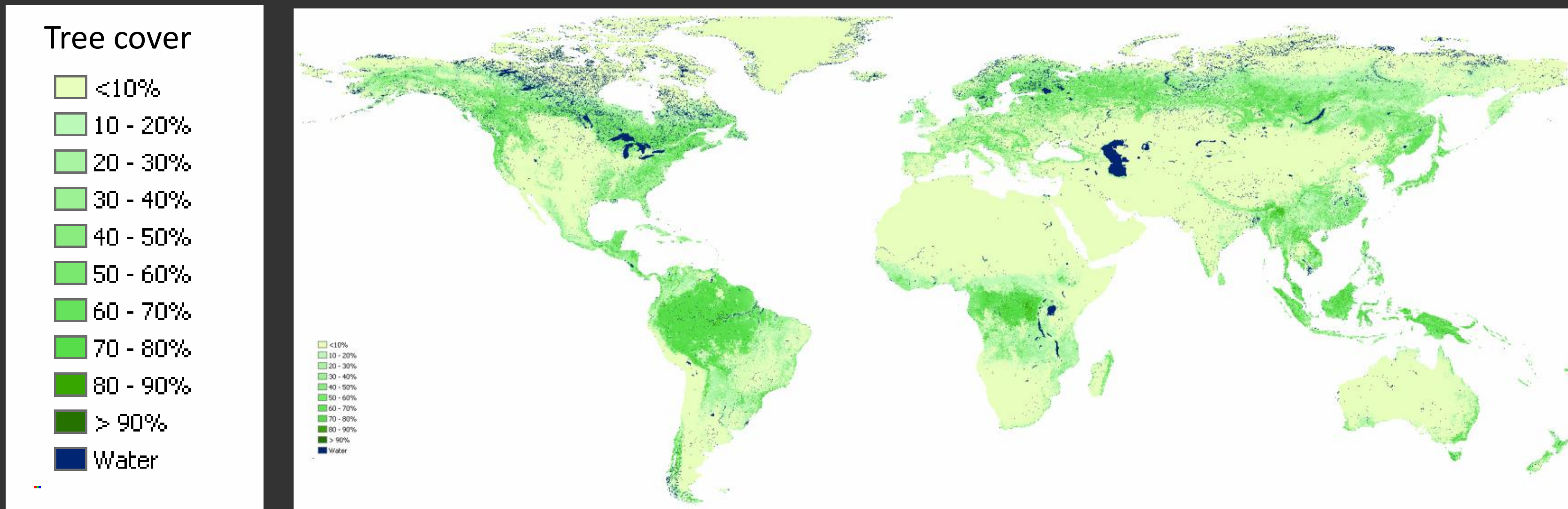


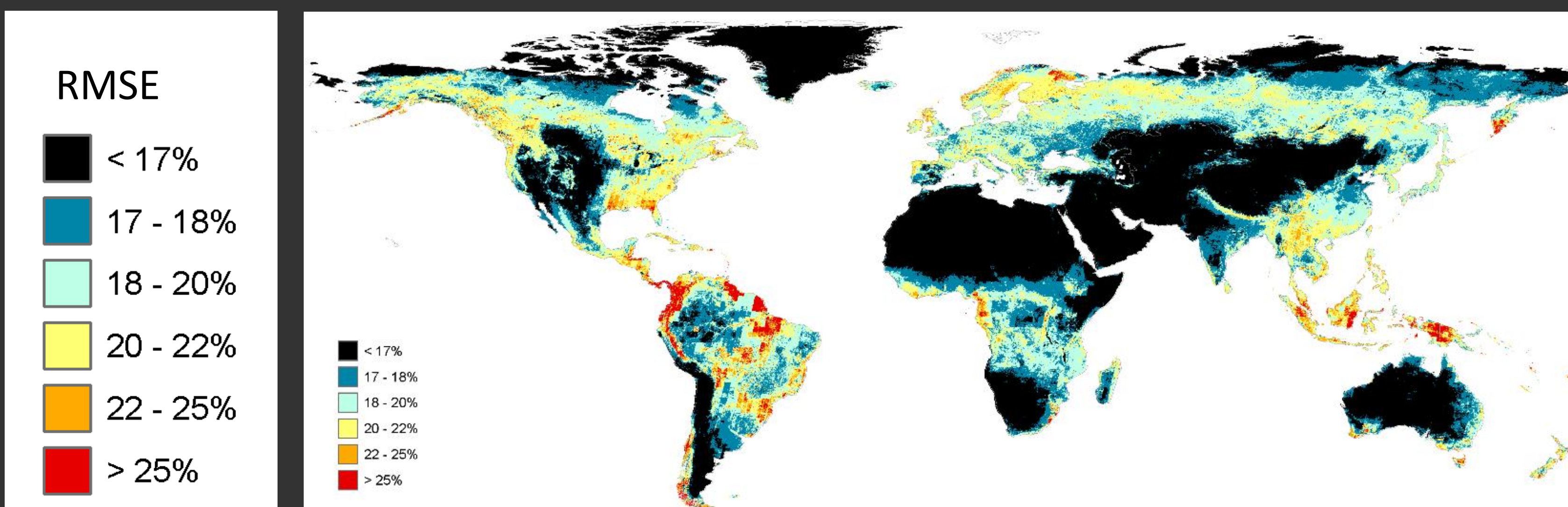




Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth 6:* 427-448.

