

Using SOM neural network to improve land use and cover training samples from satellite image time series

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*Continuous Monitoring of Our Changing Planet:
From Sensors to Decisions*





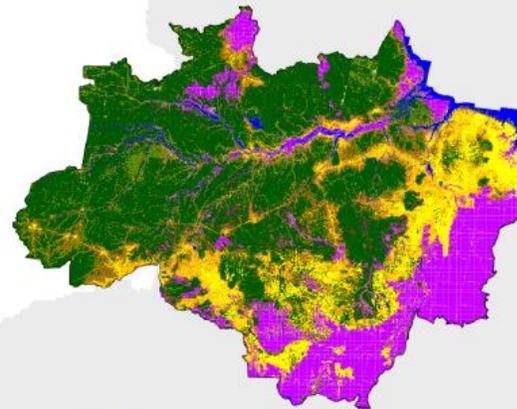
Brazil National Institute for Space Research (INPE)

We produce the official land use and cover information in Brazil using Earth Observation Data (EO).

So far, we are using **methods** based on visual interpretation of remote sensing imagery.

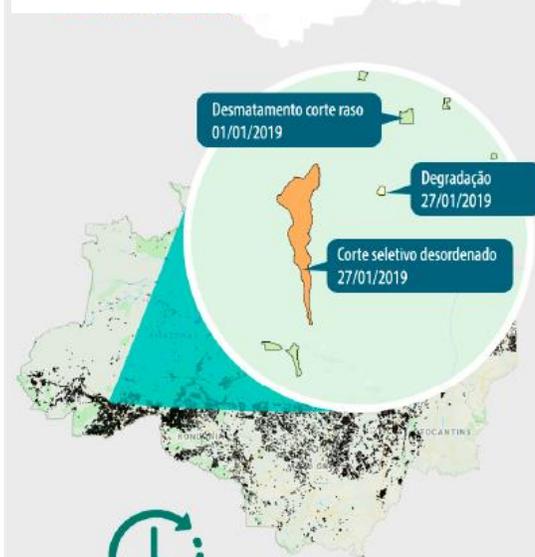


Deforestation accounting
SINCE 1988



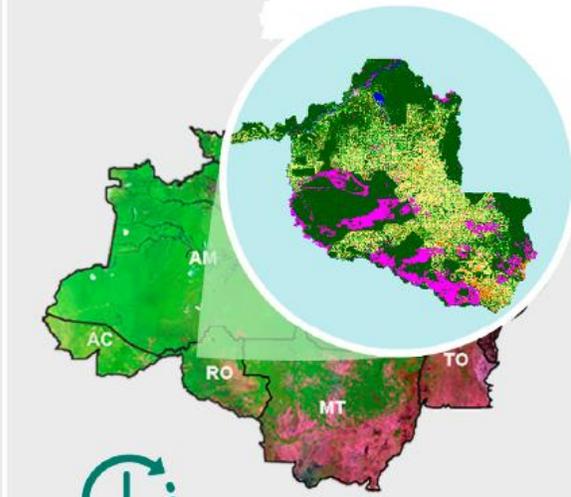
Annual maps

Deforestation monitoring
SINCE 2004



Daily alerts

Land use following in deforested areas
SINCE 2004



Biannual maps





Brazil National Institute for Space Research (INPE)

Projects

e-Sensing: to move from EO visual interpretation to **semi automatic classification** based on **machine learning**.

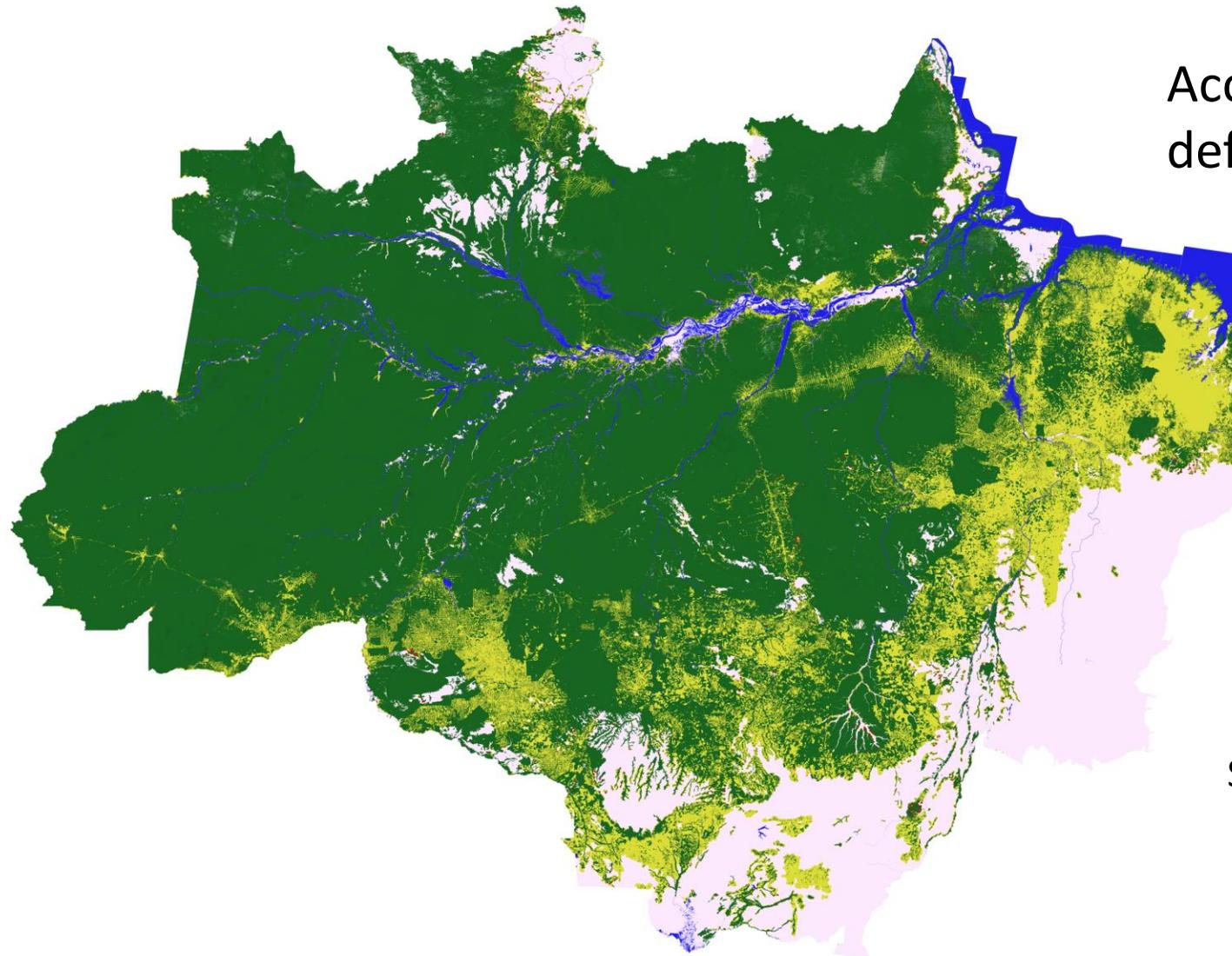
Brazil Data Cube: to produce, process and analyze **big Earth observation data sets** for land use and cover change detection.



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Why should we care about mapping land use?

