Remote Sensing, Machine Learning & Extreme Weather

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Mining imagery archives to improve weather forecasts

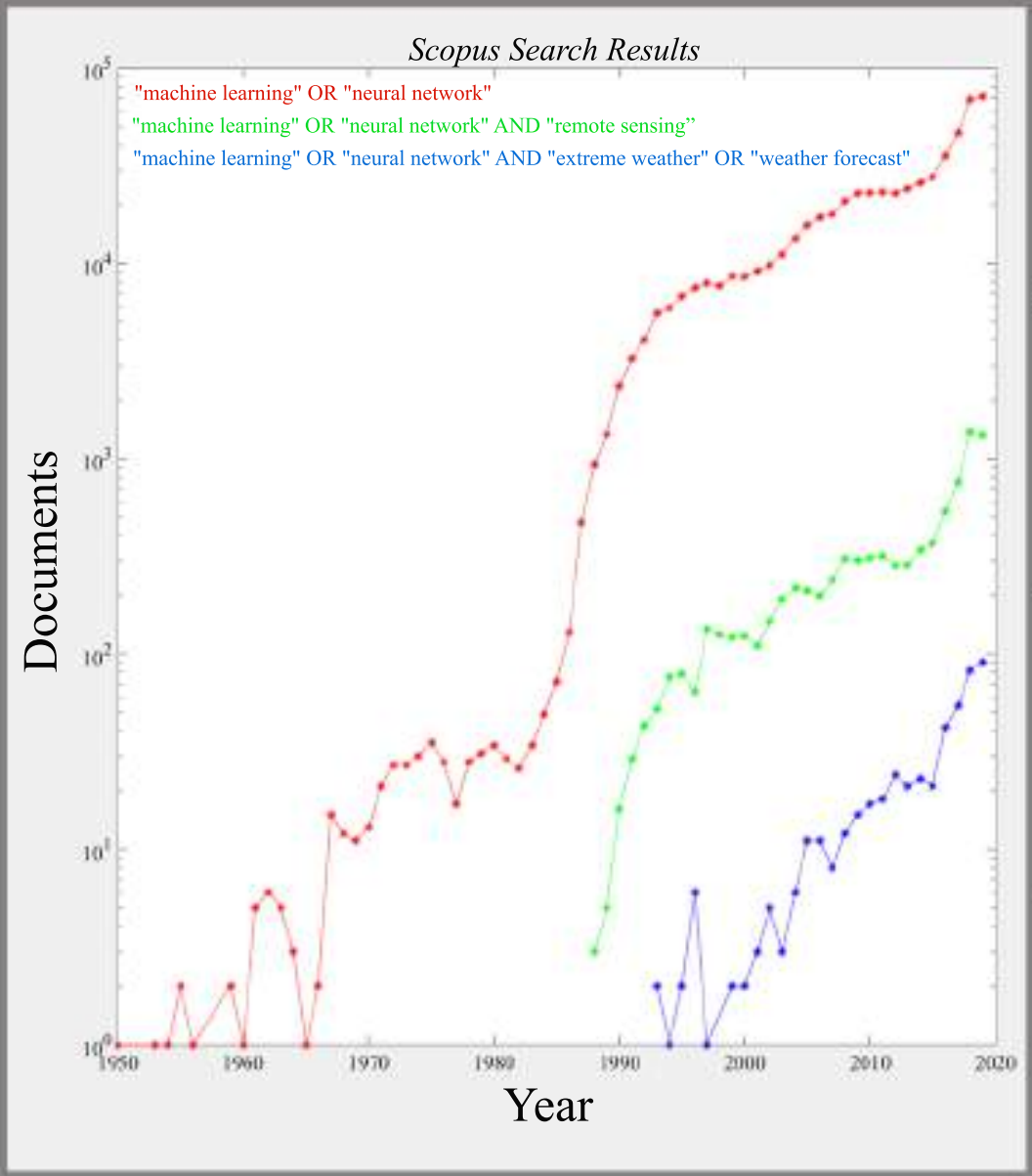
Four decades of machine learning for land cover classification

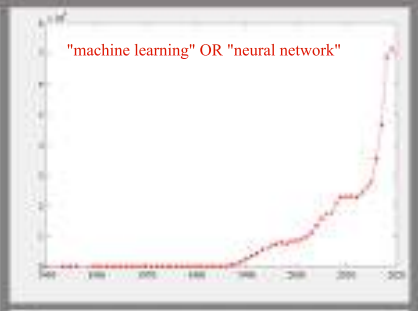
Mining imagery archives to connect events to impacts

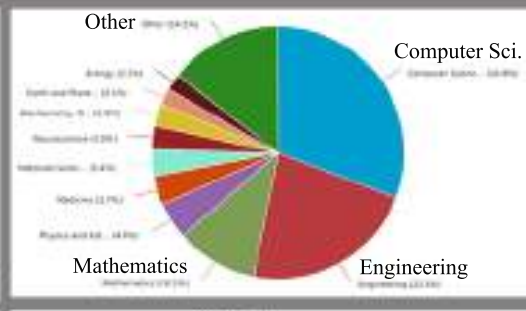
Factor Multiplicity - Cyclone impacts in coastal Bangladesh

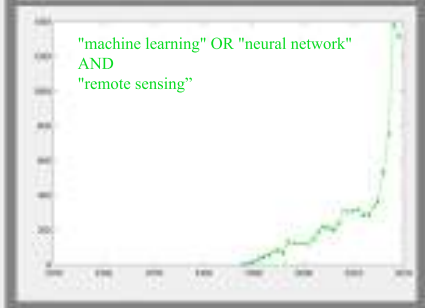
New opportunities in the near-term future

