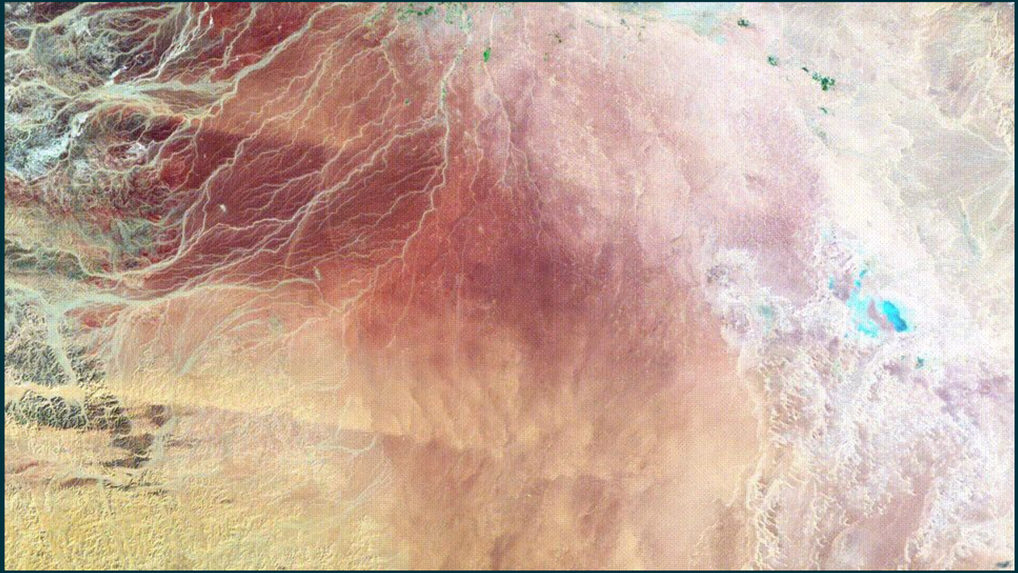
Geospatial Impact Evaluation

: remote sensing of agriculture & environment



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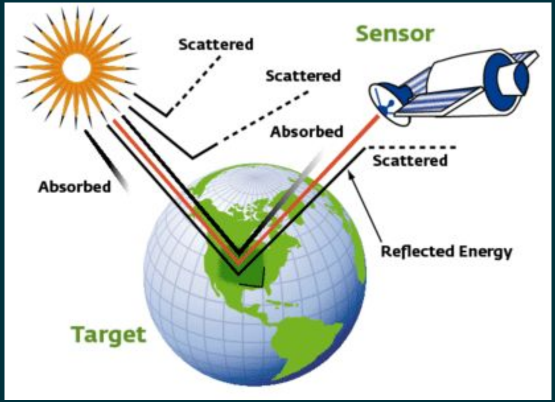
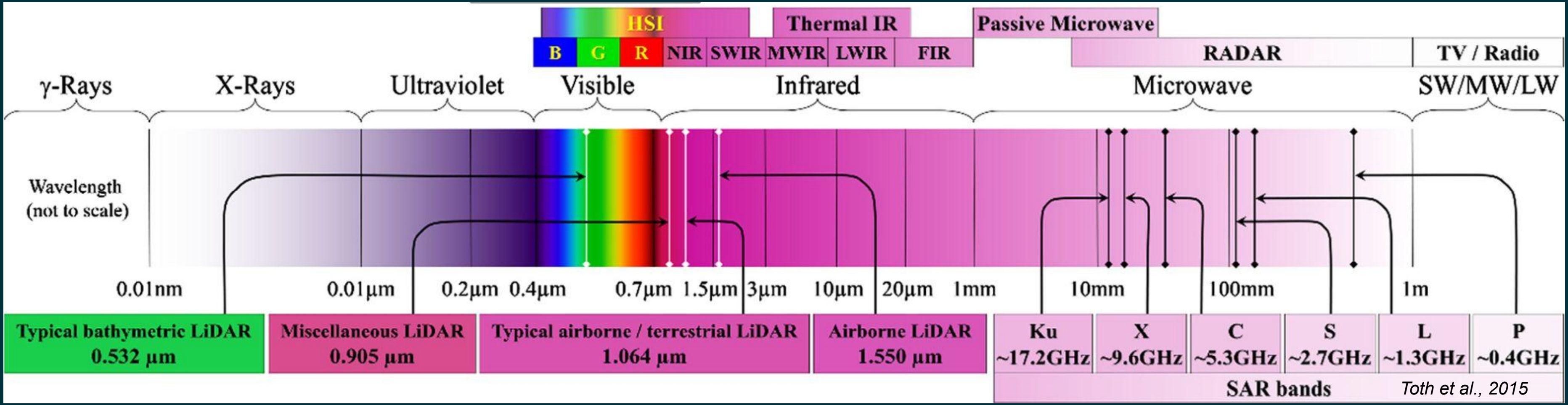
AIDDATA
A Research Lab at William & Mary

