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5b Remote Sensing Data: Image Classification and Change Detection

Julius-Maximilians-UNIVERSITÄT WÜRZBURG

DLR

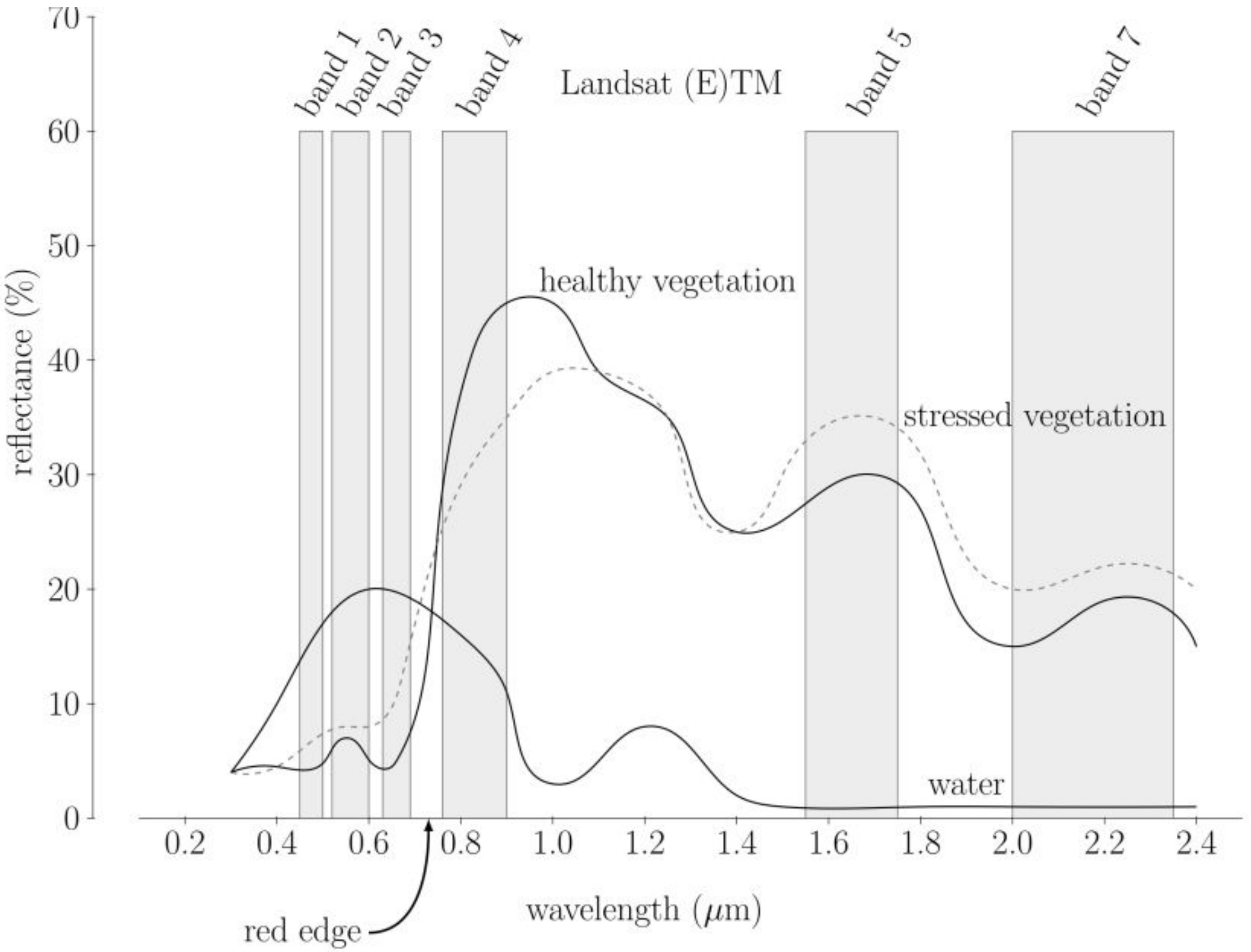
MARTIN-LUTHER-UNIVERSITÄT HALLE-WITTENBERG

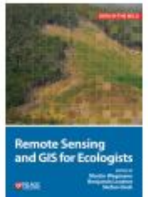
UNIVERSITY OF BOTSWANA

INES Ruhengeri Institute of Applied Sciences

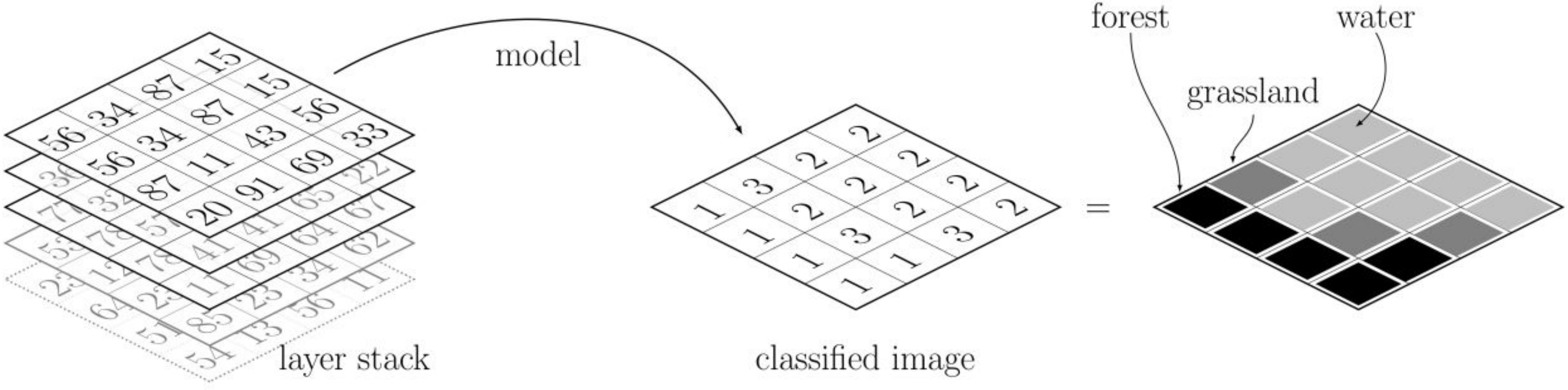
RS Data: Image Classification

From spectral signatures to …

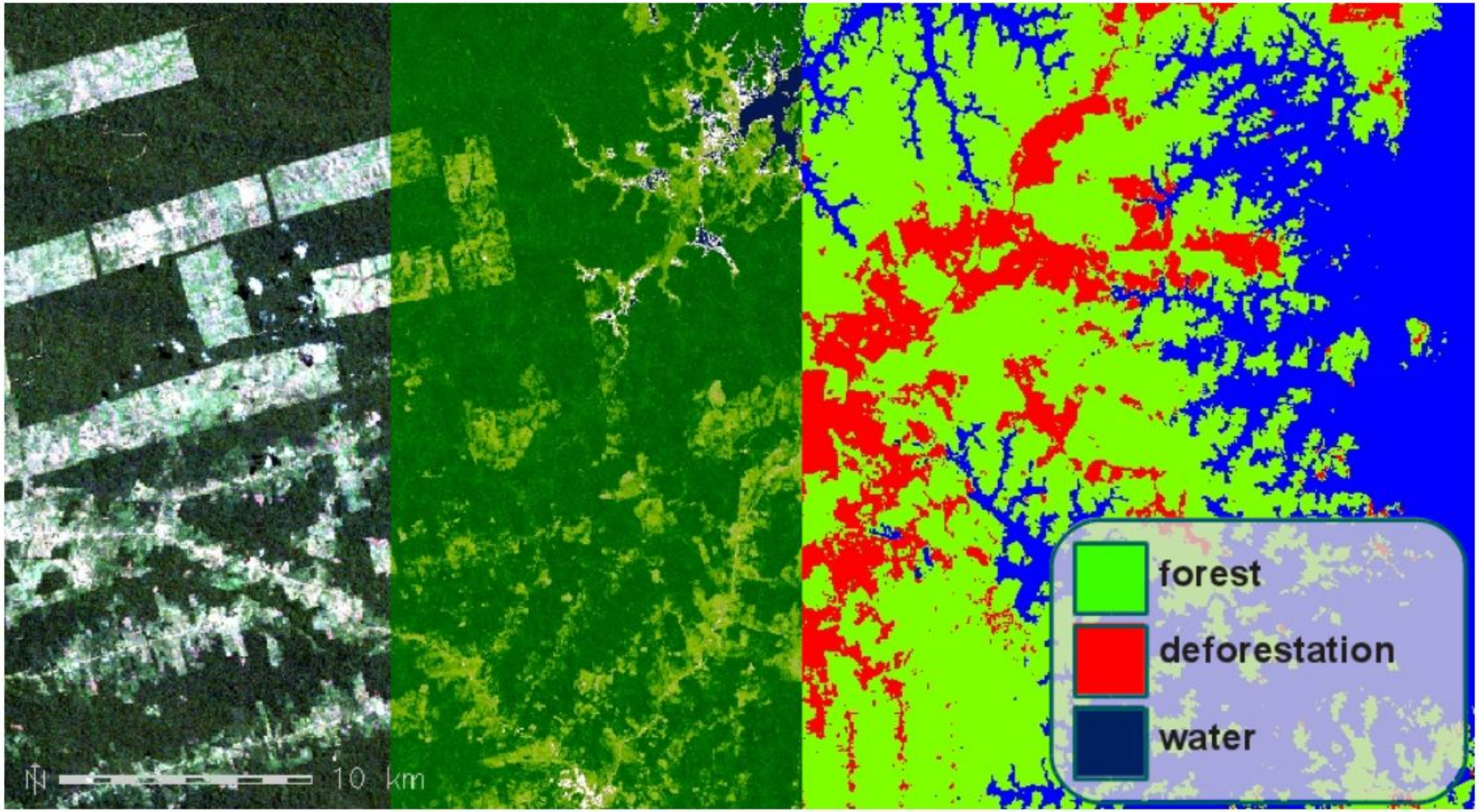




… surface properties



What is a classification?