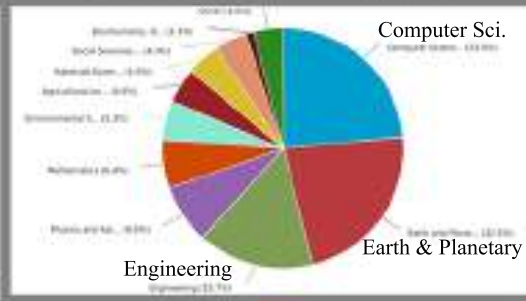
Bibliometrics

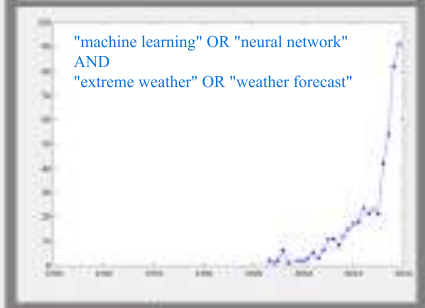


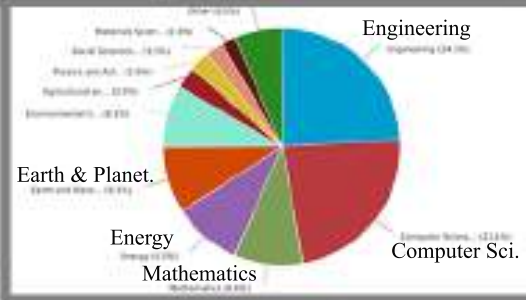


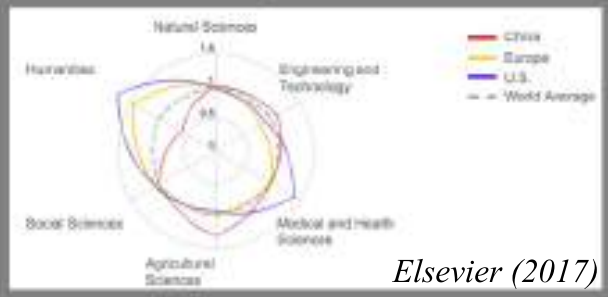












Int'l Conf. on Advances in Big Data Analytics | ABDA'16 |

Application of Deep Convolutional Neural Networks for Detecting Extreme Weather in Climate Datasets

Yunjie Liu[1],Evan Racah[1],Prabhat[1],Joaquin Correa[1],Amir Khosrowshahi[2],
David Lavers[3],Kenneth Kunkel[4],Michael Wehner[1],William Collins[1]
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[3]Scripps Institution of Oceanography, San Diego, CA, US
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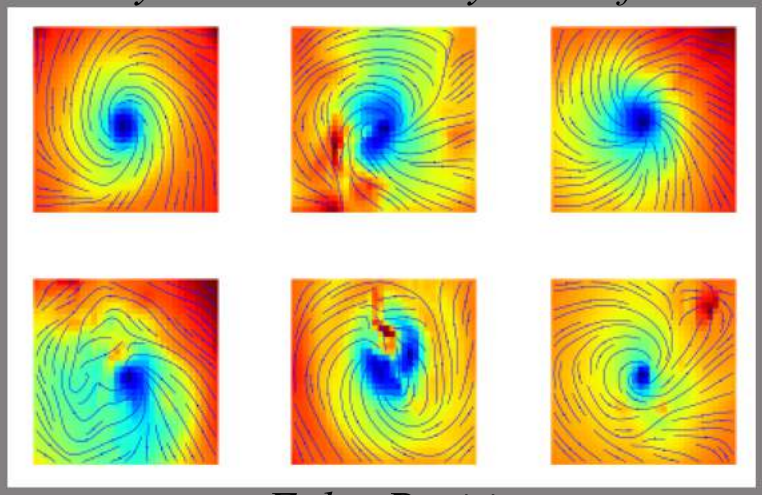
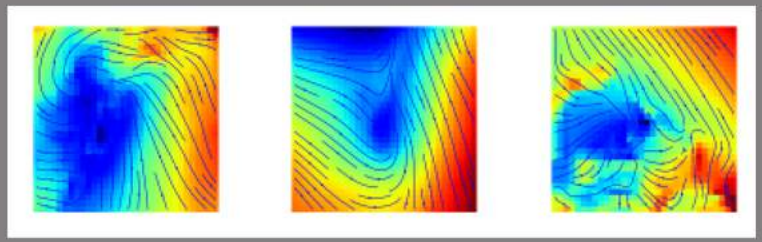
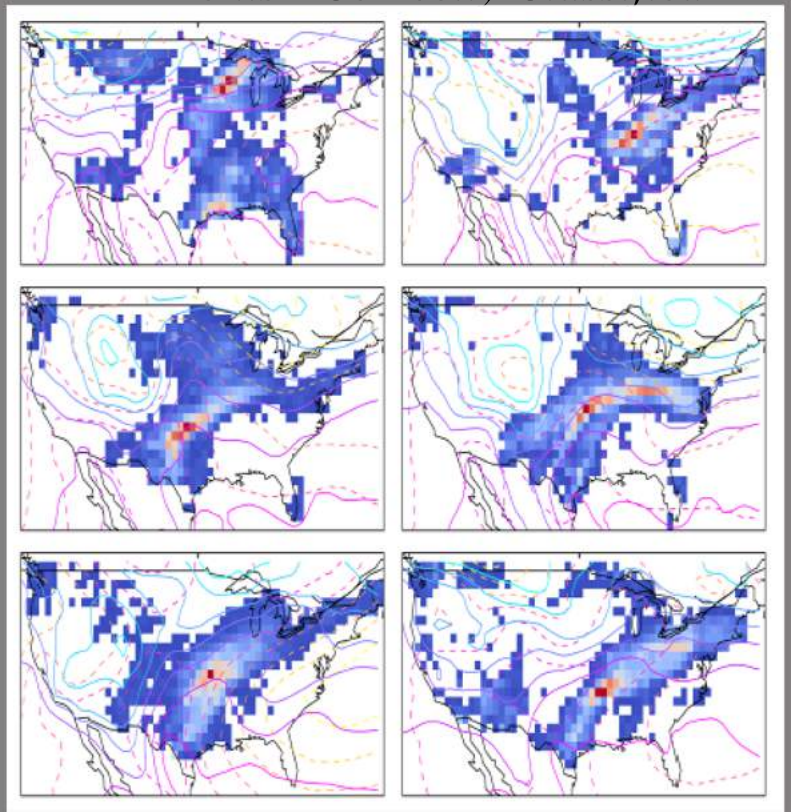
Cyclones- Correctly Classified



