EDS 223: Geospatial Analysis & Remote Sensing
Week 9

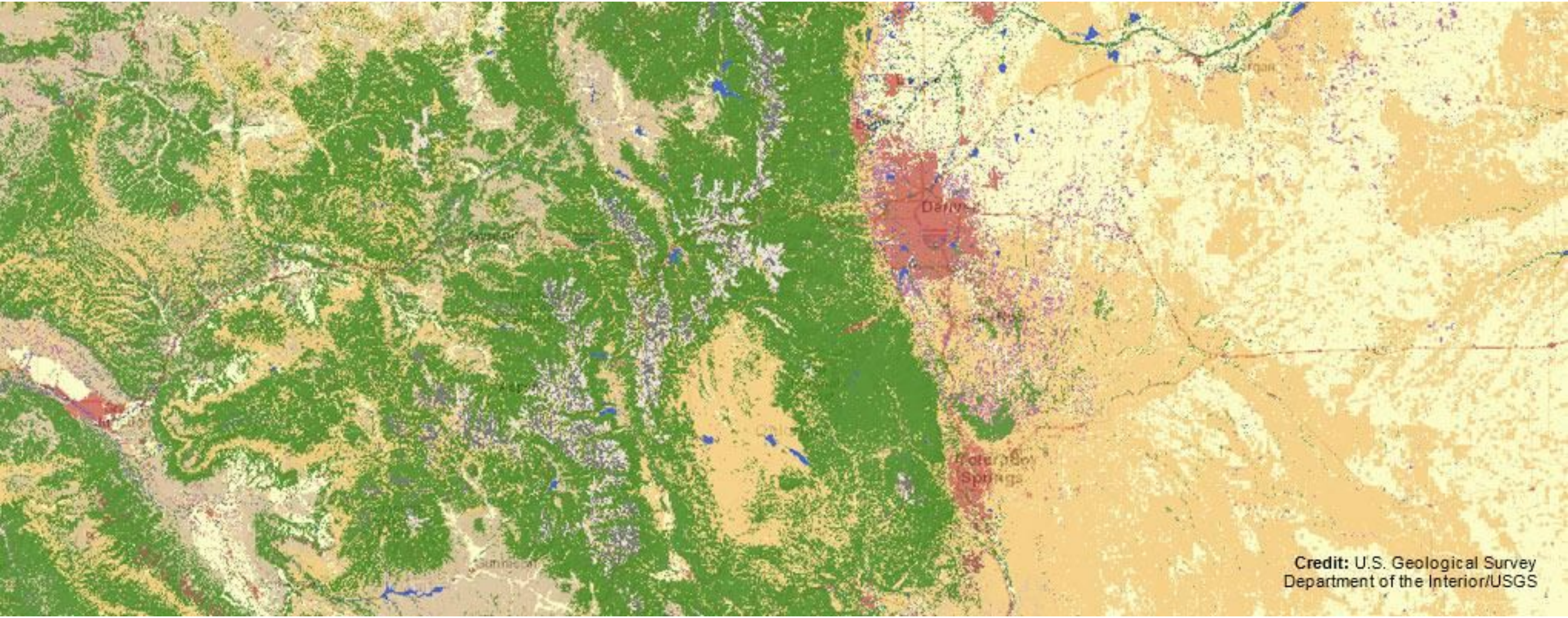


Image classification

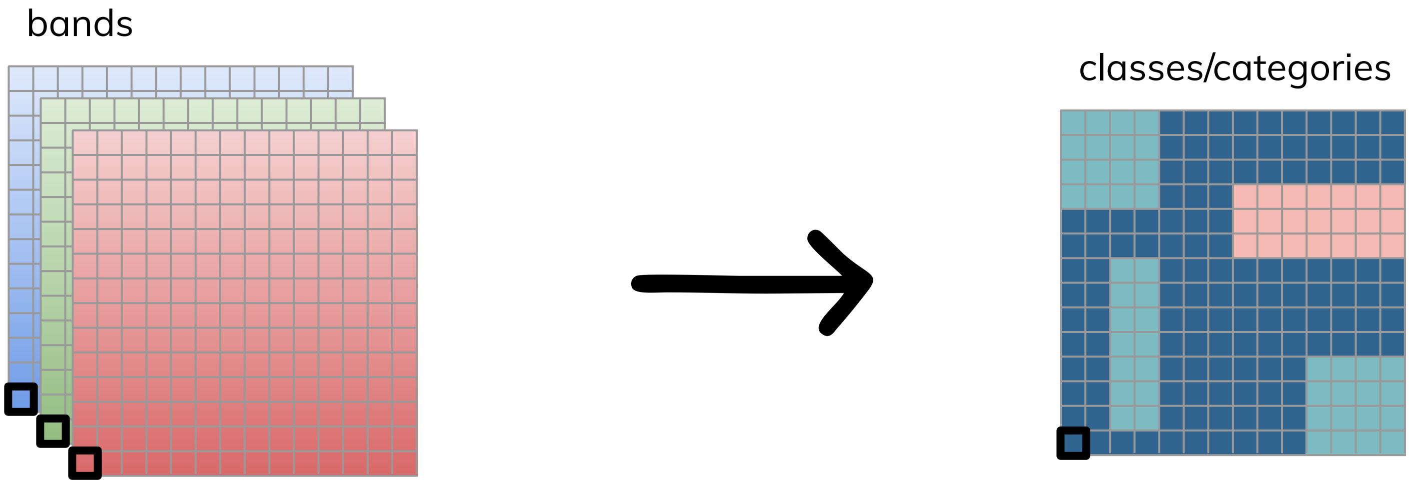
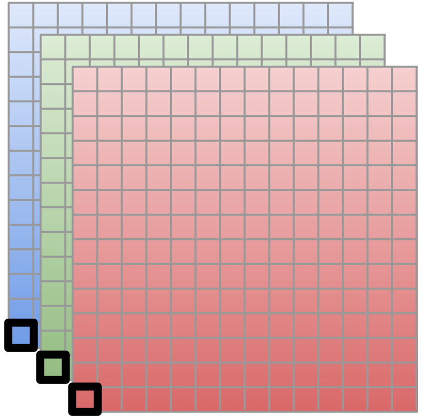
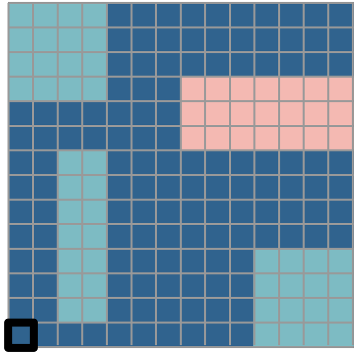