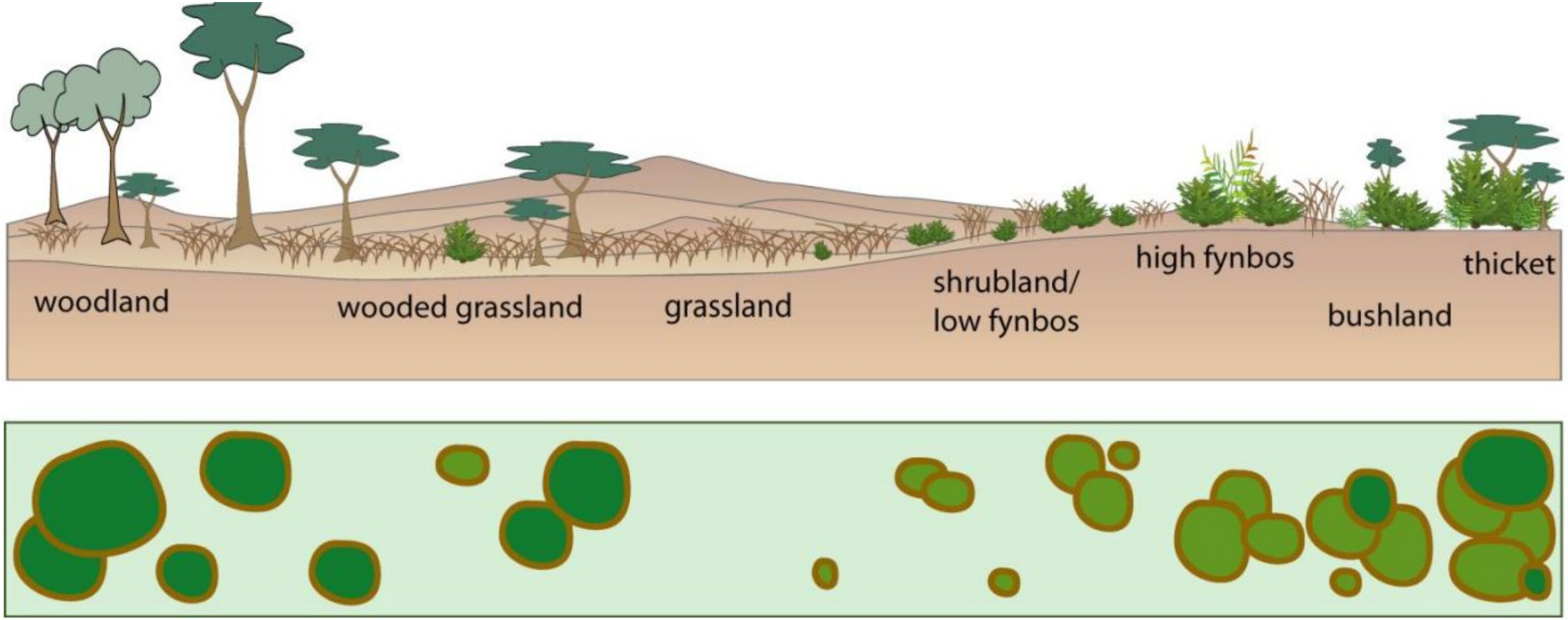
(Landcover-)classifications are needed for

- Amount of landcover (km²)
- Quantification of forest loss
- Important for e.g., REDD
- For most (political) reports actual numbers are needed

But:

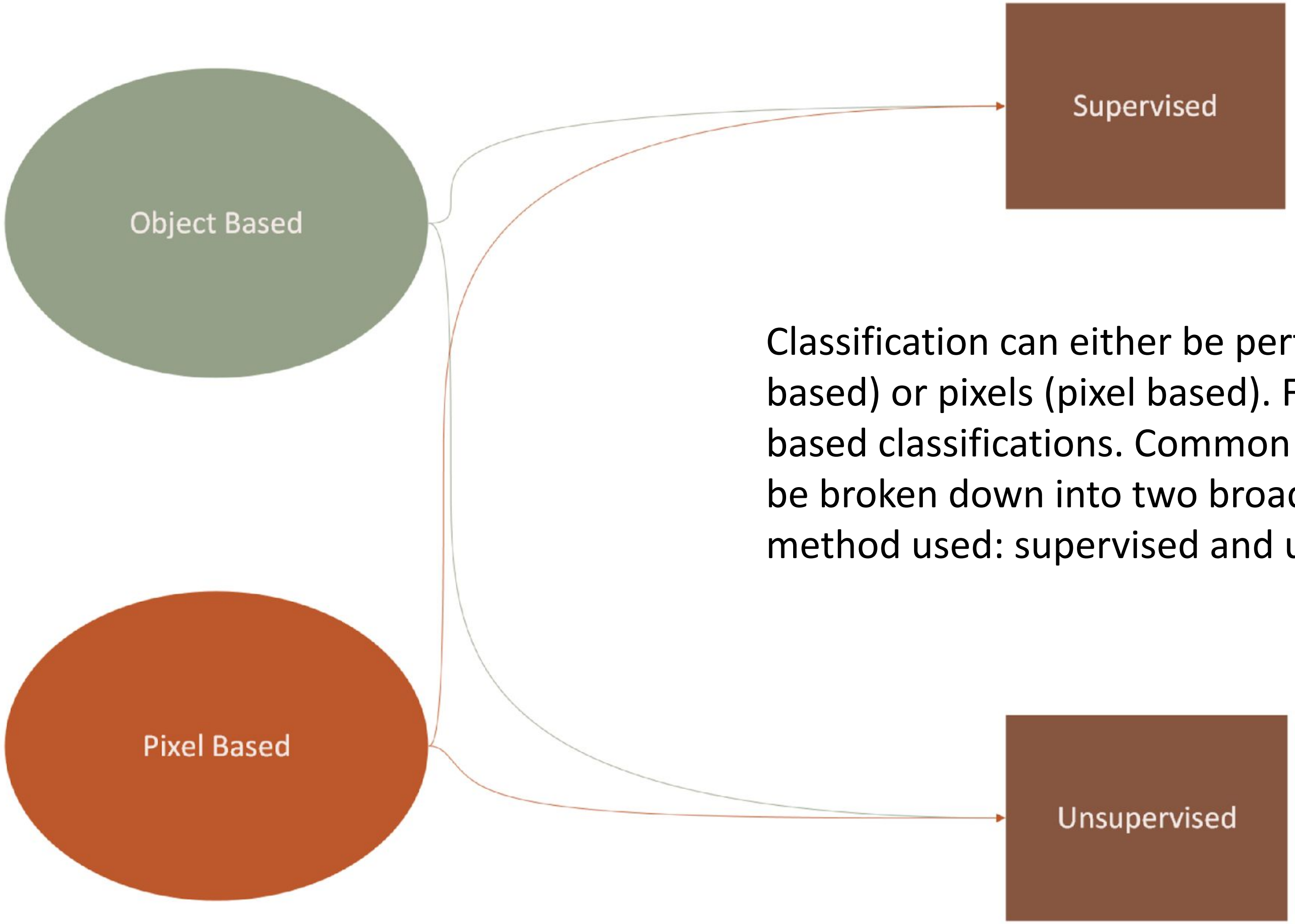
- Definition of classes is based on human perception
- Information are lost (ecotones)
- Classes might be irrelevant for some species
- Subtle differences e.g., degradation not / difficult to analyze

What is a classification?



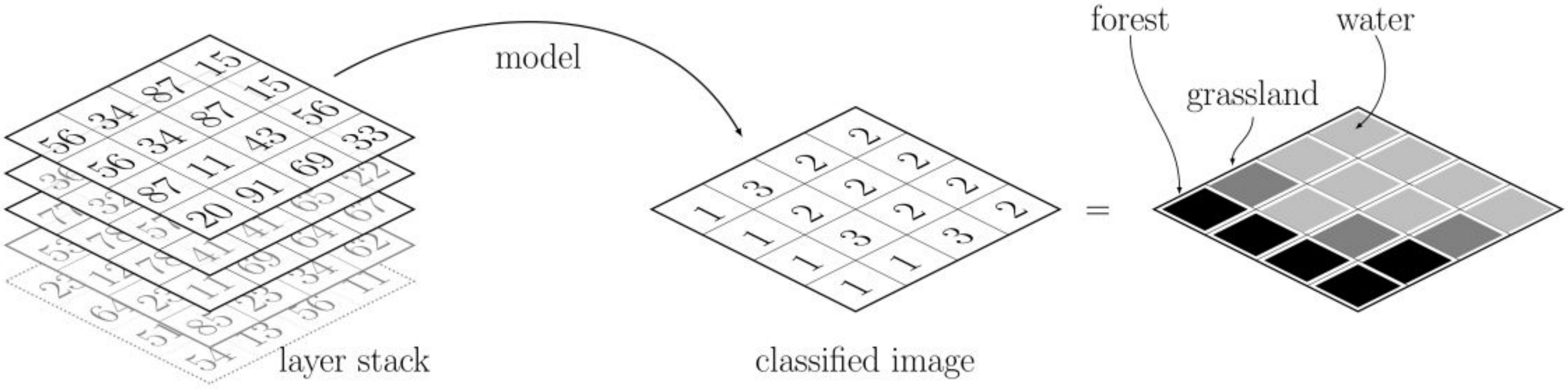
- Which landcover types to you want to classify? | What is your classification scheme?
- What can be differentiated, what not?

Classification Types



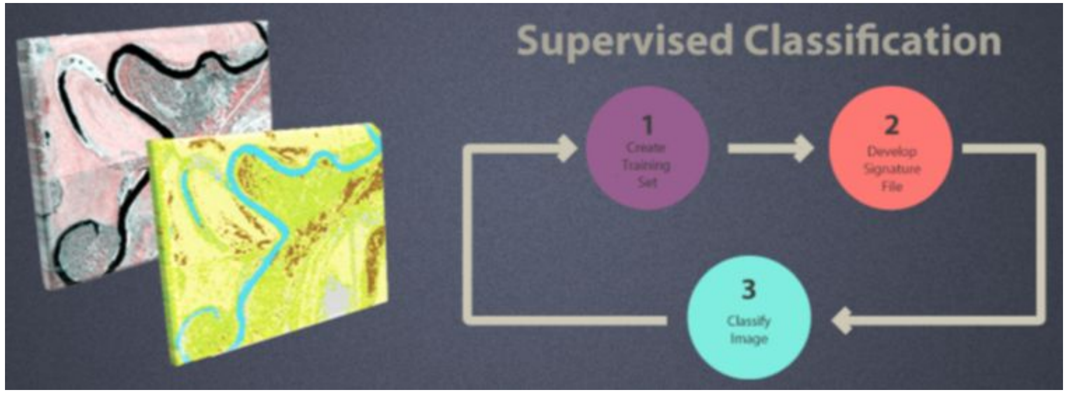
Classification can either be performed on objects (object based) or pixels (pixel based). For now, we focus on pixel based classifications. Common classification procedures can be broken down into two broad subdivisions based on the method used: supervised and unsupervised classifications.

What is a classification?



- Either the algorithm splits pixel values into n clusters purely based on spectral similarity (unsupervised classification)
- Or the algorithm uses training samples with pre-defined classes (supervised classification)

Supervised classification

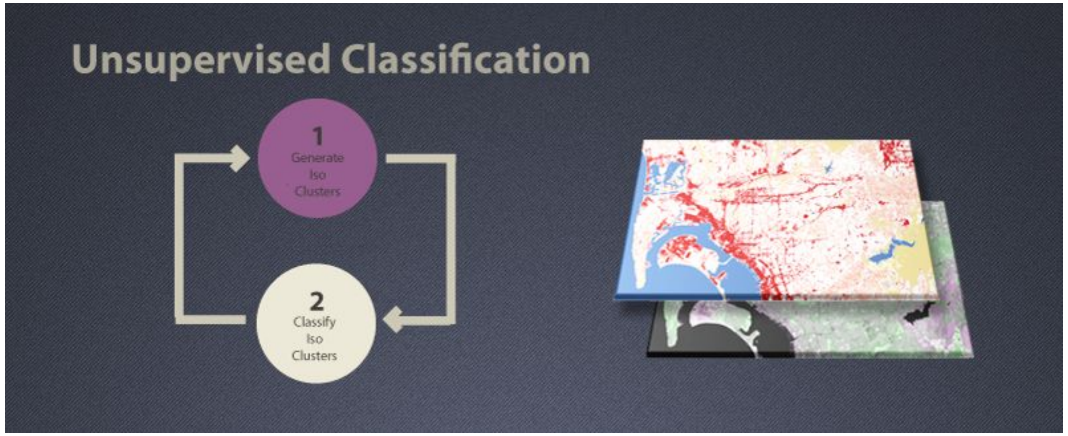


- In a supervised classification, the analyst identifies in the imagery homogeneous representative samples of the different surface cover types (information classes) of interest.
- These samples are referred to as **training areas**.
- The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and the knowledge of the actual surface cover types present in the image.
- Thus, the analyst is **"supervising" the categorisation** of a set of specific classes.

