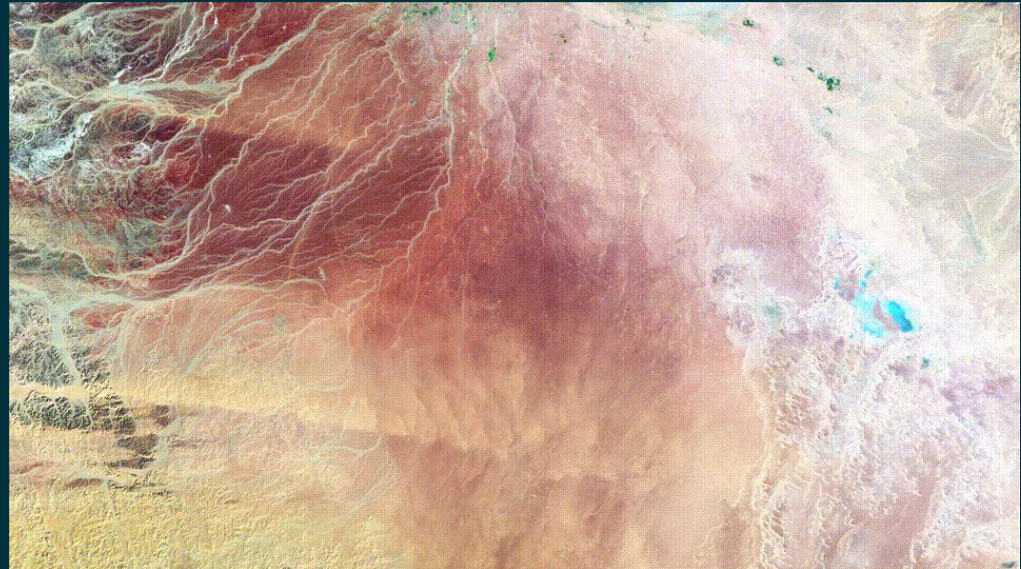


Geospatial Impact Evaluation

: remote sensing of agriculture & environment

Dr. Kunwar K. Singh
Geospatial Scientist & Affiliate Faculty

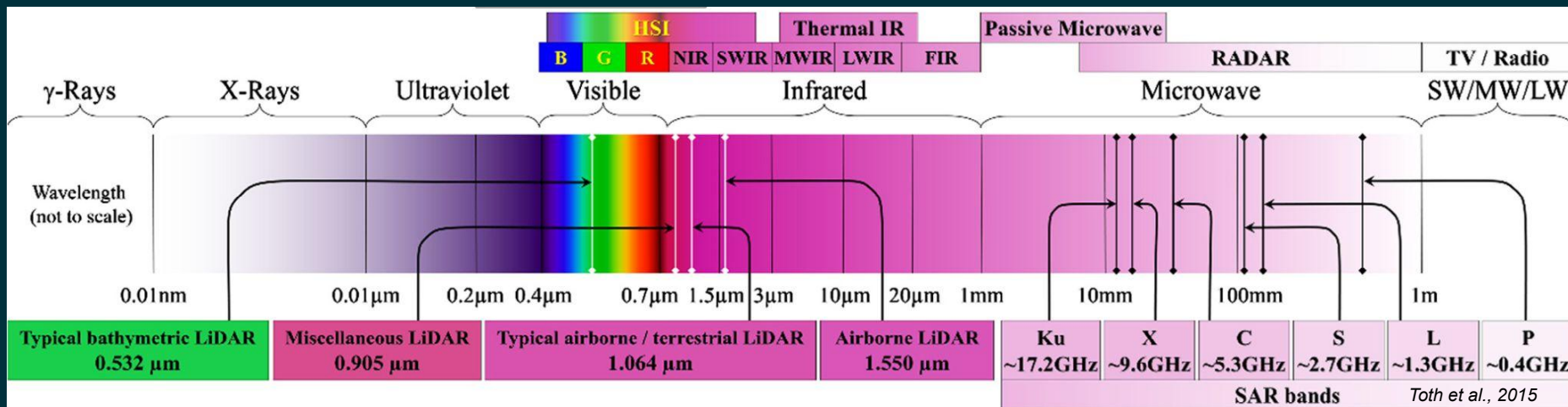
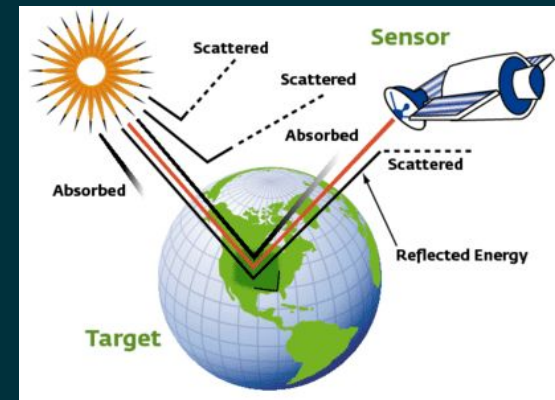