Image classification

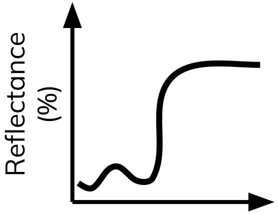
bands



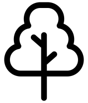
classes/categories



reflectance spectra



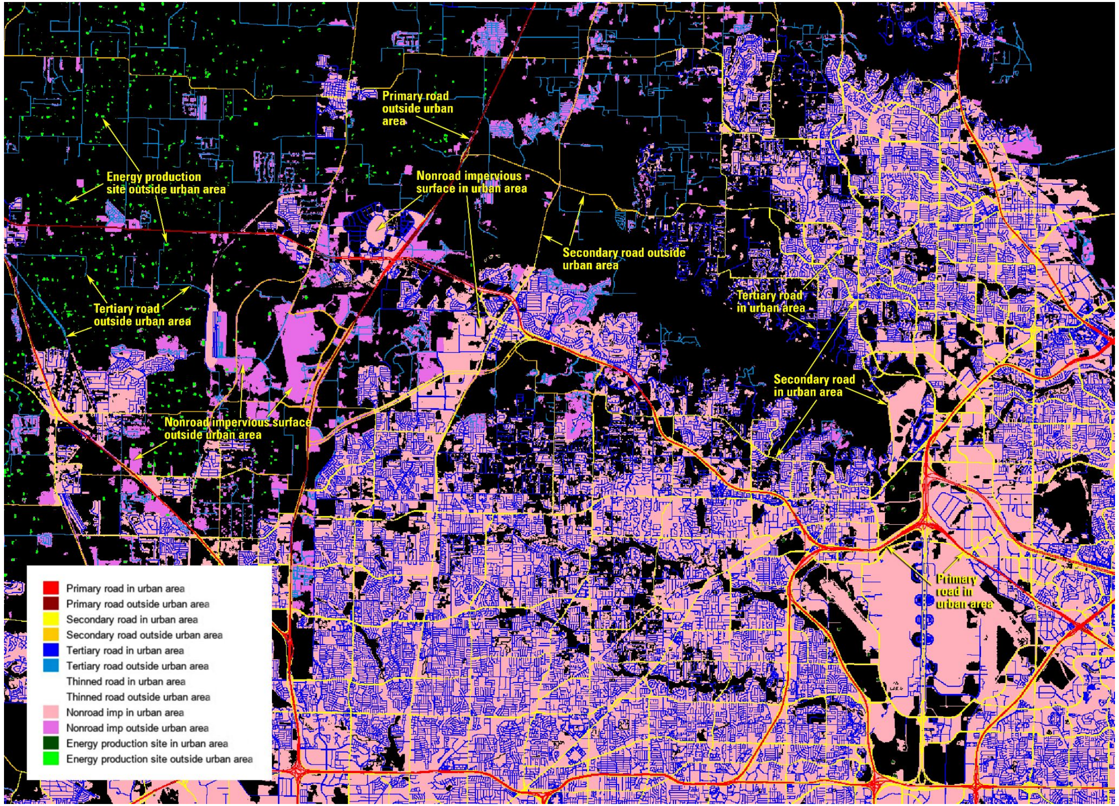
finite number of classes

 or  or 

Land cover classification

Source: USGS

Land cover classification



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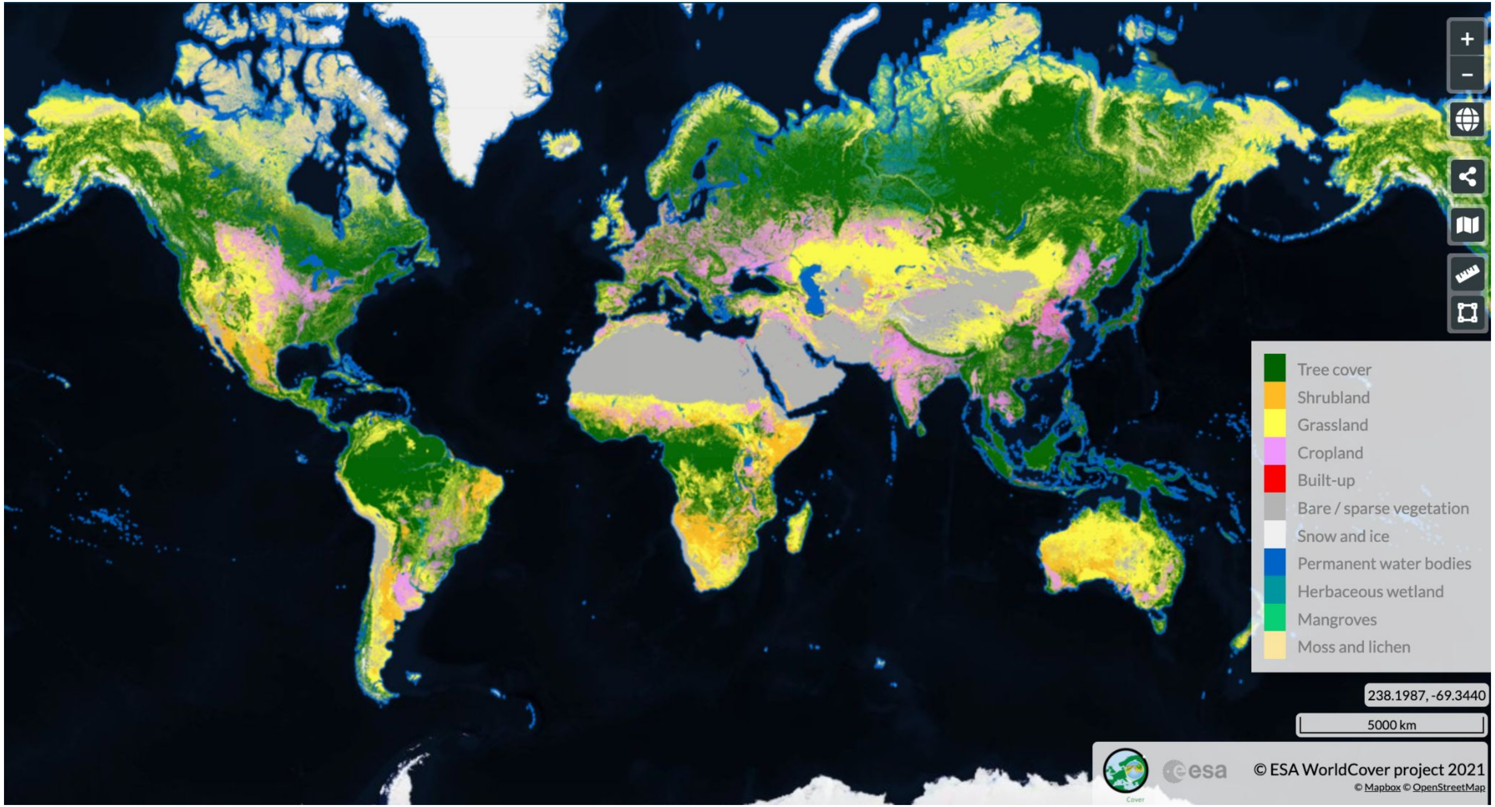
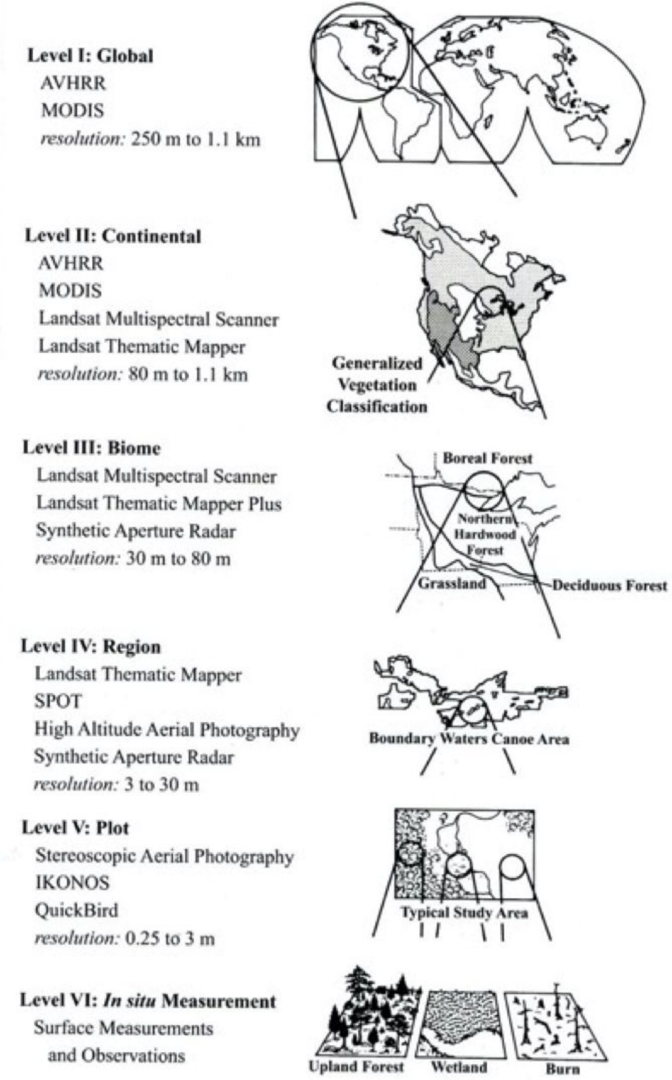


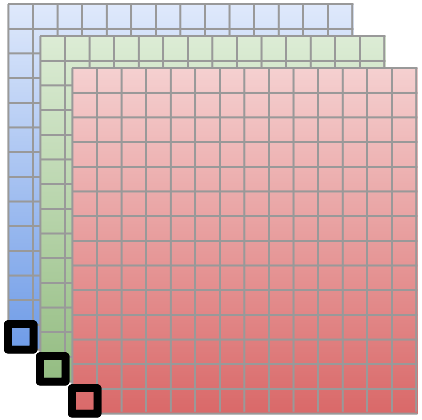
Classification scales



Source: Jensen 2007

Land cover classification

bands



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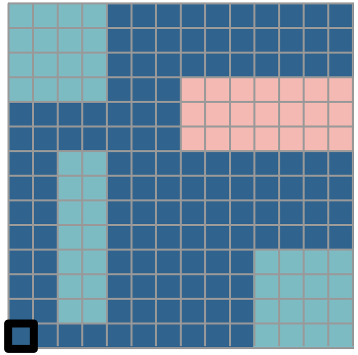

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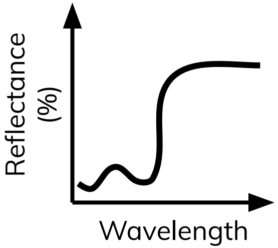

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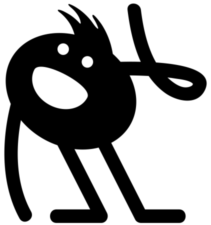
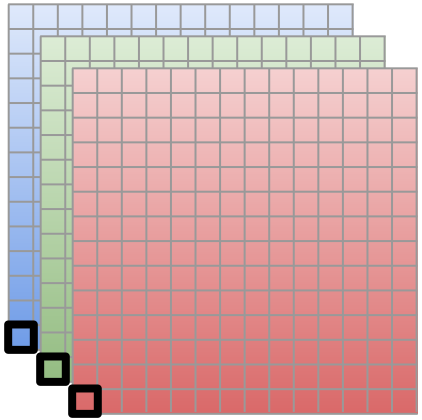
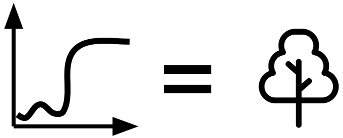


Land cover classification

bands





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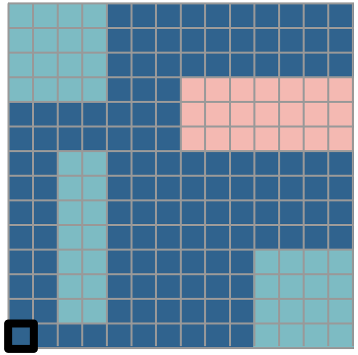

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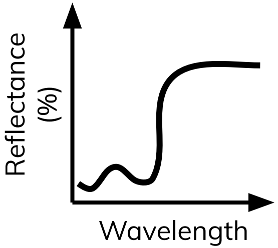

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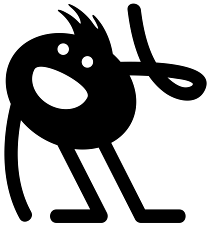

Land cover vs. land use

Land cover	Land use

Land cover vs. land use

Land cover	Land use
Refers to the type of natural and artificial materials present on a landscape	Refers to the human use of landscapes

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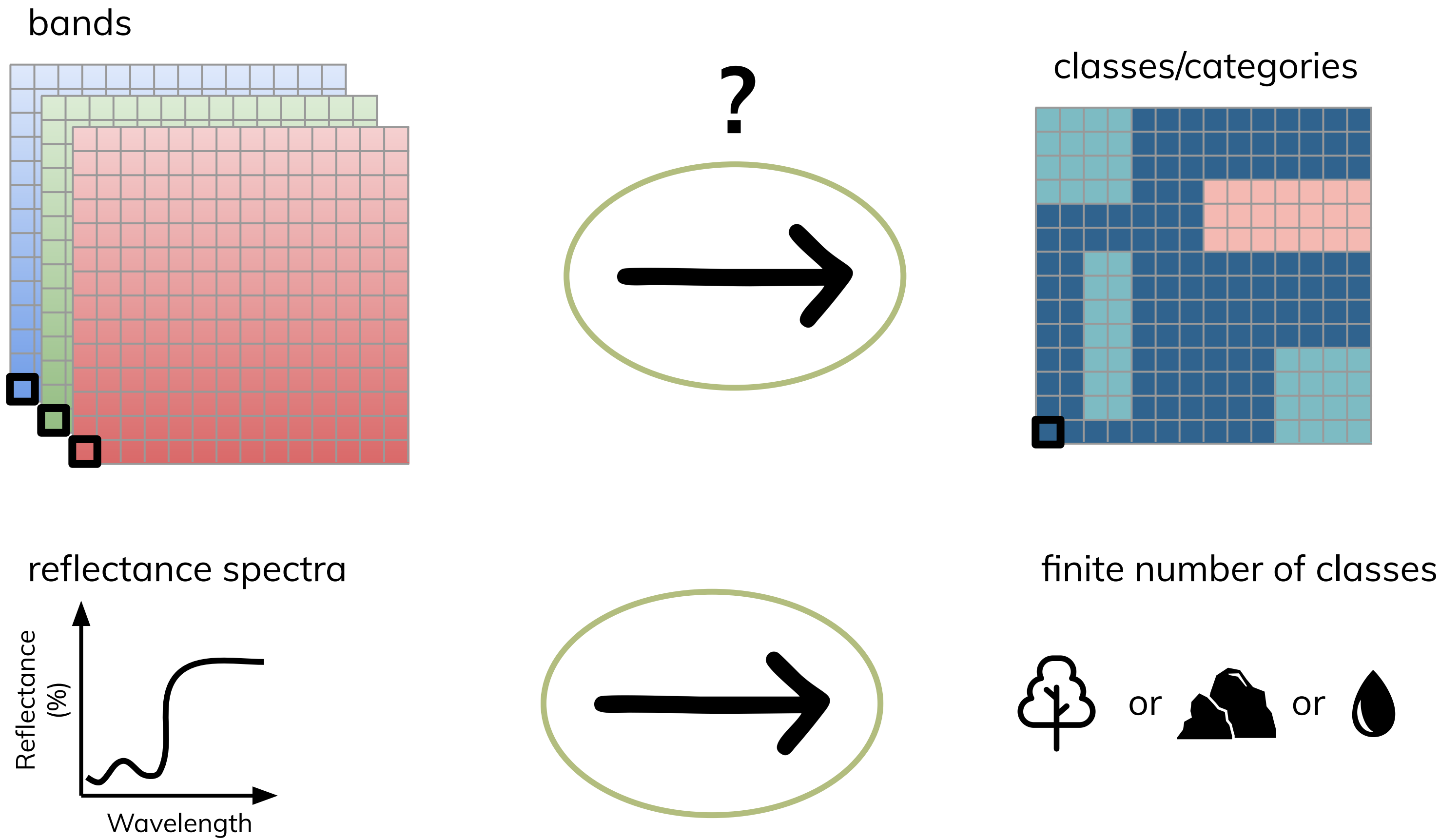
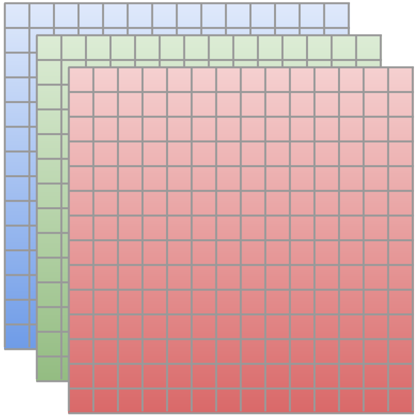
Land cover classification