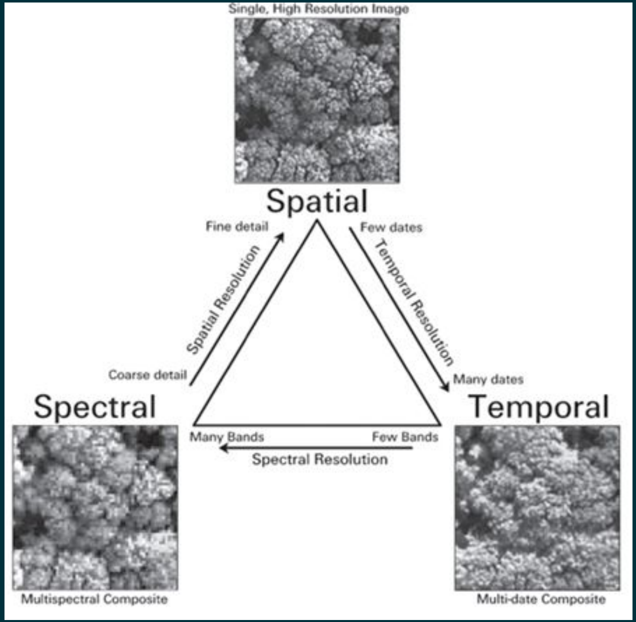
: remote sensing - *concept, resolution, and sensors*

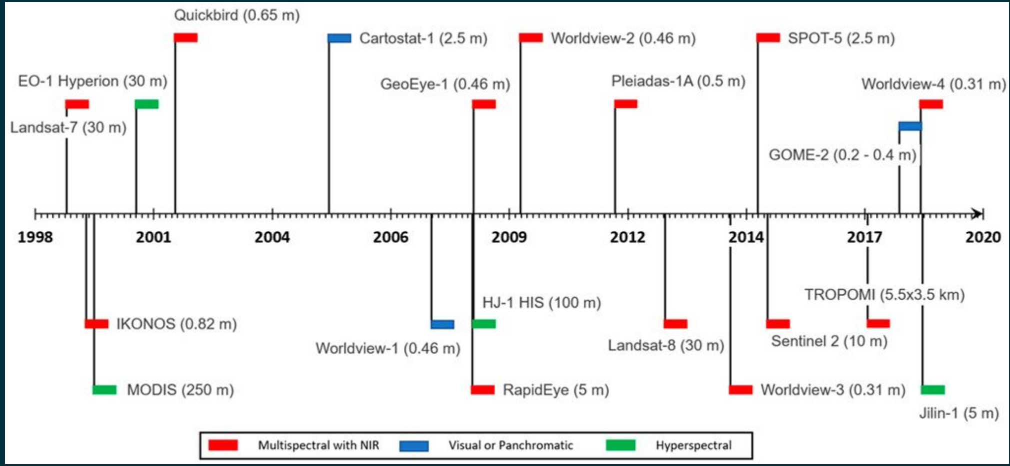
- remote sensing schematic
- electromagnetic spectrum
- resolution and sensors





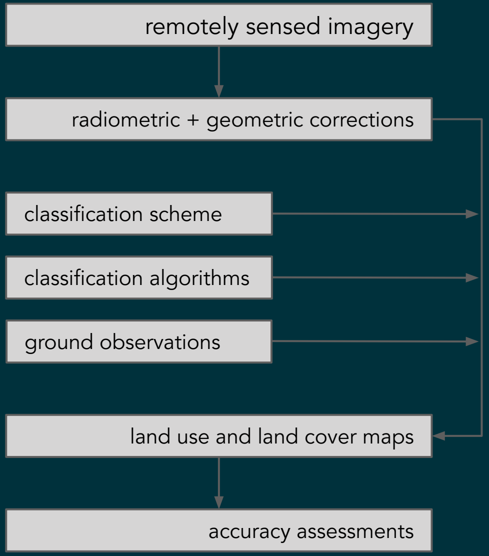
: remote sensing - *concept, resolution, and sensors*