False Positives

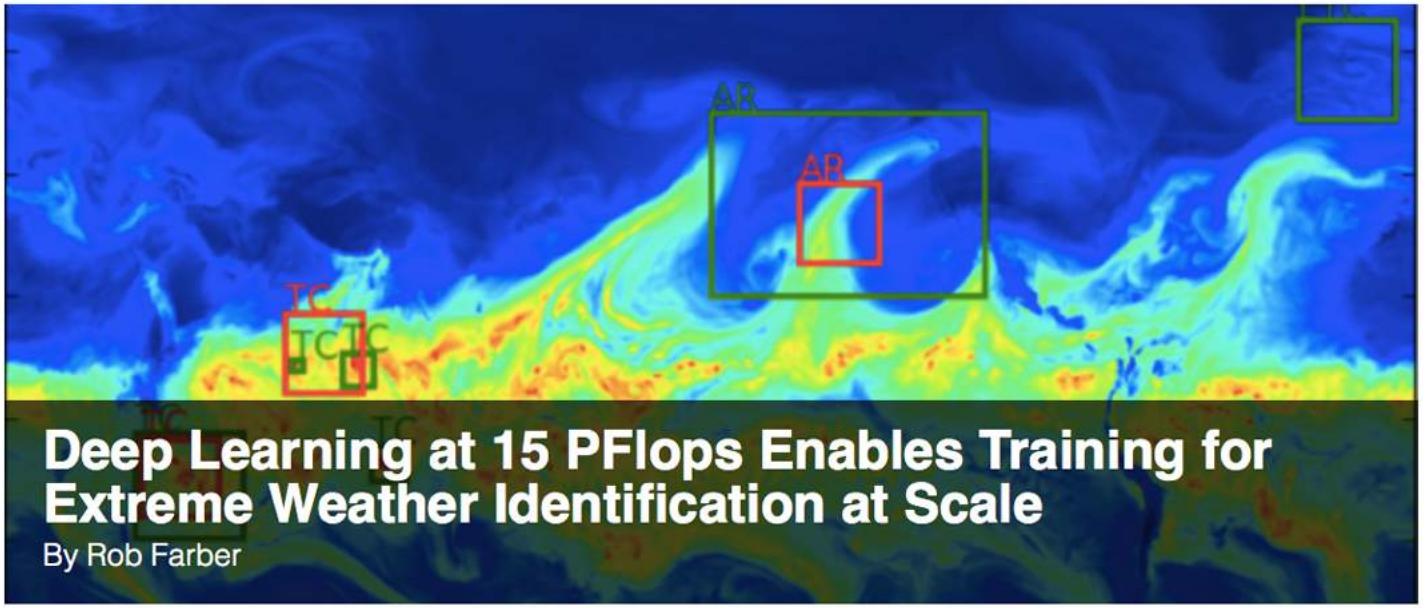


Fronts - Correctly Classified



HPC wire

Since 1987 - Covering the Fastest Computers in the World and the People Who Run Them



Deep Learning at 15 PFlops Enables Training for Extreme Weather Identification at Scale

By Rob Farber

March 19, 2018

Petaflop per second deep learning training performance on the NERSC (National Energy Research Scientific Computing Center) Cori supercomputer has given climate scientists the ability to use machine learning to identify extreme weather events in huge climate simulation datasets. Predictive accuracies ranging from 89.4% to as high as 99.1% show that trained deep learning neural networks (DNNs) can identify weather fronts, tropical cyclones, and long narrow air flows that transport water vapor from the tropics called atmospheric rivers. As with image recognition, Michael Wehner (senior staff scientist, LBNL) noted they found the machine learning output outperforms humans. [i]