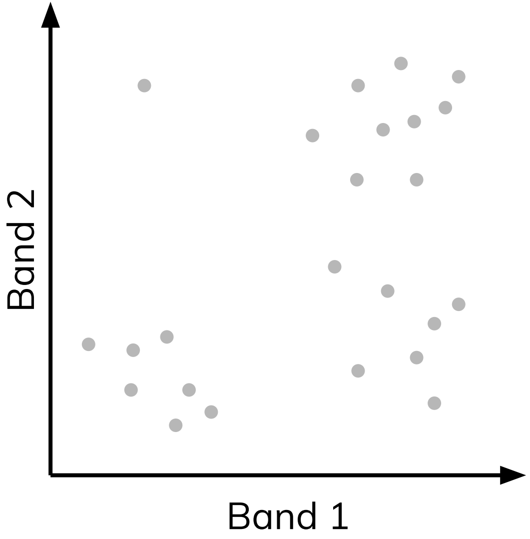
Land cover classification

Geographic space



Feature space

Points are pixels



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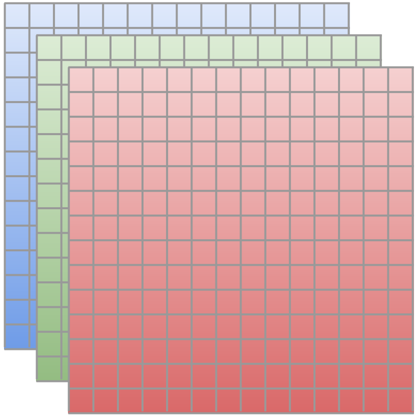

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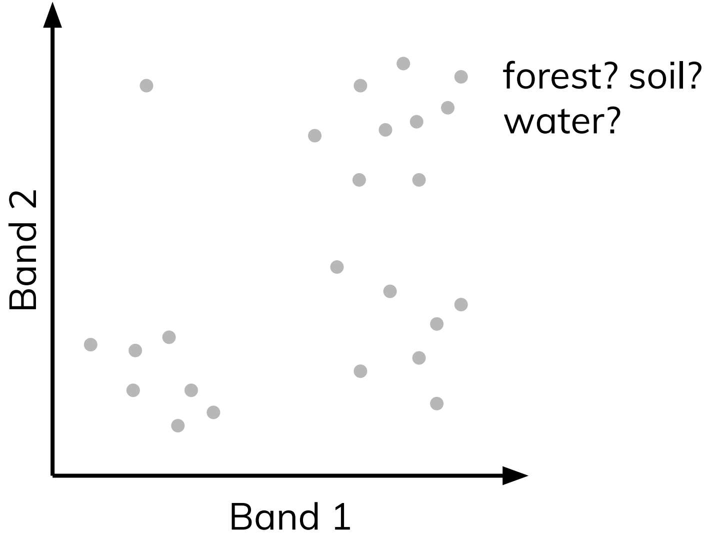

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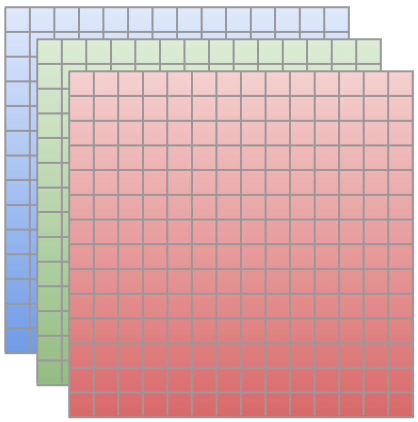

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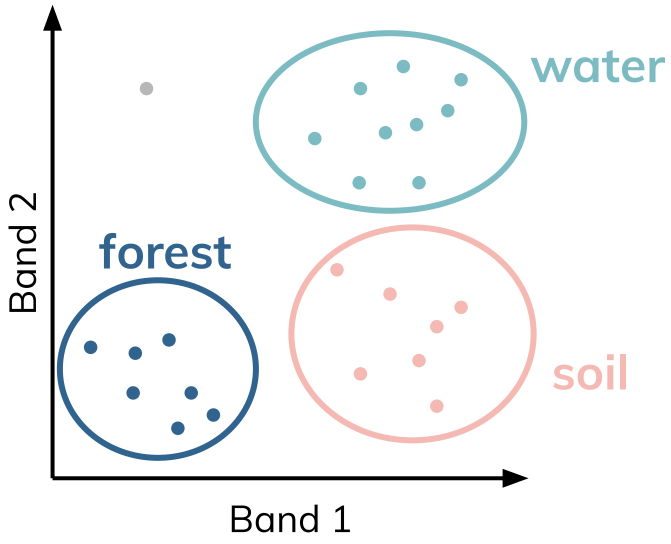

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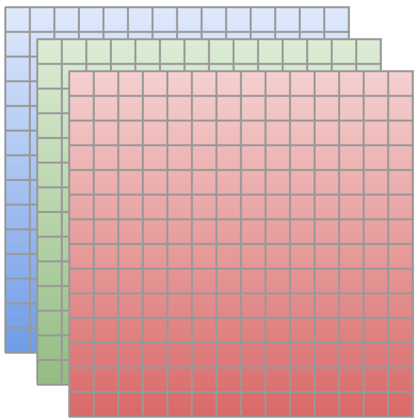
Geographic space



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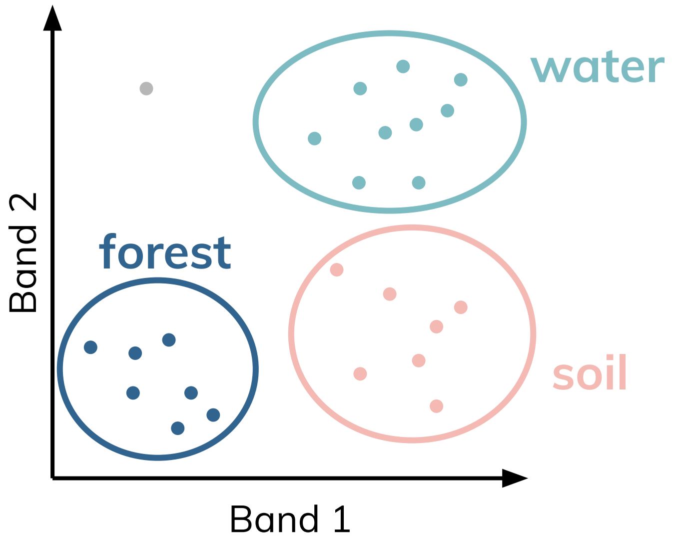

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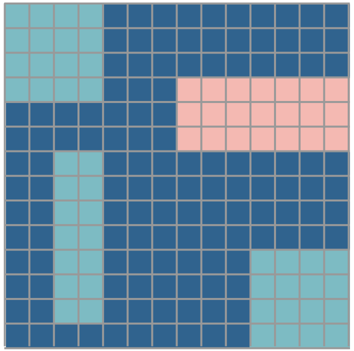

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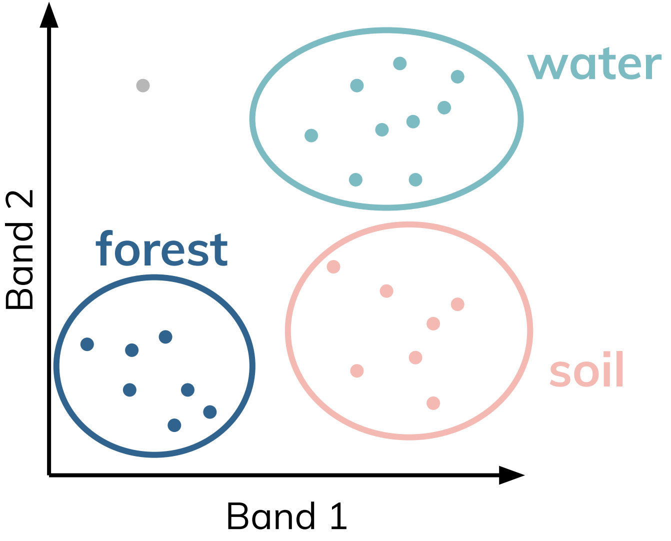

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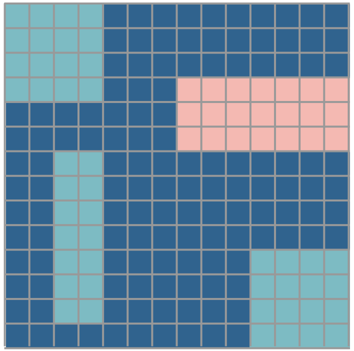
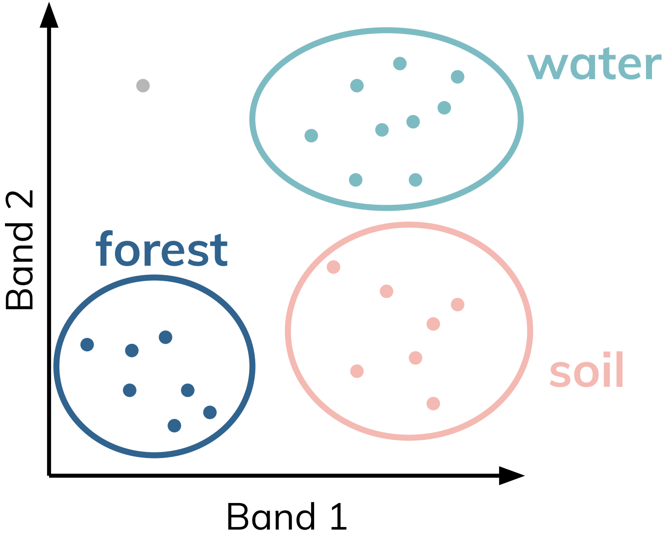


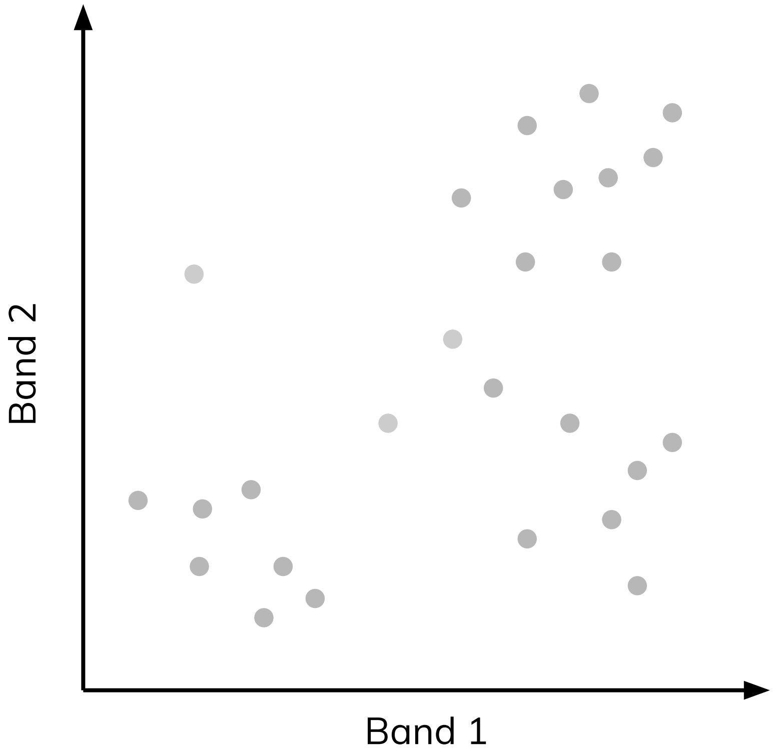
Lots of ways to assign pixels to groups!