- trade-offs in remote sensing resolution

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



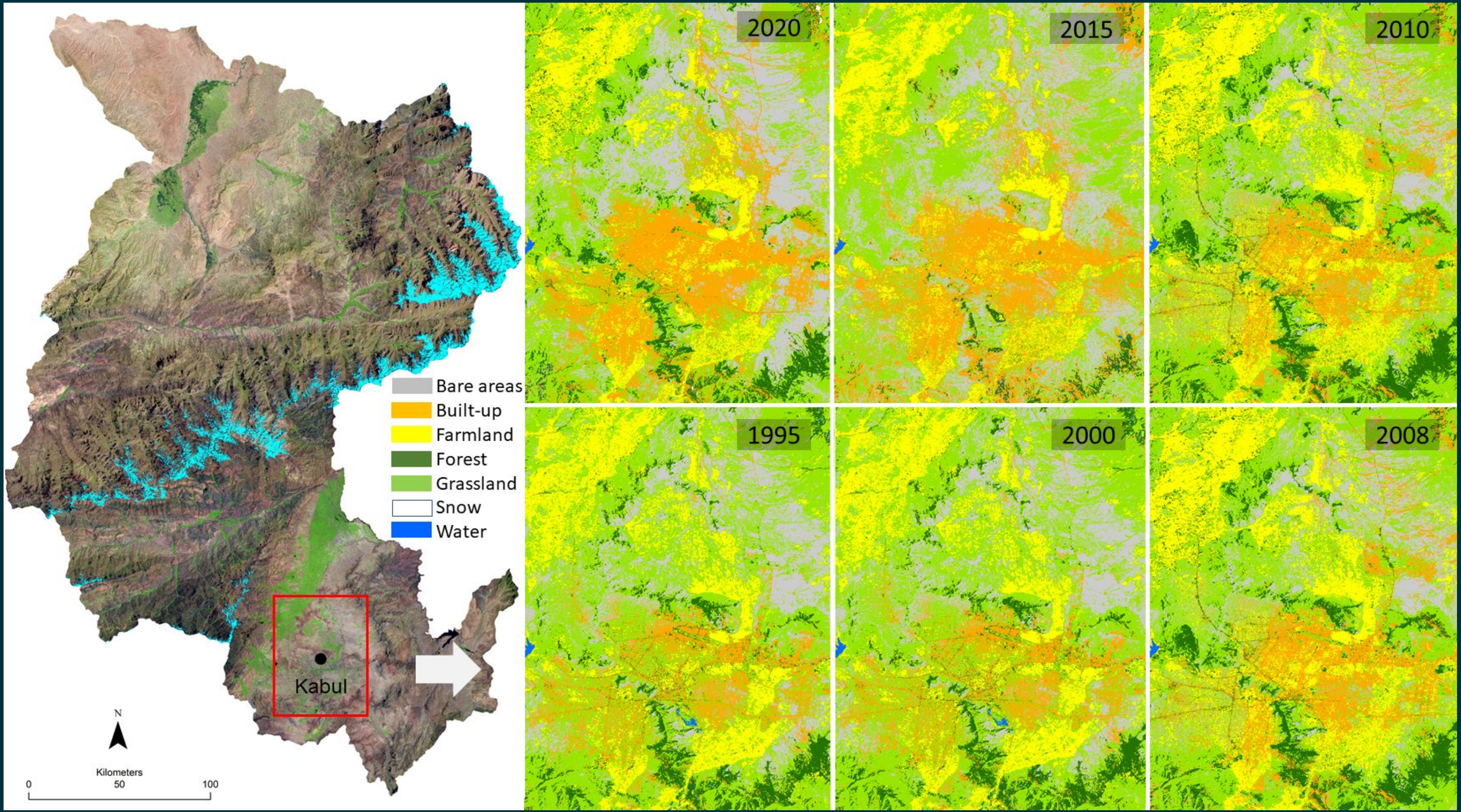
mapping workflow

Algorithm	Example			
	Area and product	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)	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 Broadley, 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 (Radoux 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