SPECIAL
Waves to Weather (W2W)
COLLECTION

Neural Networks for Postprocessing Ensemble Weather Forecasts

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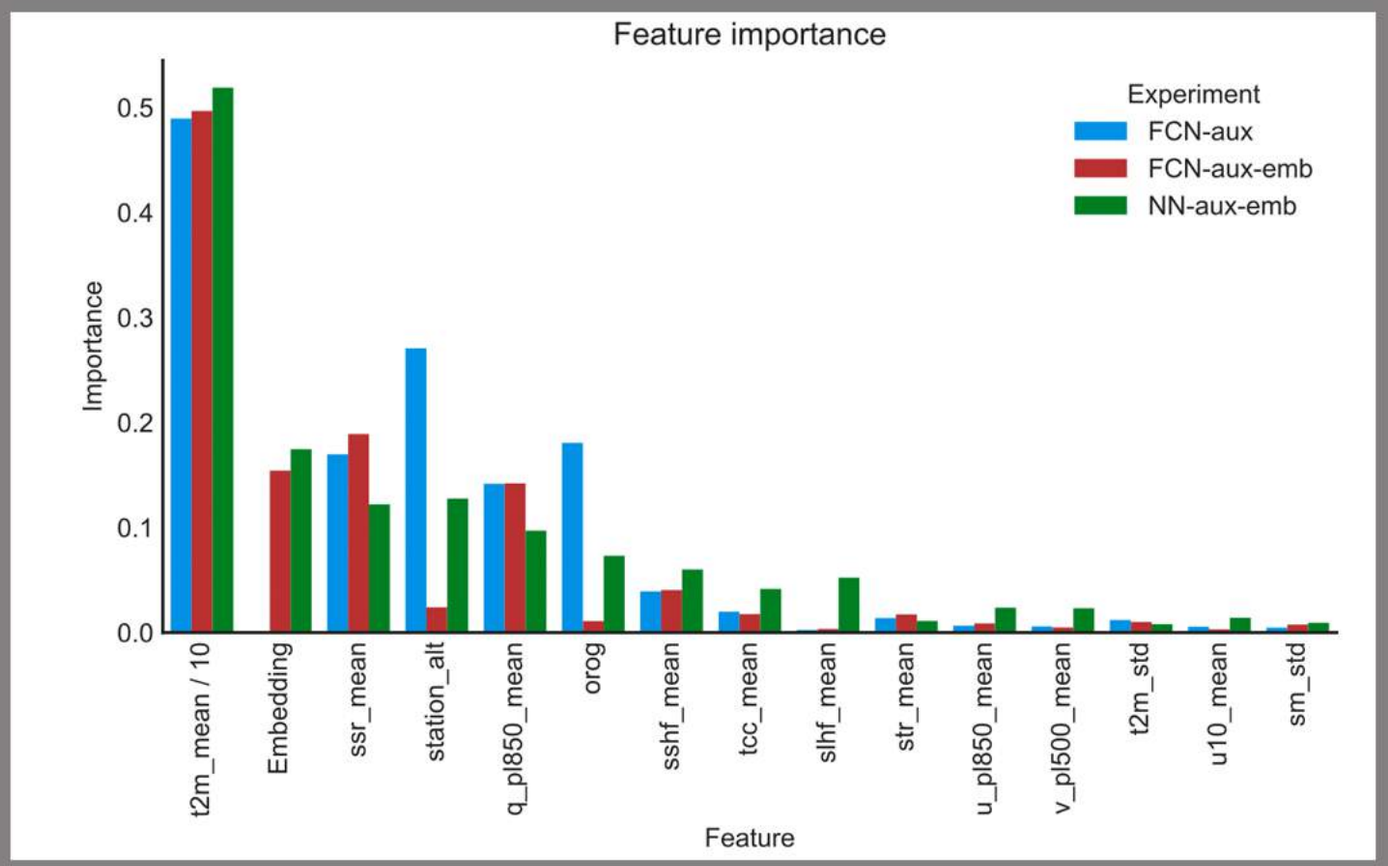
Meteorological Institute, Ludwig-Maximilians-Universität, Munich, Germany

SEBASTIAN LERCH

Institute for Stochastics, Karlsruhe Institute of Technology, Heidelberg Institute for Theoretical Studies, Karlsruhe, Germany

Incorporates nonlinear relationships between arbitrary predictor variables and forecast distribution parameters

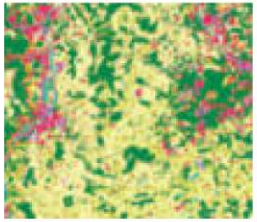
Outperforms traditional parametric methods - and provides information on nonlinear relationships among variables.



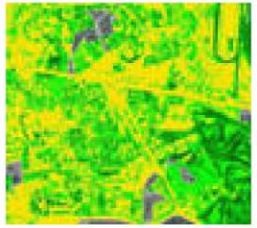
Land information extraction from satellite images