Feature space

Points are pixels

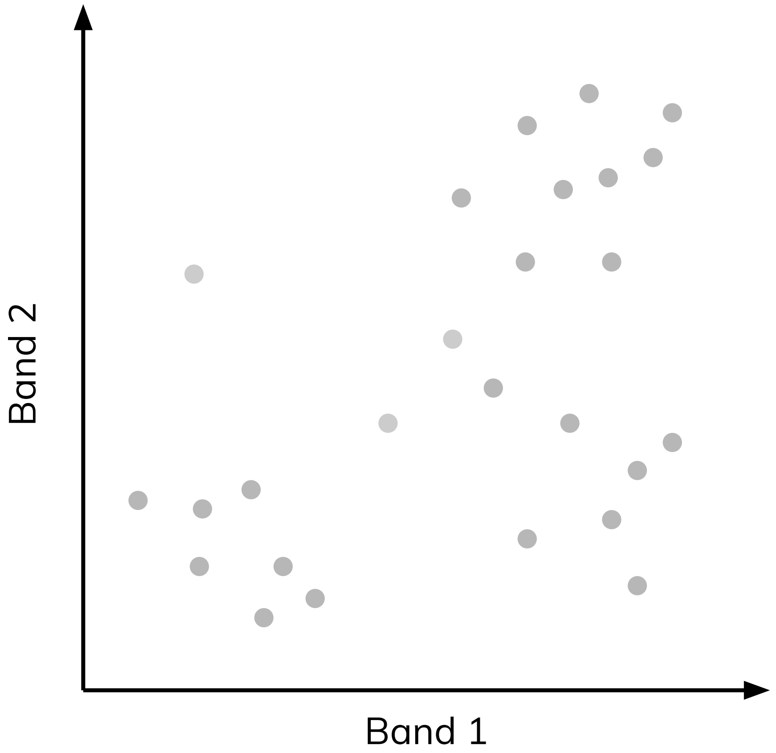


How to group pixels into land cover types



How to group pixels into land cover types

- Pick a number of groups



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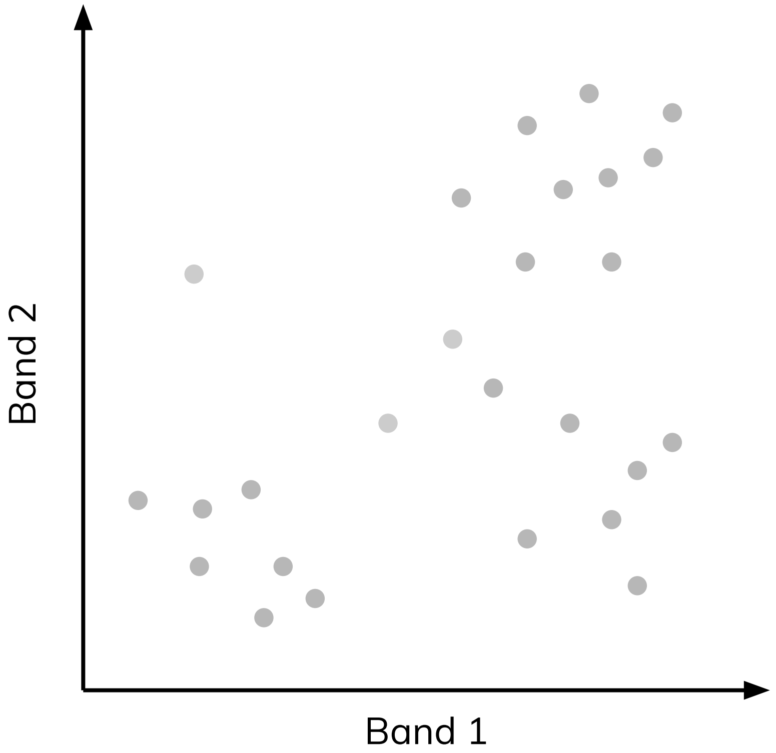

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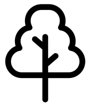
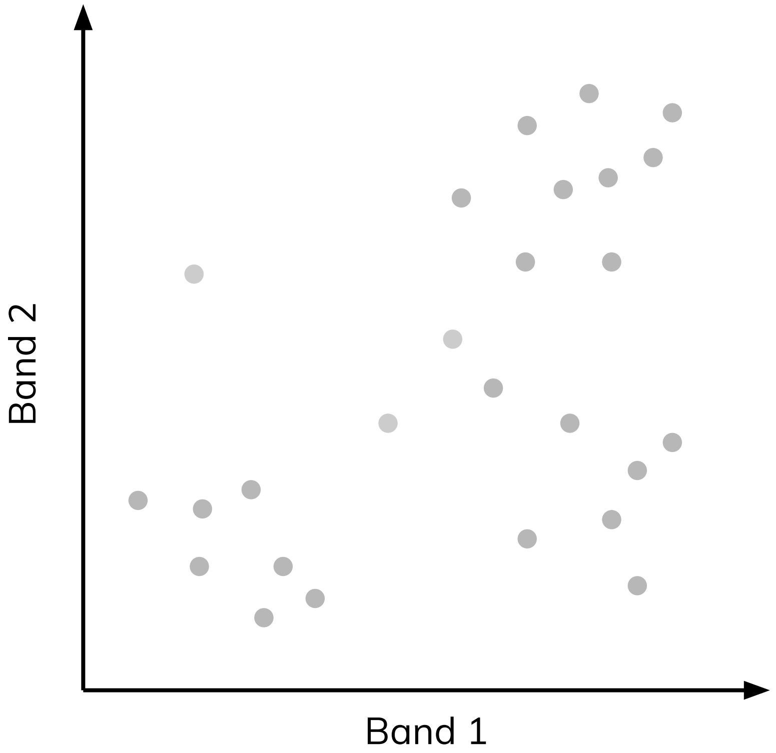
 or  or 

- Make a guess about where those groups are in feature space



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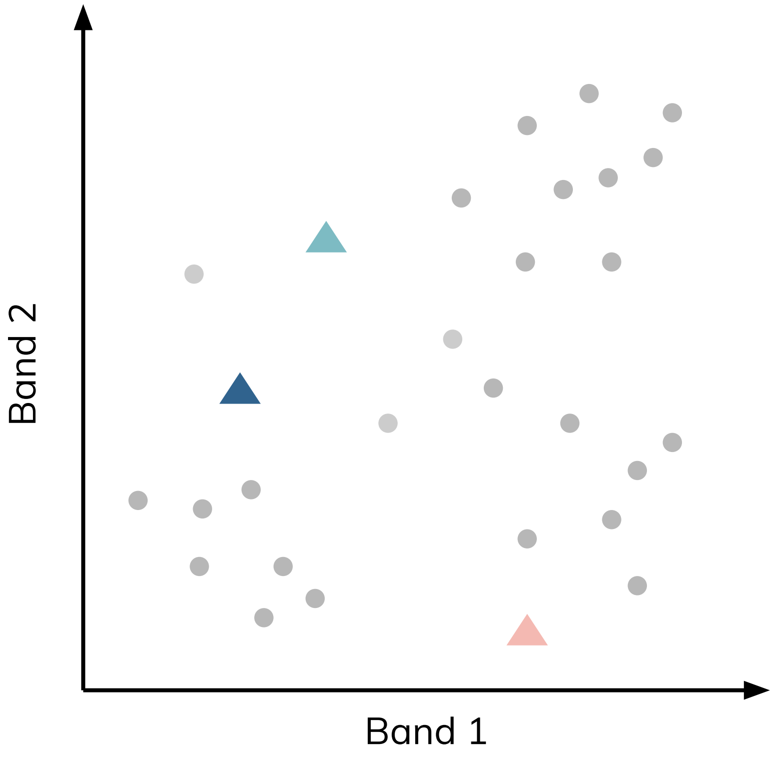
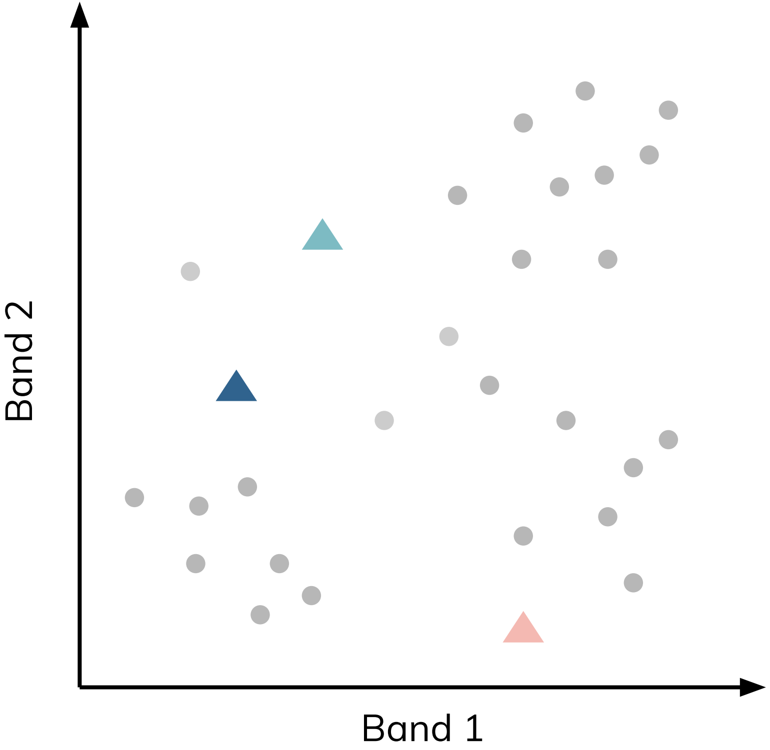


How to group pixels into land cover types

- Pick a number of groups

- Make a guess about where those groups are in feature space
- Assign each point to the closest group



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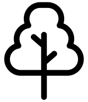 or  or 

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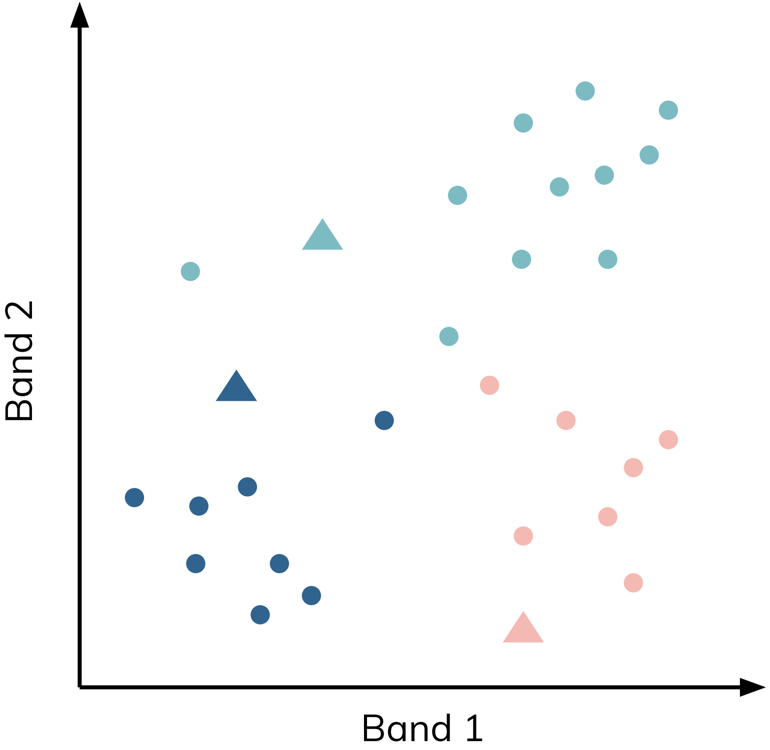
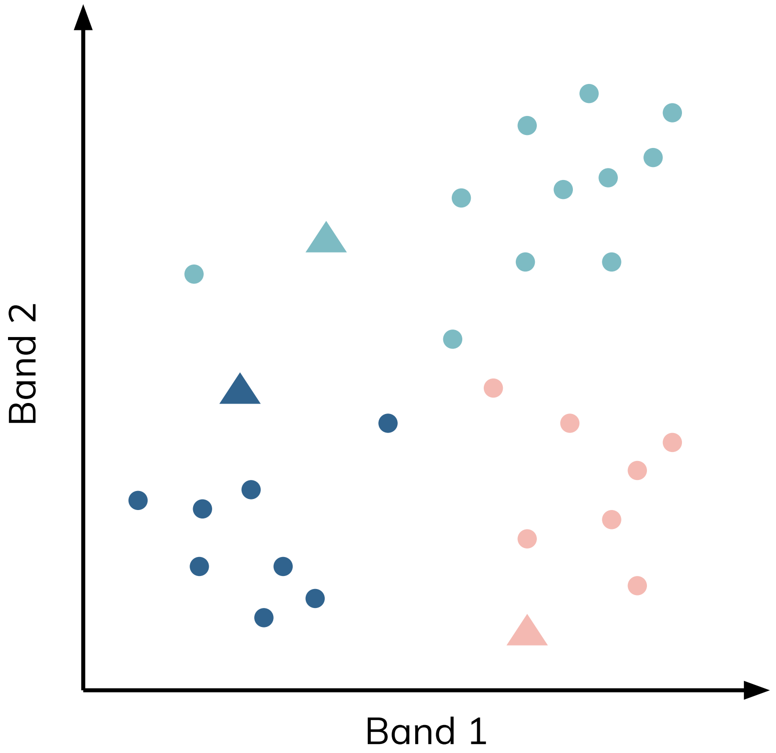