Supervised classification

- The numerical information in all spectral bands for the pixels comprising these training areas are used to "train" the computer algorithm to recognize spectrally similar areas for each class.
- Once the computer algorithm has determined the signatures for each class, each unlabelled pixel in the image is compared to these signatures and labelled as the class it most closely "resembles" digitally (see the next section on classification algorithms).
- Thus, in a supervised classification, we are first **identifying the information** classes, which are then used to **determine the spectral** classes to represent them.

Unsupervised classification

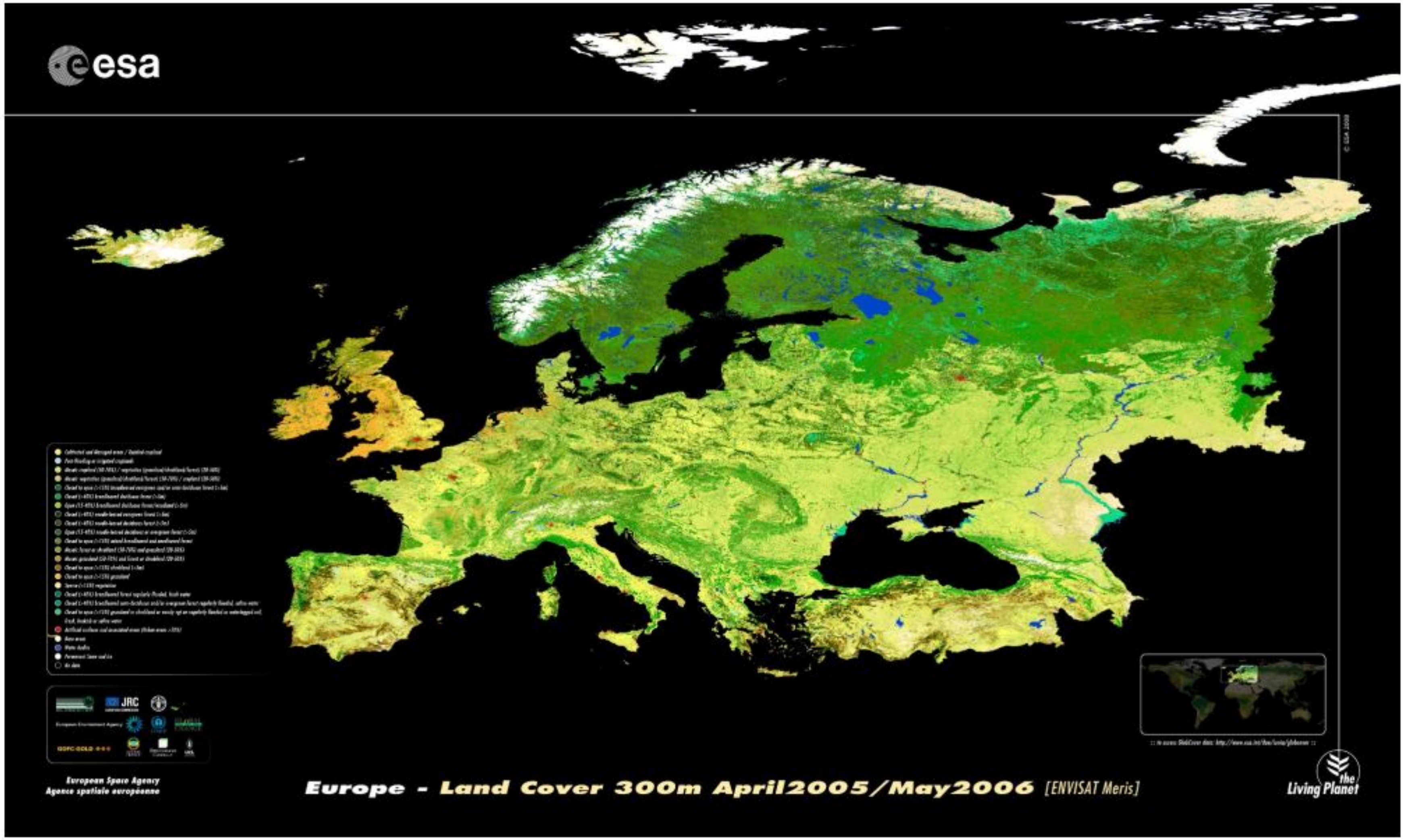


- In an unsupervised classification the spectral classes are grouped first, based solely on the numerical information in the data, and are then matched by the analyst to information classes (if possible).
- Clustering algorithms are used to determine the natural (statistical) groupings or structures in the data.
- Usually, the analyst specifies how many groups or clusters are to be looked for in the data.
- In addition to specifying the desired number of classes, the analyst may also specify parameters related to the separation distance among the clusters and the variation within each cluster.

Unsupervised classification

- The final result of this iterative clustering process may result in some clusters that the analyst will want to subsequently combine, or clusters that should be broken down further - each of these requiring a further application of the clustering algorithm.
- Thus, unsupervised classification is not completely without human intervention. However, it does not start with a pre-determined set of classes as in a supervised classification.

Global classification: Europe



Global classification: Central Europe – Classification Scheme

Classification Scheme

Before you start your classification, a classification scheme is very important:

- Think about what you want to classify (ecological relevance)
- What is feasible to differentiate (small patches of wetlands with MODIS?)
- What data sets are available
- If / how extensive you can conduct the field work
- After this points define a classification scheme (which classes are included)

Classification steps

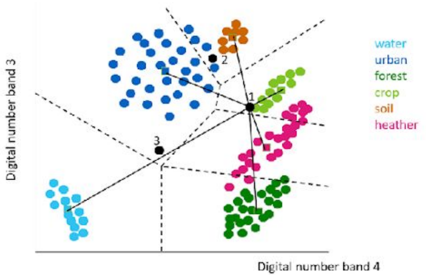
Before we look in more detail into the different classification algorithms, let's first have a look at the steps in the classification process:

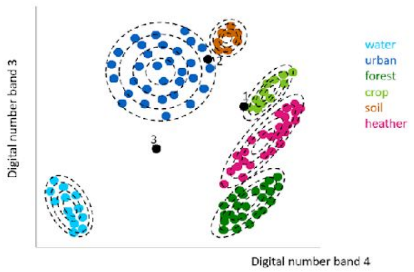
- Define classes: which classes need to be mapped, and how are they defined?
- Choose classification algorithm
- Collect training dataset (for supervised classification)
- Assign class labels to all pixels of the image (classification)
- Collect validation dataset and perform map validation (confusion matrix)
- Evaluation of classification result by looking at the image space (i.e., classification map) and by looking at the map accuracy (confusion matrix)
- If necessary, adjust classification results

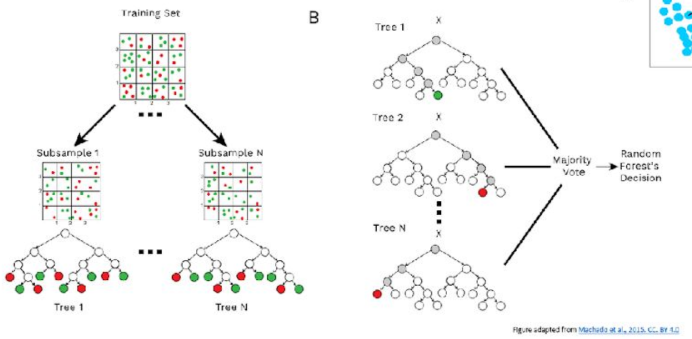
Classification Algorithms

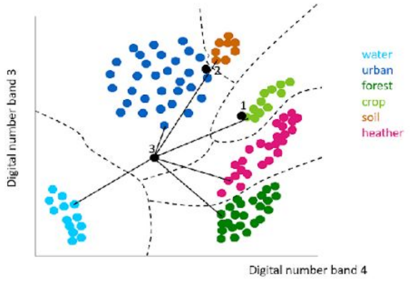
- There are different supervised classification algorithms available ranging from simple, more traditional, algorithms to machine and deep learning algorithms.
- For the more traditional algorithms a measure of distance of an unknown pixel to existing clusters or classes must be defined in order to classify this unknown pixel.
- These distances are measured in the feature space.
- By calculating these distances for a certain pixel to various surrounding clusters, the pixel can be assigned to the ‘nearest’ class.
- If all distances exceed a certain threshold, so that a pixel does not belong to any of the clusters, the pixel is not labelled, or it gets a label like “unknown”.