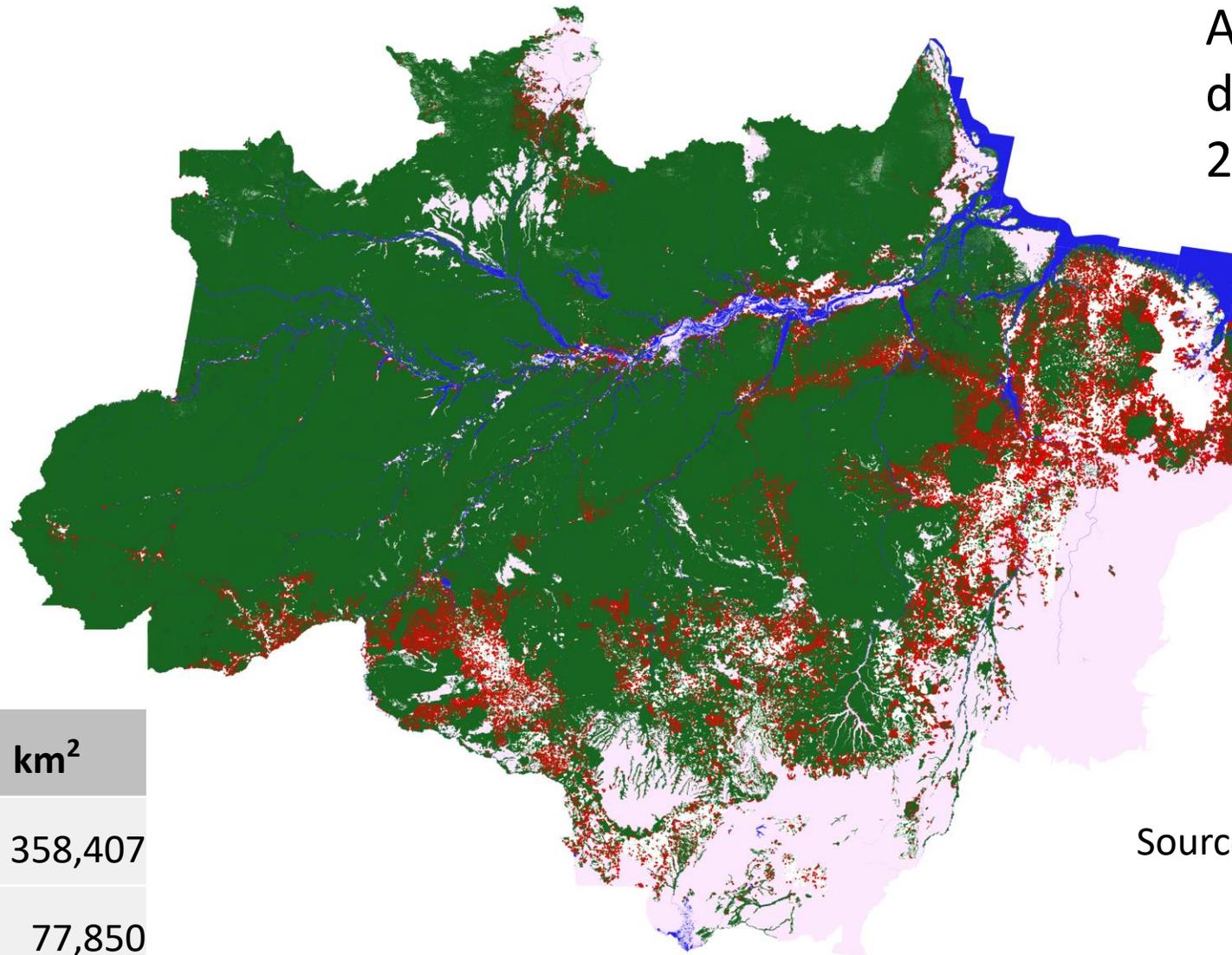


Accumulated
deforestation in 2007

Source: PRODES



Accumulated
deforestation from
2008 to 2018



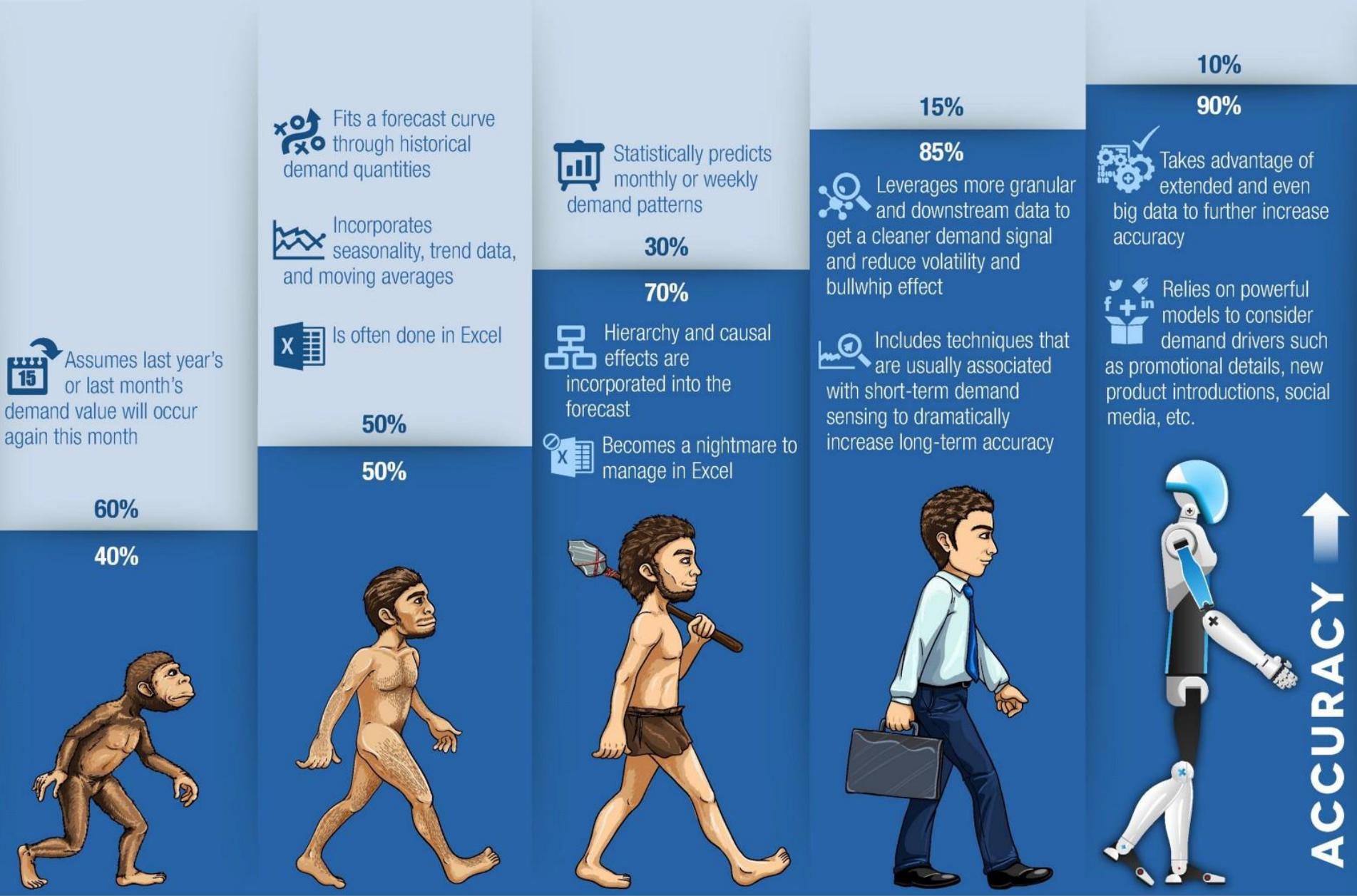
Source: PRODES

Deforestation	km ²
Until 2007	358,407
From 2008 to 2018	77,850

Forest
Deforestation until 2007
Deforestation 2008_2018
No Forest
Hydrography

Machine Learning

ERROR
↓



Assumes last year's or last month's demand value will occur again this month

Fits a forecast curve through historical demand quantities

Incorporates seasonality, trend data, and moving averages

Is often done in Excel

Statistically predicts monthly or weekly demand patterns

Hierarchy and causal effects are incorporated into the forecast

Becomes a nightmare to manage in Excel

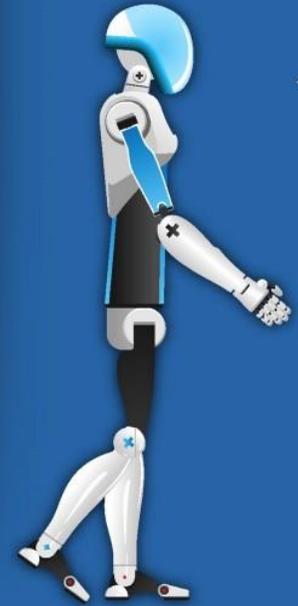
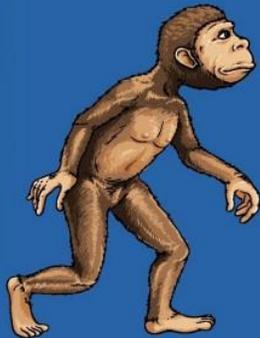
Leverages more granular and downstream data to get a cleaner demand signal and reduce volatility and bullwhip effect

Includes techniques that are usually associated with short-term demand sensing to dramatically increase long-term accuracy

Takes advantage of extended and even big data to further increase accuracy

Relies on powerful models to consider demand drivers such as promotional details, new product introductions, social media, etc.