AIDDATA

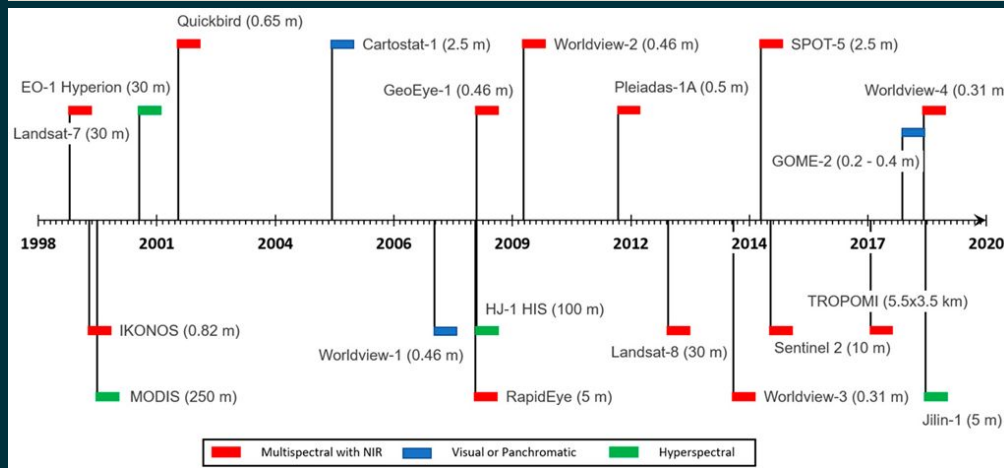
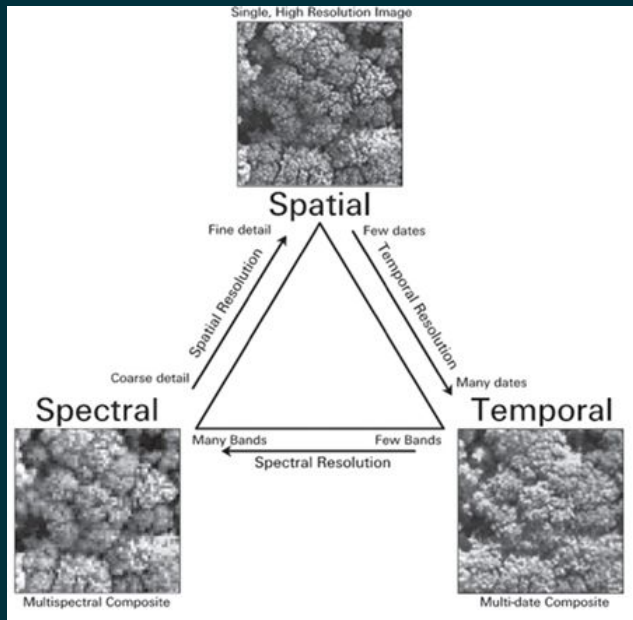
A Research Lab at William & Mary