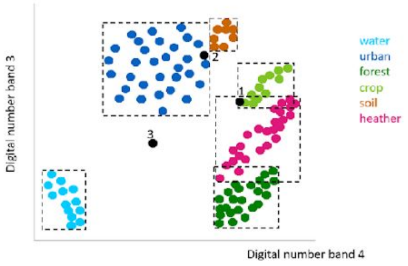
Classification Algorithms



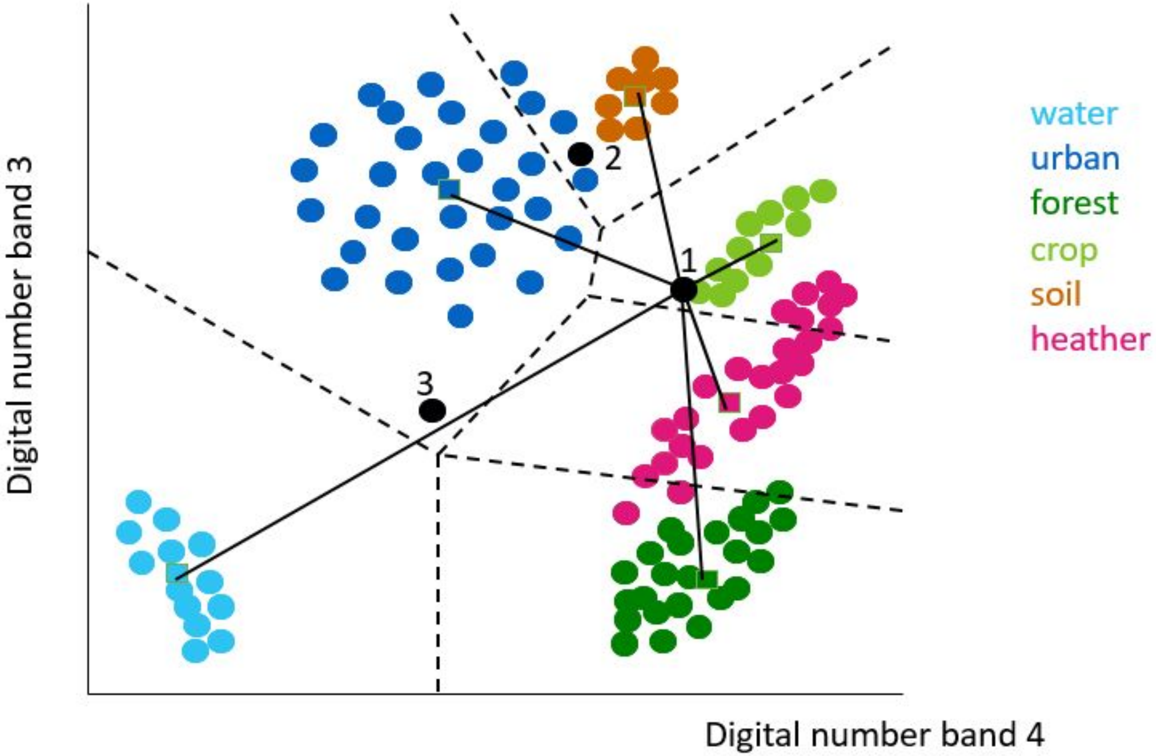






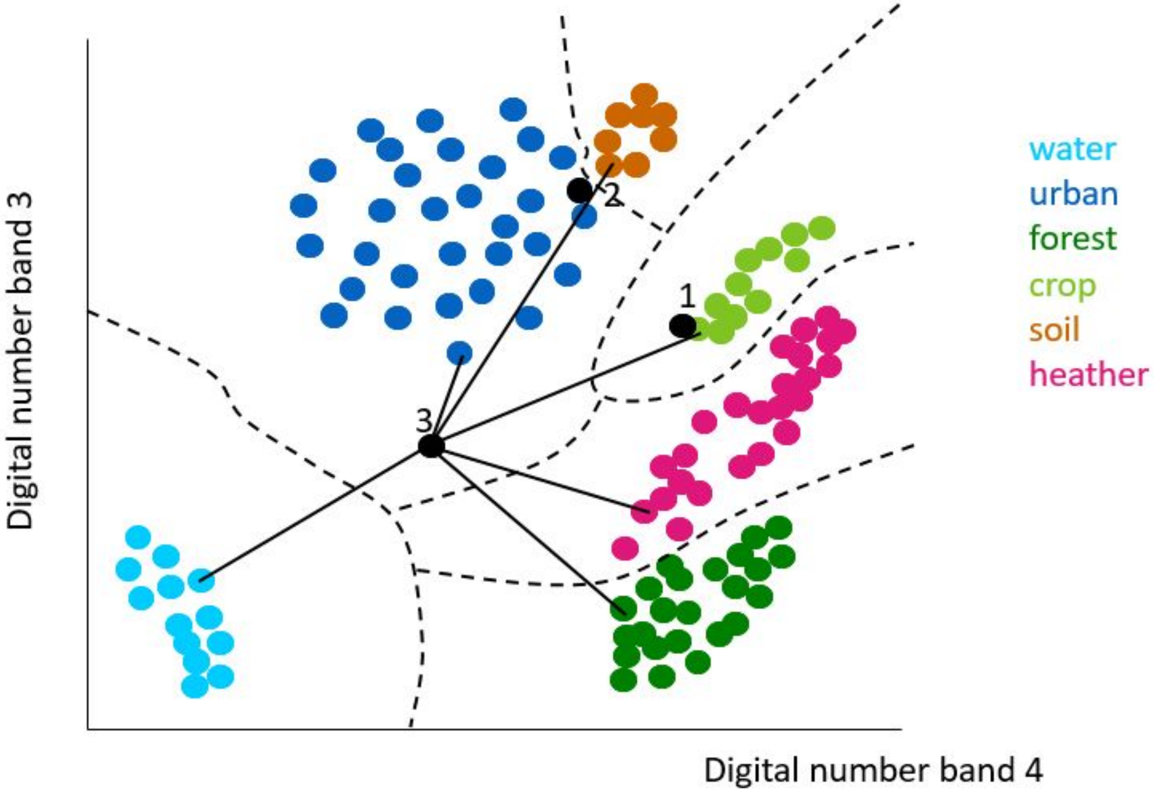


Minimum Distance to Means



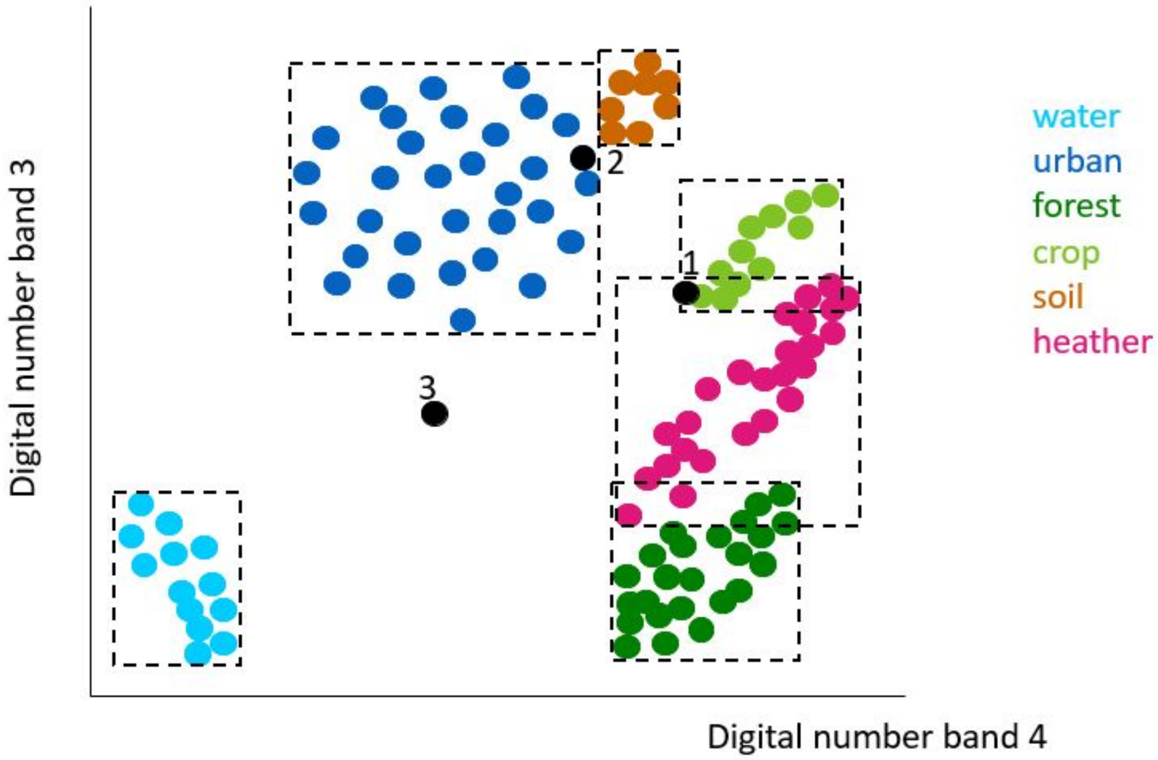
This classification is also sometimes called “nearest centroid” or “nearest prototype”. The center point of each training cluster in the feature space is determined. The distances of a new point to these centers are calculated. The point is assigned to the cluster with the center nearest to it.

K-nearest Neighbor



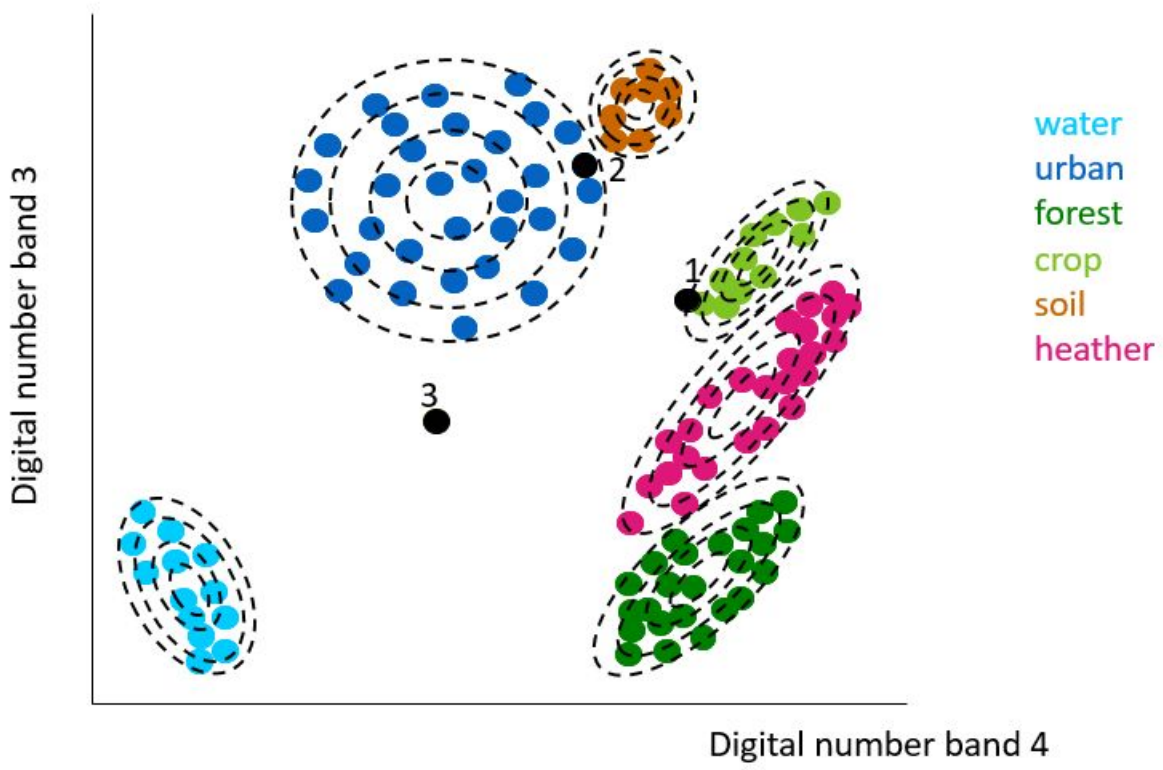
From all clusters, k points per cluster are selected nearest to the point to be assigned. This new point is assigned to the cluster for which the average distance of k points to this new point is minimum. The number k can be selected as 1, 2 or 3, etc. Even if k = 1, the amount of computation in the k-nearest neighbors method is considerably larger than with the first-mentioned method, but the k-nearest neighbors method takes the forms and sizes of the clusters into account.

Parallelpiped (box)



Rectangular areas are drawn around the clusters according to the range of pixel values in each cluster. If a new point falls inside such a rectangle, it is assigned to the cluster concerned. It is a fast classifier, but difficulties arise in overlapping zones.

Maximum Likelihood



For each cluster, ellipses are drawn about the mean and are dependent on the distribution of points in the cluster about that mean, assuming a Gaussian probability distribution. The probability of a point falling inside such an ellipse, can be computed. The larger the ellipse the greater the probability a point falls inside the ellipse if it belongs to the cluster concerned, and the smaller the probability of falling outside. The more remote from the mean, the smaller the probability of finding a point that belongs to this cluster.

For a new point to be assigned, this latter probability is computed for all surrounding clusters based on its position in the feature space. The point concerned is assigned to the cluster with the greatest probability (likelihood) to have a point in that position.

Random Forest

- Nowadays, machine learning algorithms are commonly used for supervised classification. A commonly used machine learning algorithm is the random forest model. The random forest classification algorithm is an ensemble learning method that is used for both classification and regression.

- The examples shown on the next slide so far presume the recording of two reflectance values for each pixel. Classification algorithms can be applied to more reflectance values (more spectral bands). The feature space then becomes multi-dimensional, with one additional axis for each spectral band.