Global estimates of cover *and uncertainty*

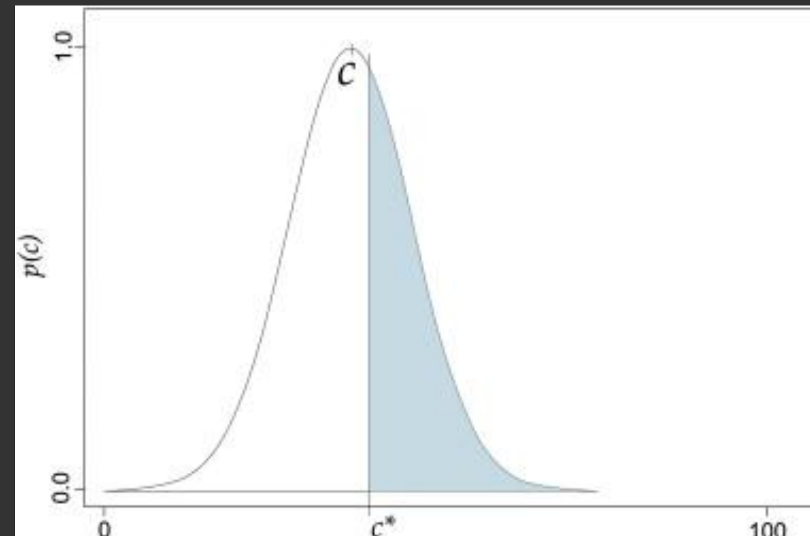




Sexton et al. 2013. *Int. J. Dig. Earth.*

From tree- and forest-cover to change

$$p(F) \stackrel{\text{def}}{=} p(c > c^*) = \int_{c^*}^{100} p(c)dc$$

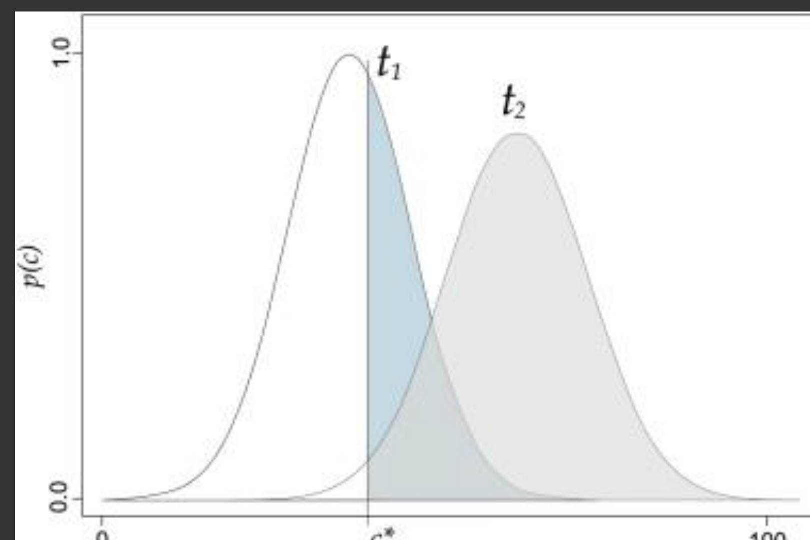


$$p(FF) = p(F_1) \times p(F_2)$$

$$p(NN) = \left(1 - p(F_1)\right) \times \left(1 - p(F_2)\right)$$

$$p(NF) = \left(1 - p(F_1)\right) \times p(F_2)$$

$$p(FN) = p(F_1) \times \left(1 - p(F_2)\right)$$



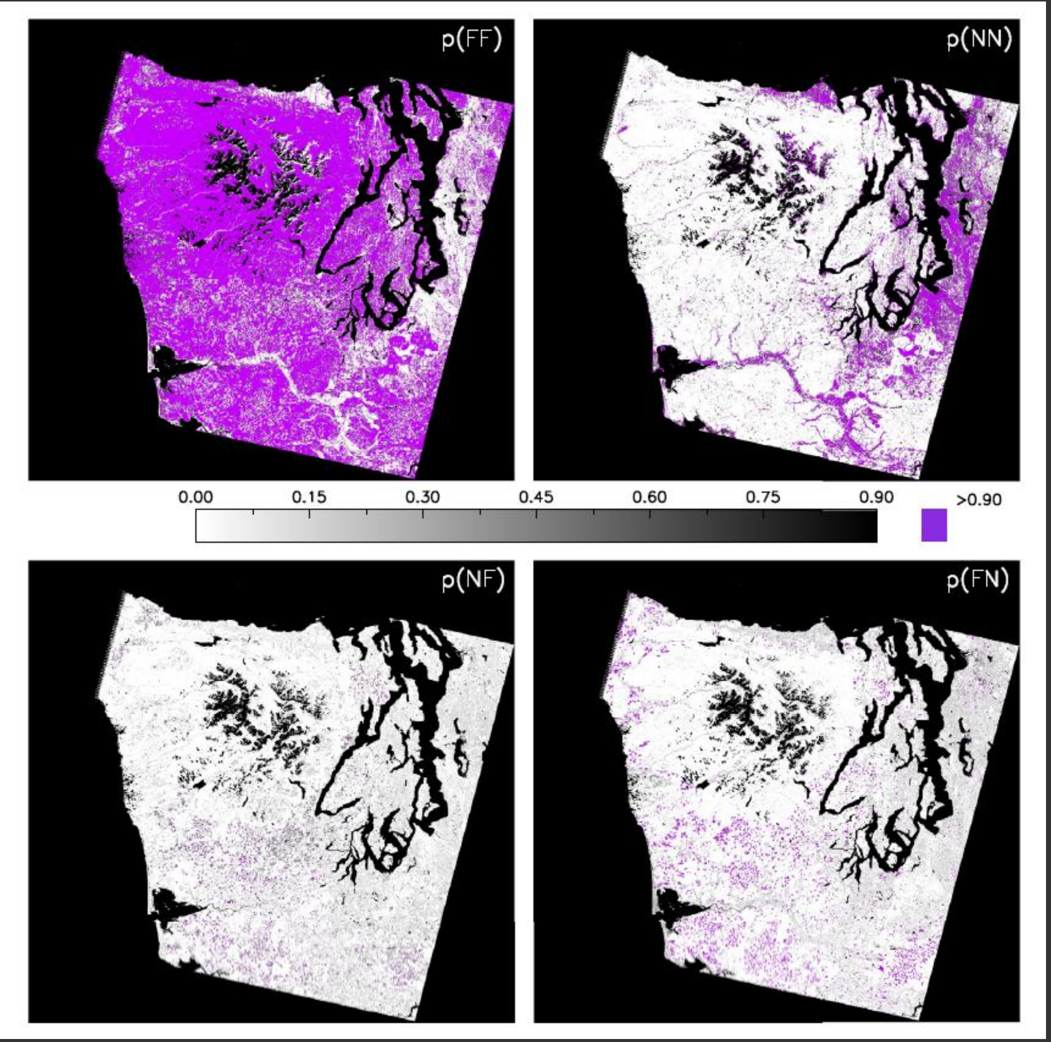
Change detection

$$p(FF) = p(F_1) \times p(F_2)$$

$$p(NN) = \left(1 - p(F_1)\right) \times \left(1 - p(F_2)\right)$$

$$p(NF) = \left(1 - p(F_1)\right) \times p(F_2)$$

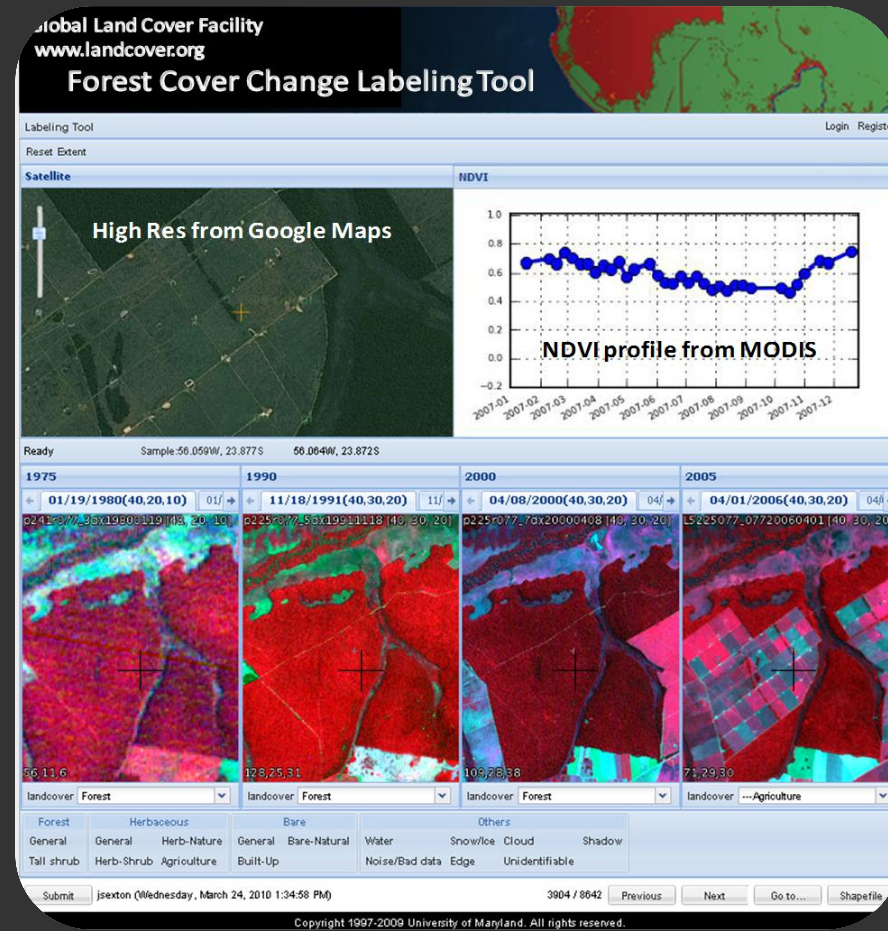
$$p(FN) = p(F_1) \times \left(1 - p(F_2)\right)$$



Sexton et al. 2015. *Remote Sensing of Environment.*

Expert validation

- Certainty ≠ accuracy
- Web interface to ingest knowledge of regional experts
  - Validate maps
  - Improve accuracy



Feng, M. et al. R. 2012. An approach for quickly labeling land cover types for multiple epochs at globally selected locations. *IGARSS 2012*, 6203–6206.

Global Forest Dynamics

Forest cover

- $33.12 \pm 0.71 \times 10^6$ km^2 in 1990 (sub-global)
- $39.13 \pm 0.70 \times 10^6$ km^2 in 2000
- $39.02 \pm 0.73 \times 10^6$ km^2 in 2005

Forest-cover change

1990-2000 (sub-global)

- Gross loss: 0.11 ± 0.03
- Gross gain: 0.05 ± 0.03 million km^2/year

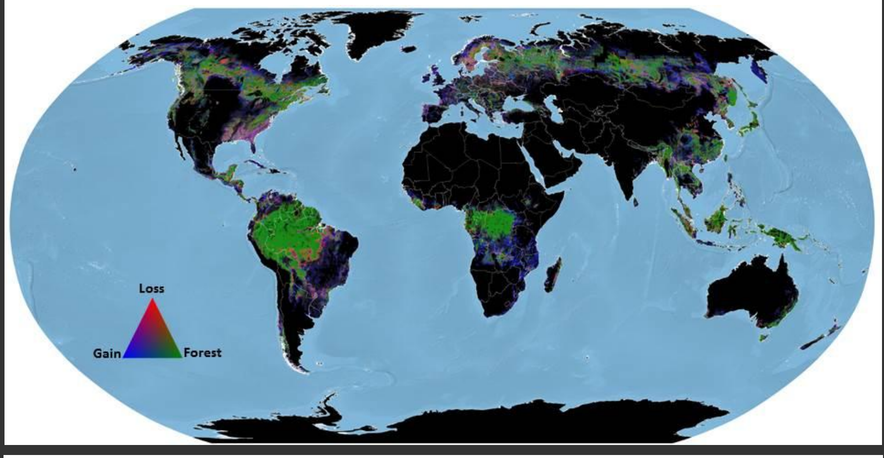
2000-2005 (global)

- Gross loss: $0.17 \pm 0.04 \times 10^6$ km^2/year
- Gross gain: $0.06 \pm 0.02 \times 10^6$ km^2/year

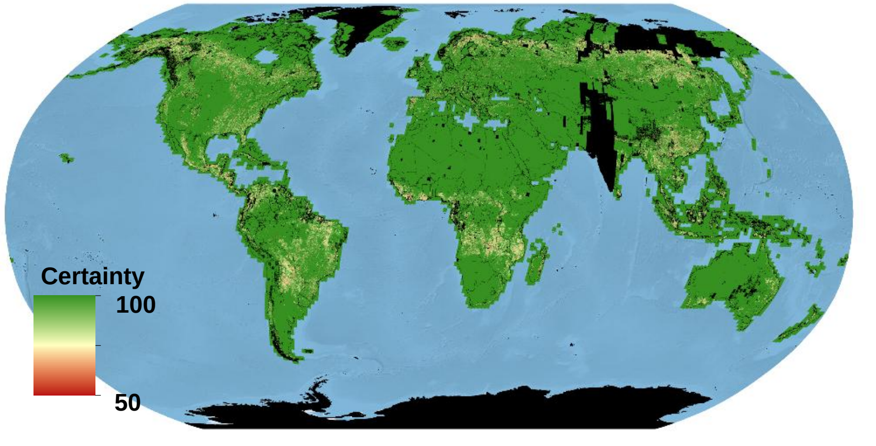
Acceleration 1990-2010 (humid tropics)

- -0.02938×10^6 km^2/yr/yr
- Peaked in 2000-2005
- Varies among countries
- Contradicts FAO claims of deceleration

Forest Change (1990-2000)



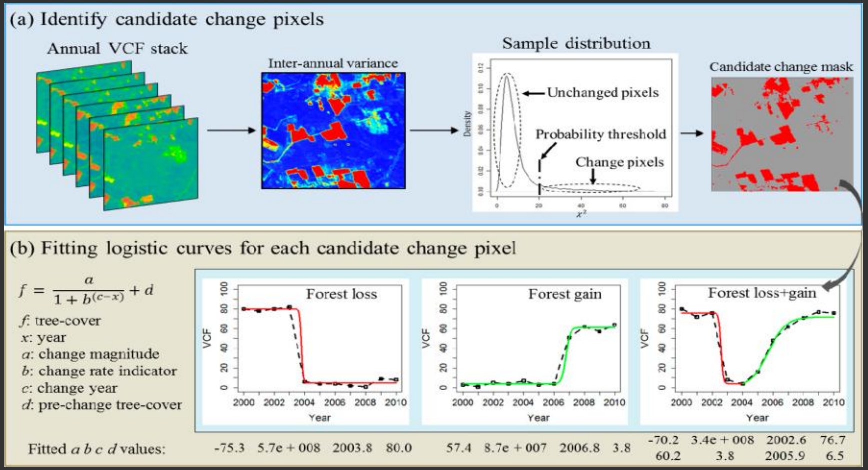
Forest-Change Certainty (1990-2000)

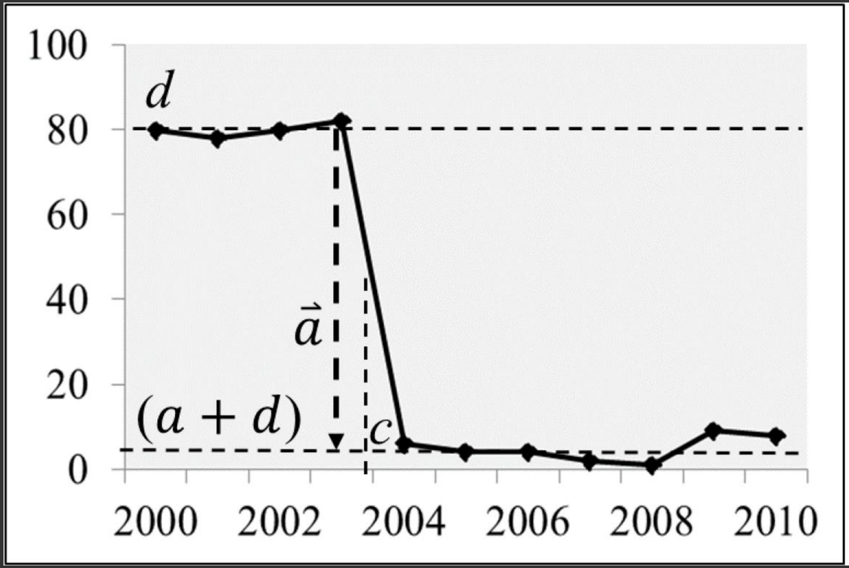


Kim et al. (2014, 2015); Sexton et al. (2015); Feng et al. (*in review*)