: remote sensing - concept, resolution, and sensors

- remote sensing schematic
- electromagnetic spectrum
- resolution and sensors

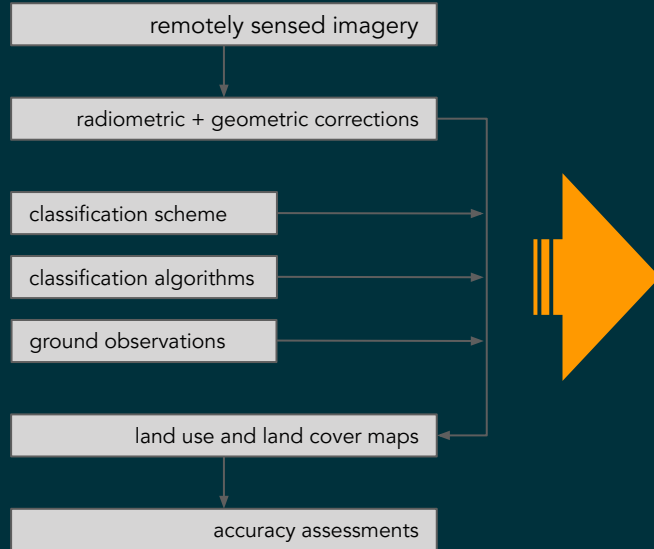


: remote sensing - *concept, resolution, and sensors*



- trade-offs in remote sensing resolution

: remote sensing - land use and land cover mapping



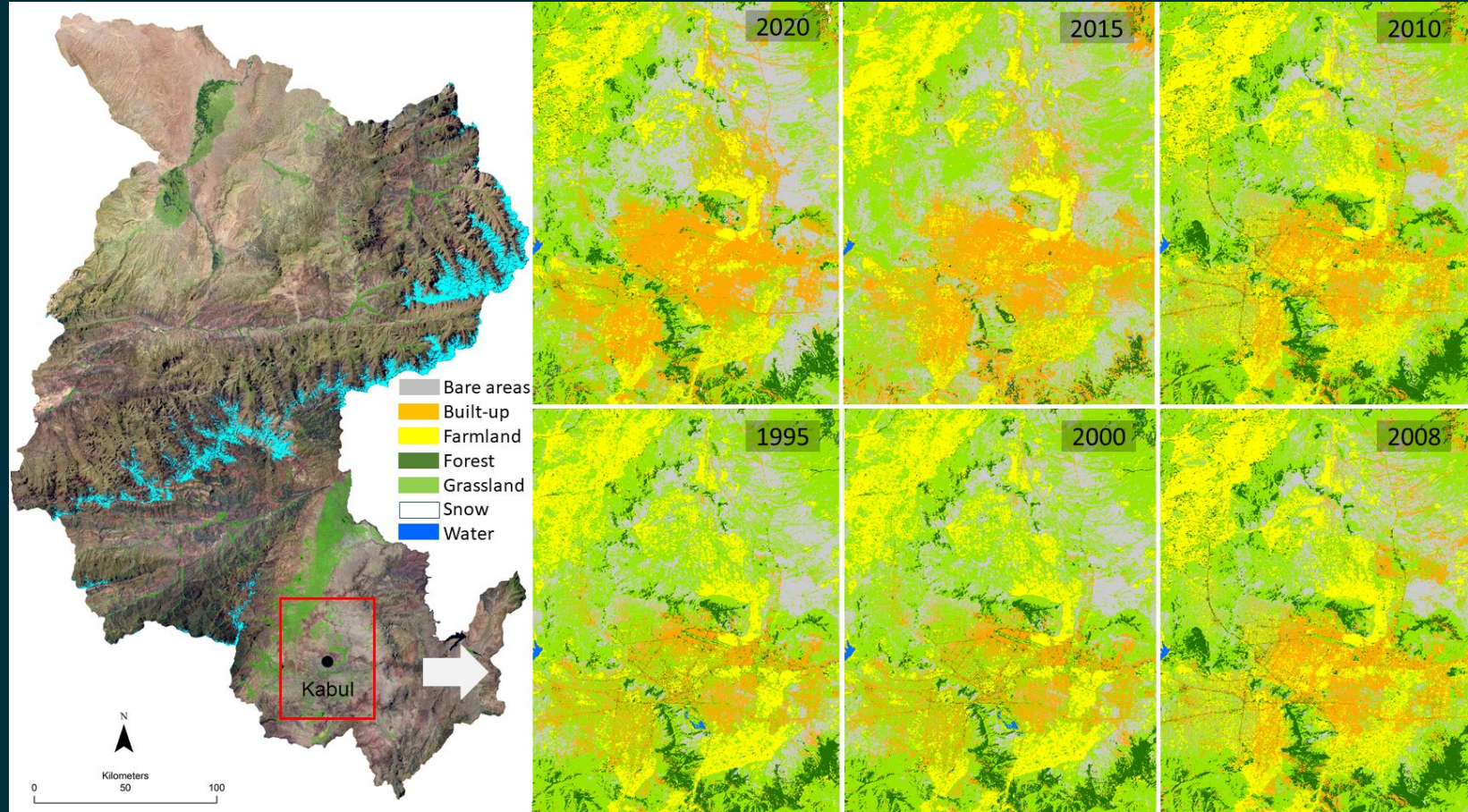
mapping workflow

Algorithm	Example	Data	Variables	OCA
Artificial Neural Network	Single date map (1987) Global (Gopal et al., 1999) Fuzzy ARTMAP	AVHRR (1°) Intra-annual series: monthly composites	Spectral parameters NDVI Latitude	0.85
	Single date map (2002) Regional: China (Bagan et al., 2005) Self-Organizing Map	MODIS (500 m) Intra-annual series: Growing season 16-day composites (17 dates)	Spectral parameters EVI	0.91
	Series of maps (1972–1988) Regional: Australia (Furby et al., 2008) Bayesian Network	Landsat (25 m)	Spectral parameters	Not reported
Clustering	Single date map (1992) Regional: Conterminous US NLCD 1992 (Vogelmann et al., 2001) CLUSTER	Landsat (30 m) (leaf-on and leaf-off mosaics)	Spectral parameters (reflectance, NDVI) Ancillary parameters (elevation, slope, aspect, pop. density)	0.6–0.8
	Single date map (2000) Regional: Africa GLC2000 (Mayaux et al., 2004)	SPOT 4VEGETATION (1000 m) Intra-annual series: 10-day and monthly composites	Statistical metrics (maximum monthly NDVI, third lowest albedo index)	Not reported
	Single date map (2000) Regional: Temperate East Asia (Boles et al., 2004) ISODATA	SPOT 4 VEGETATION (1000 m) Intra-annual series: 10-day composites during growing season (27 dates)	Spectral parameters (LSWI, EVI)	0.6
Decision Tree	Series of seven maps (1993–2008) Regional: Mexico (Gebhardt et al., 2014)	Landsat (30 m) All yearly images per scene (964–5706 images) 135 scenes	Statistical metrics NDVI, EVI, SR, ARVI, 6TCT (maximum, minimum, range, average, standard deviation) Spectral parameters (reflectance, TCT, thermal)	0.76
	Single date map (2001) Regional: Conterminous US NLCD 2001 (Homer et al., 2004)	Landsat (30 m) 3 seasonal: spring, summer, fall Nominal year 2001	Spectral parameters (reflectance, TCT, thermal) Topographic parameters	0.85