Purely reactive



ACCURACY
↑

Our analysis as good as our data



by Gary Locke

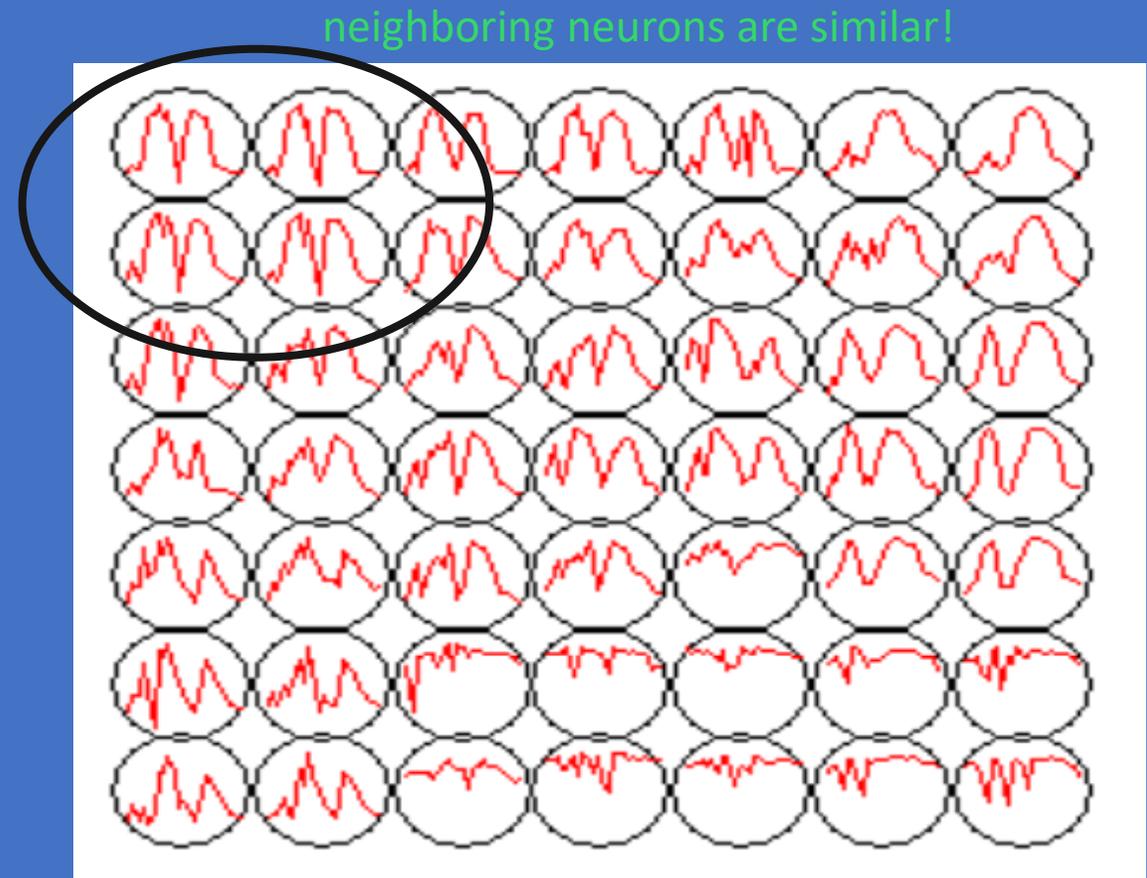
How do we improve the
samples?

Self-Organizing Maps (SOM) neural network method to cluster

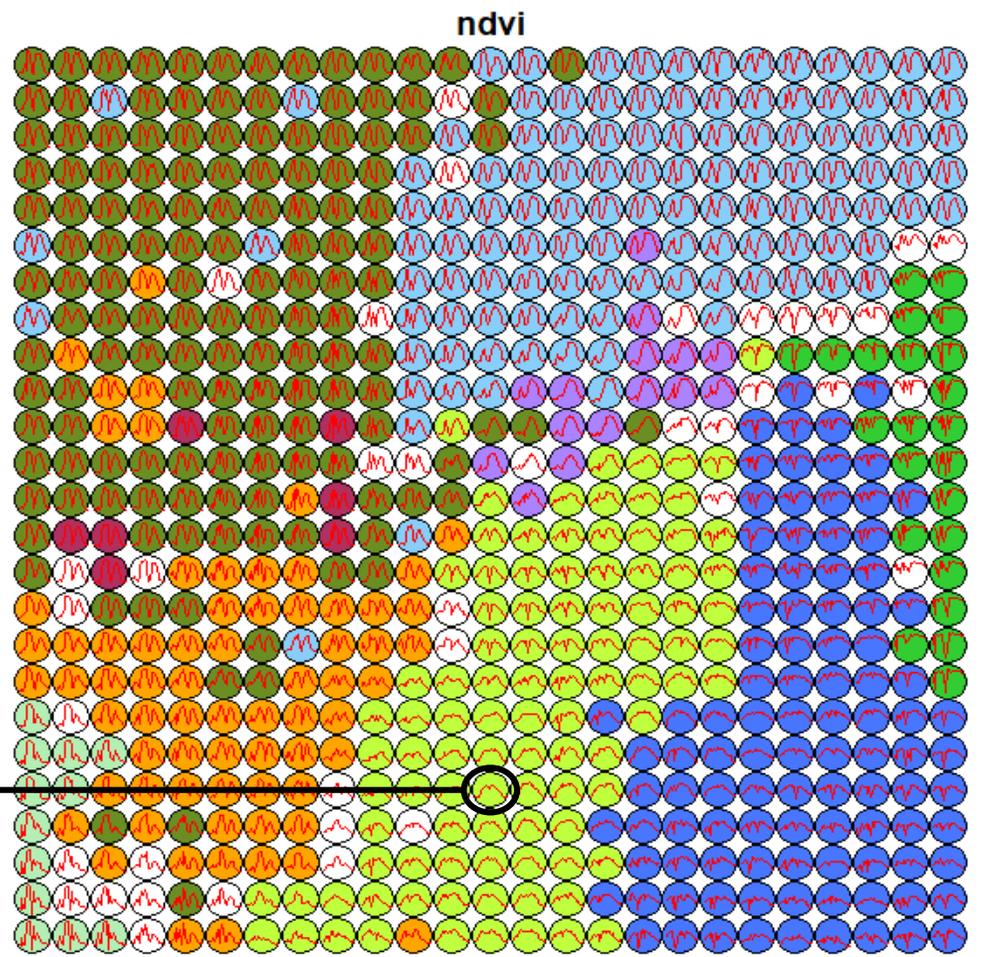
To improve the quality of the training sets for the machine learning classifiers.

To evaluate which spectral bands and vegetation indexes are best suited for splitting among land use-cover classes.

SOM generates spatial clusters of similar patterns.