Time-series analysis

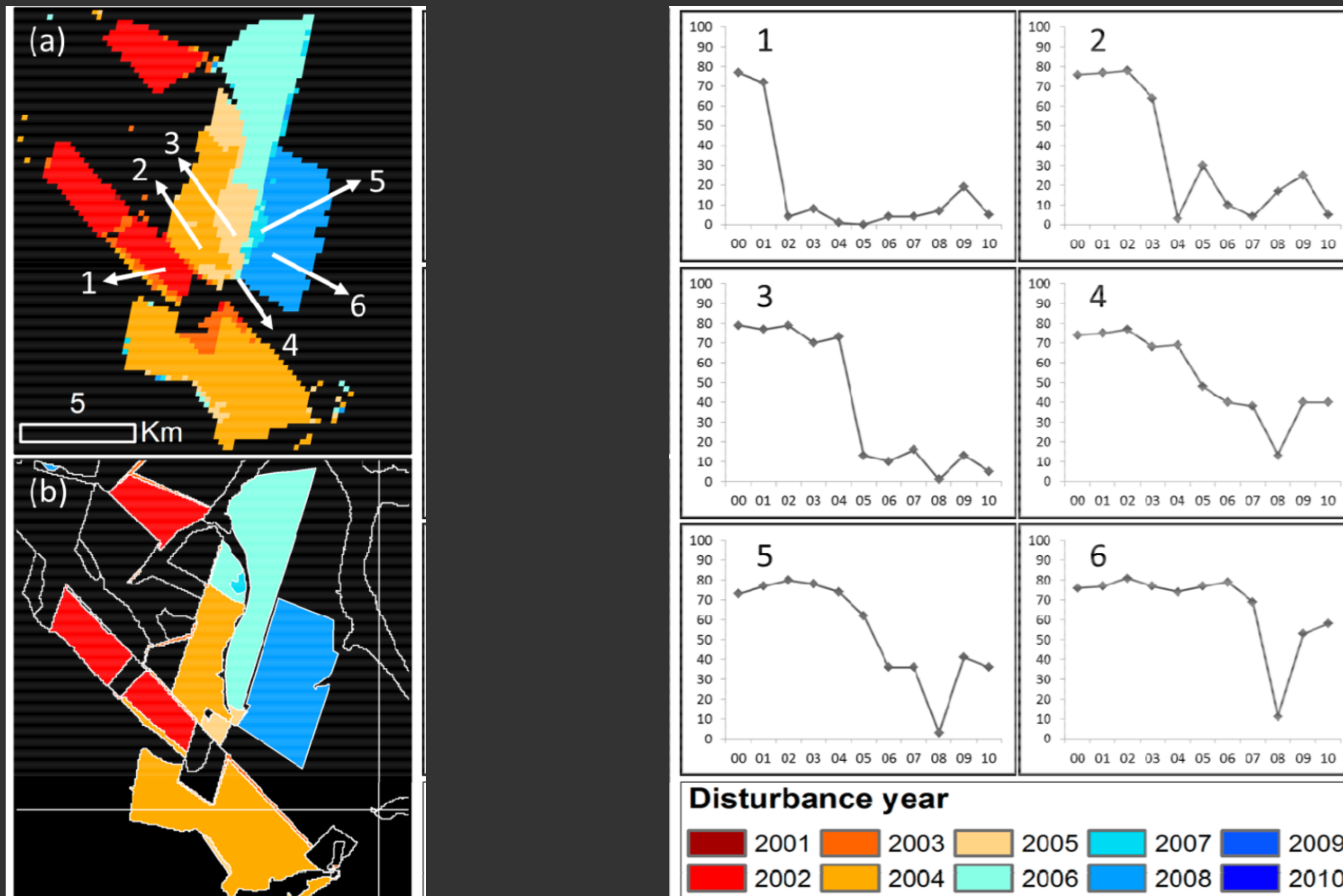
- Use full time-series of cover estimates
- Incorporates pixel-level uncertainty
- Capable of quantifying categorical change and canopy degradation
  - Initial cover (d)
  - Magnitude of change (a)
  - Time of change (c)
  - Final cover (a+d)





Song, X.-P., C. Huang, J.O. Sexton, S. Channan, J.R. Townshend. 2014. *Remote Sensing* 6(9): 8878-8903.

Time-series analysis

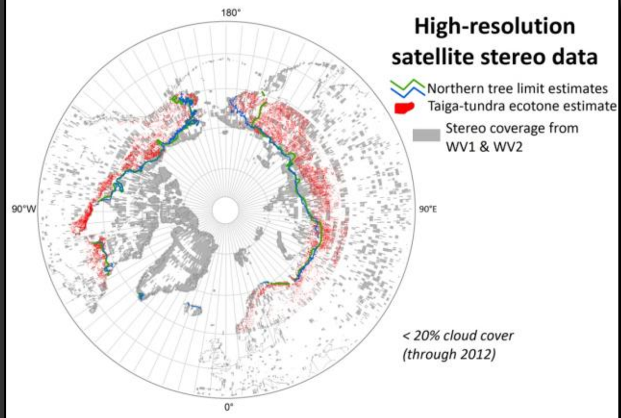


Pixel-level estimation of disturbance-year. (**a**) Patches representing the year of forest disturbance obtained from MODIS. (**b**) Reference map acquired from PRODES. Tree-cover estimates from 2000-2010 are shown on the right.

Song, X.-P., C. Huang, J.O. Sexton, S. Channan, J.R. Townshend. 2014. *Remote Sensing* 6(9): 8878-8903.

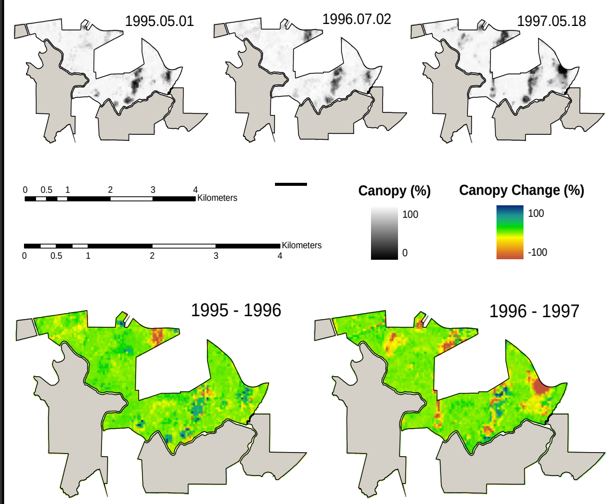
What’s next?

- Calibration by lidar/optical fusion (Ranson et al. 2014)
  - Fusion of optical (Landsat), radar (PALSAR), high-res, and lidar
  - Collaboration with NASA Goddard Space Flight Center



Previous ecotone boundary estimates with available high-resolution stereo footprints, equaling >6,400 stereo pair strips of 3-8 images over boreal Canada, Alaska and Eurasia between 60-75° N.

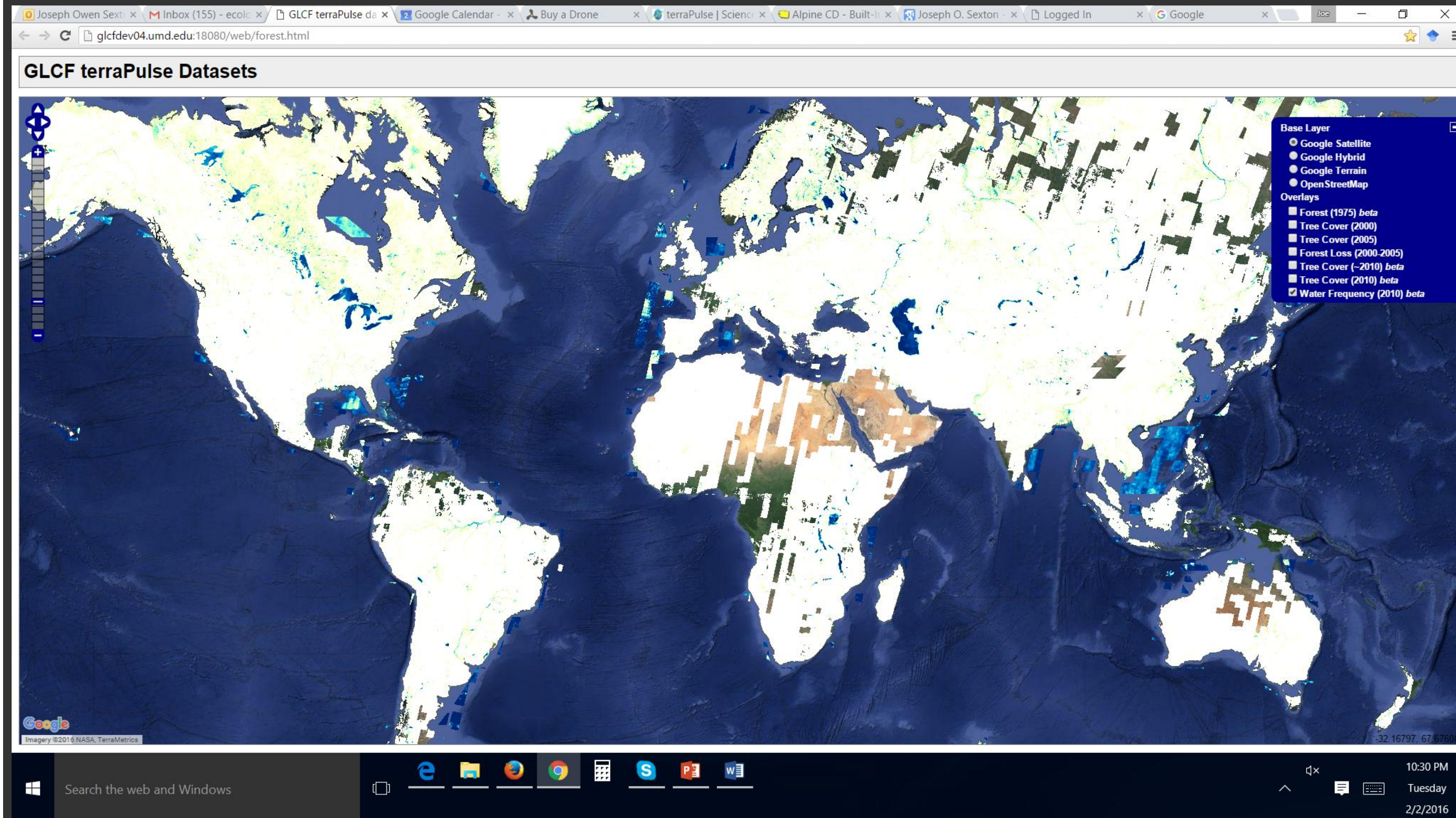
- Multi-source imaging of time-serial tree and water cover at continental to global scales (Townshend et al. 2015)
  - Global and continental mapping of tree-canopy, surface water, and biomass at epochal and annual frequency
  - Fusion of optical (Landsat, Sentinel-2) and radar (PALSAR)