	Single date map (1987) Global (Friedl and Brodley, 1997)	AVHRR (1°) Intra-annual series: monthly composites	Spectral parameters (maximum monthly NDVI) Latitude	0.88
Ensemble (same base classifier)	Single date map (2000) Global MODIS Collection 4 Land Cover product (Friedl et al., 2002) Boosted decision tree	MODIS (1000 m) Intra-annual series: 16-day composites	Spectral parameters (reflectance, EVI, LST, texture, water mask) Topographic parameters	~0.75
	Series of annual maps (2001–2012) Global MODIS Collection 5 Land Cover product (Friedl et al., 2010) Boosted decision tree	MODIS (500 m) Multiple intra-annual series: 32-day composites	Spectral parameters (reflectance, EVI, LST) Statistical metrics (minimum, maximum, mean annual)	0.75
	Series of annual maps (2001–2010) Regional: Latin America and Caribe (Clark et al., 2012) Random Forest	MODIS (250 m) Multiple intra-annual series: 16-day composites	Statistical metrics (maximum, minimum, range, standard deviation of 3-, 6-, and 12-month periods) (reflectance, NDVI, EVI)	0.85
Gaussian Maximum Likelihood	Single date map Regional: Eurasia (Rádoux et al., 2014)	MERIS (300 m) Multi-annual (2008–2012) series: 7-day composites	Spectral parameters (reflectance, summer and autumn composites)	0.82
	Single date map (2013) Regional: China (partial) (Jia et al., 2014a)	Fused Landsat – MODIS Intra-annual series: 16-day composites	Statistical metrics (phenology) NDVI (growing season: begin, end, length, amplitude, maximum)	0.95
	Single date map (1987) Global (DeFries and Townshend, 1994)	AVHRR (1°) Intra-annual series: monthly composites	Spectral parameters NDVI Latitude	0.78
Support Vector Machine	Single date map (2000) Regional: Portugal (Gonçalves et al., 2005)	MODIS (500 m) Intra-annual series: 8-day composites	Shape stationary (parameters)	0.78
	Single date map (2000) Regional: Portugal (Carrão et al., 2008)	MODIS (500 m) Intra-annual series: 43 composites	Spectral parameters (Reflectance, NDVI, EVI)	0.88
	Single date map (2003) Regional: Wisconsin (Dash et al., 2007)	MERIS (300 m) Two images: August, September	Spectral parameters Vegetation indices: MGVI, MTCI	0.73