How to group pixels into land cover types

- Pick a number of groups

- Make a guess about where those groups are in feature space
- Assign each point to the closest group
- Move group centers to better represent groups



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- Pick a number of groups

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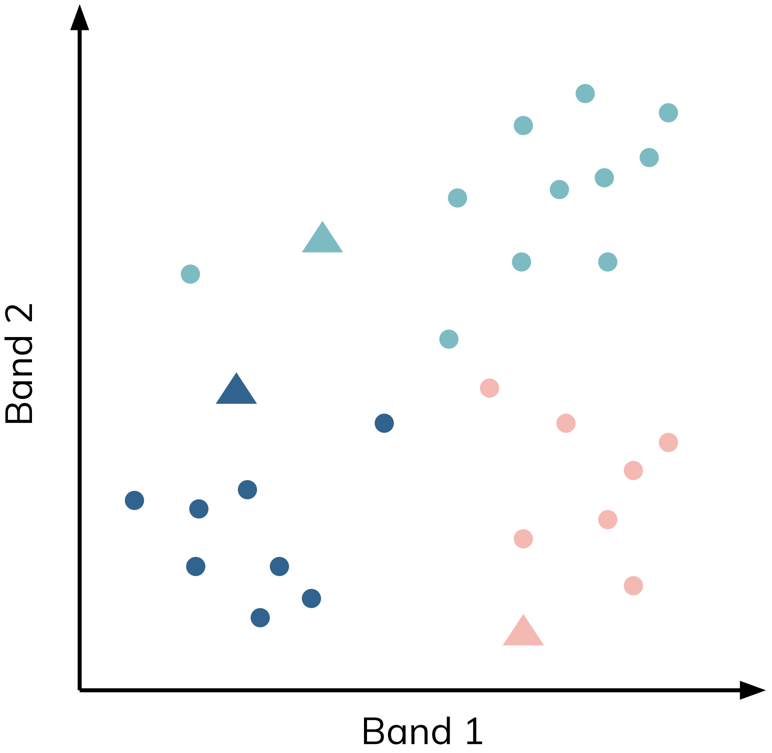
    - Use the mean!



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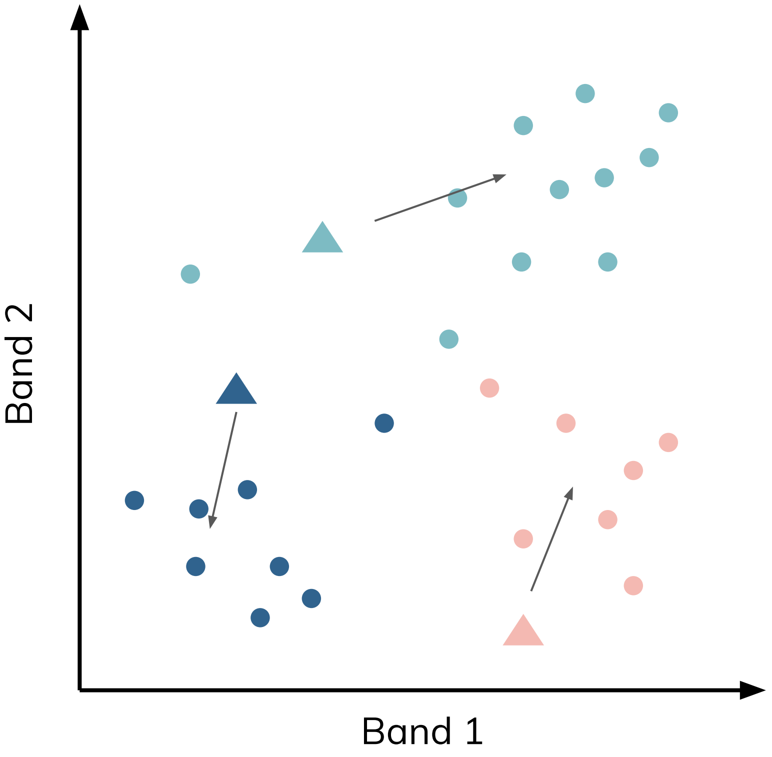

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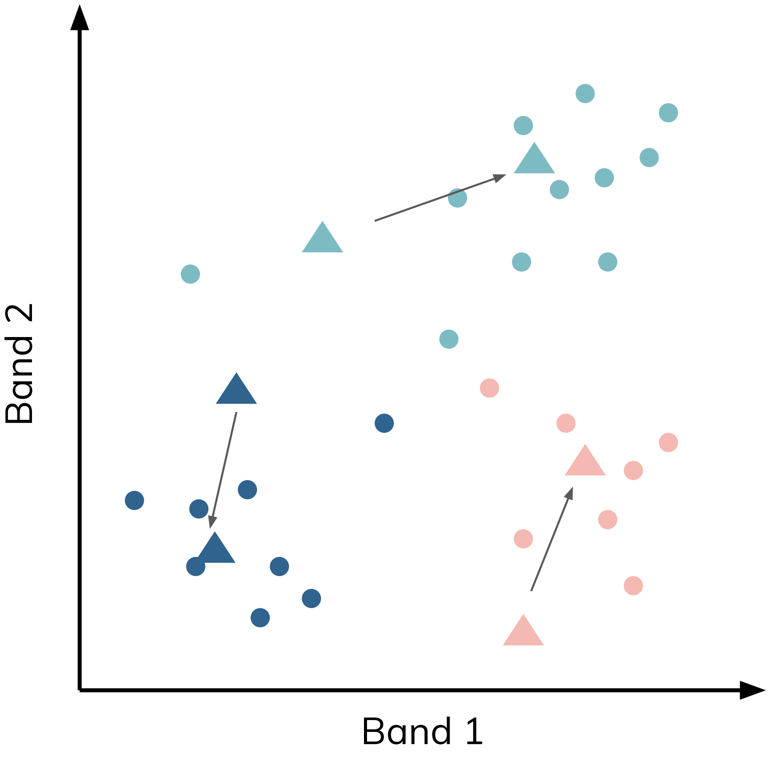

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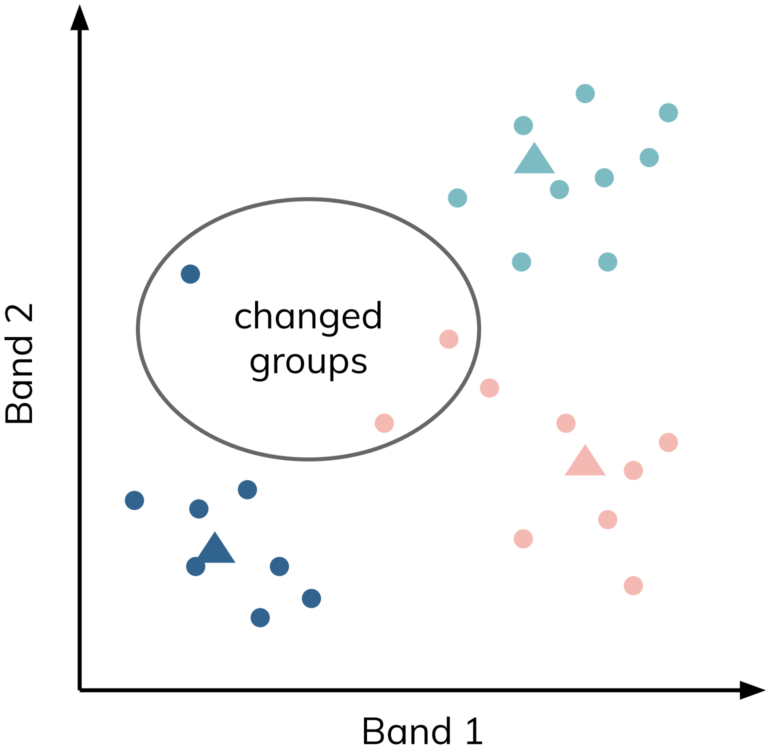

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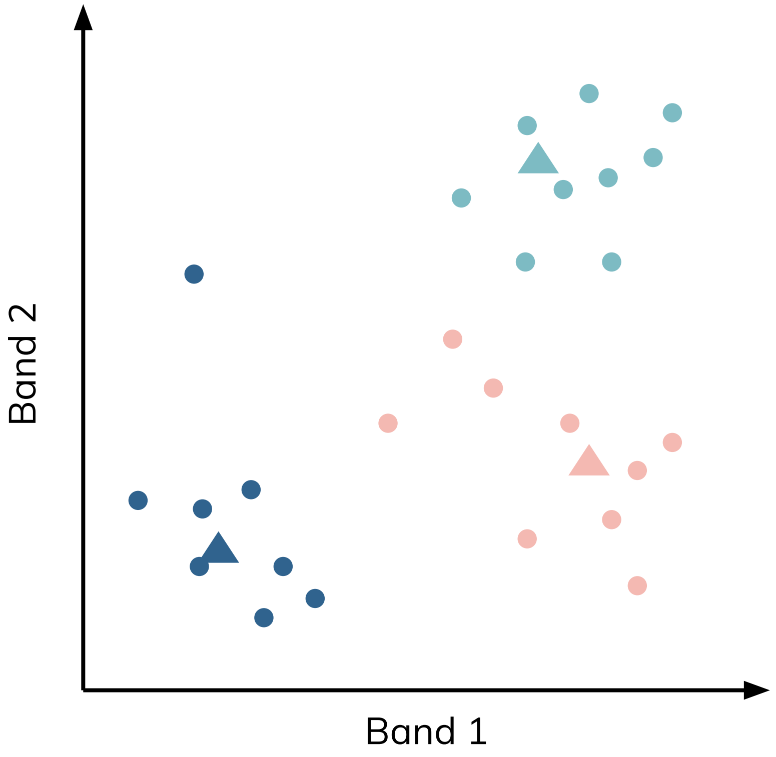
- Keep going until distances are minimized



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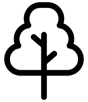 or  or 