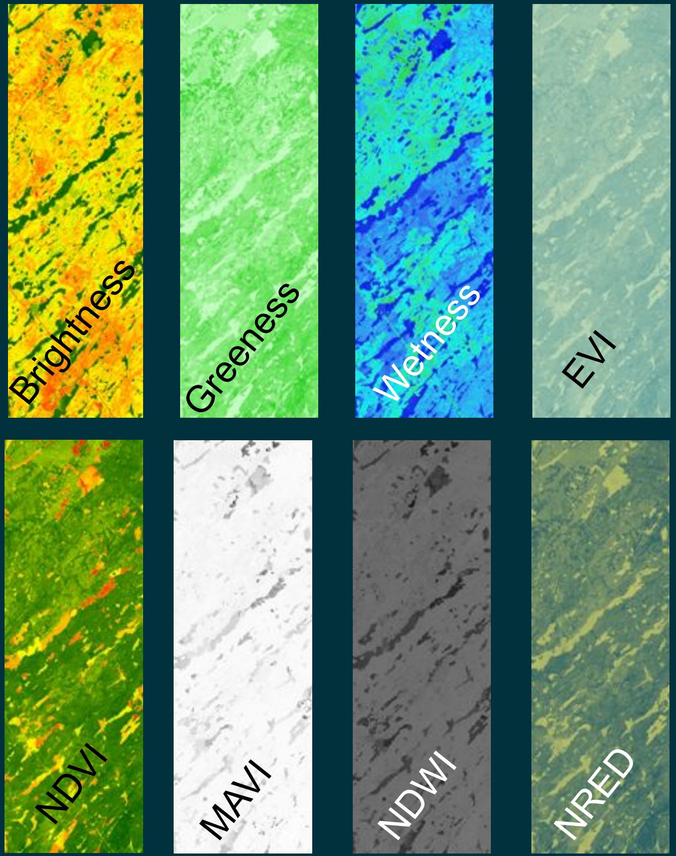
: remote sensing - *land use and land cover mapping*

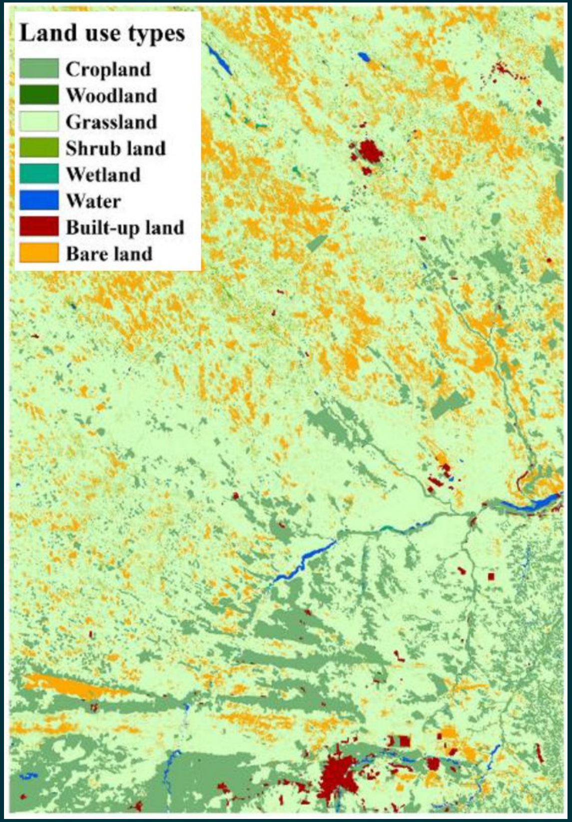
Algorithm	Strengths/characteristics	Weaknesses
Artificial Neural Networks Non-parametric	• Manage well large feature space • Indicate strength of class membership • Generally high classification accuracy • Resistant to training data deficiencies—requires less training data than DT	• Needs parameters for network design • Tends to overfit data • Black box (rules are unknown) • Computationally intense • Slow training
Clustering (partitioning)	• Do not need previous knowledge • Do not need samples	• Cluster-class correspondence not assured • Complex identification of classes • Computationally intense
Decision trees Non-parametric	• 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	• Sensitive to noise • Tend to overfit • Not as good as others in large feature spaces • Large training sample needed
Gaussian Maximum likelihood Parametric	• Simple application • Easy to understand and interpret • Predicts class membership probability	• Parametric • Assumes normal distribution of data • Large training sample needed
Support Vector Machines Non-parametric	• Manages well large feature space • Insensitive to Hughes effect • Works well with small training dataset • Does not overfit	• Needs parameters: regularization and kernel • Poor performance with small feature space • Computationally intense • Designed as binary, although variations exist
Random Forests Non-parametric	• Capacity to determine variable importance • Robust to data reduction • Does not over-fit • Produces unbiased accuracy estimate • Higher accuracy than DT	• Decision rules unknown (black box) • Computationally intense • Needs input parameters (#trees and #variables per node)
Bagging	• Provides measures of classification confidence • Does not overfit	• Complex incomprehensible classifiers
Boosting	• Provides measures of classification confidence • Does not overfit • Robust to noise	• Stops if a classifier achieves zero training set error • Complex incomprehensible classifiers • Ineffective if excessive error in training sample