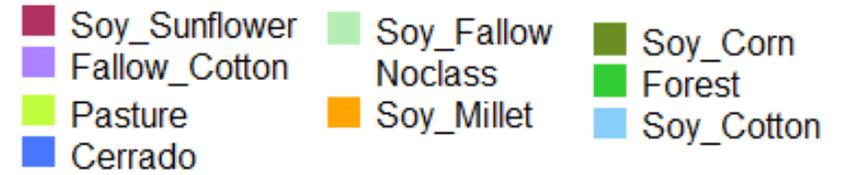
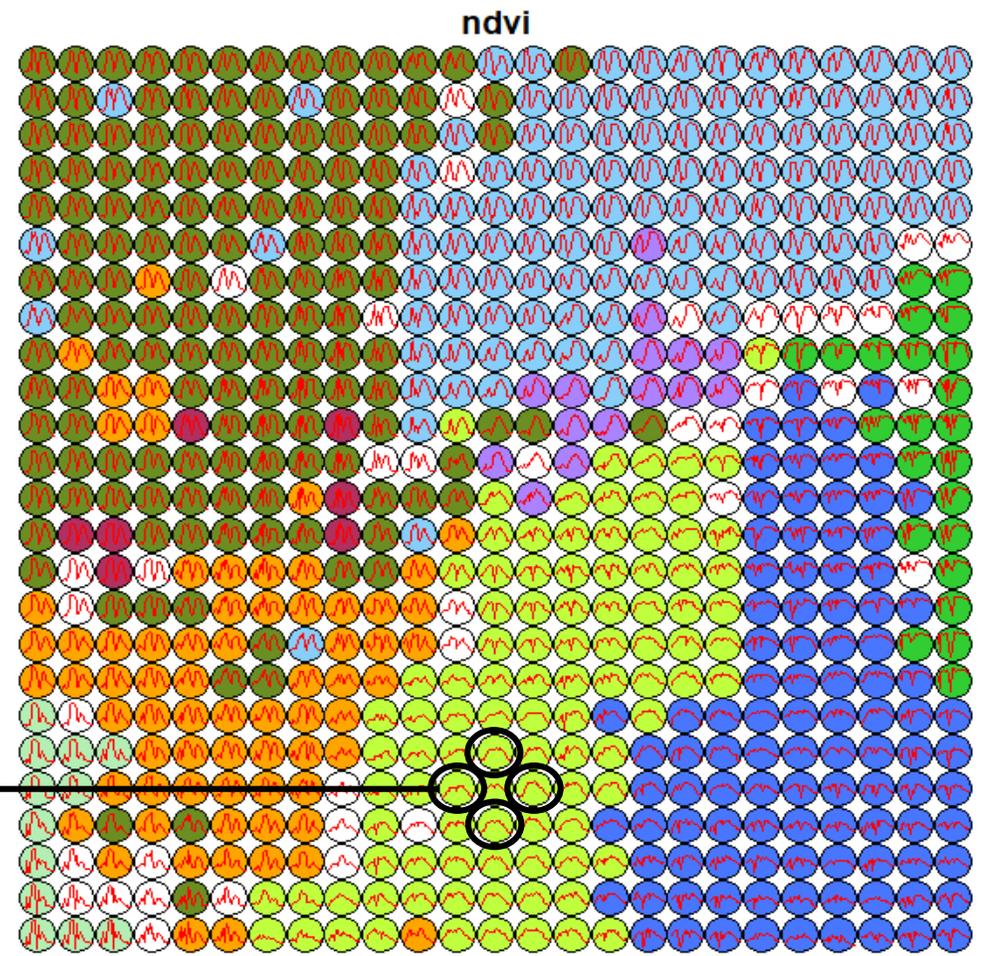
Neuron



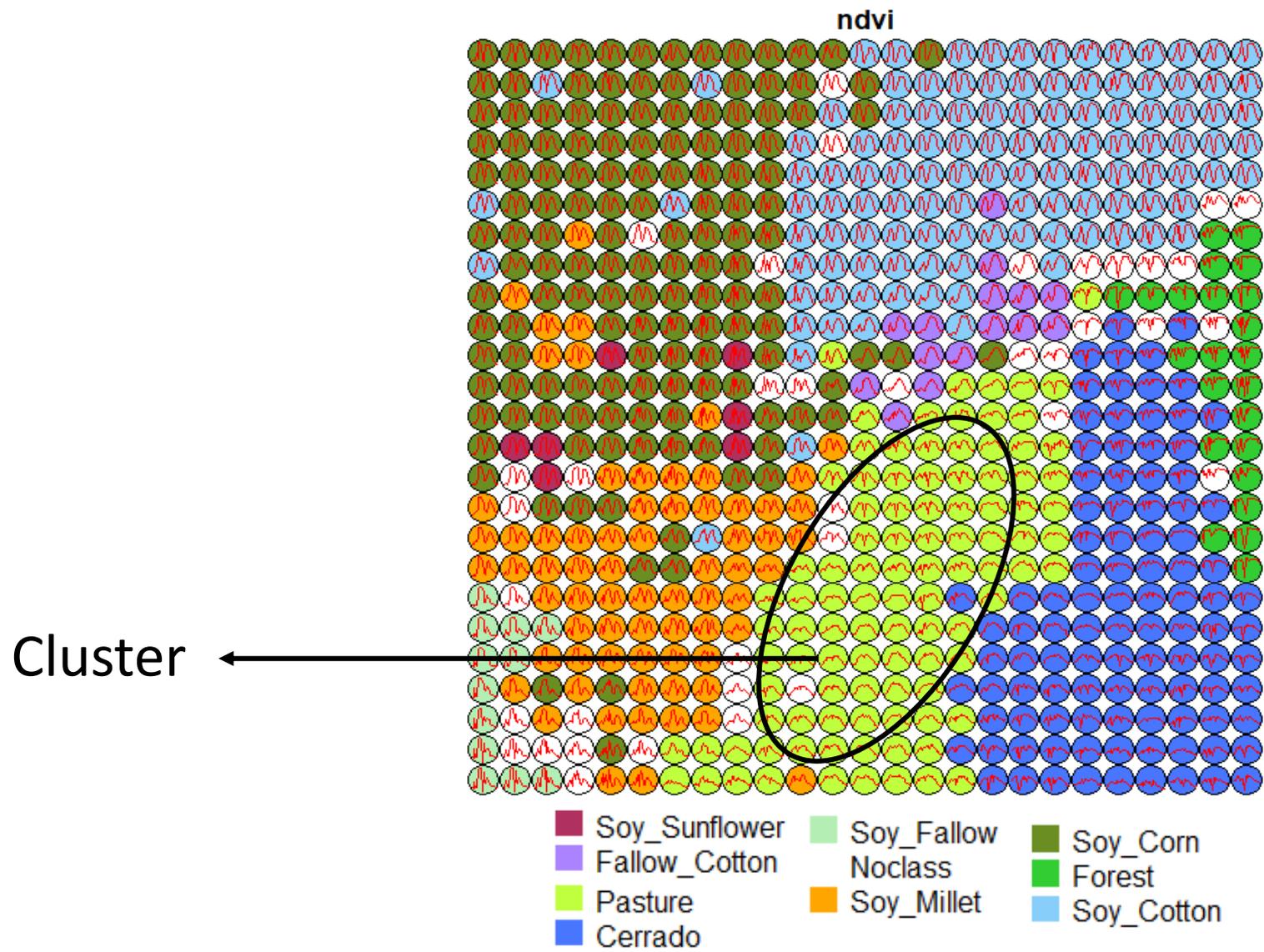
- | | | |
|-----------------|--------------|--------------|
| ■ Soy_Sunflower | ■ Soy_Fallow | ■ Soy_Corn |
| ■ Fallow_Cotton | ■ Noclass | ■ Forest |
| ■ Pasture | ■ Soy_Millet | ■ Soy_Cotton |
| ■ Cerrado | | |

Source: Santos et al. (2019)