Random Forest

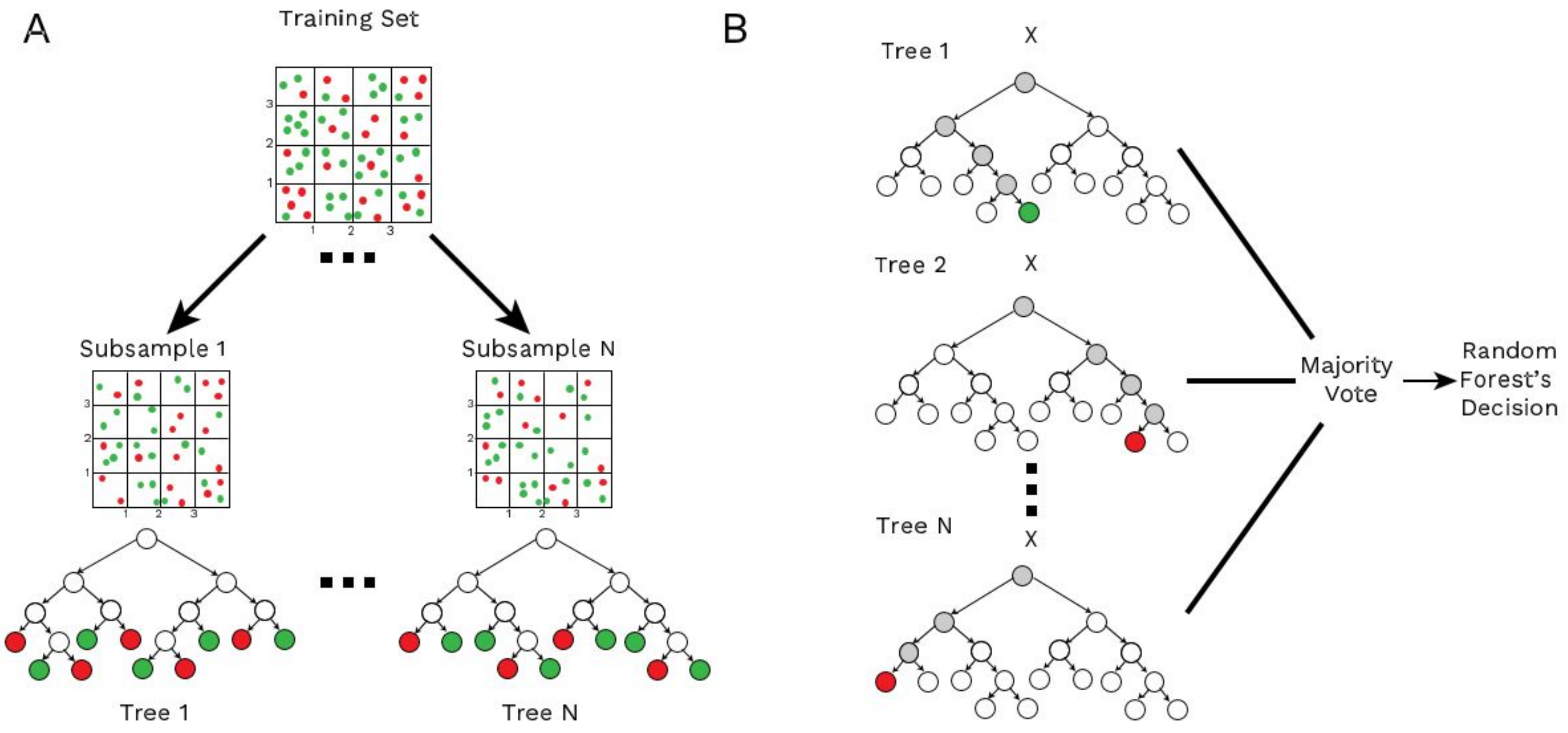
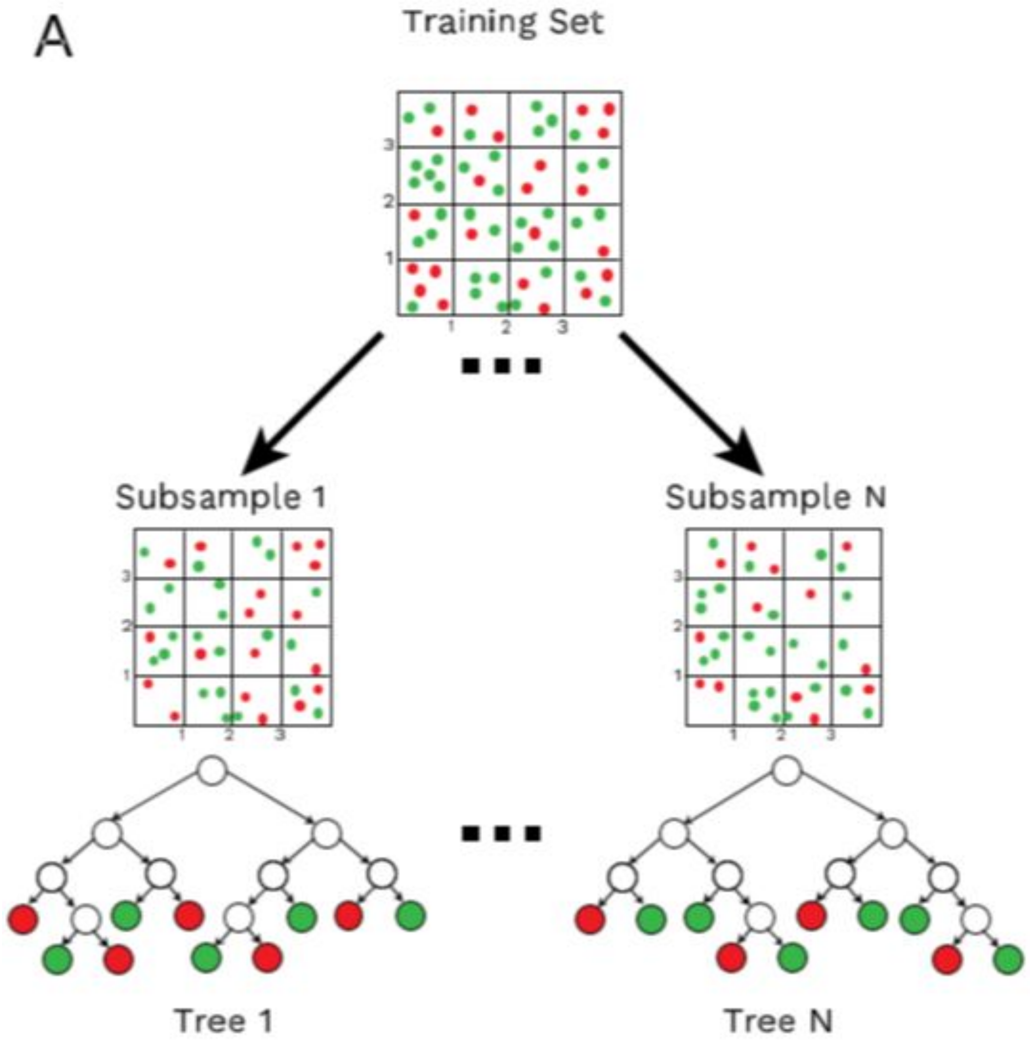


Figure adapted from Machado et al., 2015. CC. BY 4.0

Random Forest



For classification purposes, the Random Forest method takes random subsets from a training dataset and constructs classification trees using each of these subsets. Trees consist of branches and leaves.

Branches represent nodes of the decision trees, which are thresholds of input variables (spectral bands) that help separate classes from one another. Leaves are the class labels assigned to the pixels at the end of the decision tree.

Random Forest

Sampling many subsets at random will result in many trees being built.

Classes are then assigned based on classes assigned by all of these trees based on a majority rule, as if each class assigned by a decision tree were considered to be a vote.

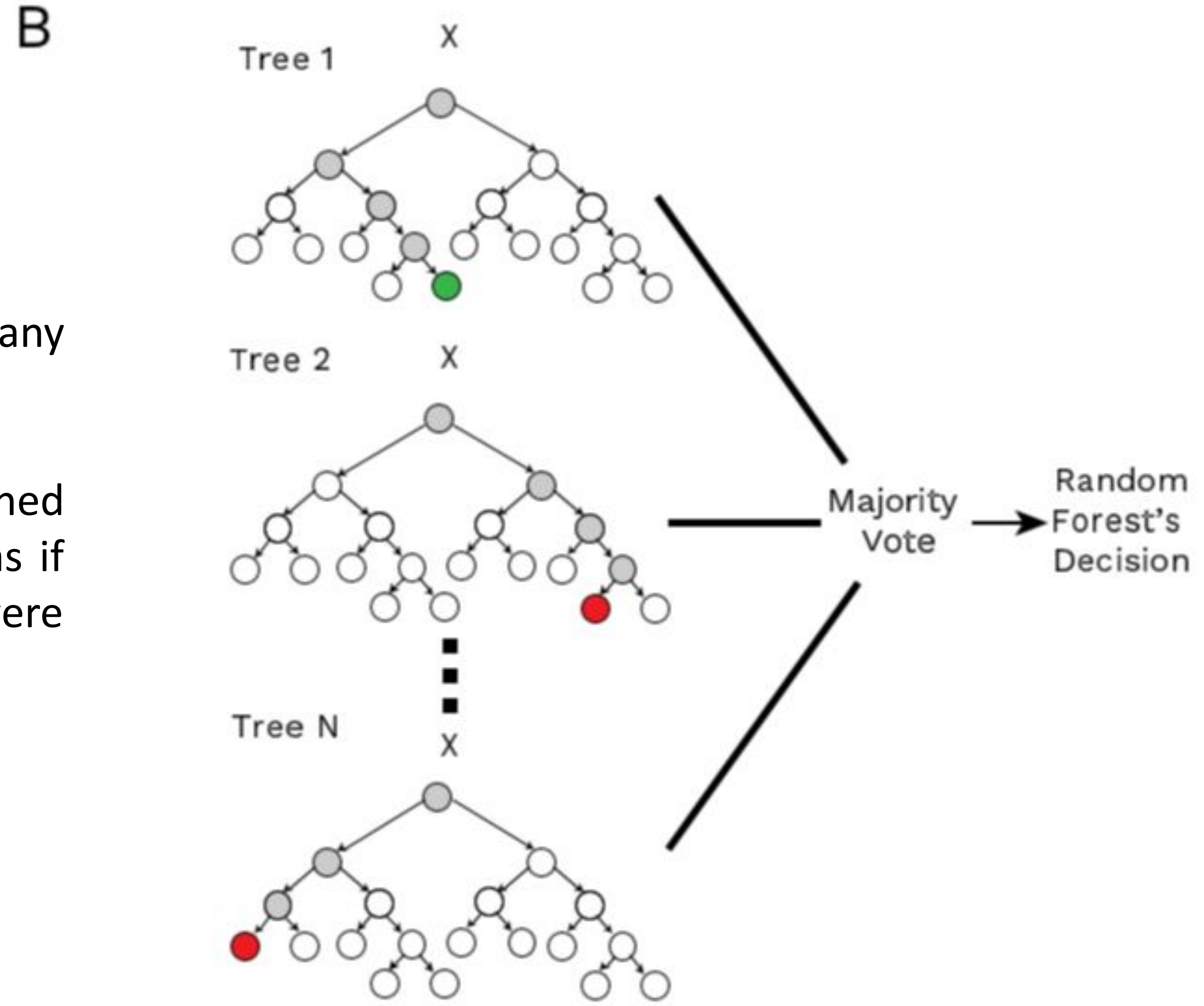


Figure adapted from Machado et al., 2015. CC. BY 4.0

RS Data: Change Detection

Landcover change analysis

What do we want to know about our ecosystems (incl. wetlands) in the 80ies and today?