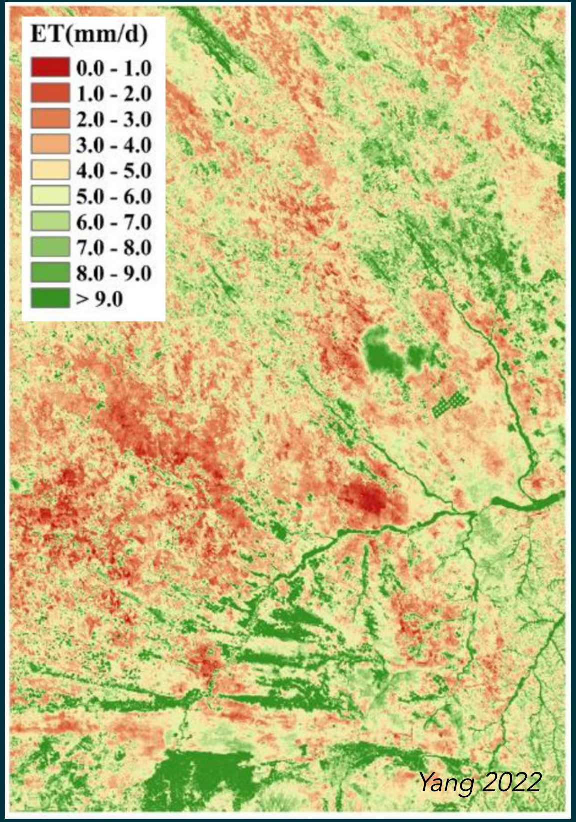
: remote sensing - *land use and land cover mapping*