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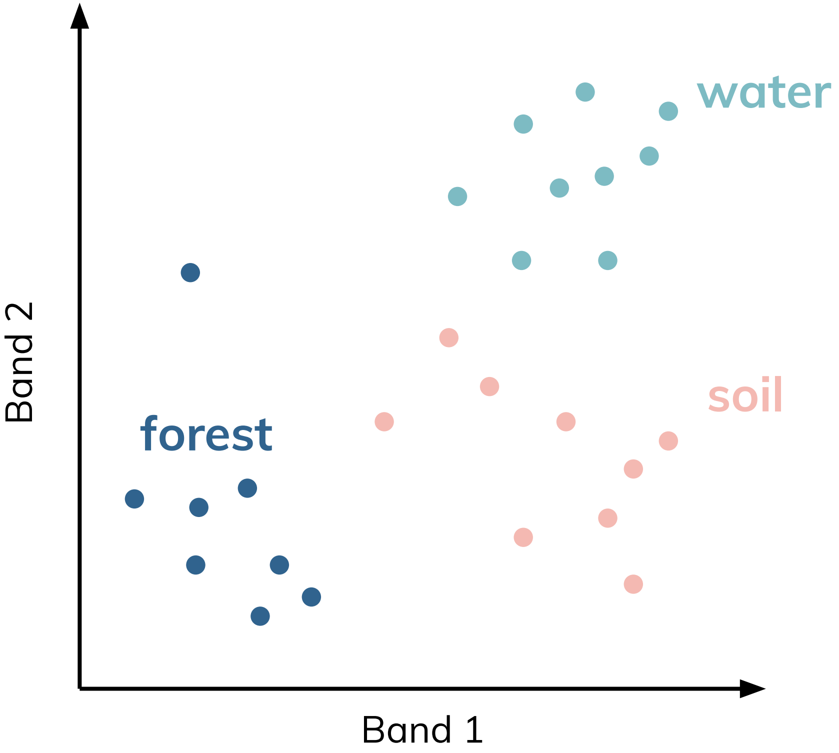
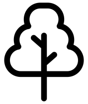


k-means clustering

- Pick a number of groups

 or  or 

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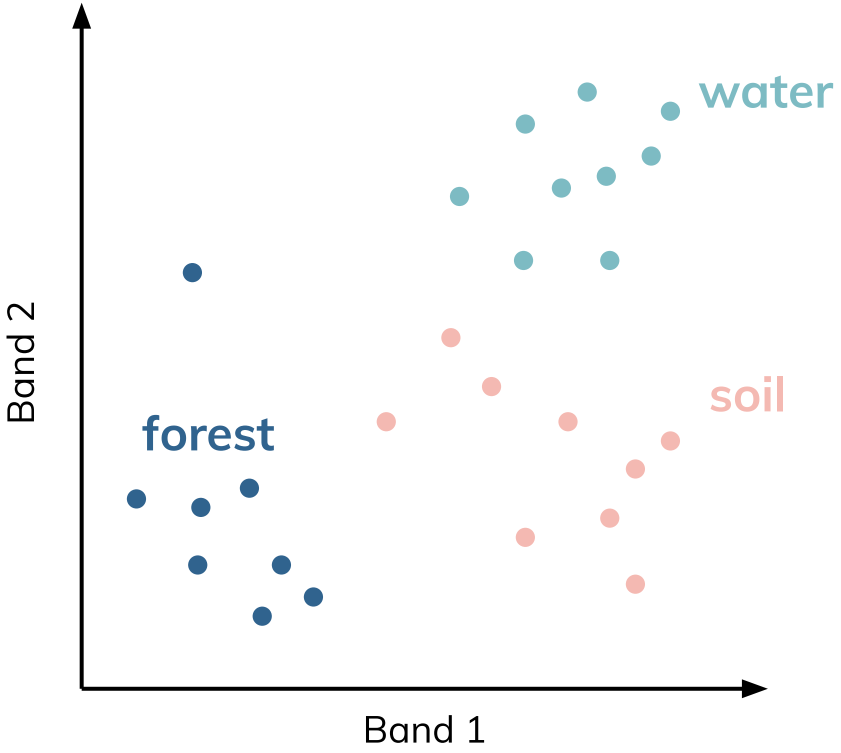

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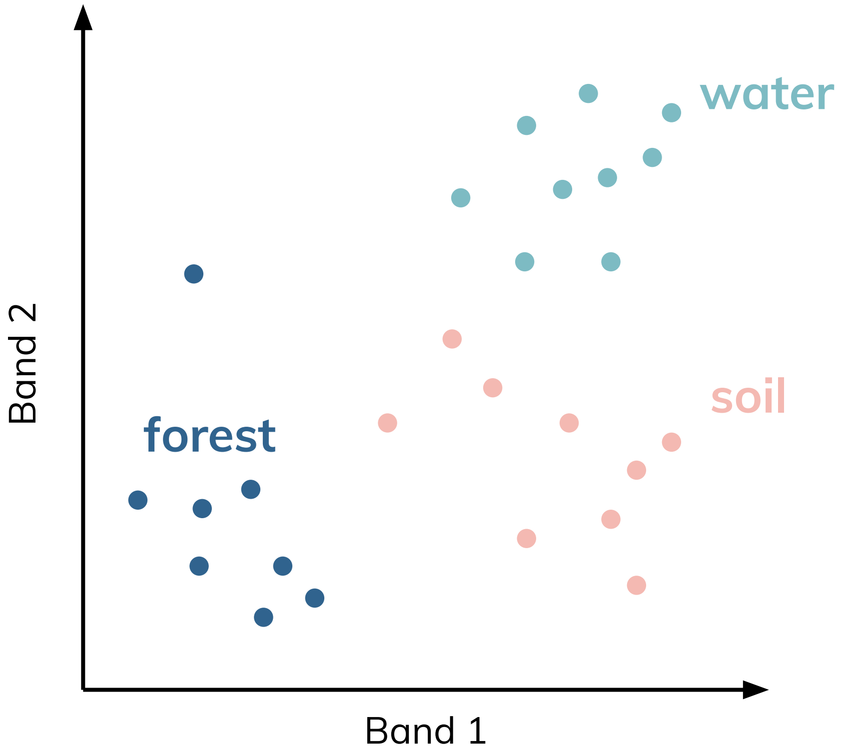
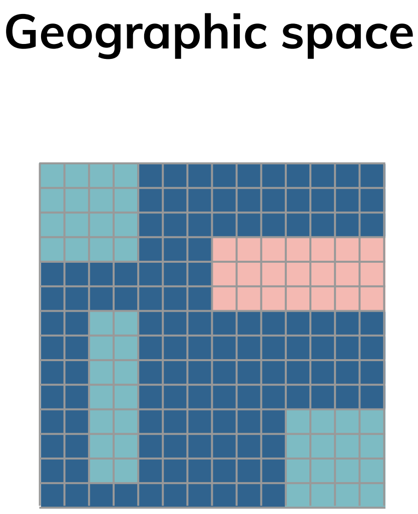
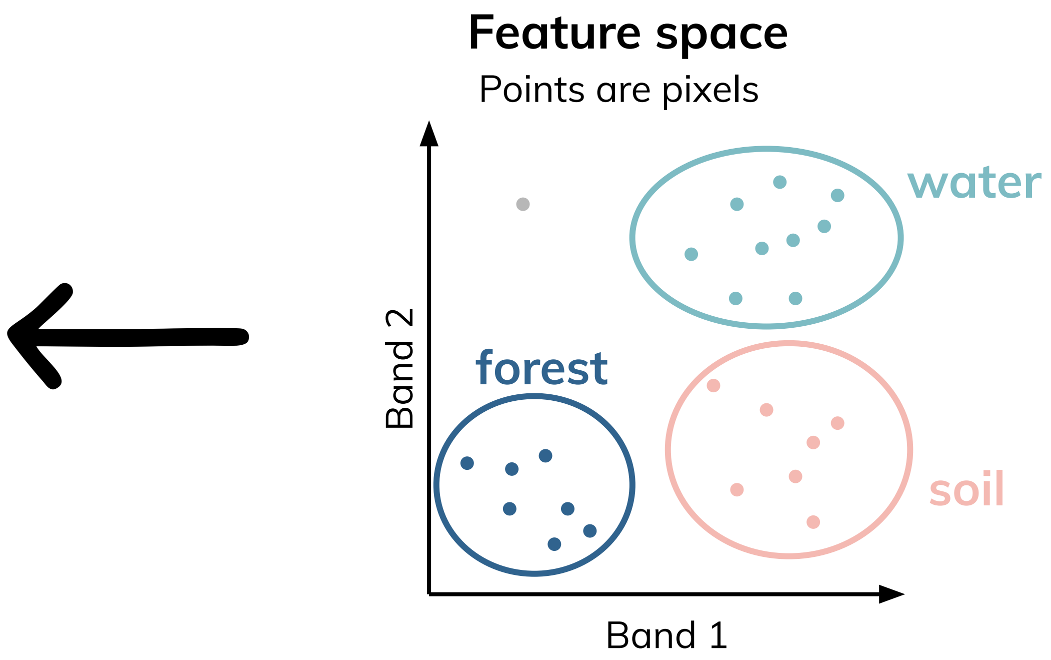


k is the number of groups (or clusters)

clusters are based on the group mean

k-means clustering





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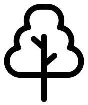 or  or 

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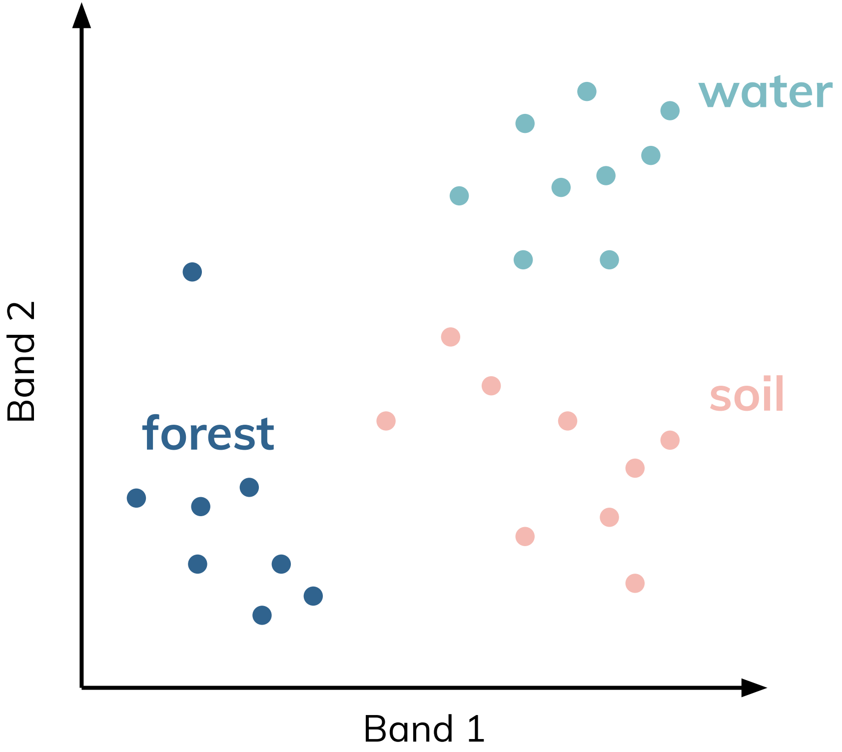
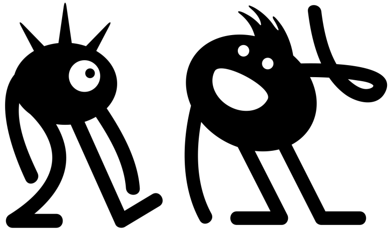


Pros/Cons



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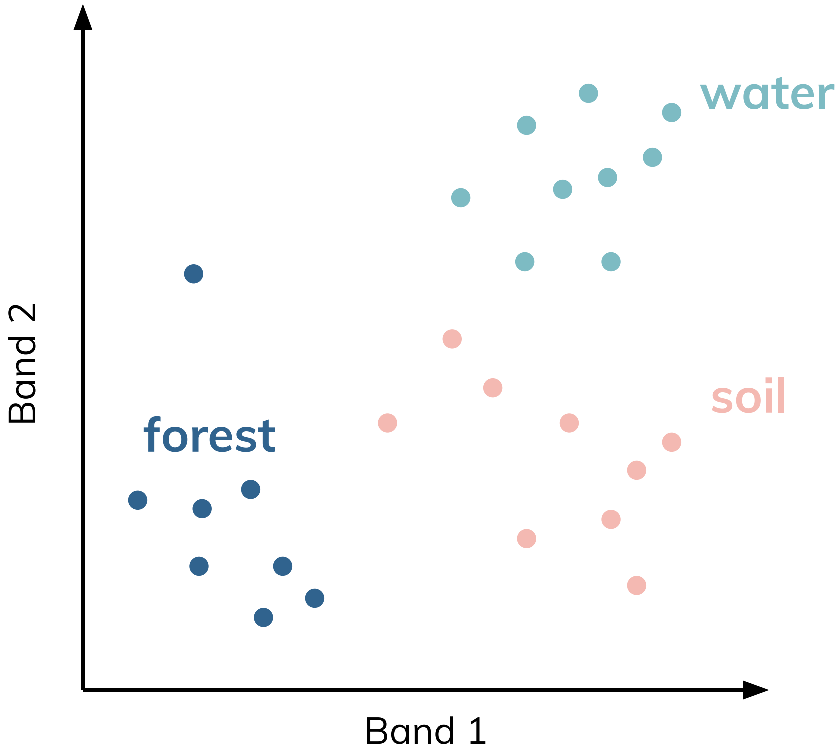