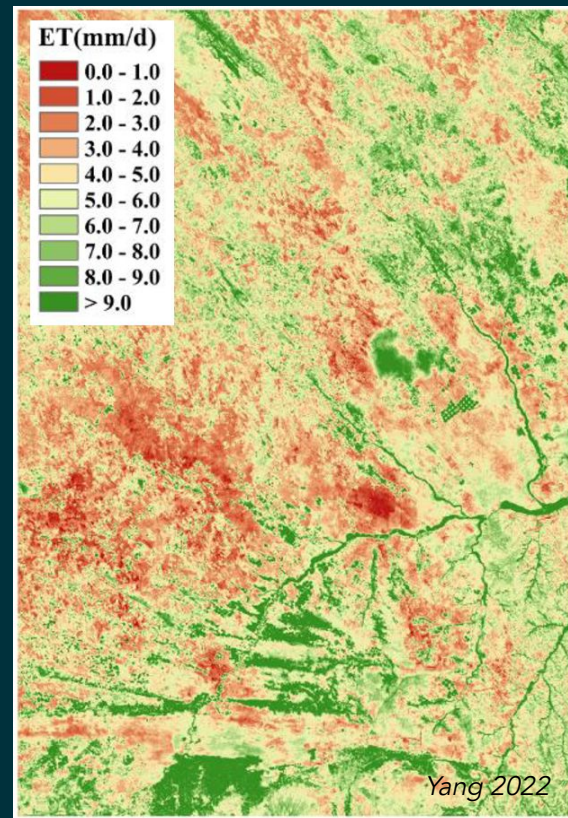
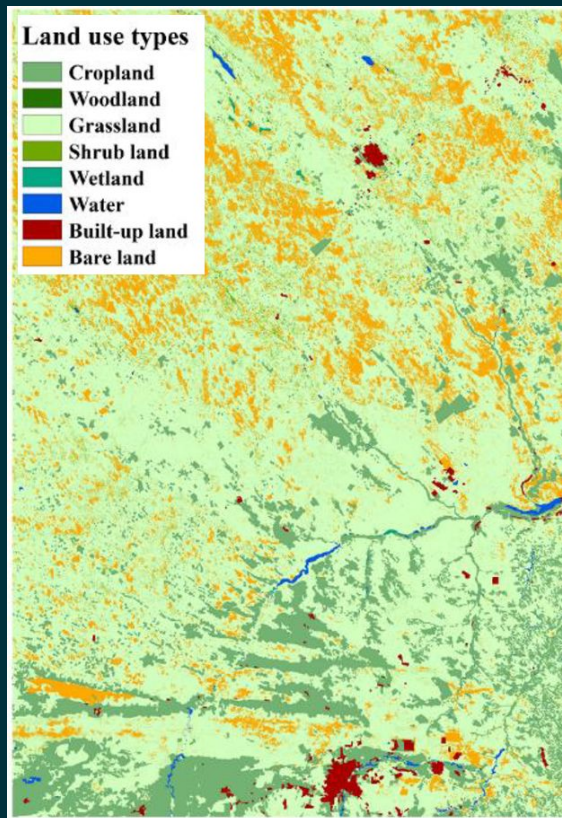
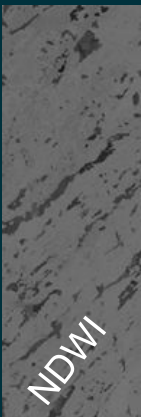
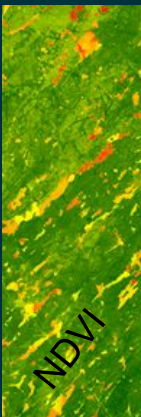
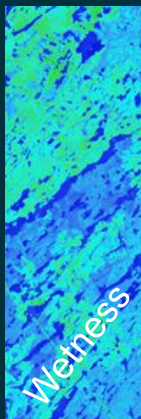
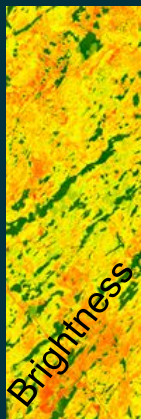
: remote sensing - land use and land cover mapping