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

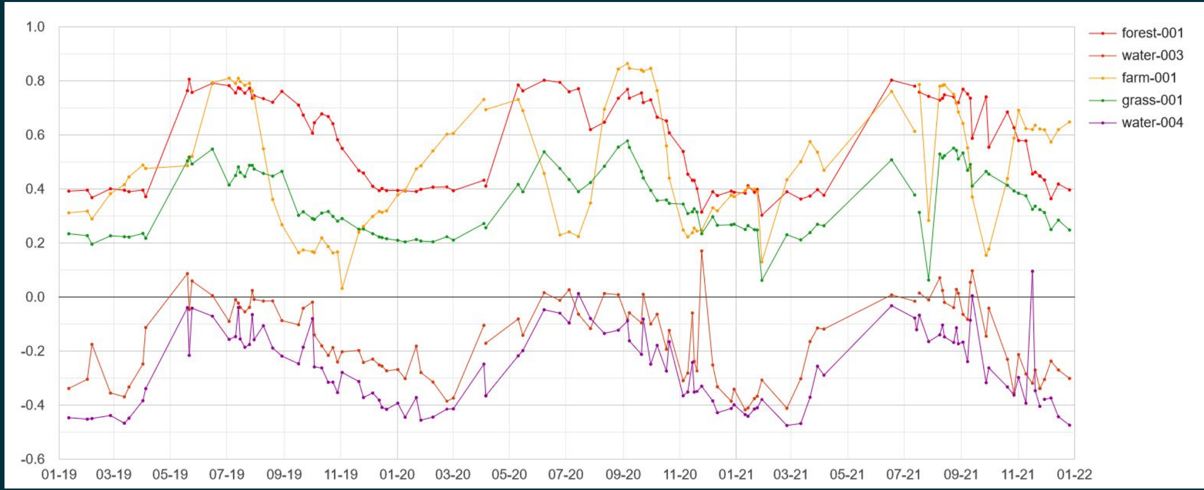






: remote sensing - *vegetation indices*

normalized difference vegetation index



NDVI values

dates

Geospatial Impact Evaluation

: remote sensing and google earth engine