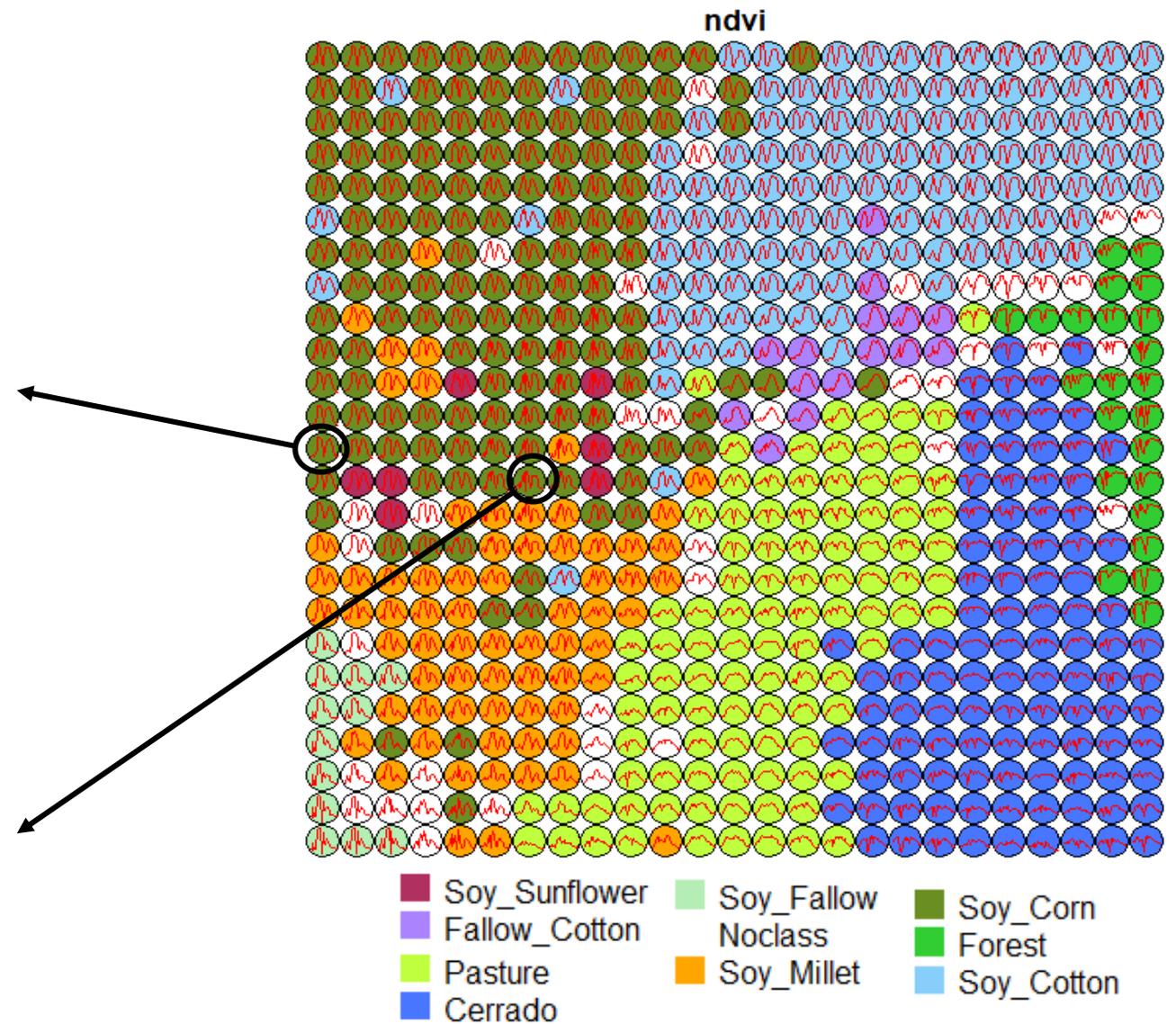
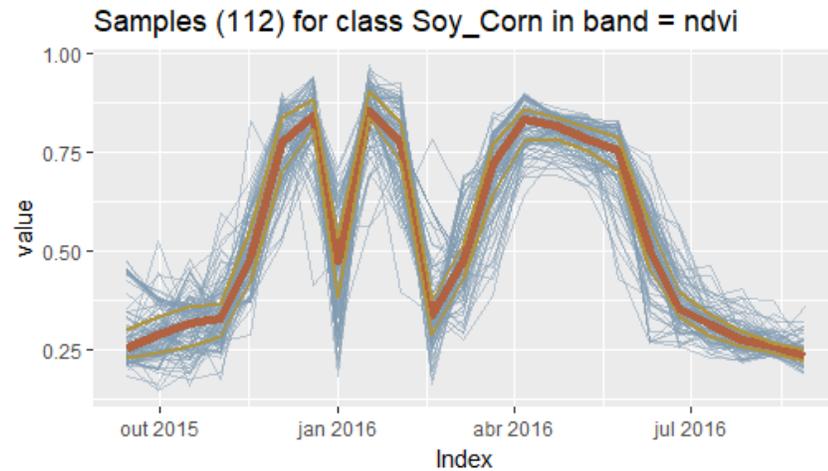
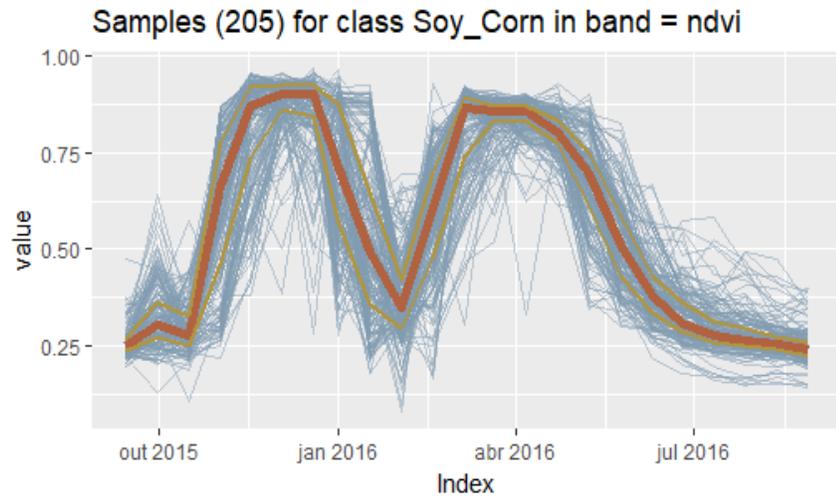
Neighbors ←



Source: Santos et al. (2019)



Source: Santos et al. (2019)