Algorithm	Strengths/characteristics	Weaknesses
<i>Artificial Neural Networks</i> Non-parametric	<ul style="list-style-type: none"> • Manage well large feature space • Indicate strength of class membership • Generally high classification accuracy • Resistant to training data deficiencies—requires less training data than DT 	<ul style="list-style-type: none"> • Needs parameters for network design • Tends to overfit data • Black box (rules are unknown) • Computationally intense • Slow training
<i>Clustering</i> (partitioning)	<ul style="list-style-type: none"> • Do not need previous knowledge • Do not need samples 	<ul style="list-style-type: none"> • Cluster-class correspondence not assured • Complex identification of classes • Computationally intense
<i>Decision trees</i> Non-parametric	<ul style="list-style-type: none"> • No need of any kind of parameter • Easy to apply and interpret • Handle missing data • Handle data of different types (e.g. continuous, categorical) and scales • Handle non-linear relationships • Insensitive to noise 	<ul style="list-style-type: none"> • Sensitive to noise • Tend to overfit • Not as good as others in large feature spaces • Large training sample needed
<i>Gaussian Maximum likelihood</i> Parametric	<ul style="list-style-type: none"> • Simple application • Easy to understand and interpret • Predicts class membership probability 	<ul style="list-style-type: none"> • Parametric • Assumes normal distribution of data • Large training sample needed
<i>Support Vector Machines</i> Non-parametric	<ul style="list-style-type: none"> • Manages well large feature space • Insensitive to Hughes effect • Works well with small training dataset • Does not overfit 	<ul style="list-style-type: none"> • Needs parameters: regularization and kernel • Poor performance with small feature space • Computationally intense • Designed as binary, although variations exist
<i>Random Forests</i> Non-parametric	<ul style="list-style-type: none"> • Capacity to determine variable importance • Robust to data reduction • Does not over-fit • Produces unbiased accuracy estimate • Higher accuracy than DT 	<ul style="list-style-type: none"> • Decision rules unknown (black box) • Computationally intense • Needs input parameters (#trees and #variables per node)
<i>Bagging</i>	<ul style="list-style-type: none"> • Provides measures of classification confidence • Does not overfit 	<ul style="list-style-type: none"> • Complex incomprehensible classifiers
<i>Boosting</i>	<ul style="list-style-type: none"> • Provides measures of classification confidence • Does not overfit • Robust to noise 	<ul style="list-style-type: none"> • Stops if a classifier achieves zero training set error • Complex incomprehensible classifiers • Ineffective if excessive error in training sample