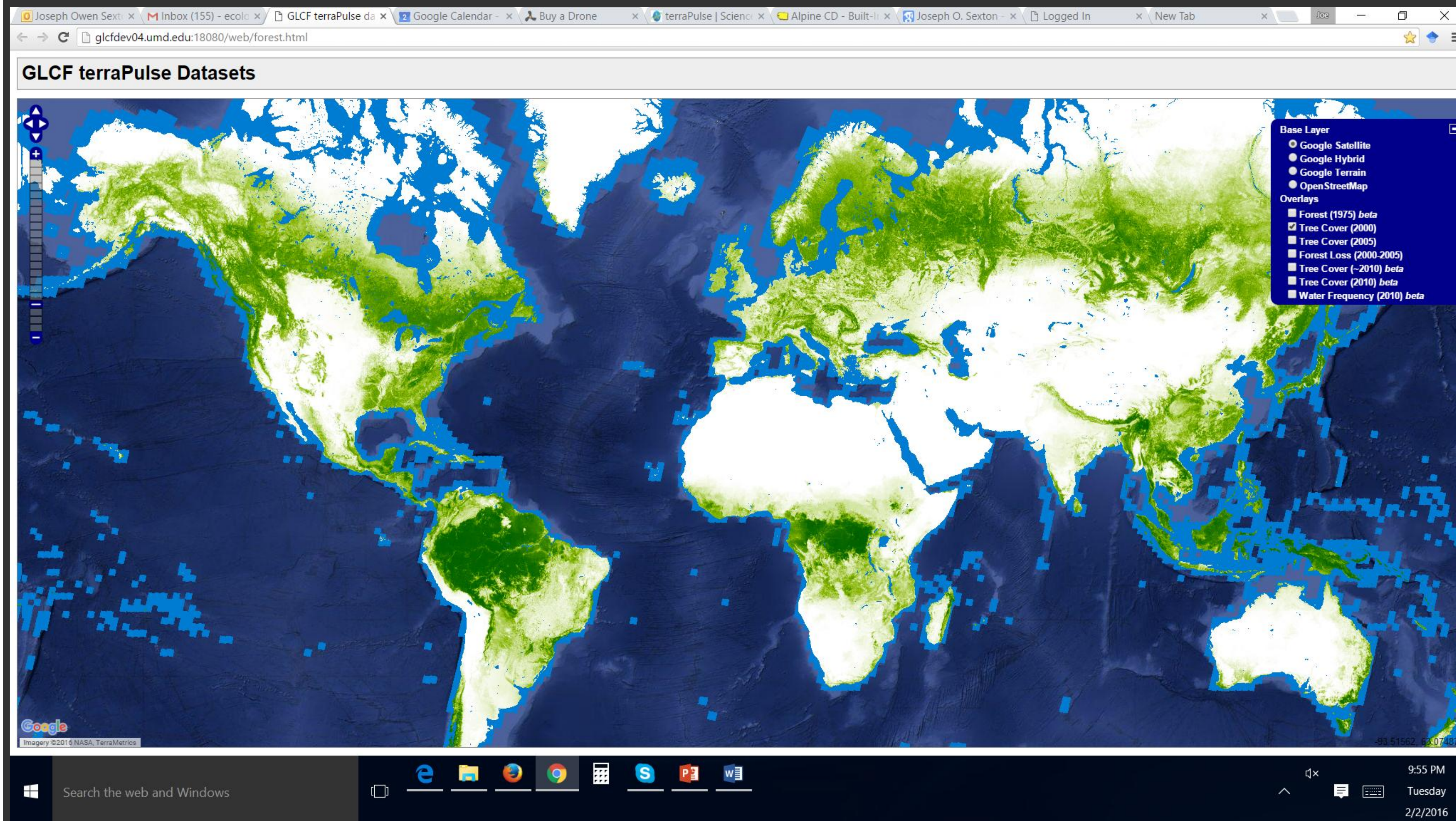
Forest disturbance from Hurricane Fran (1996) and subsequent salvage logging in the Duke Forest, NC detected by time-series analysis of Landsat-based tree cover estimates (Sexton et al. *in prep.*)