- Its condition
- Its area covered

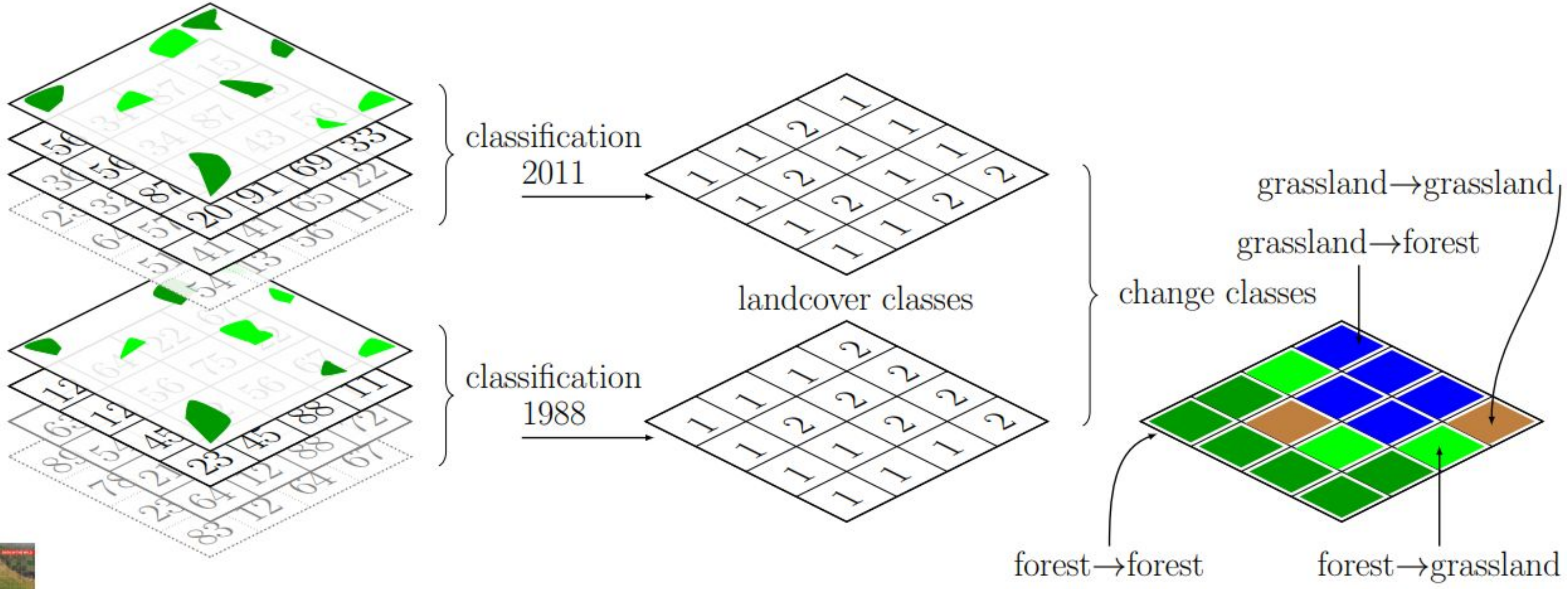
To analyze actual land cover change values, we need to conduct a land cover change analysis

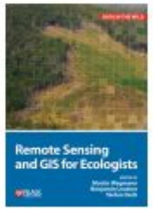
Landcover change analysis

Any idea how to do that - technically?

- Classifying the old and the more recent image and then subtract them?
- Classifying change instead of a land cover?

Different concepts to analyse change - **postclassification**

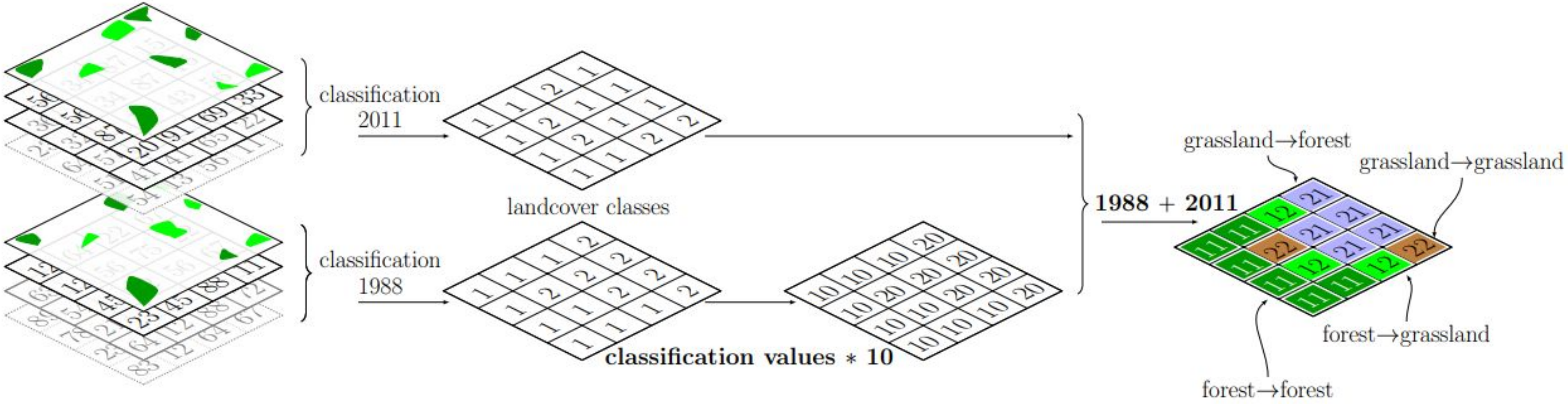




Postclassification – **Change Detection Approach**

- Postclassification approach requires two separate classifications
- Multiply 1988 by 10 and keep 2011 as it is
- Add both image values
- This results in 11, 12, 13, … which refers to class 1 in 1988, class 1 in 2011; class 1 in 1988, class 2 in 2011
- Now you can plot change classes and compare them to the multidate result or a change vector

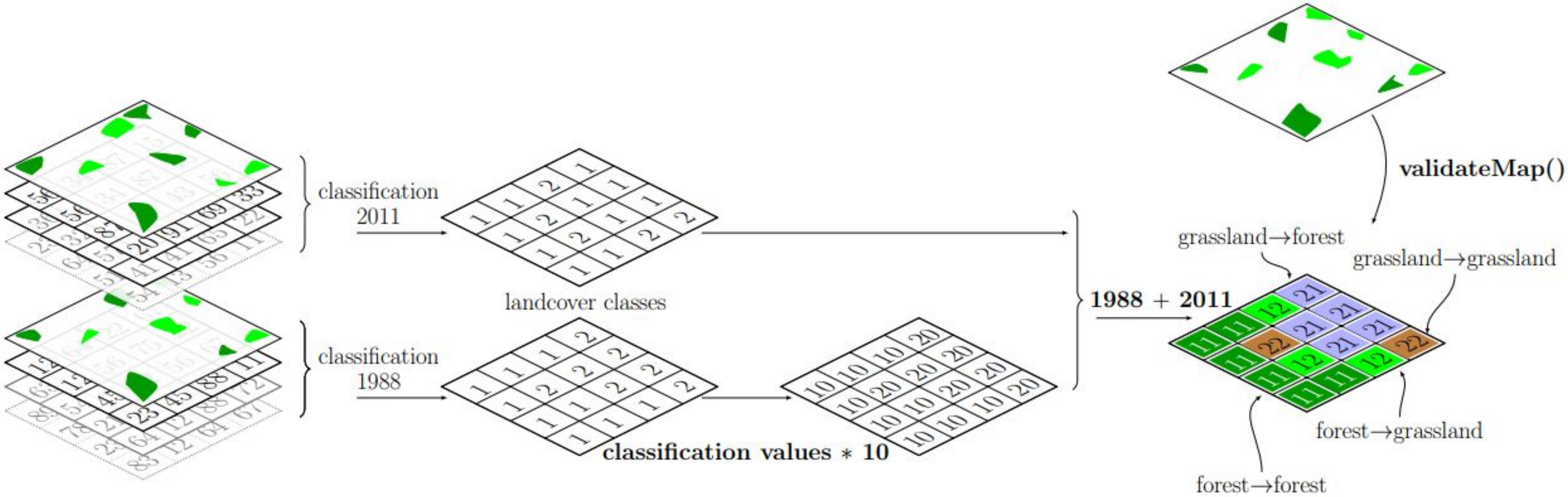
Postclassification—**Change Detection Approach**



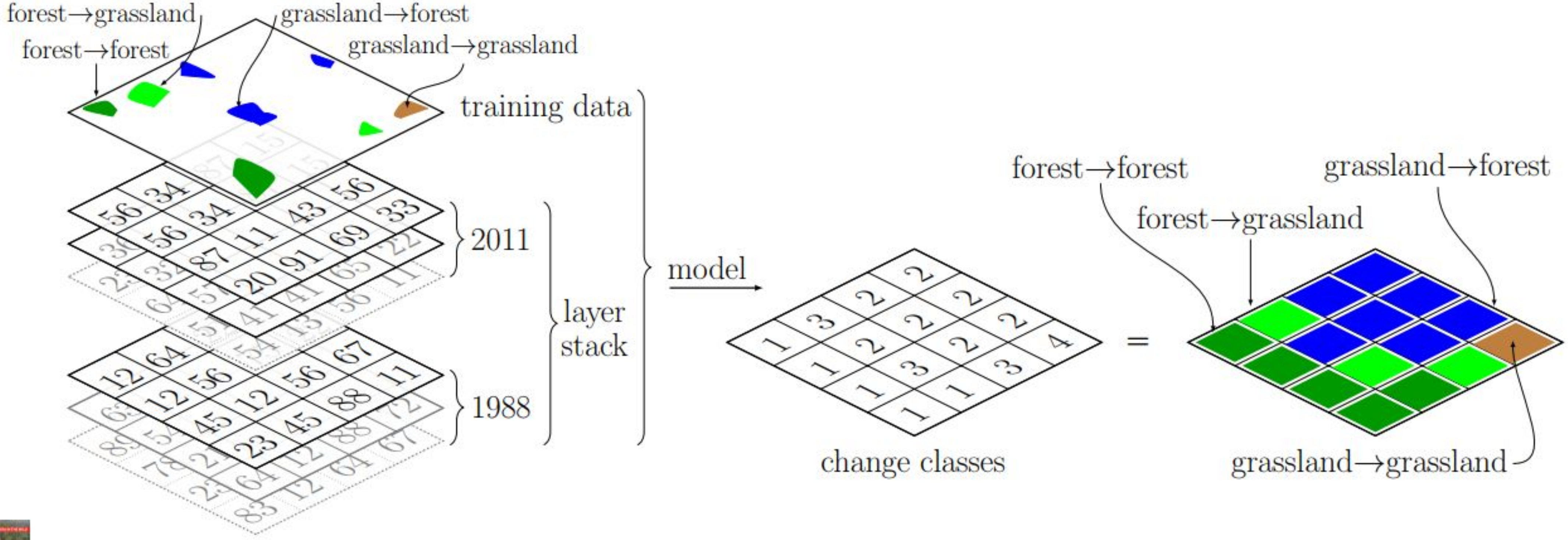
Validate post classification map

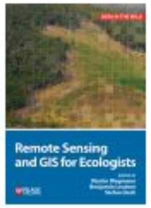
- Validate your post classification (or multidate) change map with another training vector
- Validation classes have to correspond to land cover change classification classes
- Also used to validate existing classification e.g., global ones as GlobCover