Map of categorical variables

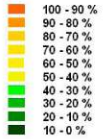
Map of thematic classes



Land cover maps
Burned area maps
Flooded maps
Agriculture maps
Forest maps



Map of continuous variables



Leaf area index
Biomass
Tree volume

Thematic remote sensing

Image classification

Quantitative remote sensing

Modelling

M. Caetano, ESA 2009

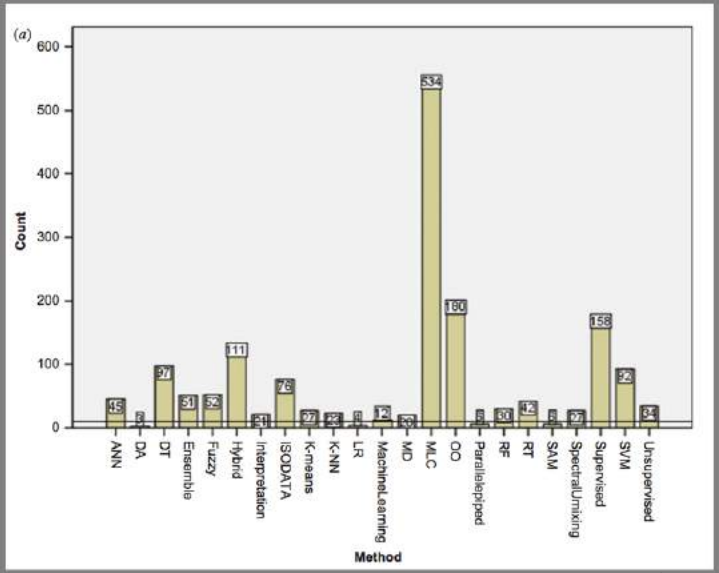
Classification Methods & Accuracy

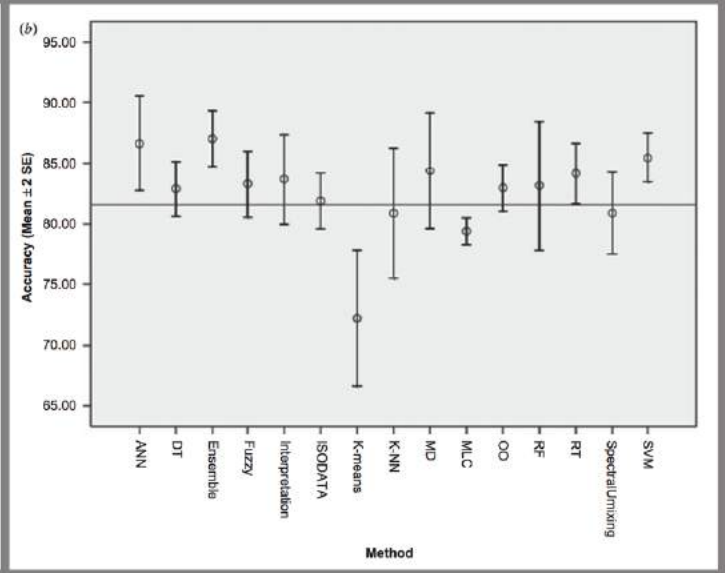
Meta-analysis of 6771 publications (1976-2012) of land cover classification

Almost all classification methods could be considered some form of machine learning

Variability of accuracy for most methods is greater than differences among methods

Self-reported accuracy often based on subjective visual interpretation of imagery





Yu et al., IJRS 2014

What Influences Classification Accuracy?

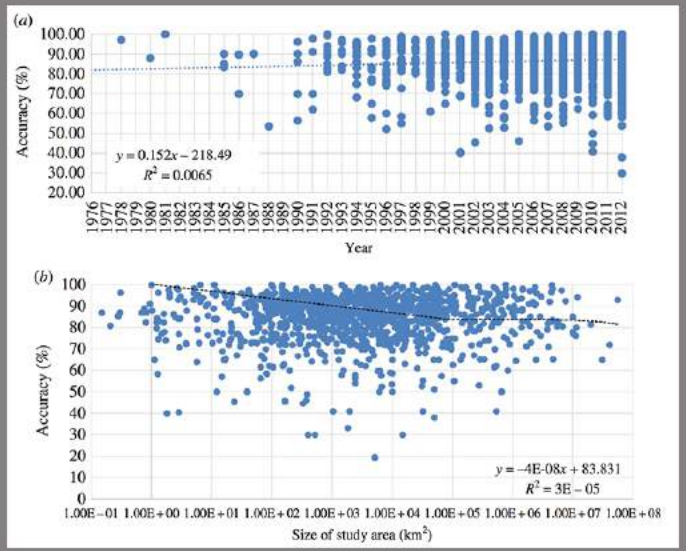
Self-reported accuracy shows no significant increase since 1976

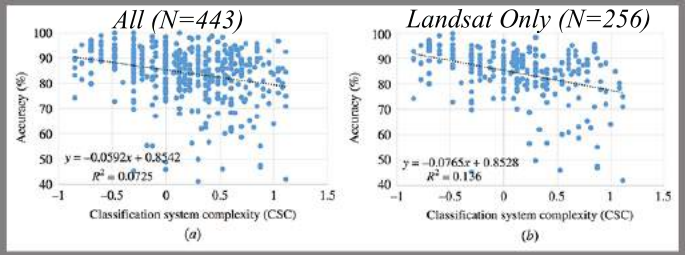
Self-reported accuracy shows no significant scale-dependence

Lower tail of accuracy distribution sensitive to classification complexity - and N.