: remote sensing - *land use and land cover mapping*

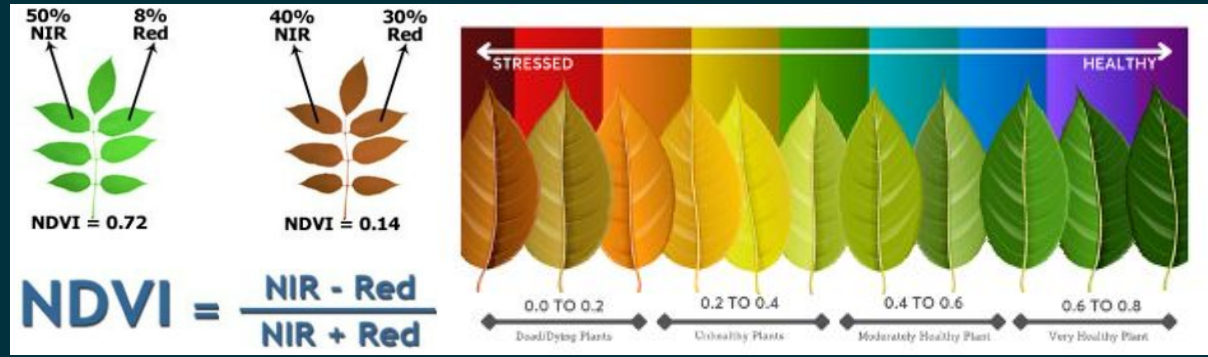


: remote sensing - *land use and land cover mapping*

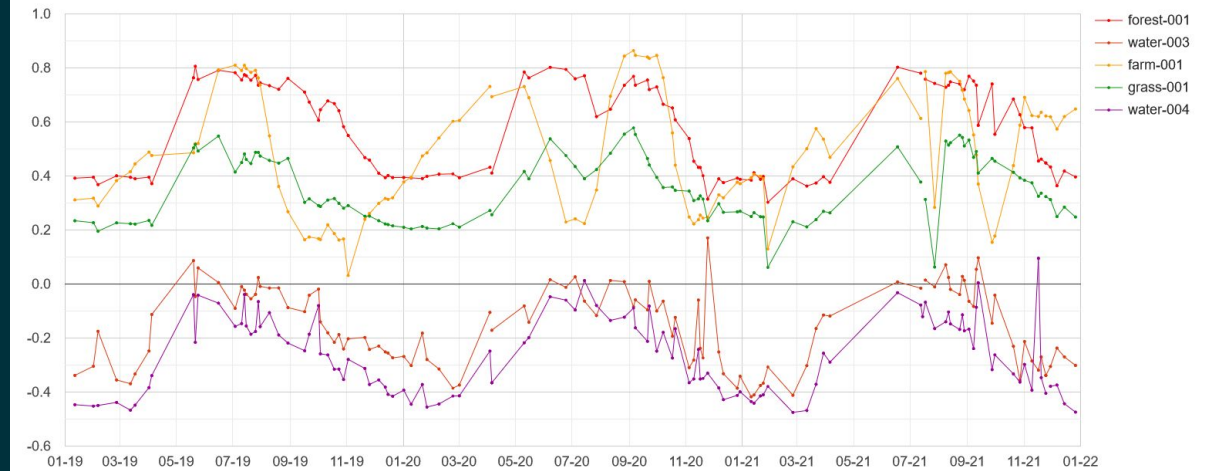


: remote sensing - vegetation indices

normalized difference
vegetation index



NDVI values



dates

Geospatial Impact Evaluation

: remote sensing and google earth engine



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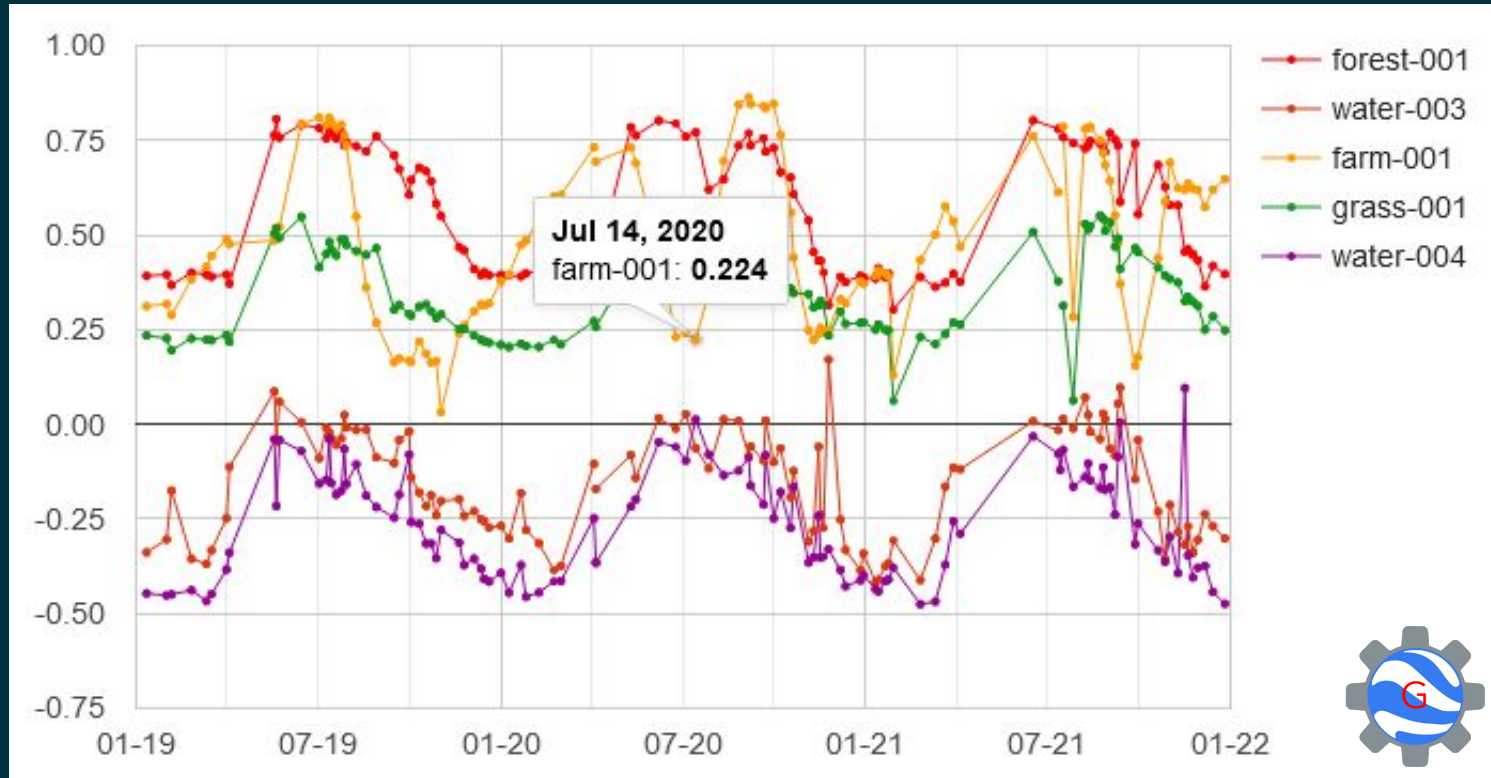
: remote sensing - google earth engine