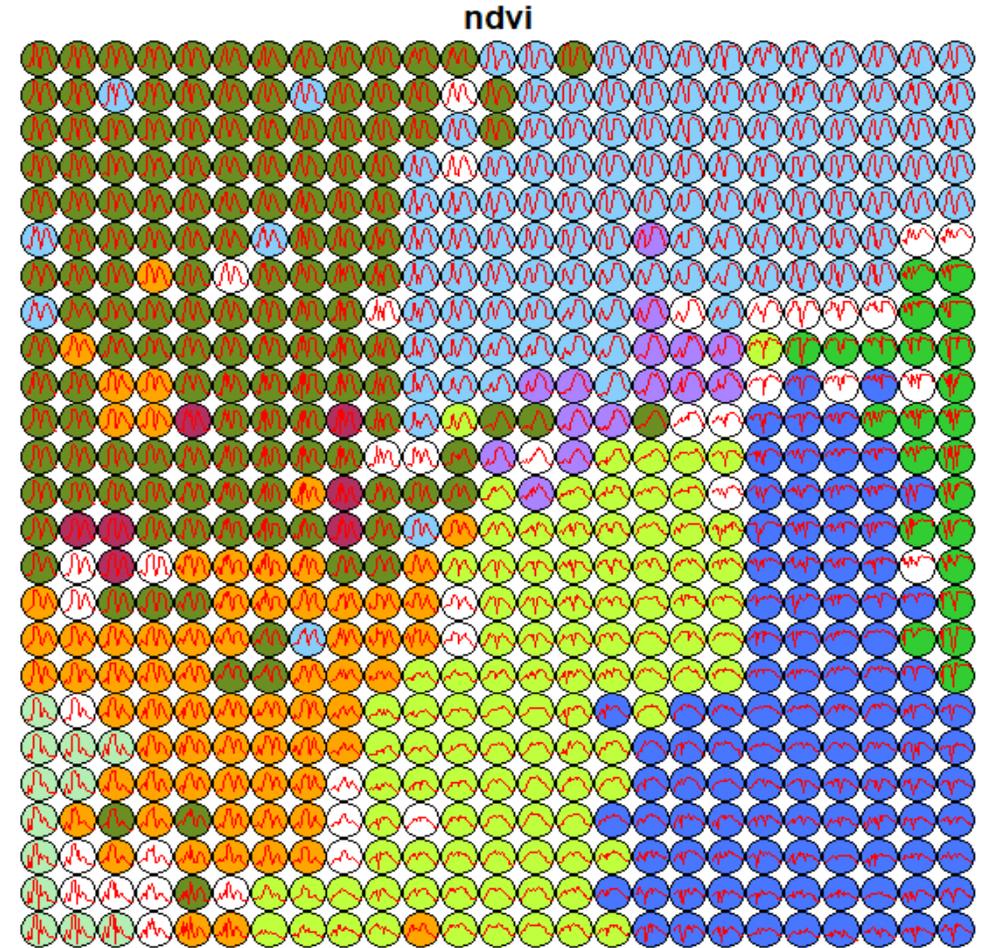


SOM can deal with the variability of vegetation phenology better than other methods.

Source: Santos et al. (2019)

We link each sample to the closest neuron. We minimize the distance iteratively.

To label a neuron, we choose the most frequent sample label.

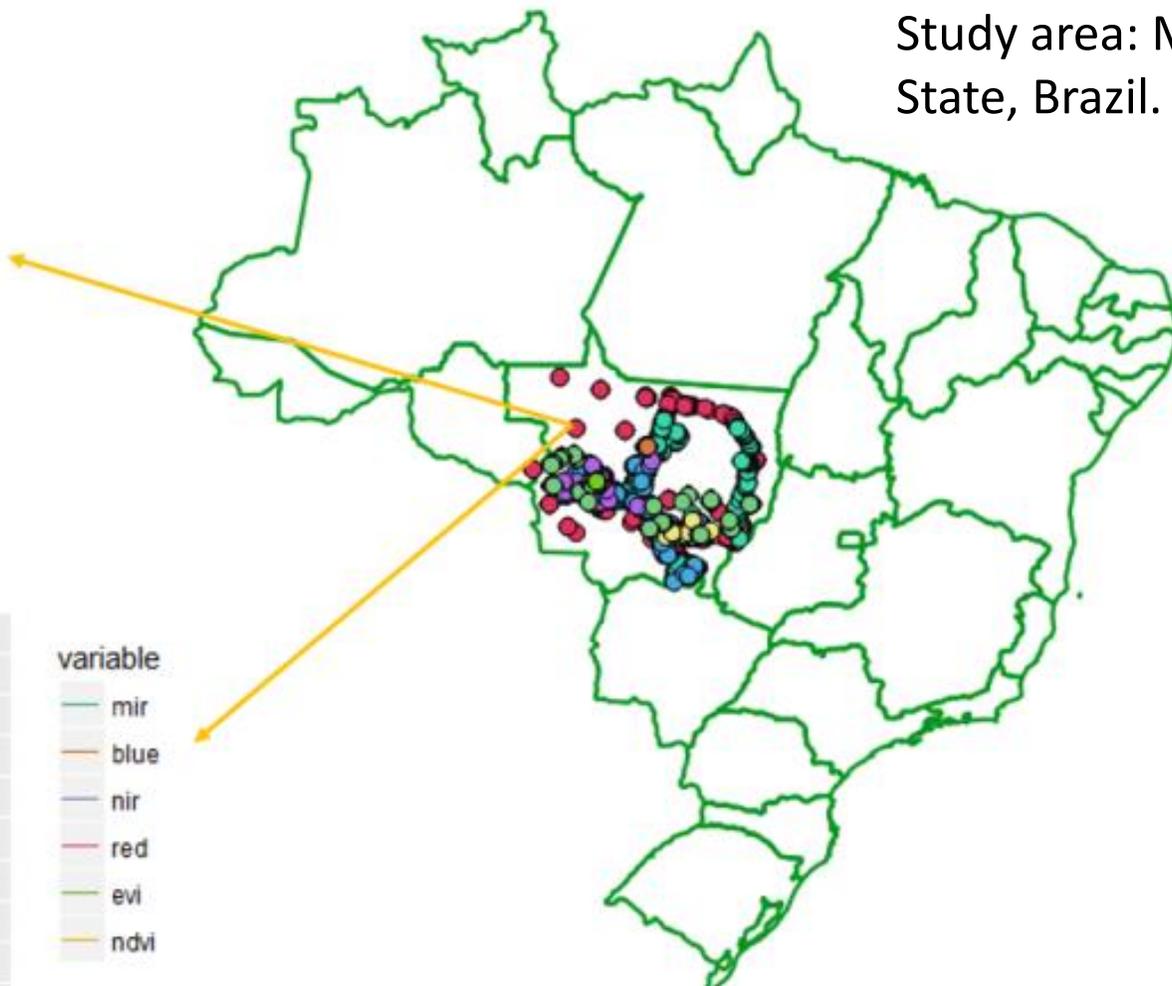


Experiment - Data

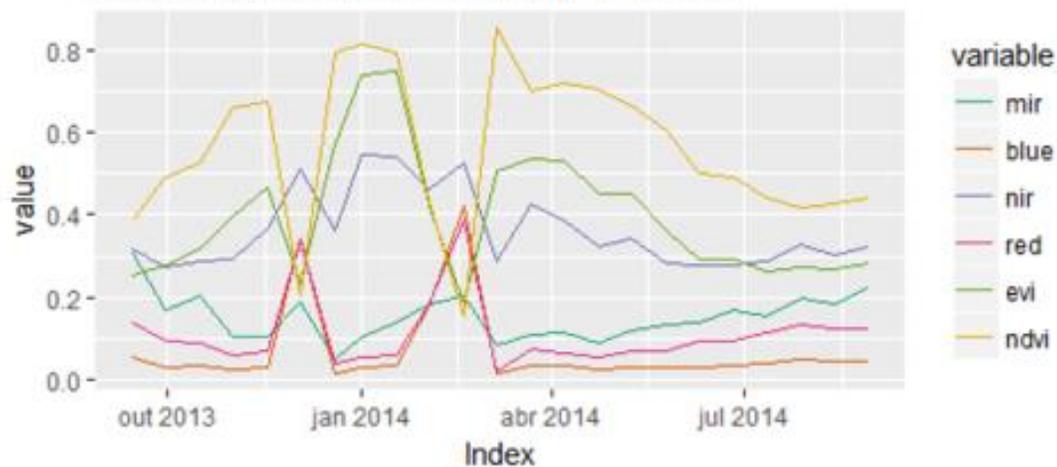
2,115 ground sample points (from 2000 to 2013) of nine land use and cover classes.

longitude	latitude	start_date	end_date	label
-55.1852	-10.8378	2013-09-14	2014-08-29	Pasture
-57.7940	-9.7573	2006-09-14	2007-08-29	Pasture
-51.9412	-13.4198	2014-09-14	2015-08-29	Pasture
-55.9643	-10.0621	2005-09-14	2006-08-29	Pasture
-54.5540	-10.3749	2013-09-14	2014-08-29	Pasture

Study area: Mato Grosso State, Brazil.