Upper tail of accuracy distribution sensitive to analyst confirmation bias

Accuracy distribution may say more about analysts than methods





Yu et al., IJRS 2014

Journal of Coastal Research	32	5	1149–1161	Coconut Creek, Florida	September 2016

Observations of Cyclone-Induced Storm Surge in Coastal Bangladesh

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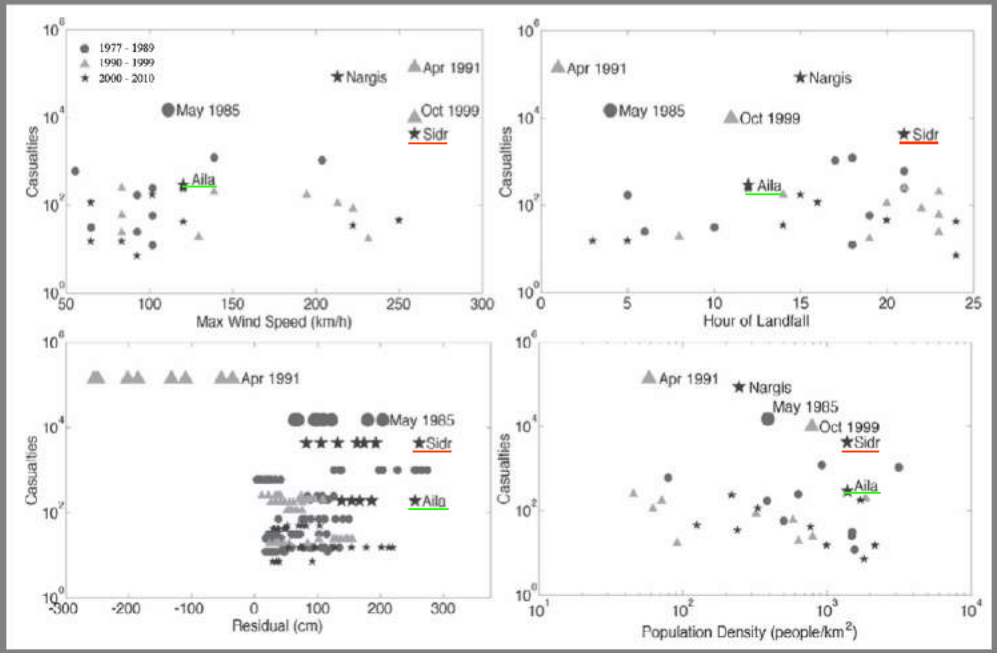
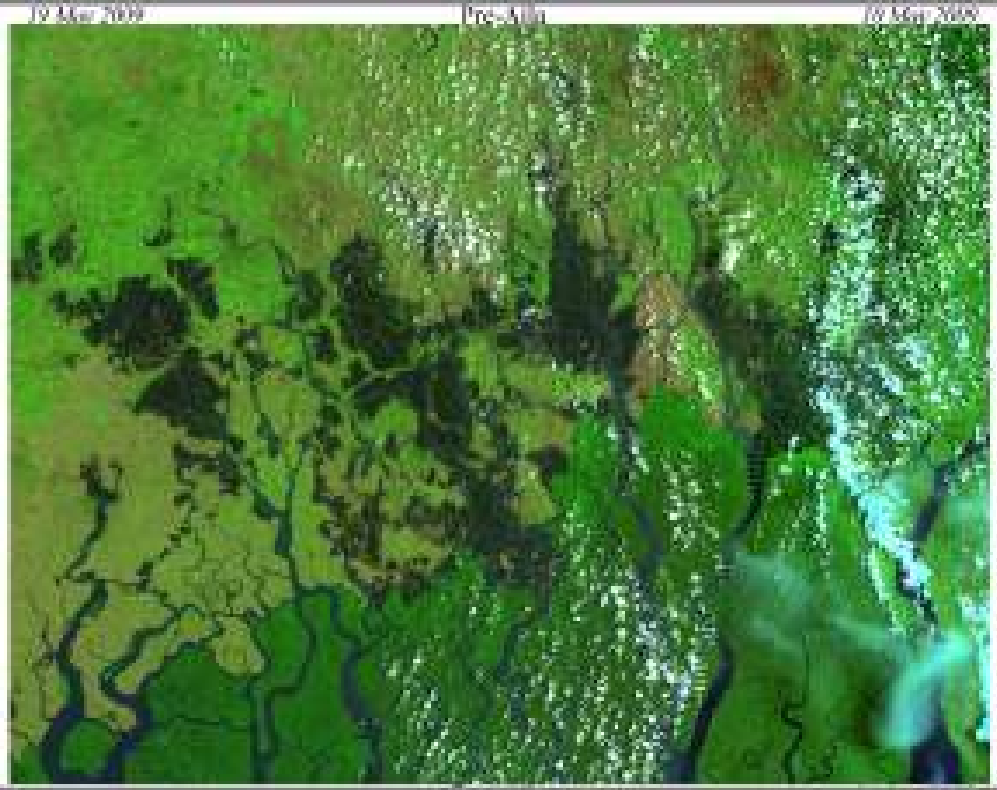
www.cerf-jcr.org

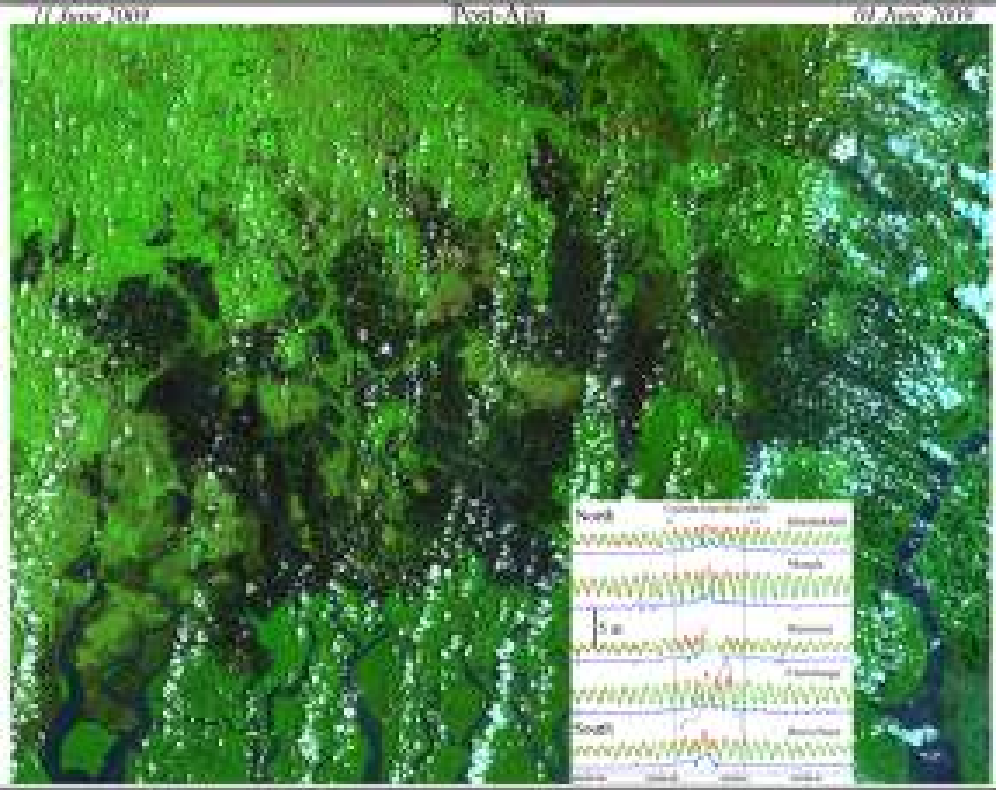
Multiplicity: No single factor consistently explains cyclone casualties