Status of data products

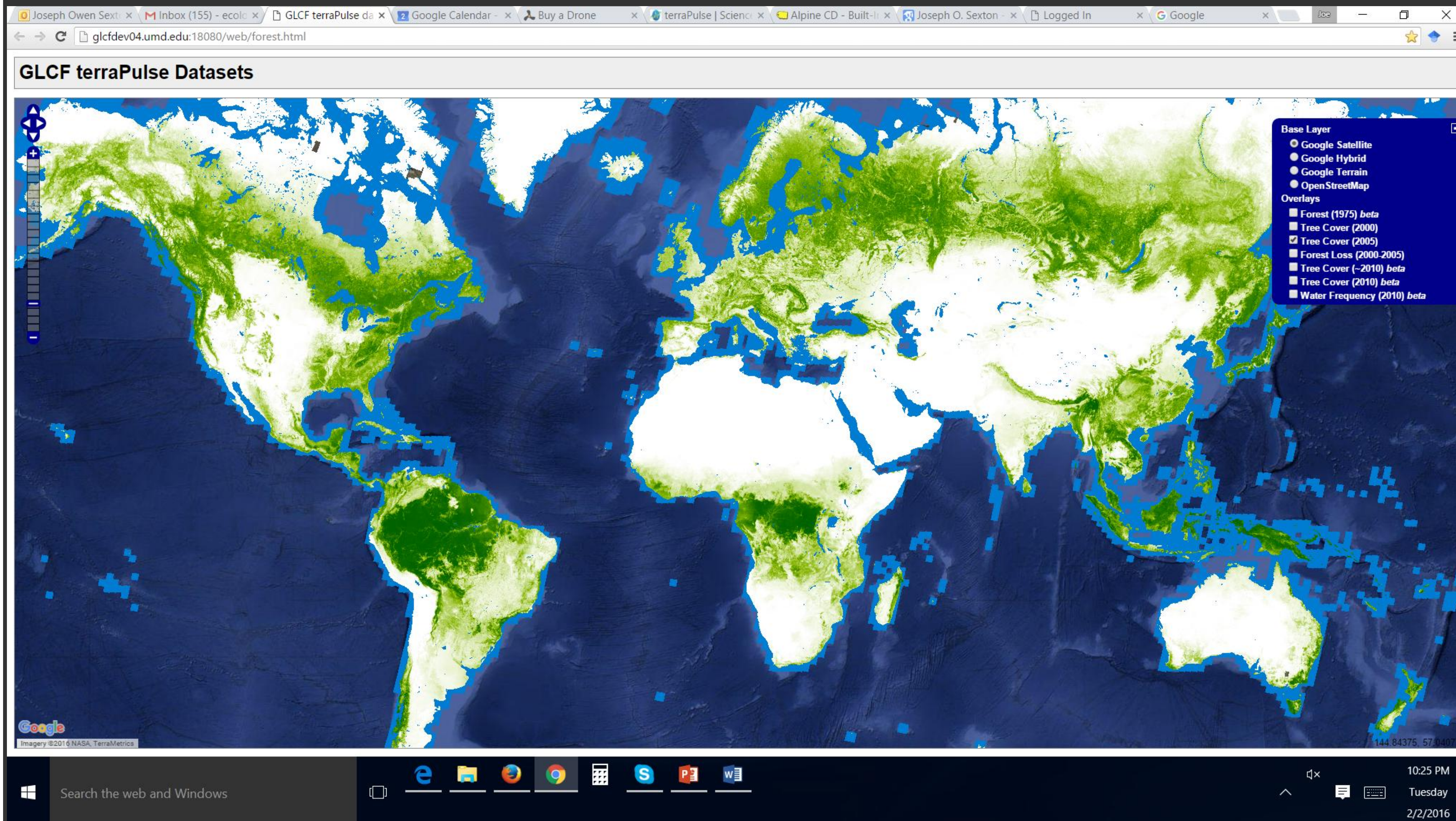
2010 Water Cover



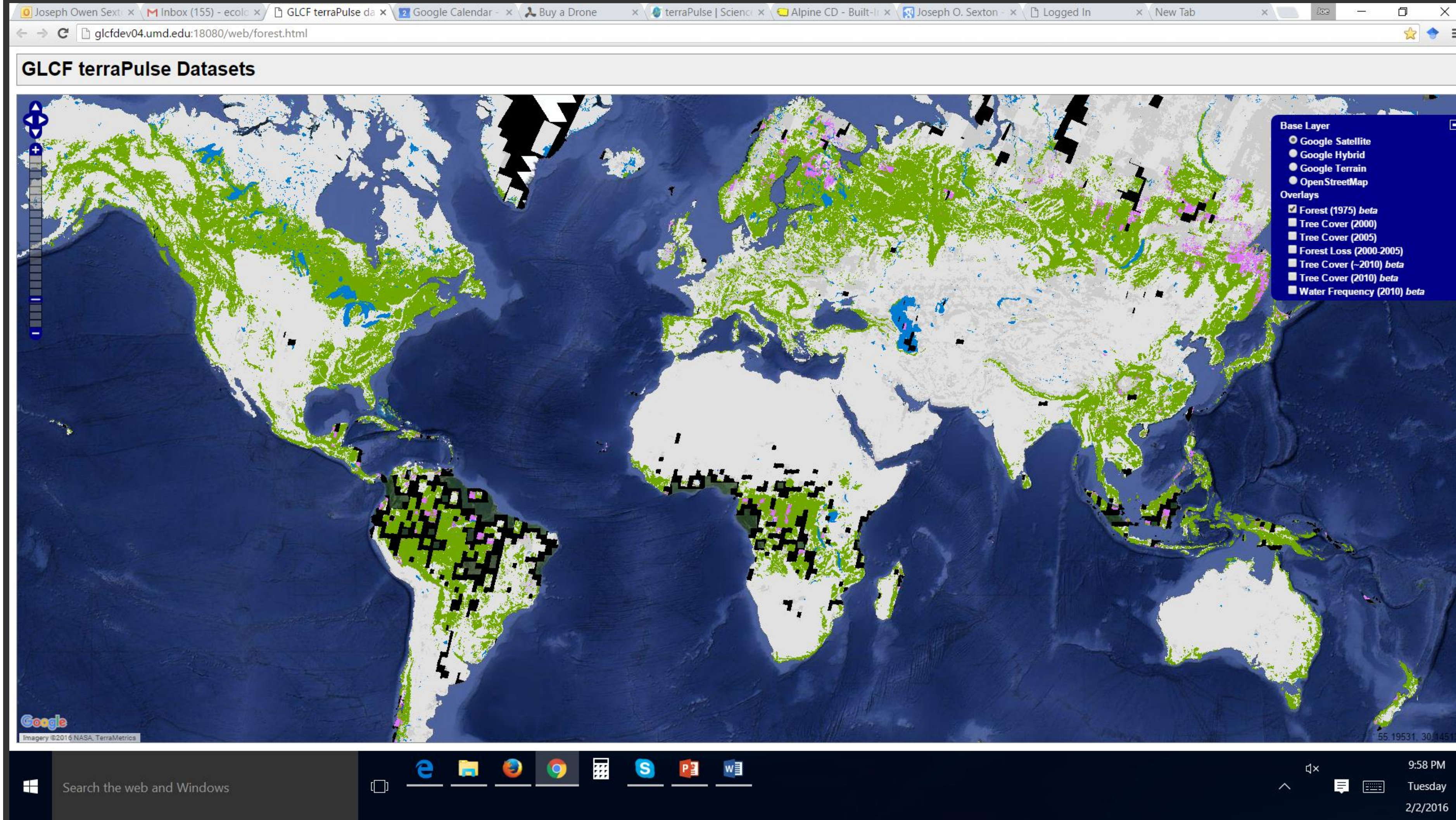
2000 Tree Cover



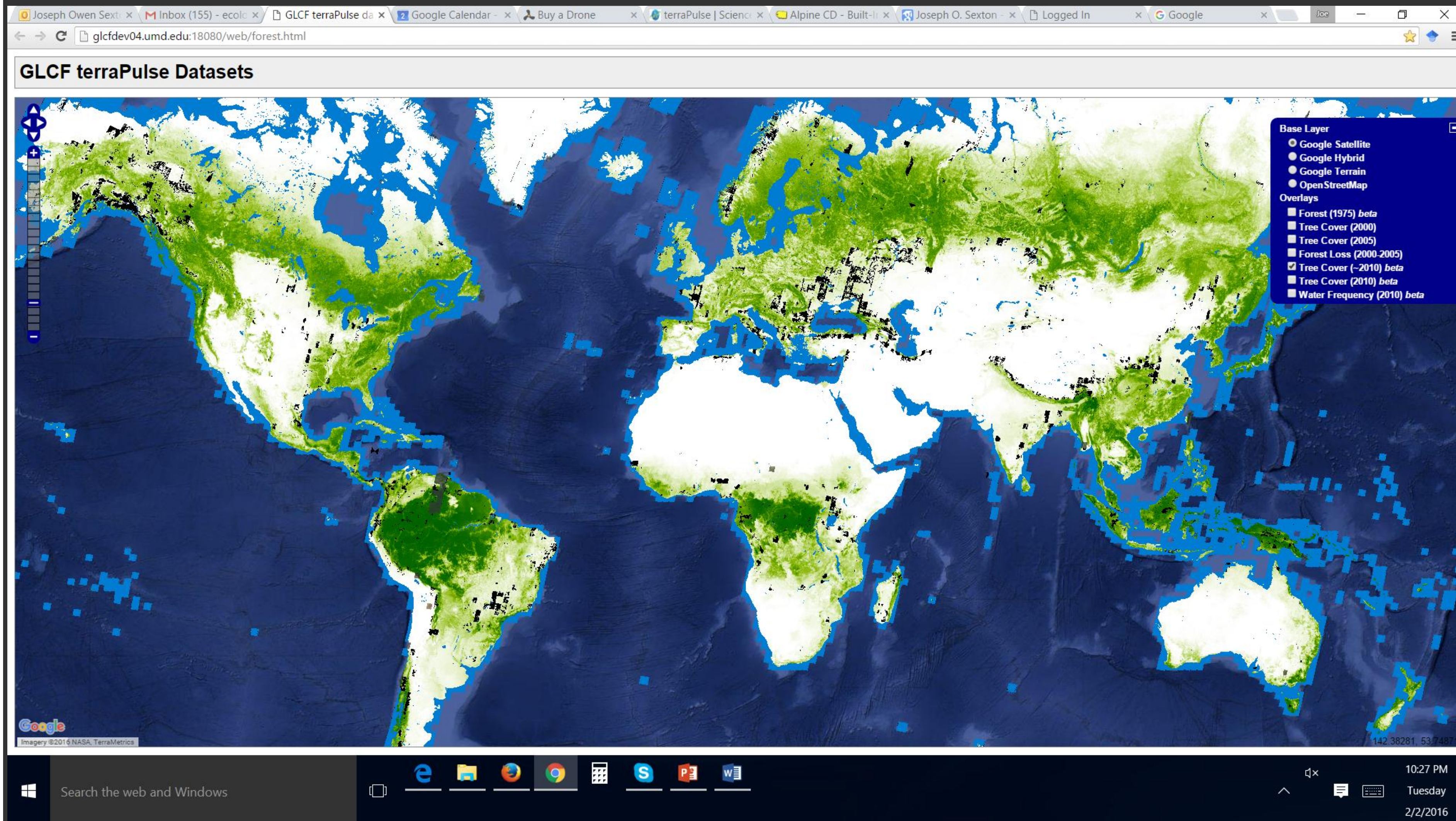
2005 tree cover



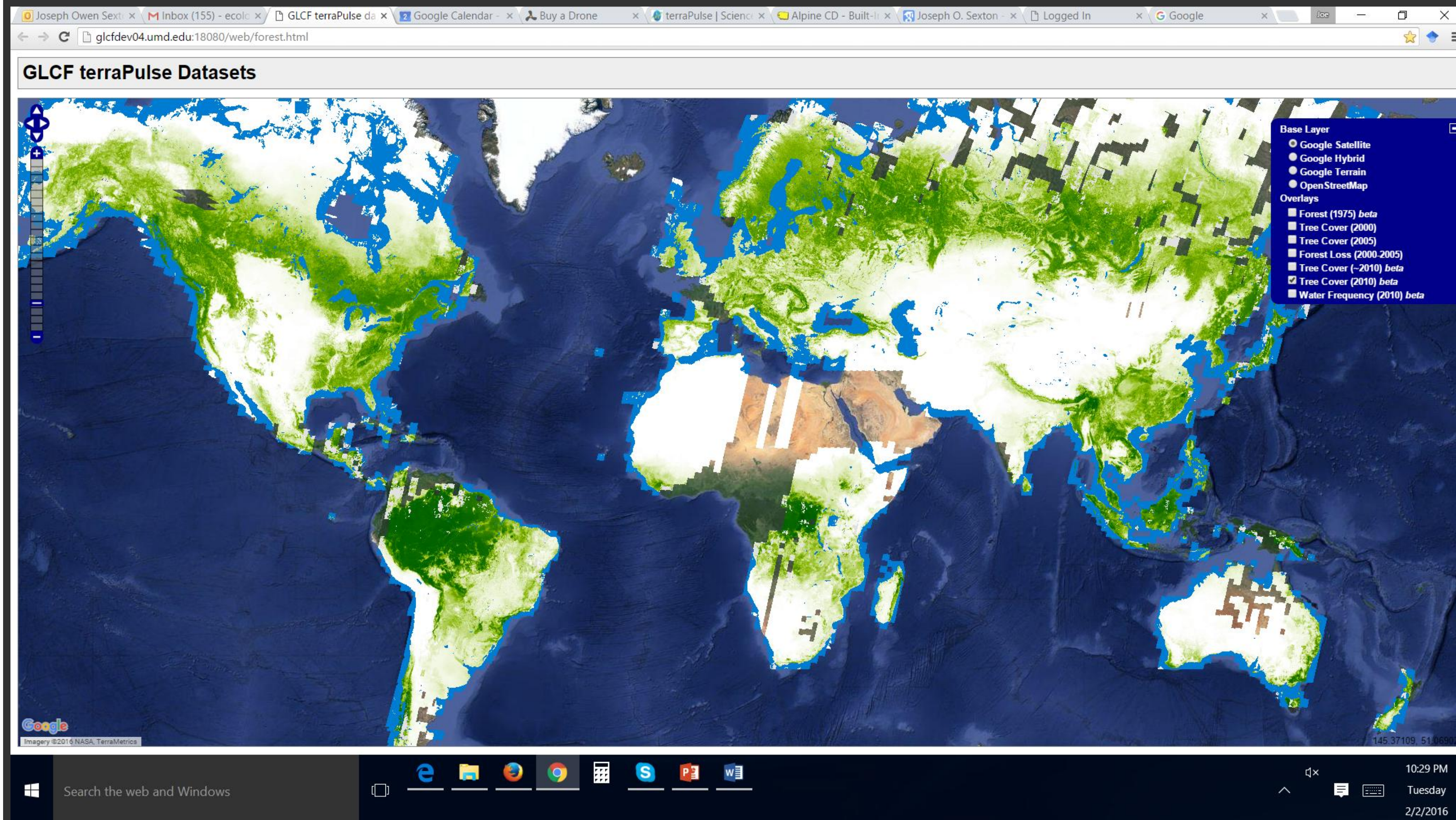
1975 Forest Cover



~2010 Tree Cover



2010 Tree Cover



GLCF Publications

2016

- Song, X.-P., J.O. Sexton, C. Huang, S. Channan, J.R. Townshend. 2016. Characterizing the magnitude, timing, and duration of urban growth from time series of Landsat-based records of impervious cover. Remote Sensing of Environment 175: 1-13.
- Liu, F.-J., C. Huang, Y. Pang, M. Li, D.-X. Song, X.-P. Song, S. Channan, J.O. Sexton, D. Jiang, Y. Guo, Y.-F. Li, J.R. Townshend. 2016. Assessment of the three factors affecting Myanmar's forest cover change using Landsat and MODIS vegetation continuous fields data. International Journal of Digital Earth (in press)
- Sexton, J.O., P. Noojipady, X.-P. Song, M. Feng, D.-X. Song, D.-H. Kim, A. Anand, C. Huang, S. Channan, S.L. Pimm, J.R. Townshend. 2016. Conservation policy and the measurement of forests. Nature Climate Change (in press)

2015

- Channan, S., M. Feng, D.-H. Kim, J.O. Sexton, X.-P. Song, D. Song, P. Noojipady, K. Collins, A. Anand, J.R. Townshend. 2015. The GLS+: an enhancement of the Global Land Survey datasets. Photogrammetric Engineering & Remote Sensing 81: 521-525.
- Jenkins, C.N., K.S. Van Houtan, S.L. Pimm, J.O. Sexton. 2015. US protected lands mismatch biodiversity priorities. Proceedings of the National Academy of Sciences 112: 5081-5086
- Haddad, N.M., L.A. Brudvig, J. Clobert, K.F. Davies, A. Gonzalez, R.D. Holt, T.E. Lovejoy, J.O. Sexton, M.P. Austin, C.D. Collins, W.M. Cook, E.I. Damschen, R.M. Ewers, B.L. Foster, C. Jenkins, A. King, W.F. Laurance, D.J. Levey, C.R. Margules, B.A. Melbourne, A.O. Nicholls, J.L. Orrock, D.-X. Song, J.R. Townshend. 2015. Habitat fragmentation and its lasting impact on Earth's ecosystems. Science Advances 1: e1500052 DOI: 10.1126/sciadv.1500052
- Feng, M., J.O. Sexton, S. Channan, J.R. Townshend. 2015. A global, high-resolution (30-m) inland water body dataset for 2000: first results of a topographic-spectral classification algorithm. International Journal of Digital Earth. DOI: 10.1080/17538947.2015.1026420
- Kim, D.-H., J.O. Sexton, J.R. Townshend. 2015. Accelerated deforestation across the humid tropics from the 1990s to the 2000s. Geophysical Research Letters 42: 3495-3501
- Nagol, J., D.-H. Kim, J.O. Sexton, D.C. Morton, E.F. Vermote, J.R. Townshend. 2015. Bidirectional effects in Landsat reflectance estimates: is there a problem to solve? ISPRS Journal of Photogrammetry and Remote Sensing 103: 129-135.
- Song, D., C. Huang, J.O. Sexton, S. Channan, M. Feng. J.R. Townshend. 2015. Use of Landsat and Corona Data for Mapping Forest Cover Change from the mid-1960s to 2000s: Case Studies from the Eastern United States and Central Brazil. ISPRS Journal of Photogrammetry and Remote Sensing 103: 81-92.
- Sexton, J.O., P. Noojipady, A. Anand, X.-P. Song, C. Huang, S.M. McMahon, M. Feng, S. Channan, J.R. Townshend. 2015. A model for the propagation of uncertainty from continuous estimates of tree cover to categorical forest cover and change. Remote Sensing of Environment 156: 418-425.