Pros

- Only needed remote sensing data
- Explored how similar different areas are

Cons

- Clusters might not always work out this well
- Number of groups was arbitrary
- Starting guess on clusters might impact results
- Needed to figure out what the clusters meant

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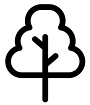 or  or 

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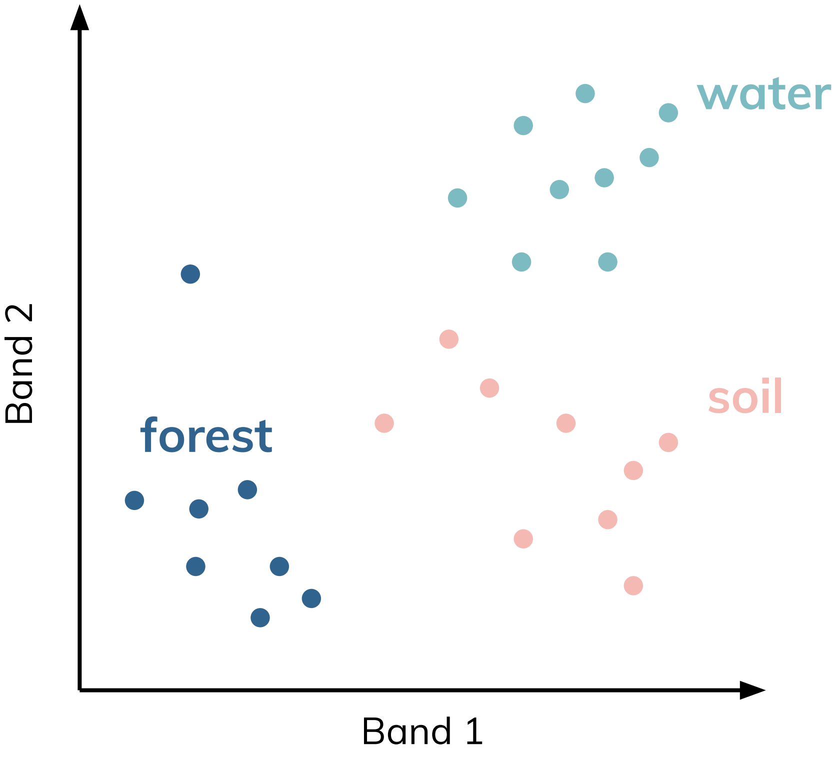

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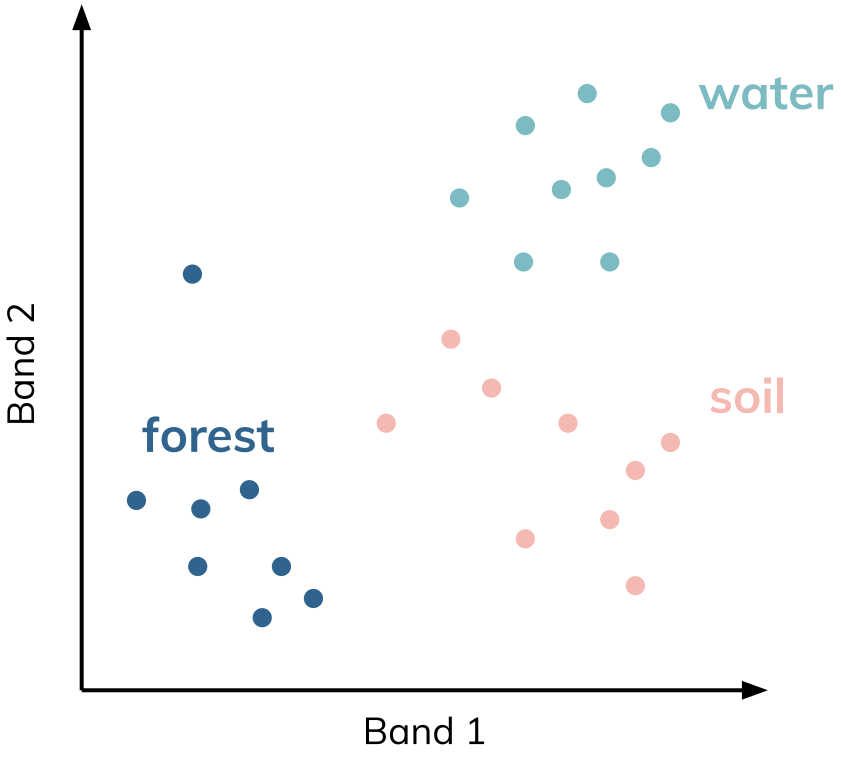

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- **Needed to figure out what the clusters meant**

Image classification

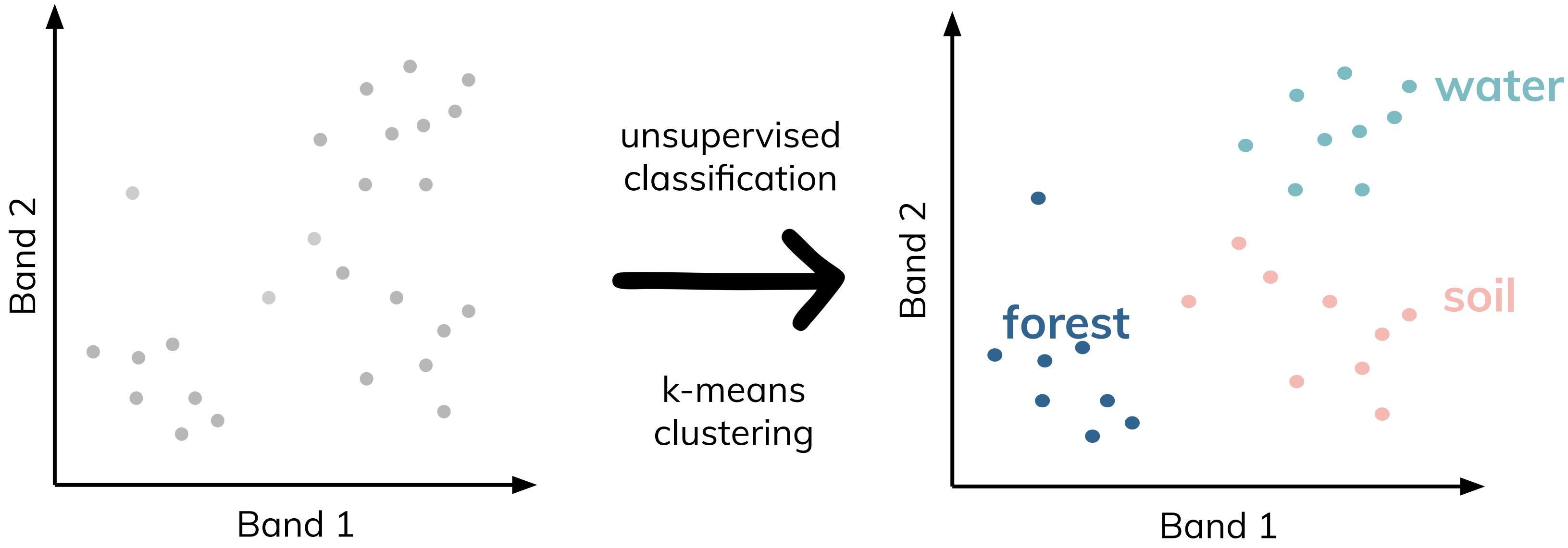


Image classification

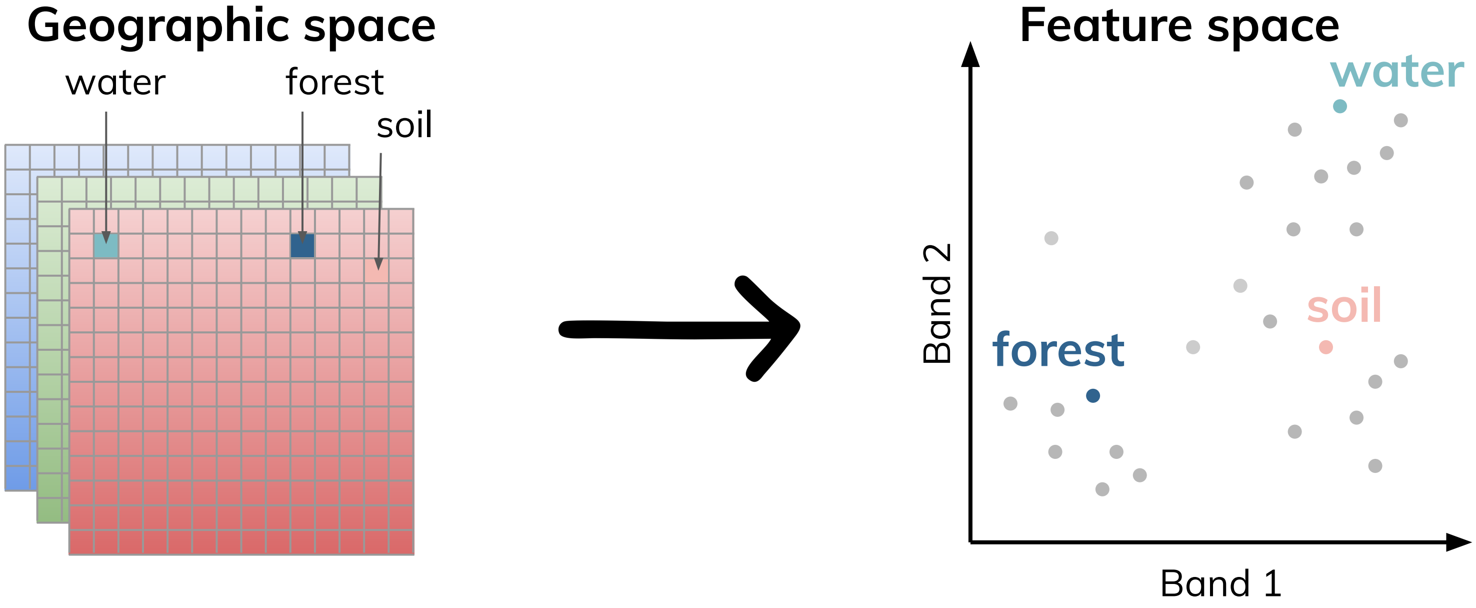
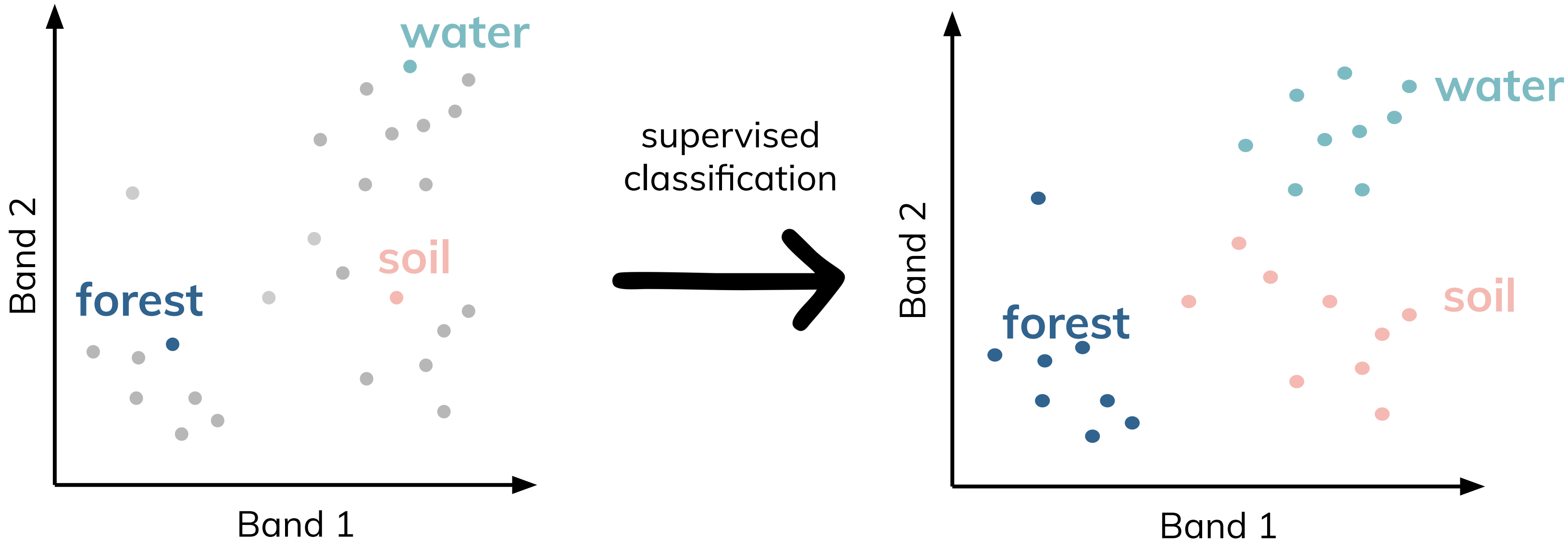
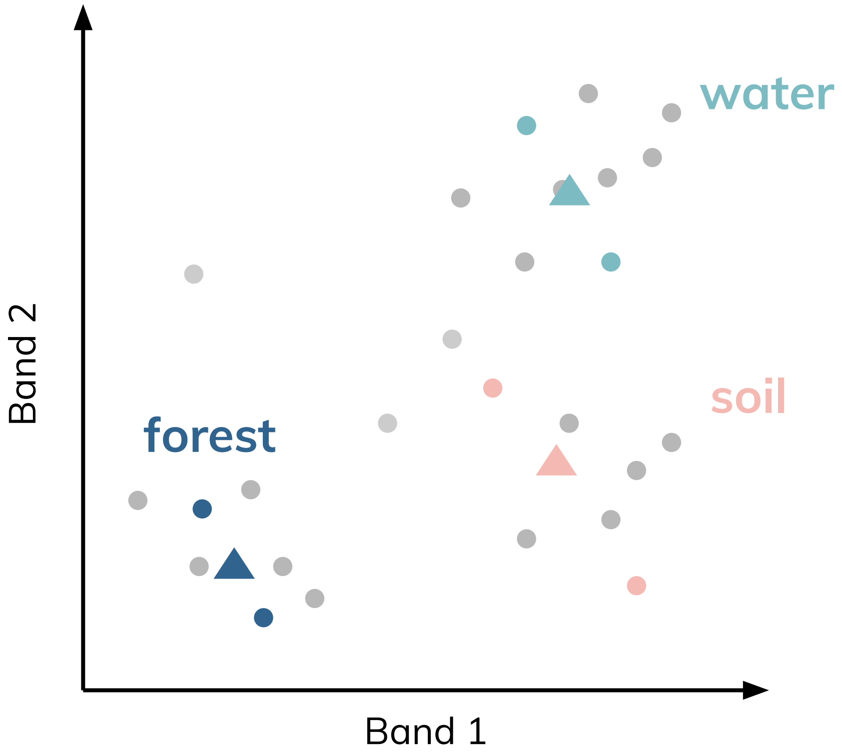