Cyclone Aila 2009

Westward landfall drove onshore winds,higher storm surge & flooding





remote sensing
MDPI
Article

Spatiotemporal Characterization of Mangrove Phenology and Disturbance Response: The Bangladesh Sundarban

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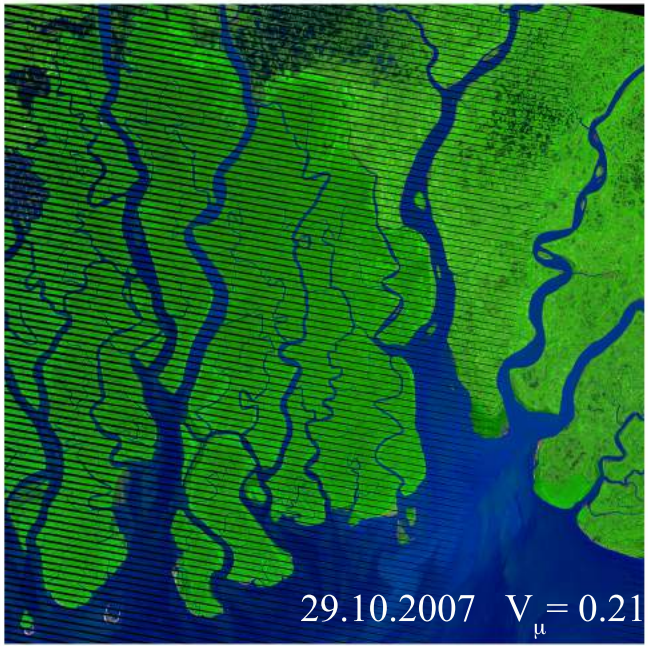
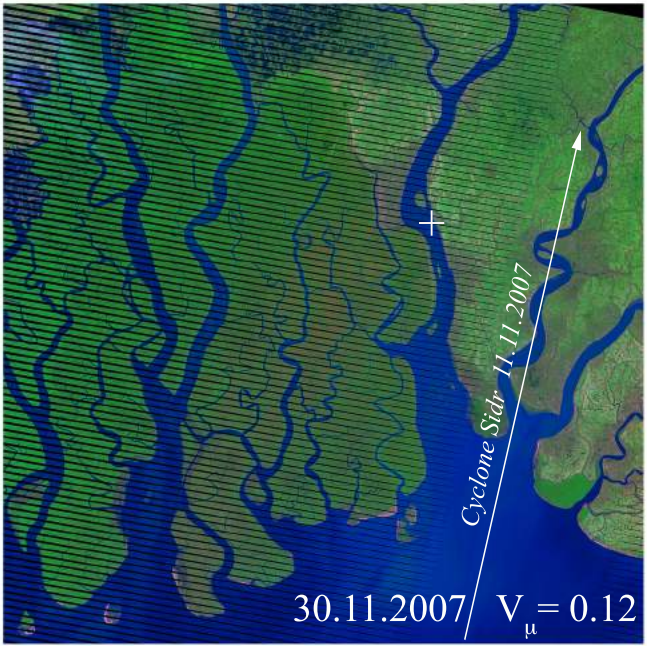
check for updates

Cyclone Sidr 2007

Unusually high wind speed causes identifiable mangrove defoliation and crop damage

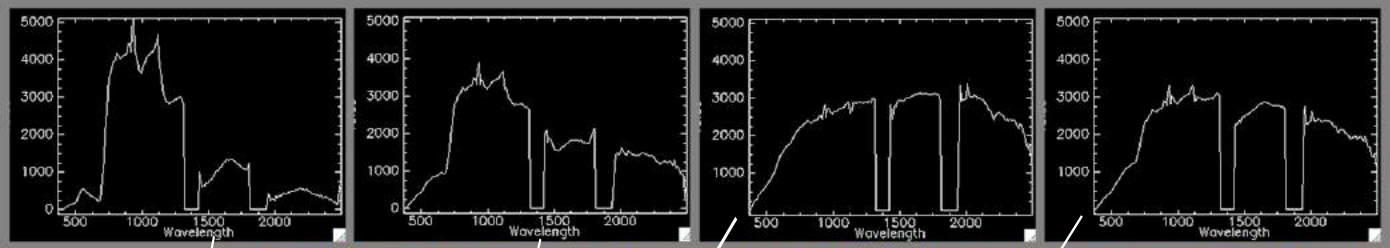




Hyperspectral Imaging

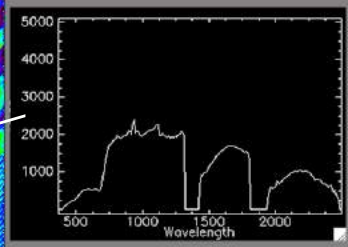
Visible to Shortwave Infrared reflectance spectra resolve distinct molecular absorption features

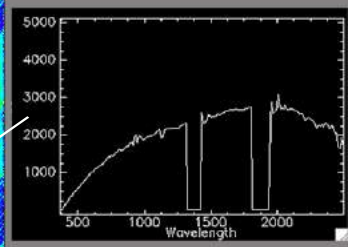
Allows for mapping of soil composition & moisture, vegetation health, leaf water content & moisture stress, N content...