2014

- Chen, D. et al. 2014. Long-Term Record of Sampled Disturbances in Northern Eurasian Boreal Forest from Pre-2000 Landsat Data. *Remote Sensing* 6(7): 6020-6038
- Jiang, H. et al. 2014. An Automated Method for Extracting Rivers and Lakes from Landsat Imagery. *Remote Sensing* 6: 5067-5089
- Pimm, S. L. et al. 2014. The biodiversity of species and their rates of extinction, distribution, and protection. *Science* 344(6187): 1246752.
- Morton, D.C. et al. 2014. Amazon forests maintain consistent canopy structure and greenness during the dry season. *Nature.*
- Song, X.-P., et al. 2014. Integrating global land cover products for improved forest cover characterization: an application in North America. *International Journal of Digital Earth*. DOI: 10.1080/17538947.2013.856959

2013

- Tan, B., et al. 2013. Improved forest change detection with terrain illumination-corrected images. *Remote Sensing of Environment* 136: 469-483
- Sexton, J.O. et al. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth* 6(5): 427-448
- Feng, M. et al. 2013. Global surface reflectance products from Landsat: Assessment using coincident MODIS observations. *Remote Sensing of Environment* 134:276-293
- Meineke, E. et al. 2013. Urban warming drives insect pest abundance on street trees. *PLoS One* 8(3): e59687
- Trainor, A.M. et al. 2013. Empirical estimation of dispersal resistance surfaces: a case study with red-cockaded woodpeckers. *Landscape Ecology* 28: 755-767.
- Sexton, J.O. et al. 2013. Urban growth of the Washington, D.C. - Baltimore, MD metropolitan region from 1984 to 2010 by annual estimates of impervious cover. *Remote Sensing of Environment* 129:42-53.
- Sexton, J.O. et al. 2013. Long-term landcover dynamics by multi-temporal classification across the Landsat-5 record. *Remote Sensing of Environment* 128: 246-258

2012

- Townshend, J.R. et al. 2012. Global characterization and monitoring of forest cover using Landsat data: opportunities and challenges. *International Journal of Digital Earth* 5:373-397.
- Feng, M. et al. 2012. Quality assessment of Landsat surface reflectance products using MODIS data. *Computers & Geosciences*, 38, 9-22
- McManus, K. et al. 2012. Satellite-based evidence for shrub and graminoid tundra expansion in northern Quebec since 1986. *Global Change Biology* 18:2313-2323
- Smart, L.S. et al. 2012. Three-dimensional characterization of pine forest type and red-cockaded woodpecker habitat by small-footprint, discrete-return lidar. *Forest Ecology and Management* 281:100-110.

Questions/Discussion

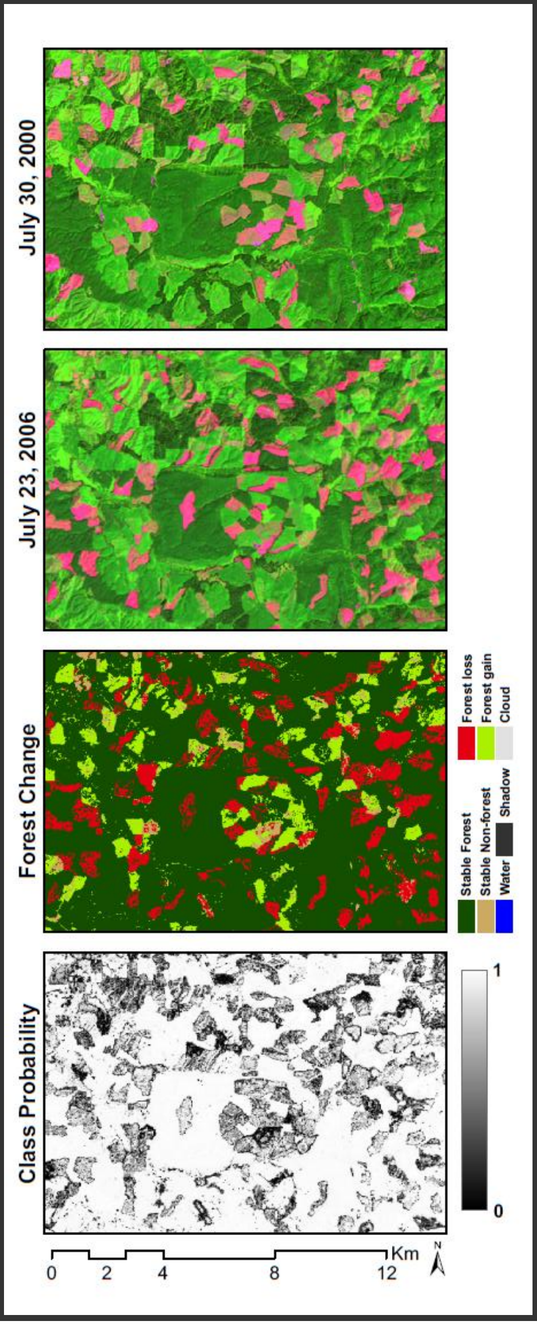
Change detection

$$p(FF) = p(F_1) \times p(F_2)$$

$$p(NN) = \left(1 - p(F_1)\right) \times \left(1 - p(F_2)\right)$$

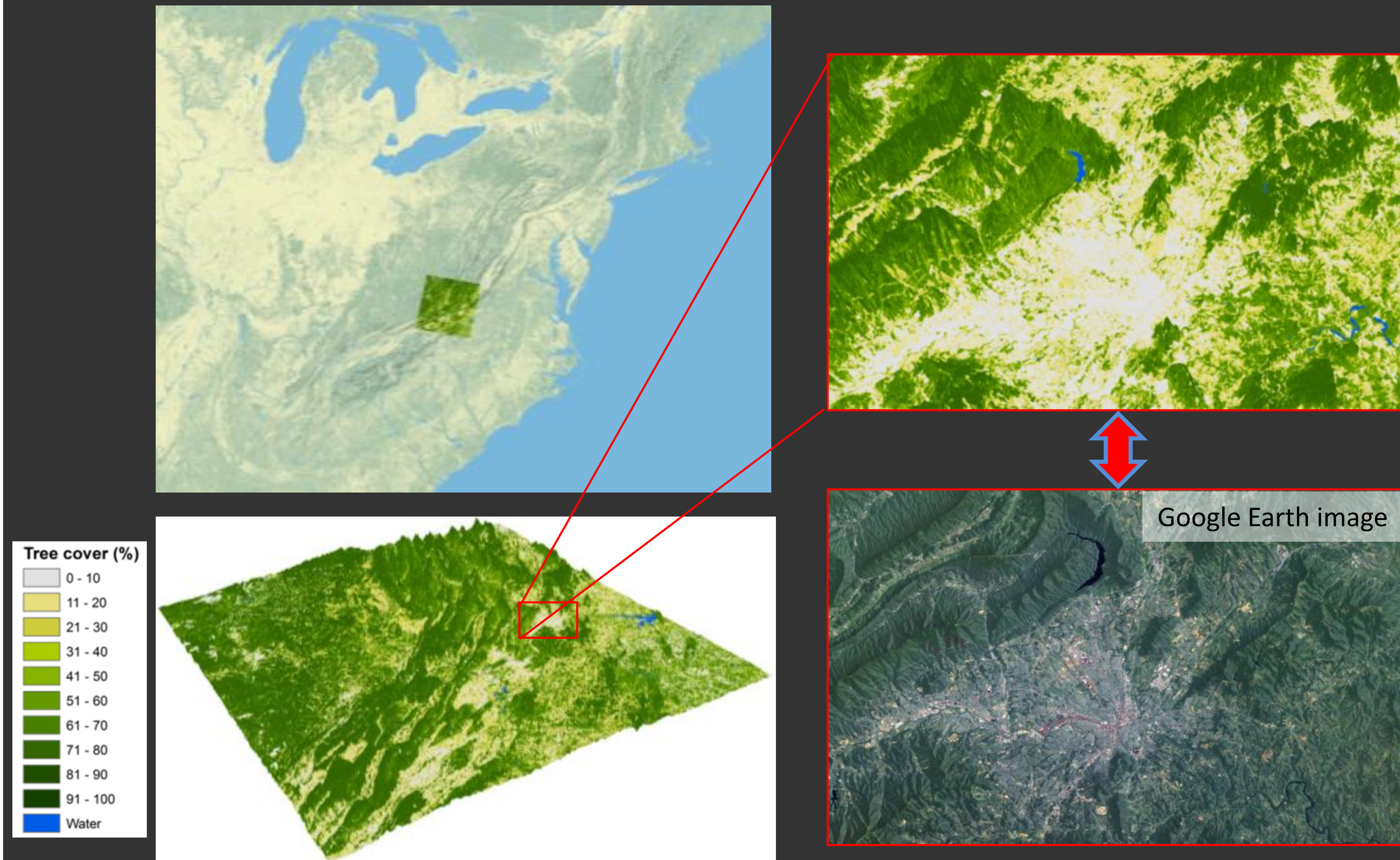
$$p(NF) = \left(1 - p(F_1)\right) \times p(F_2)$$