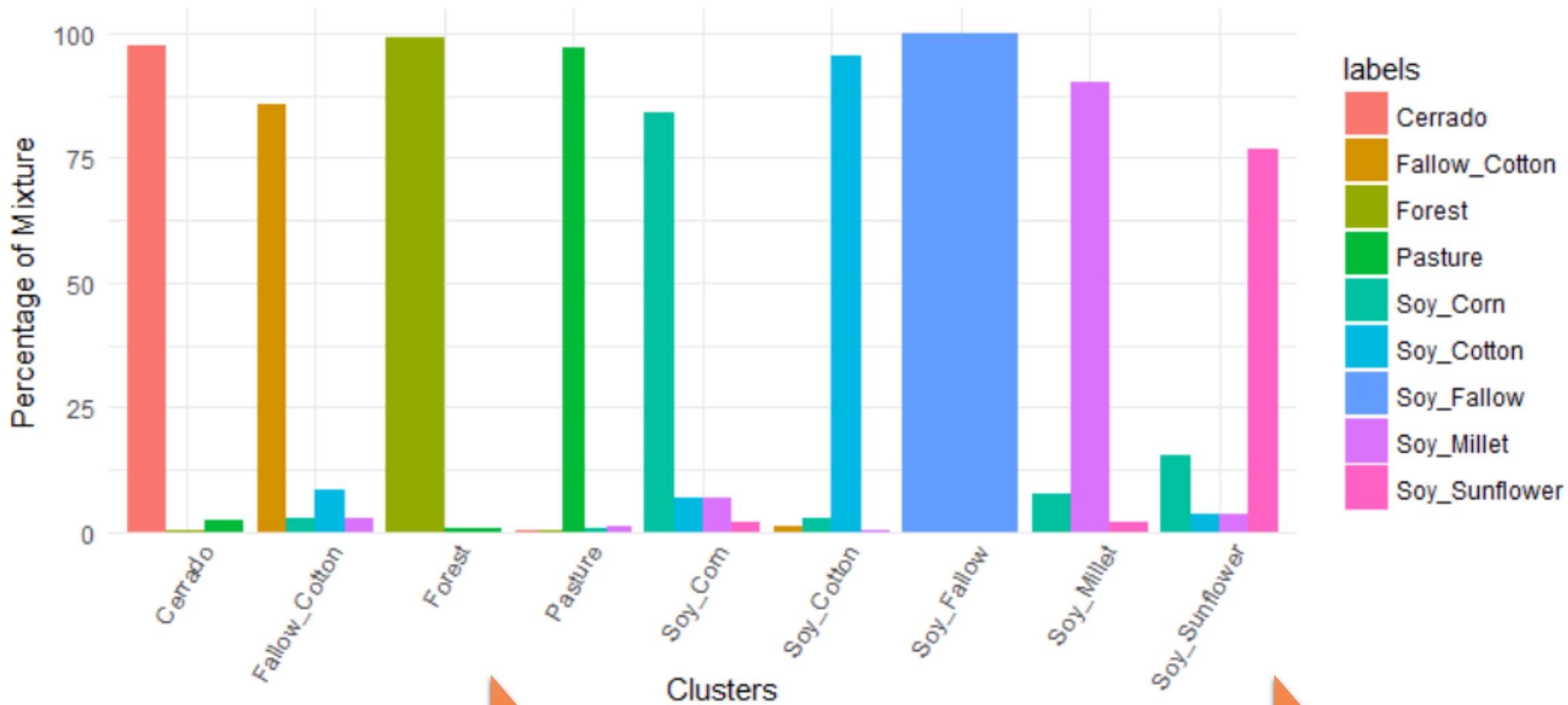
location (-10.8378, -55.1852) - Pasture



- Cerrado
- Pasture
- Soy_Fallow
- Fallow_Cotton
- Soy_Corn
- Soy_Millet
- Forest
- Soy_Cotton
- Soy_Sunflower

Source: Camara et al. (2017)

Experiment - Results



ground samples: 2,115

After
SOM

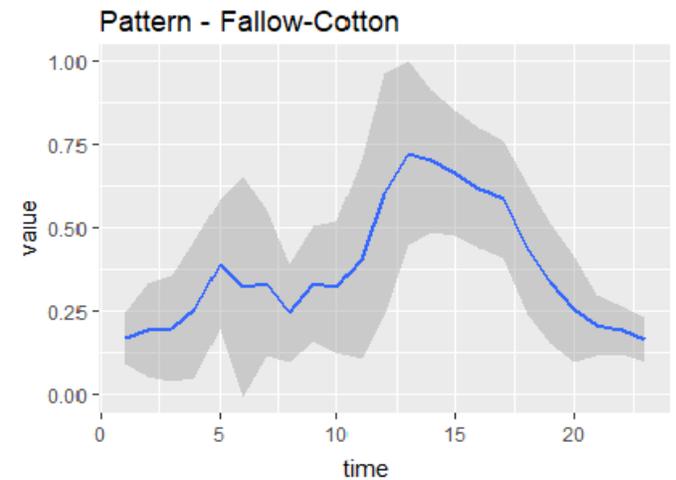
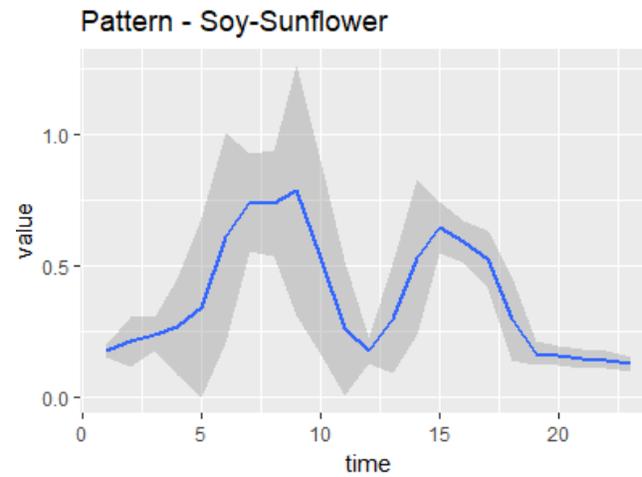
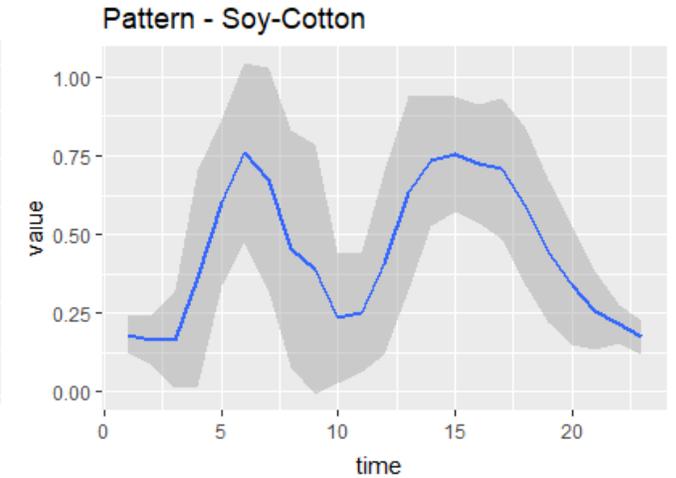
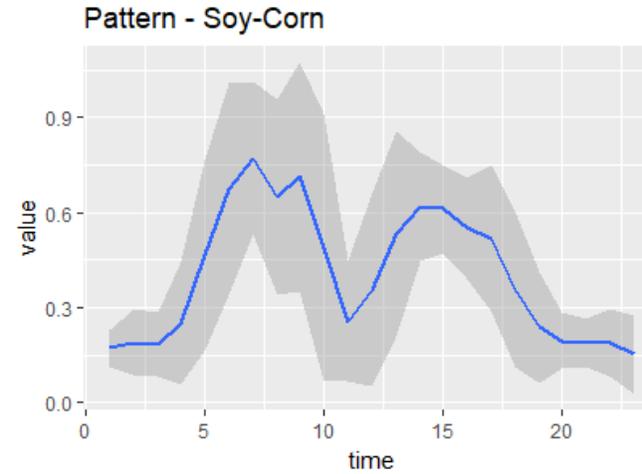
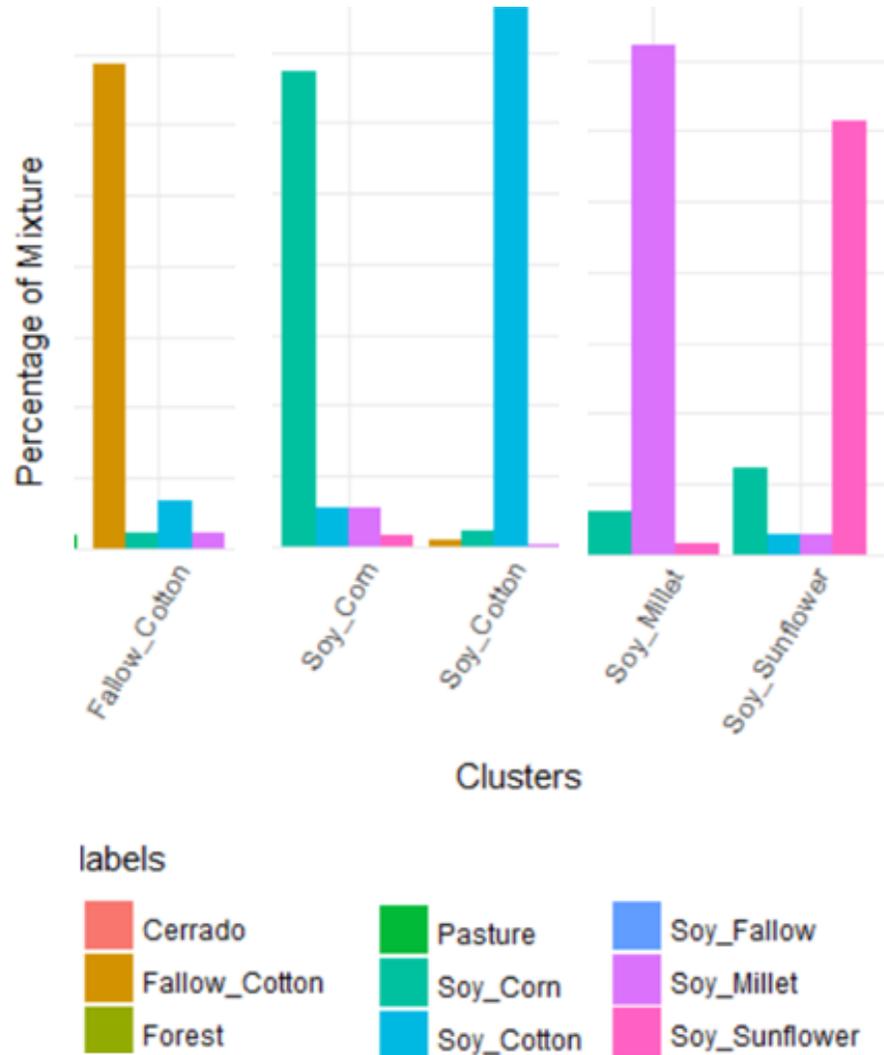
1,892