NASA AVIRIS
Airborne Visible Infrared Imaging Spectrometer

224 channels x 10 nm

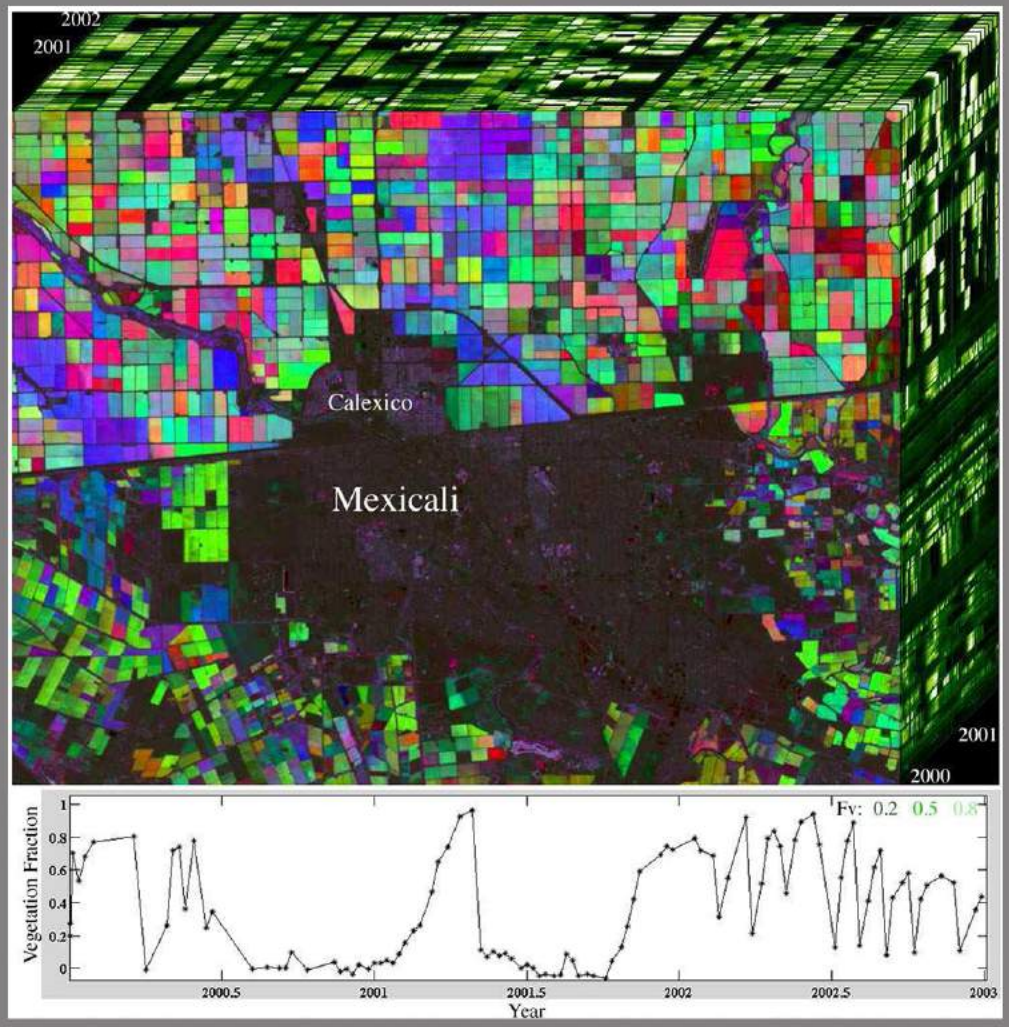




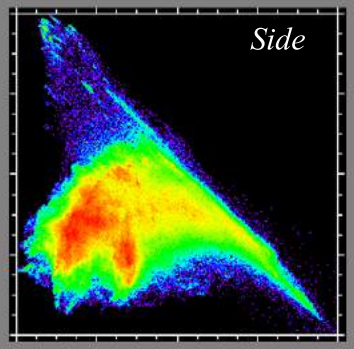
High Frequency Revist Satellite Constellations

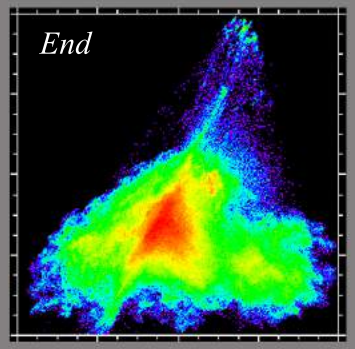
Temporal evolution of visible+infrared spectral characteristics allow process mapping

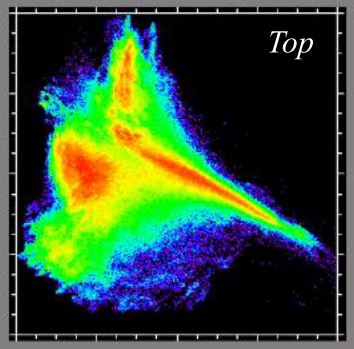
SpectroTemporal feature spaces are higher dimensional, more complex and more strongly clustered than spectral feature spaces. High dimensional characterization of change patterns



Landsat + Sentinel
SpectroTemporal Feature Space







Point Density
Lower Higher