The image shows a screenshot of the Google Earth Engine web interface with several components annotated by arrows and text labels:

- Search for datasets or places**: Points to the search bar at the top.
- Script manager**: Points to the 'Scripts' tab on the left sidebar.
- API documentation**: Points to the 'Docs' tab on the left sidebar.
- Asset manager**: Points to the 'Assets' tab on the left sidebar.
- Get a link (URL) to the script**: Points to the 'Get Link' button above the code editor.
- Save the script**: Points to the 'Save' button above the code editor.
- Run the script**: Points to the 'Run' button above the code editor.
- Help button**: Points to the help icon in the top right corner.
- Feedback button**: Points to the feedback icon in the top right corner.
- Code Editor**: A large central text label pointing to the code editor window.
- Inspector**: Points to the 'Inspector' tab on the right sidebar.
- Console output**: Points to the 'Console' tab on the right sidebar.
- Task manager**: Points to the 'Tasks' tab on the right sidebar.
- Inspect locations, pixel values, objects on the map**: Points to the 'Inspector' and 'Console' tabs.
- Geometry Tools**: Points to the toolbar on the left side of the map.
- Zoom**: Points to the zoom controls on the left side of the map.
- Map**: A large central text label pointing to the map area.
- Layer manager**: Points to the 'Layers' panel on the right side of the map.

```
1 // This example uses the Sentinel-2 QA band to cloud mask
2 // the collection. The Sentinel-2 cloud flags are less
3 // selective, so the collection is also pre-filtered by t
4 // CLOUDY_PIXEL_PERCENTAGE flag, to use only relatively
5 // cloud-free granule.
6
7 // Function to mask Sentinel-2 QA band.
8 function mask(qa) {
9   var qa = Image(qa);
10
11   // Bits 10 and 11 are clouds and cirrus, respectively.
12   var cloudyMask = qa.bitwiseAnd(1023, qa).eq(0);
13   var cirrusMask = qa.bitwiseAnd(1024, qa).eq(0);
14
15   // Both flags are 1 indicating clear conditions.
16   var mask = qa.bitwiseAnd(cloudyMask, cirrusMask).eq(0);
17
18   // Return the masked and scaled data, without the QA band
19   return image.updateMask(mask, qa.divide(10000));
20 }
21
22 console.log(image.select("B4").mask(mask));
```

: remote sensing - google earth engine



GEE eg.: time series NDVI estimation