overall accuracy: 93%

After
SOM

96%

Experiment - Results

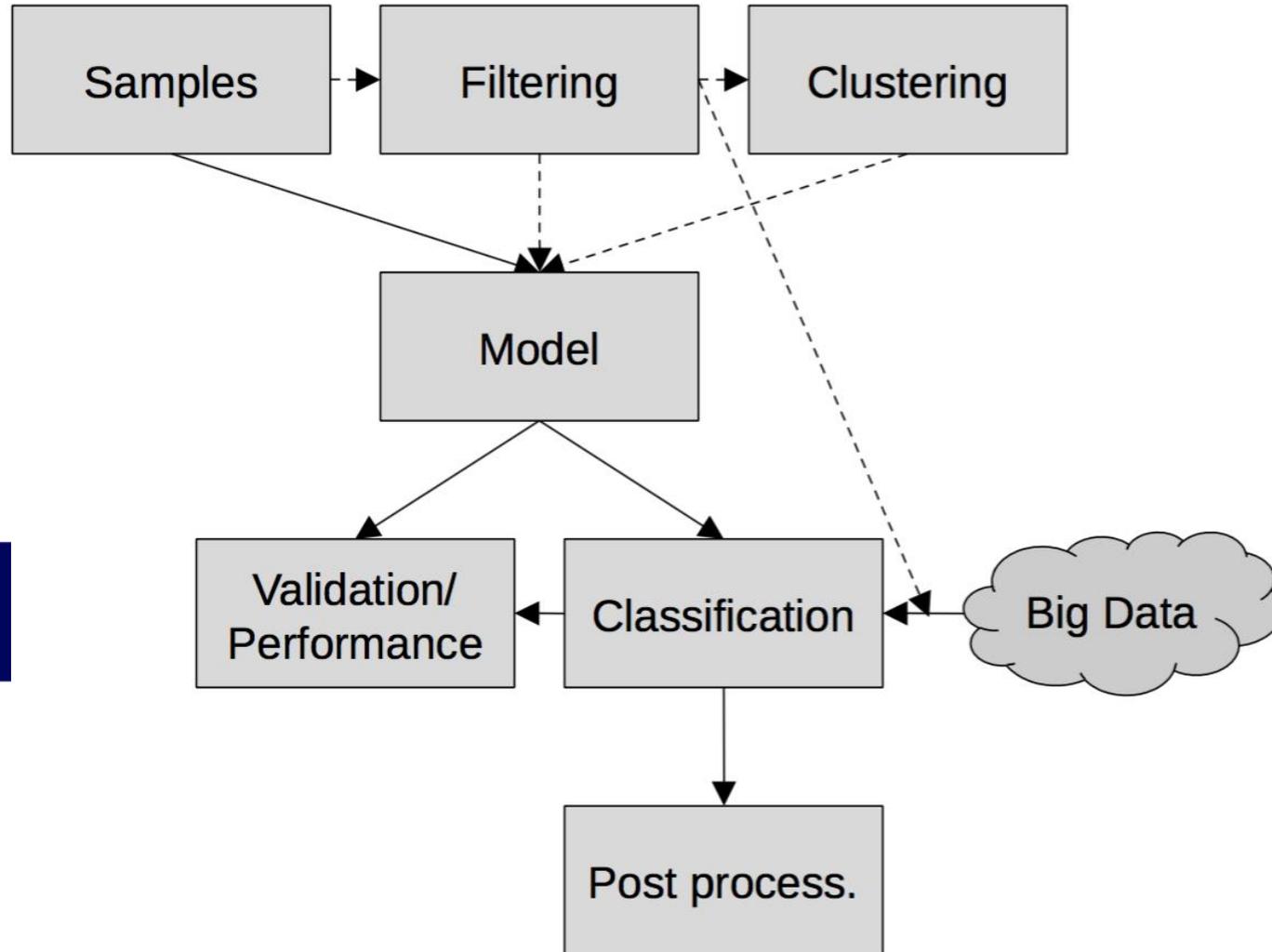


The clusters Soy-Corn and Soy-Sunflower are the most confusing.

sits (Satellite Image Time Series) - R package



github.com/e-sensing/sits



Clustering:

Self-Organizing Maps – SOM (kohonen)

Machine Learning Models:

Support Vector Machine (e1071/LibSVM)

Random Forest (RandomForest)

Deep Learning (Keras/TensorFlow)

Linear/Quadratic Discriminant Analysis

...

References

Santos et al. (2019) **Self-Organizing Maps in Earth Observation Data Cubes Analysis.**

https://doi.org/10.1007/978-3-030-19642-4_7

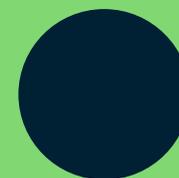
Camara et al. (2017) **Land cover change maps for Mato Grosso State in Brazil: 2001-2016**

<https://doi.org/10.1594/PANGAEA.881291>

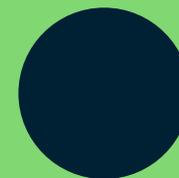


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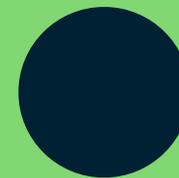
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FUND



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Thank you!