$$p(FN) = p(F_1) \times \left(1 - p(F_2)\right)$$

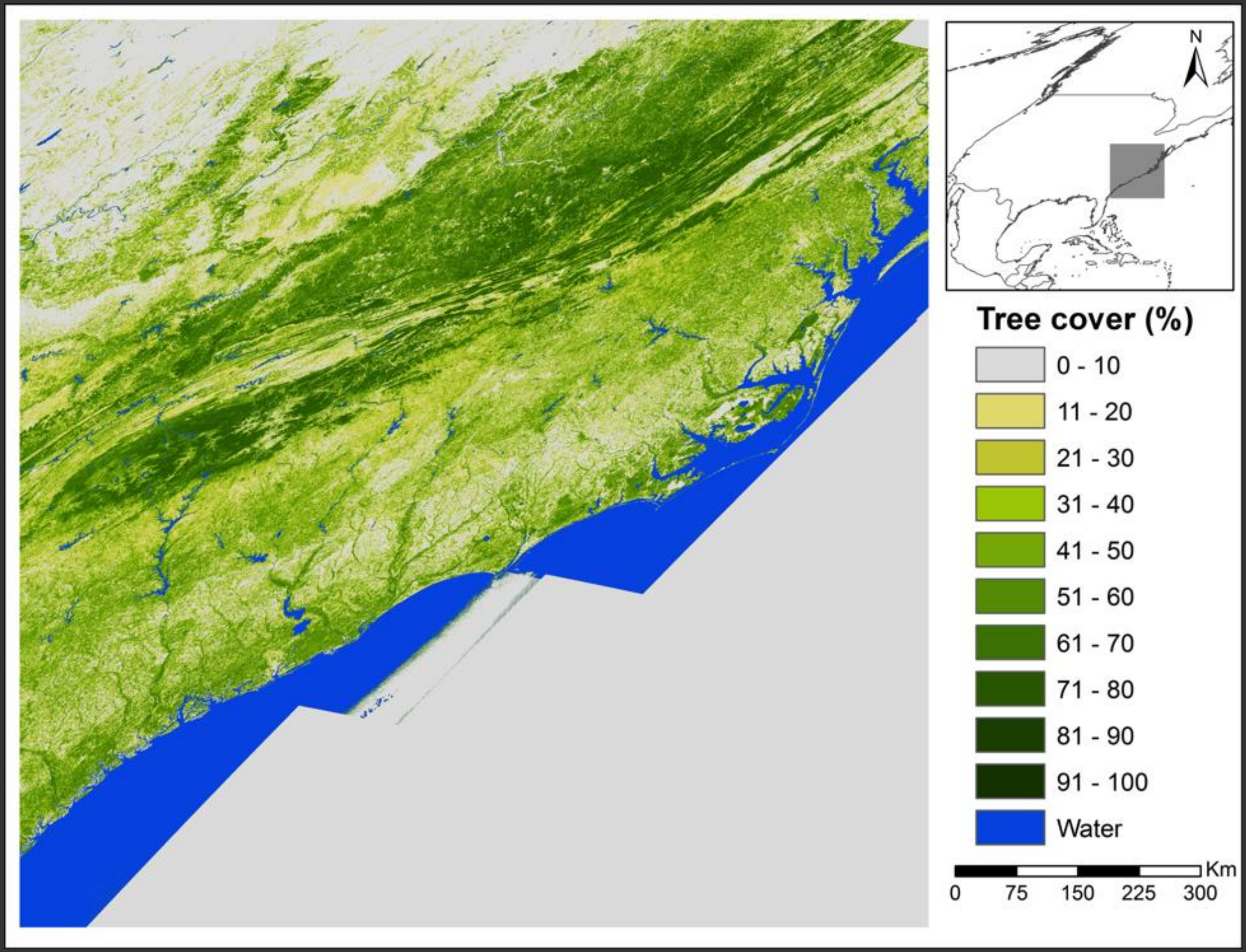


Sexton et al. 2015. *Remote Sensing of Environment.*

Landsat VCF over Appalachian mountains



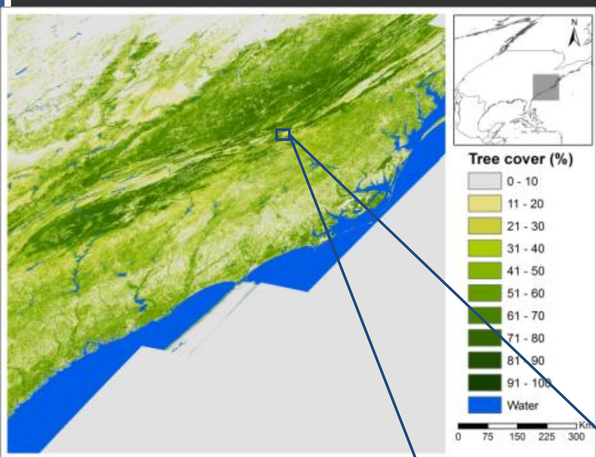
Landsat VCF over the eastern US



Shown area corresponds to MODIS tile h11v05 and covers 57 Landsat WRS2 images.

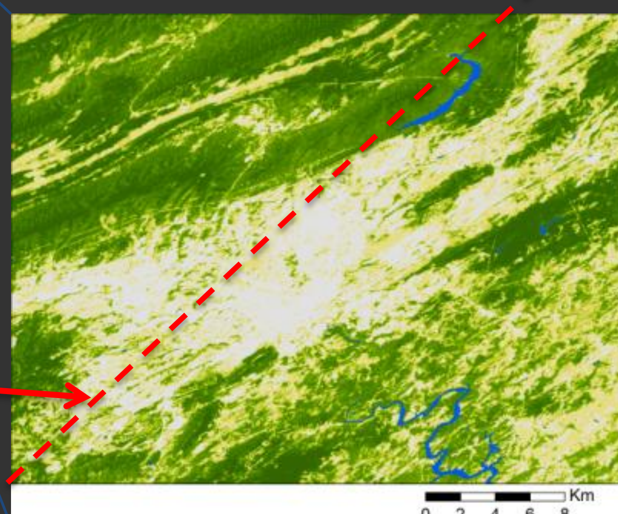
Landsat VCF in Eastern US

inset: Roanoke, Virginia



Temperate forests + urban + cropland

VCF % tree cover



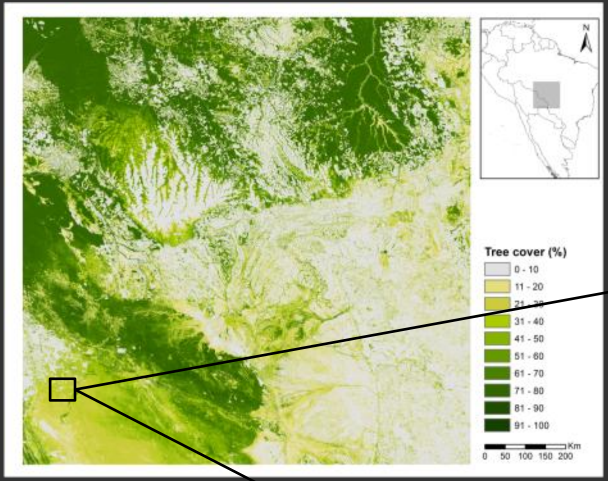
Google Earth image

Landsat WRS-2 boundary

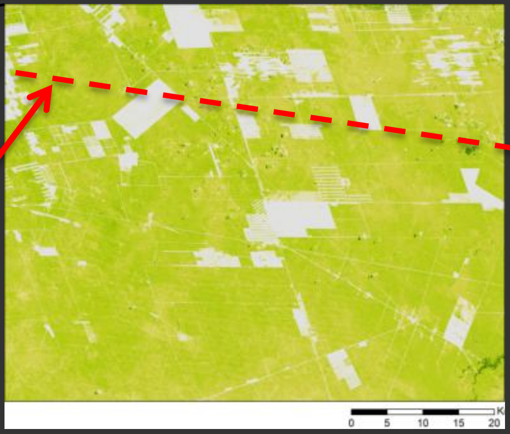
Landsat VCF in Southern Amazon

inset: Gran Chaco, Eastern Bolivia

Dry tropical forest



VCF % tree cover



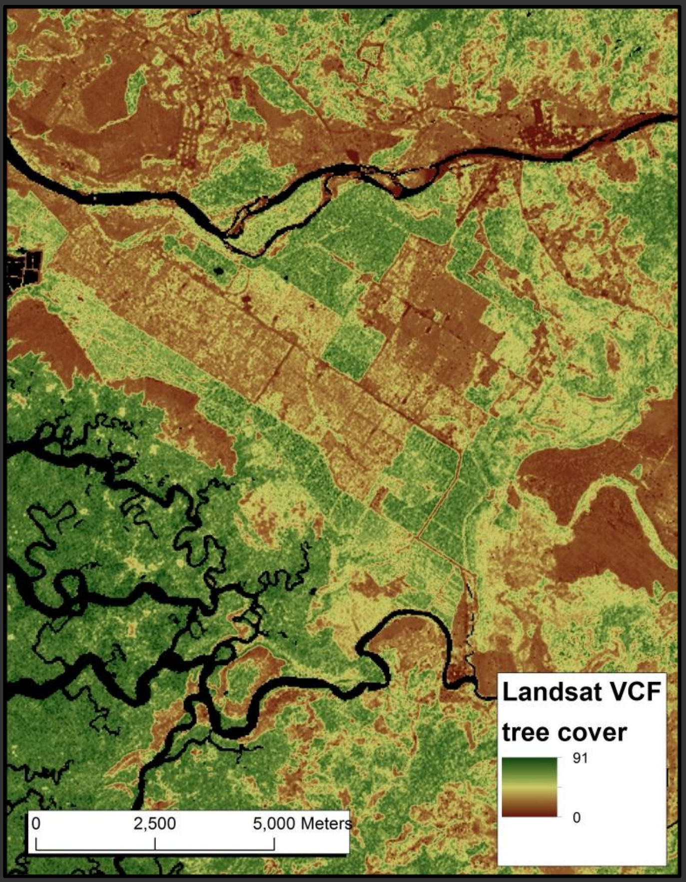
Google Earth image

Landsat WRS-2 boundary

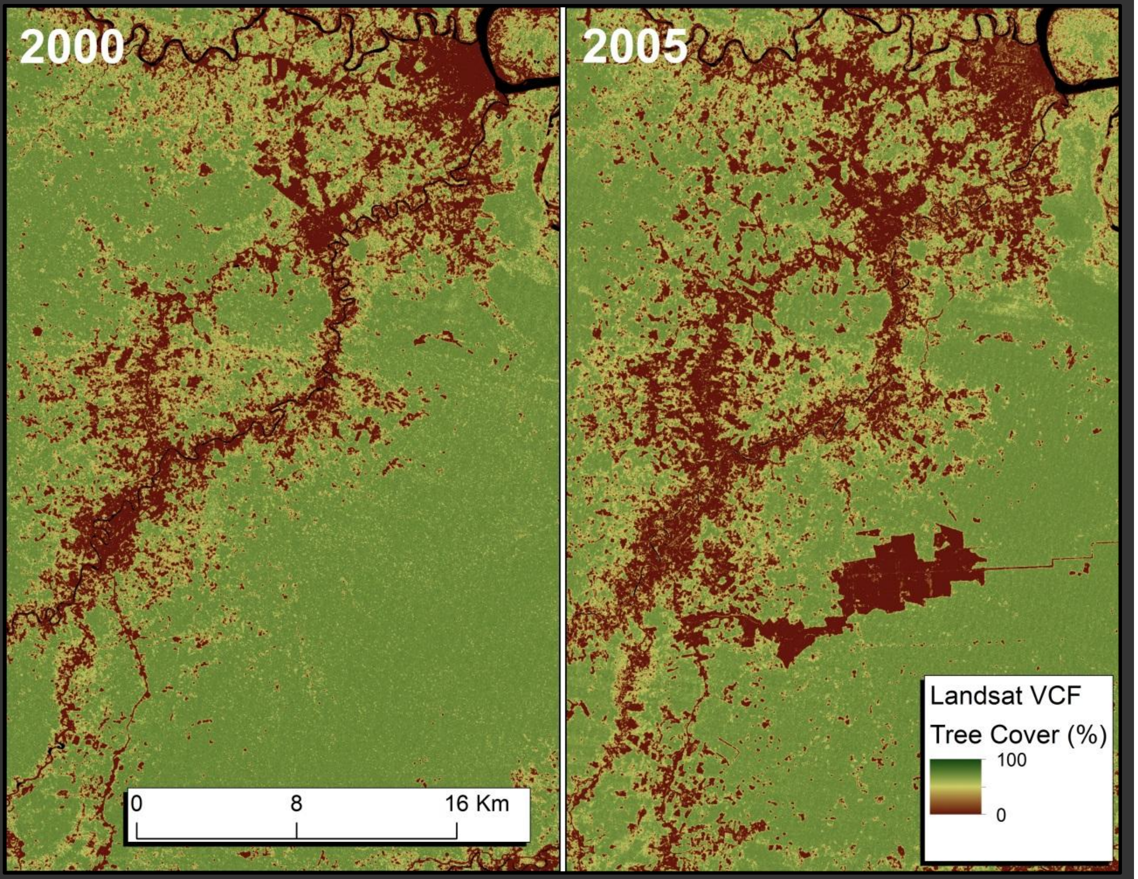
“Best-pixel” compositing in image overlap areas