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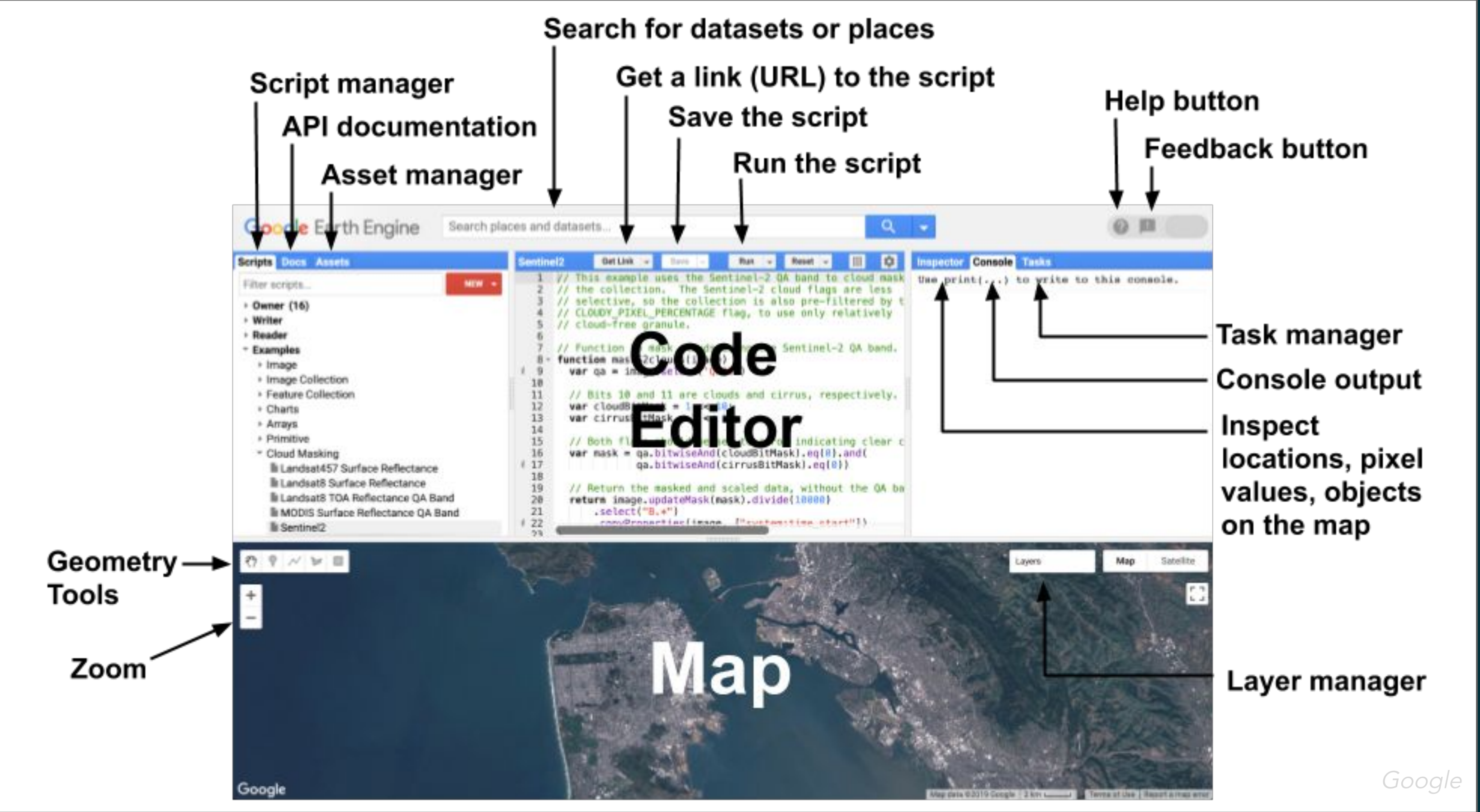
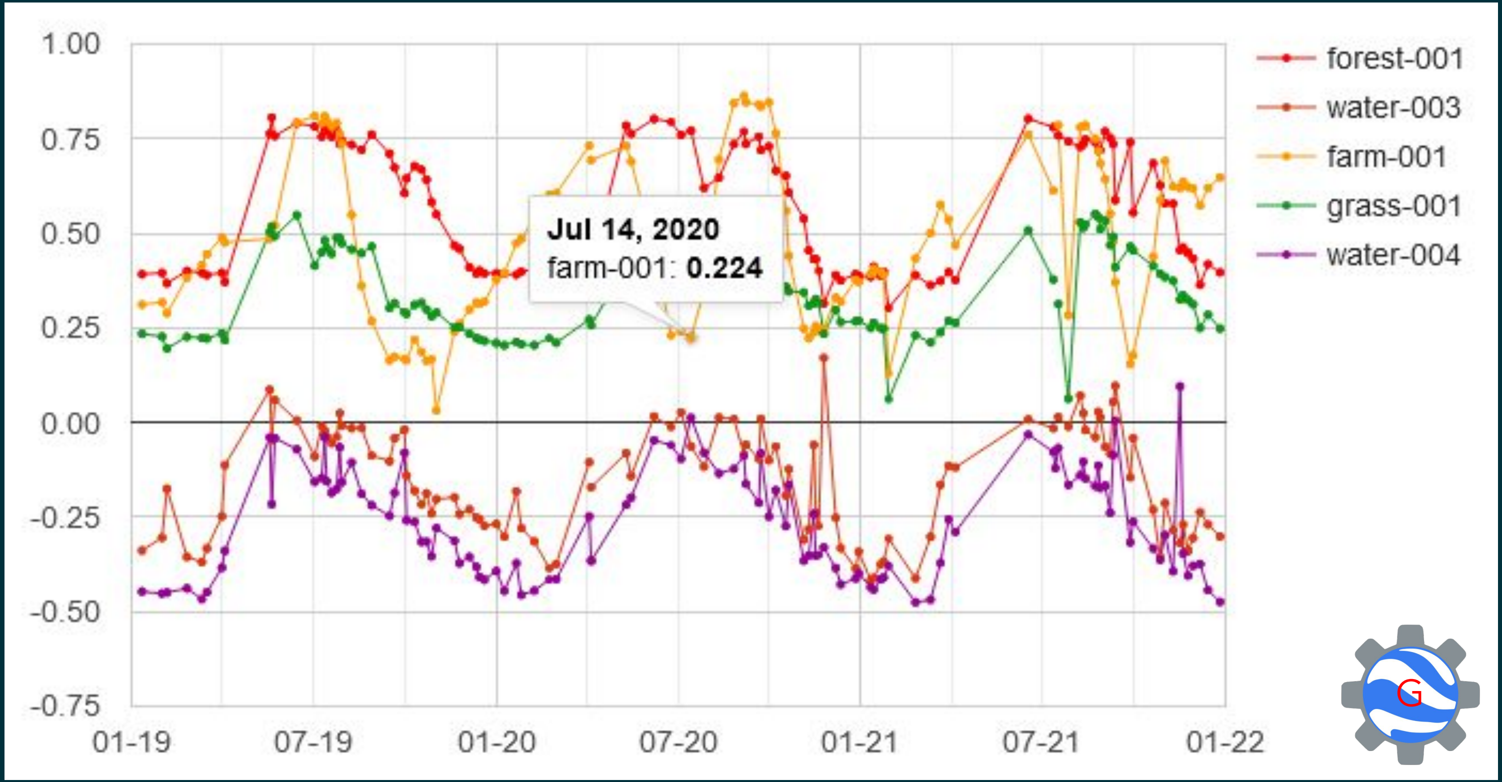
: remote sensing - *google earth engine*



Google

: remote sensing - *google earth engine*



GEE eg.: time series NDVI estimation