Validate postclassification map

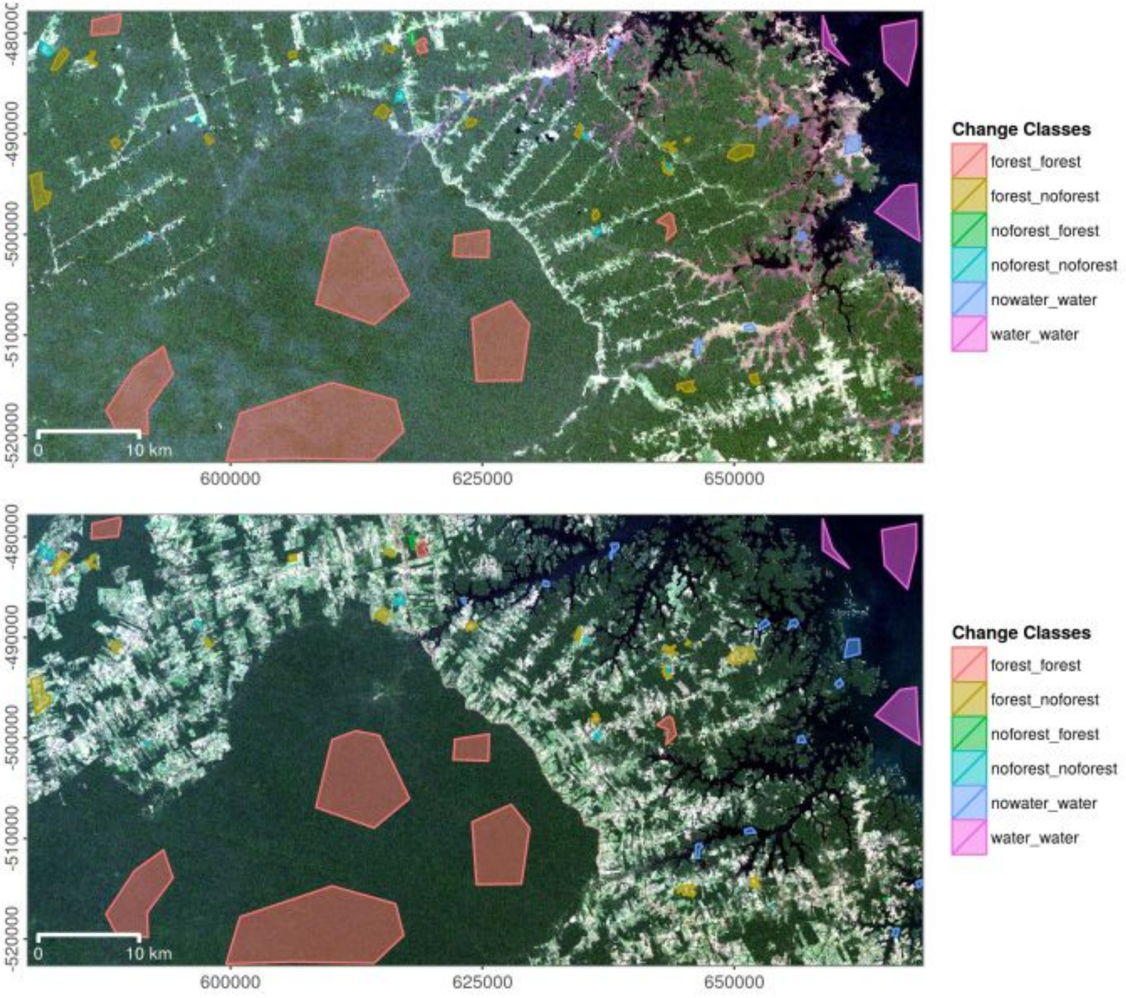


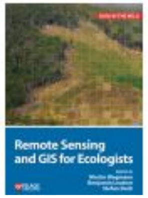
Different concepts to analyse change - **multidate**