- Based on uncertainty layers
  - Get the best pixel with the lowest uncertainty
  - Clean cloud and shadow

Oil palm & tropical deforestation

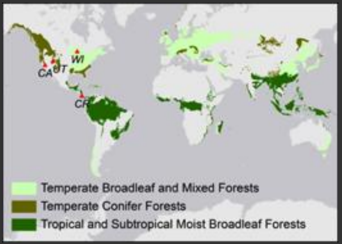


Costa Rica



Peru

Landsat *vs.* LiDAR & MODIS



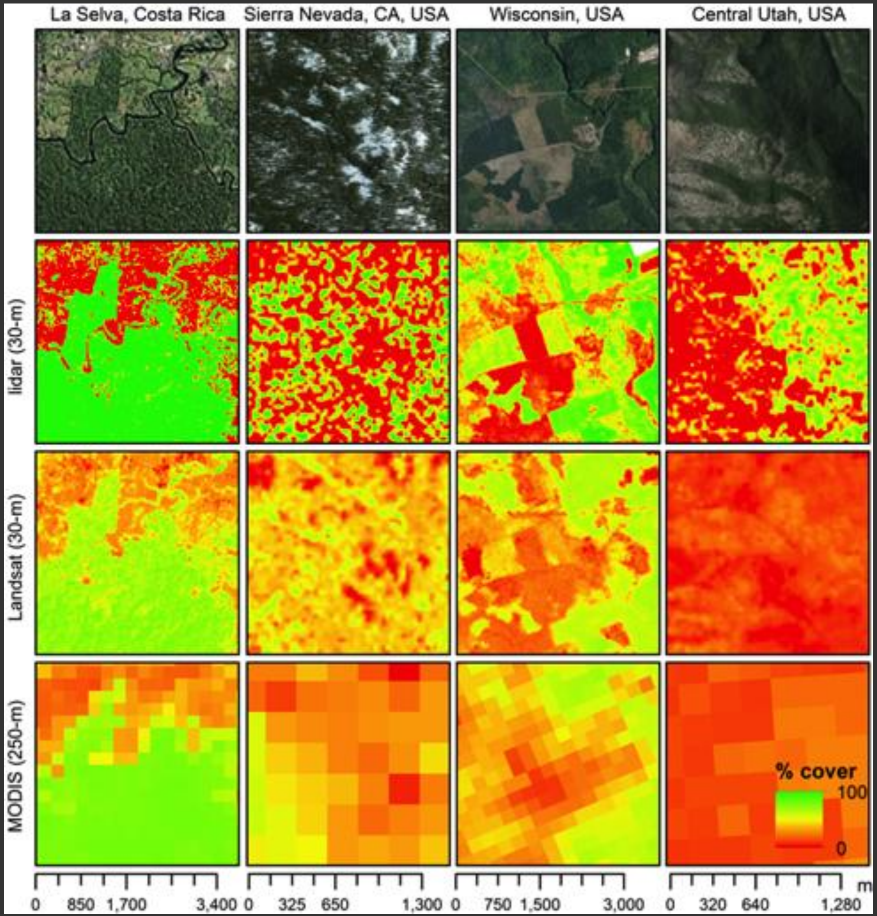
- Lidar is reference
  - High resolution
  - High accuracy

  …but rare

- Landsat & MODIS are consistent

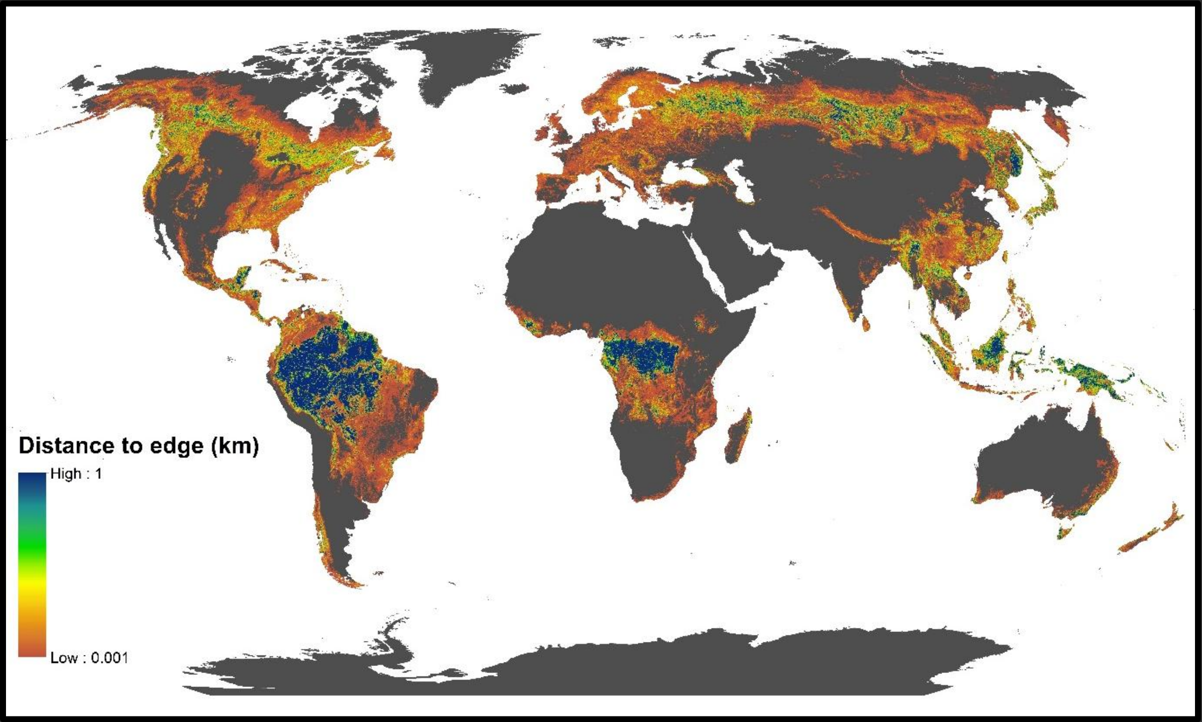
- Landsat > MODIS
  - Resolution of small patches
  - Accuracy over agriculture

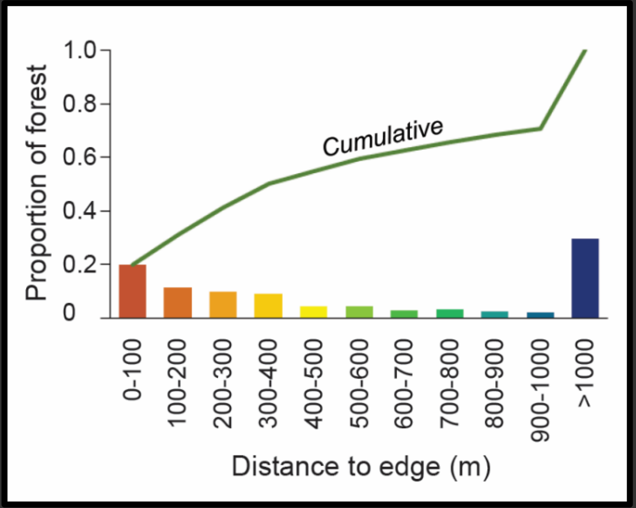
- Savannas & shrublands are a persistent problem

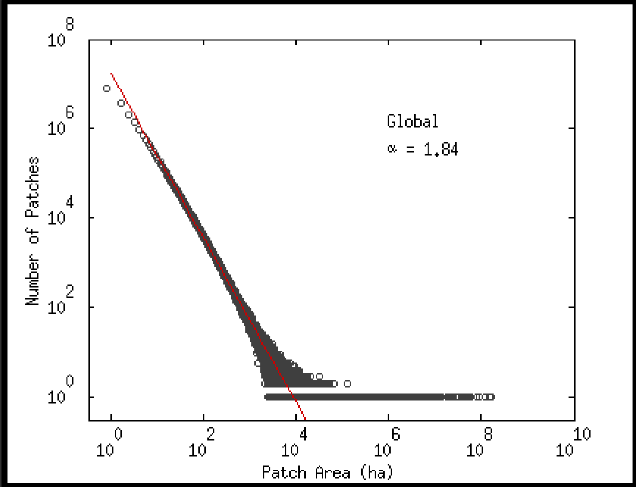


Sexton, J.O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K.M. Collins, S. Channan, C. DiMiceli, J.R. Townshend. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS continuous fields and lidar-based estimates of error. *International Journal of Digital Earth.* DOI: 10.1080/17538947.2013.786146

Forest Fragmentation





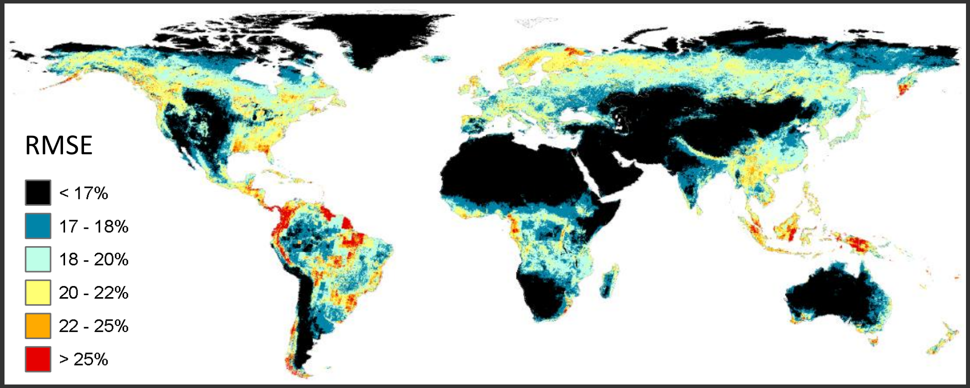


- 20% of Earth's forest cover is < 100 m from an edge
- 70% of Earth's forest cover is < 1 km from an edge
- > 50% of Earth's forest patches are < 1 ha in area

Haddad et al. 2015. *Science Advances*

A pragmatic approach to error estimation:

- Represent certainty at the scale of data
  - "Per-pixel certainty"
- Validation *and* propagation
- Leveraging uncertainty
  - Targeting calibration
  - Filtering & quality flags
  - Harmonization
  - Data fusion



Sexton et al. 2013. *Int. J. Dig. Earth.*