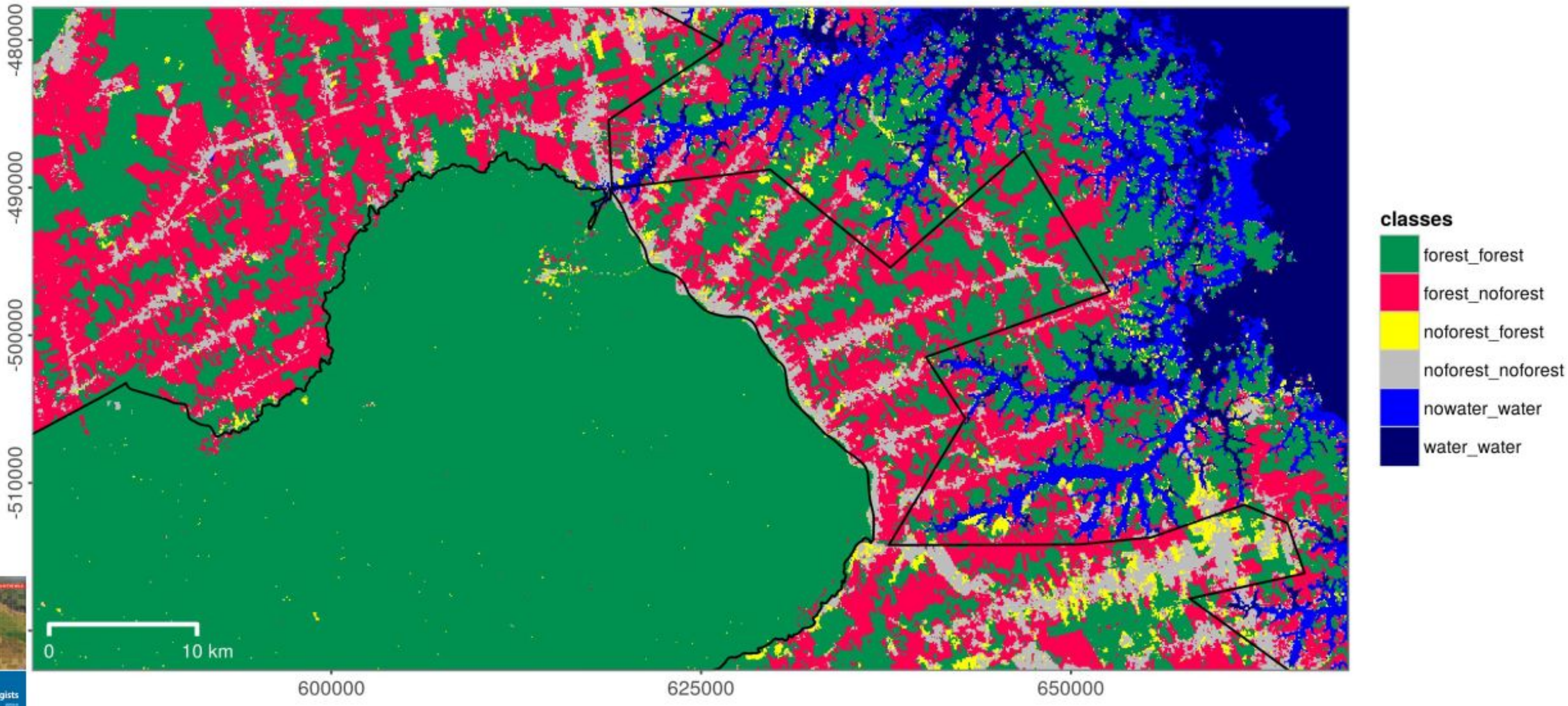


Multidate training data

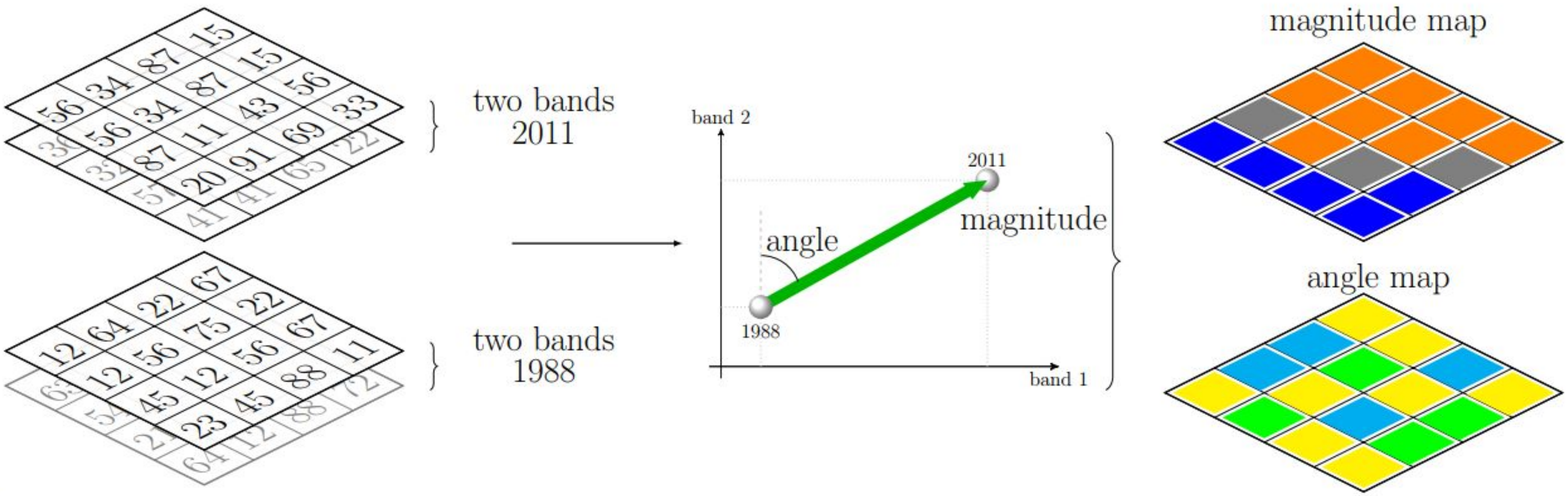


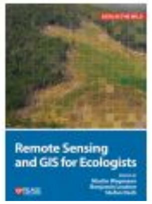


Multidate results

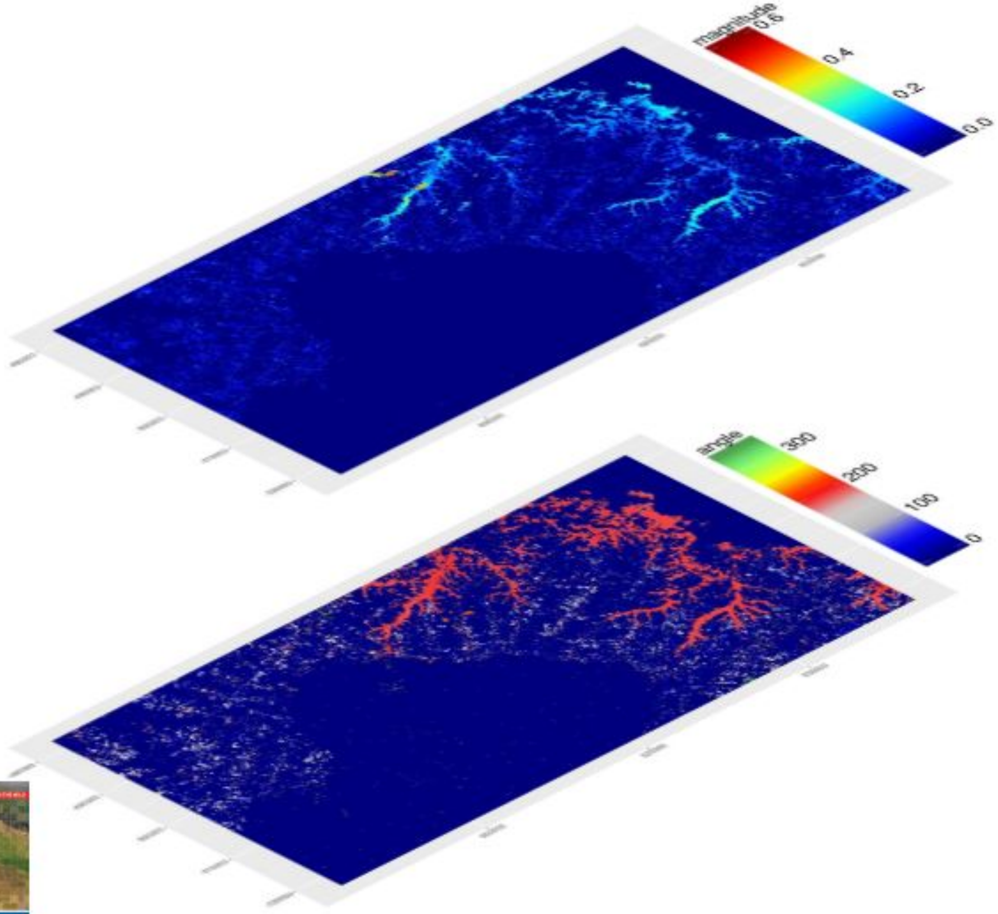


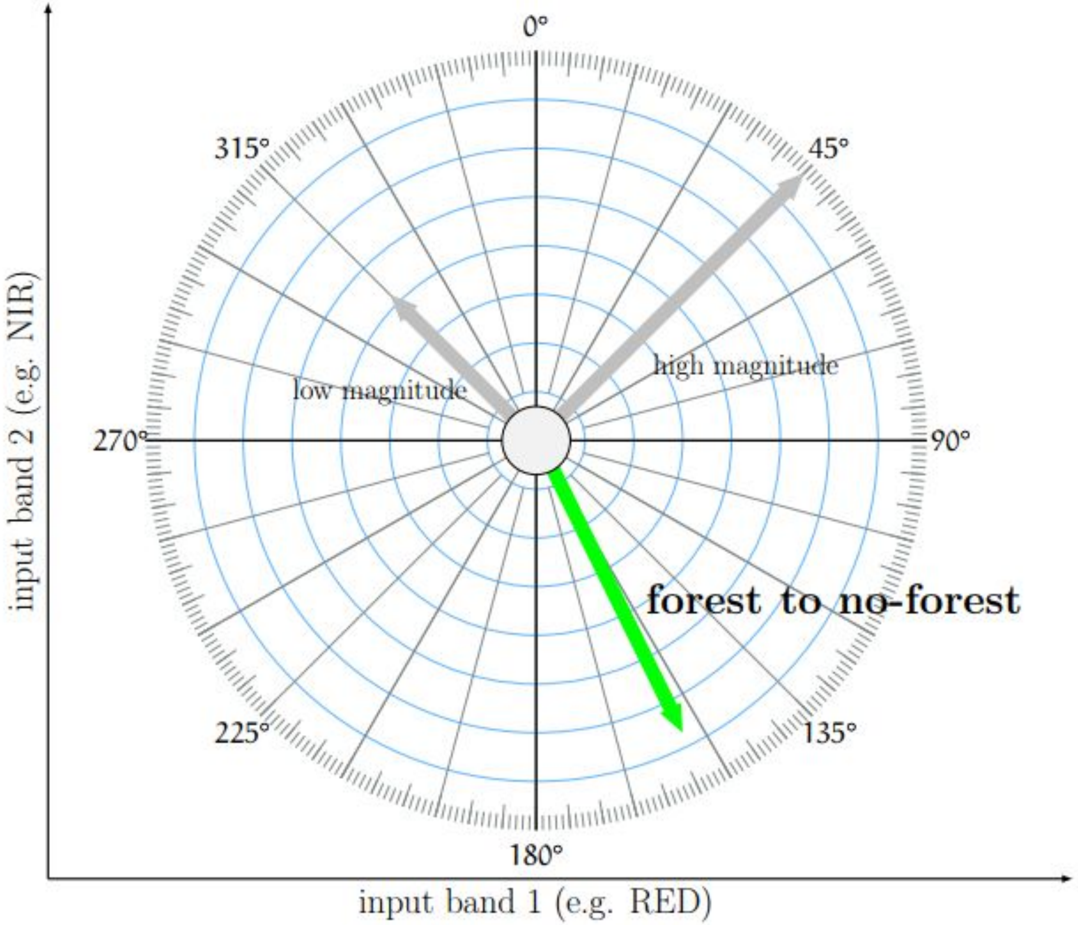
Different concepts to analyse change – **change vector**



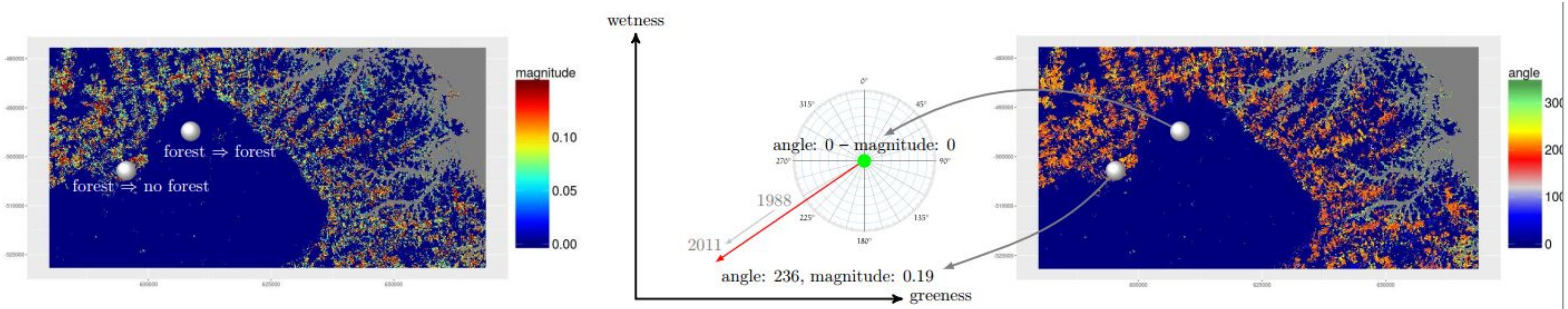


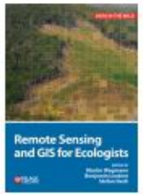
Different concepts to analyse change – **change vector**



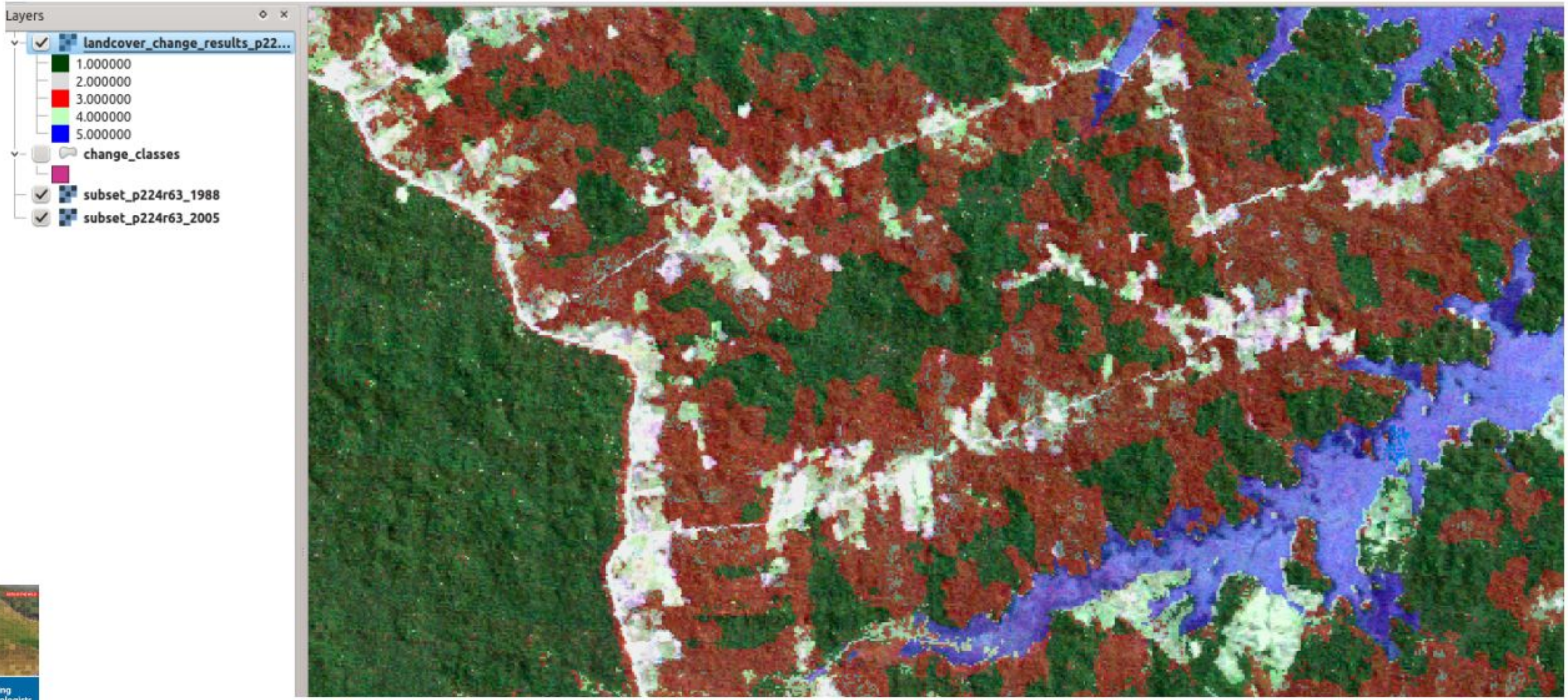


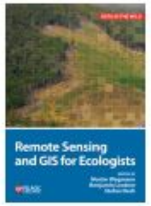
Different concepts to analyse change – **change vector**





Resulting change vector data





Any preferences? Where would you see challenges or problems?

- **Postclassification** is based on two classifications including their errors and errors are propagated in the change analysis – what is higher? Change or error?
- **Multi-date classification** is only one classification (incl. accuracy) but more work to find change areas for training and potentially more complex in case of many classes
- **Change vector analysis** is interesting but requires sound understanding of spectral responses and landcover, also it dies not give area, further processing needed

For more information on classification errors and landcover change e.g.:

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https://pdfs.semanticscholar.org/56e2/7d1903be7744d0bfa22af6b200dc383b4d4b.pdf
http://www.tandfonline.com/doi/abs/10.1080/01431160903131018
http://www-personal.umich.edu/~danbrown/papers/aburnick_CEUS_proof.pdf
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EARTH OBSERVATION RESEARCH

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EOCap 4Africa

Thank you for your attention!

Dr. Insa Otte (on behalf of the EOCap4Africa Team) and colleagues

insa.otte@uni-wuerzburg.de

Julius-Maximilians-UNIVERSITÄT WÜRZBURG

DLR

MARTIN-LUTHER-UNIVERSITÄT HALLE-WITTENBERG

UNIVERSITY OF BOTSWANA

INES Ruhengeri Institute of Applied Sciences