Image classification



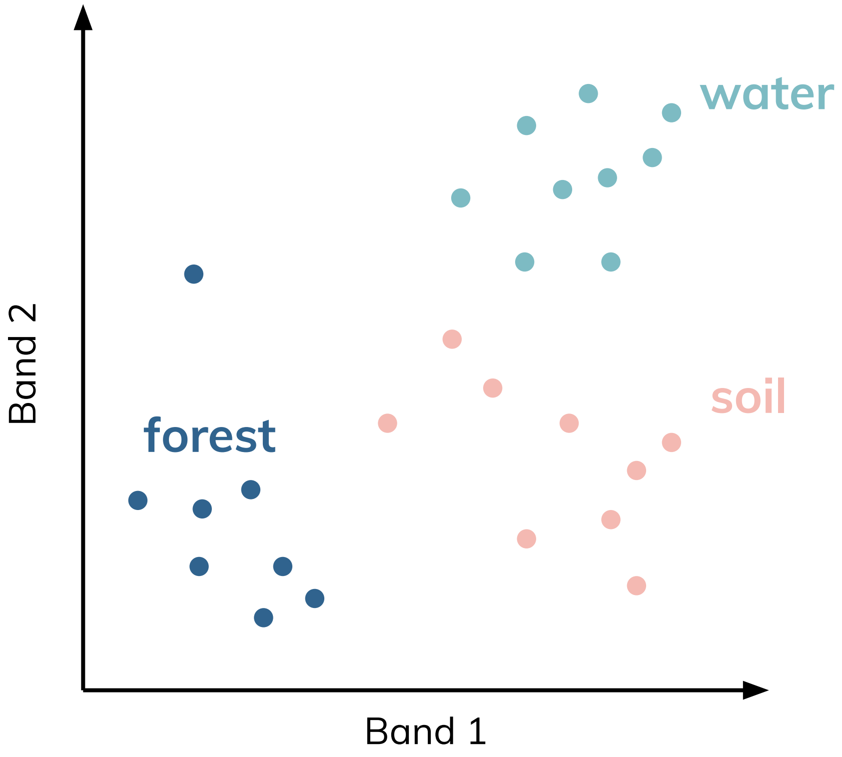
Supervised classification

- Find means for each group based on known points



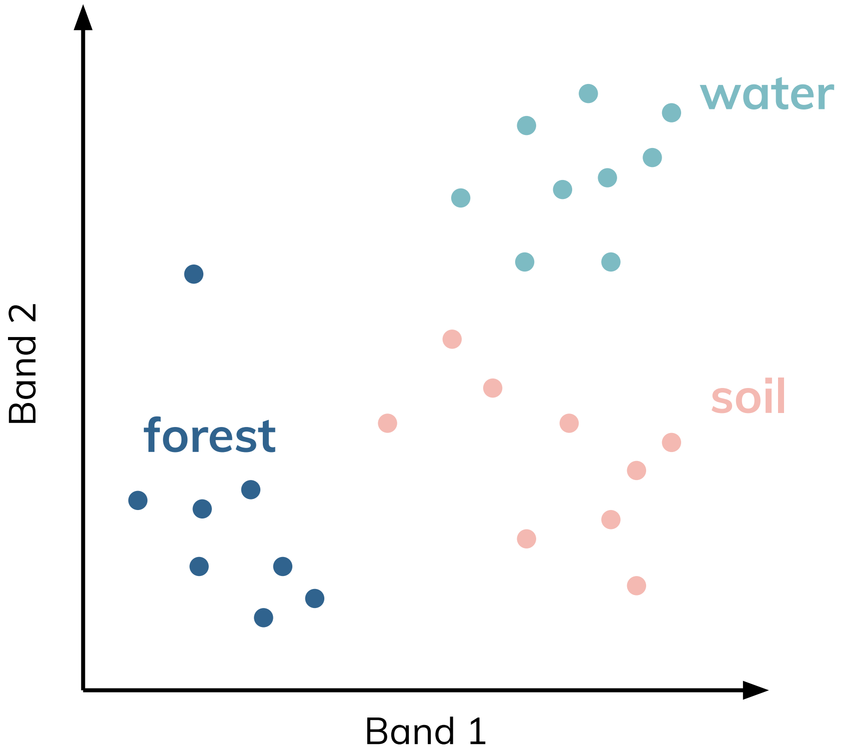
Supervised classification

- Find means for each group based on known points
- Assign each point to the closest group



Minimum distance to mean algorithm

- Find means for each group based on known points
- Assign each point to the closest group



Pros

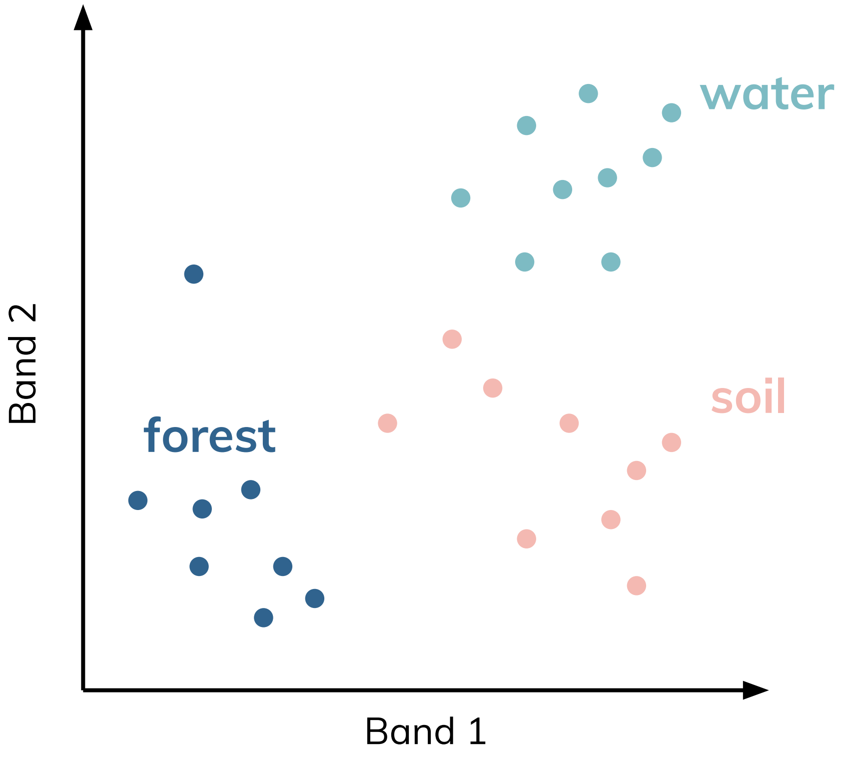
- fast/easy

Cons

- only uses means, not other statistical differences between classes

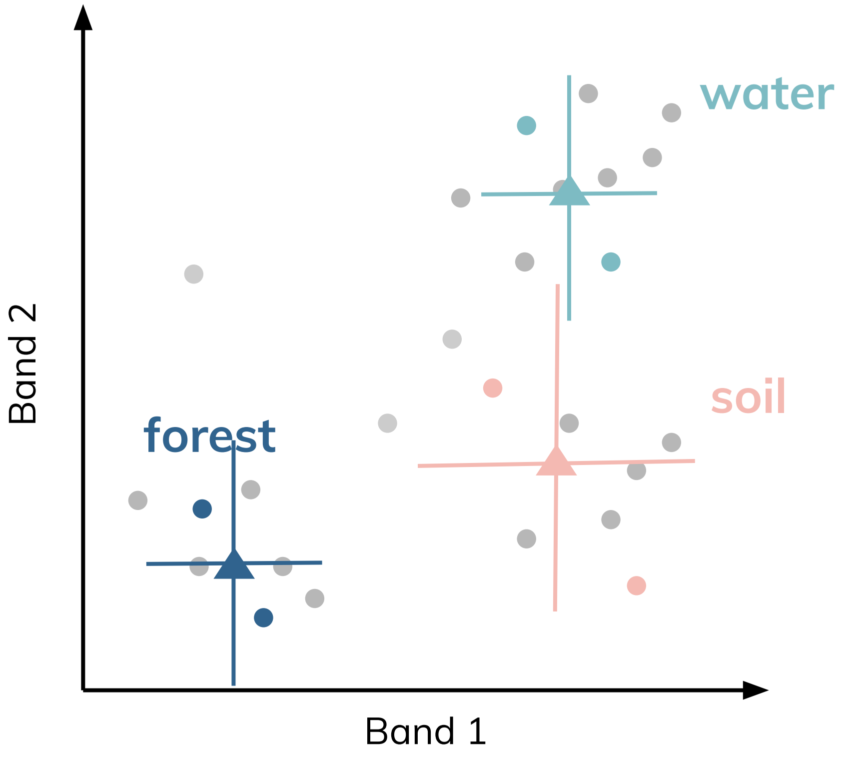
Minimum distance to mean algorithm

- Find means for each group based on known points
- Assign each point to the closest group



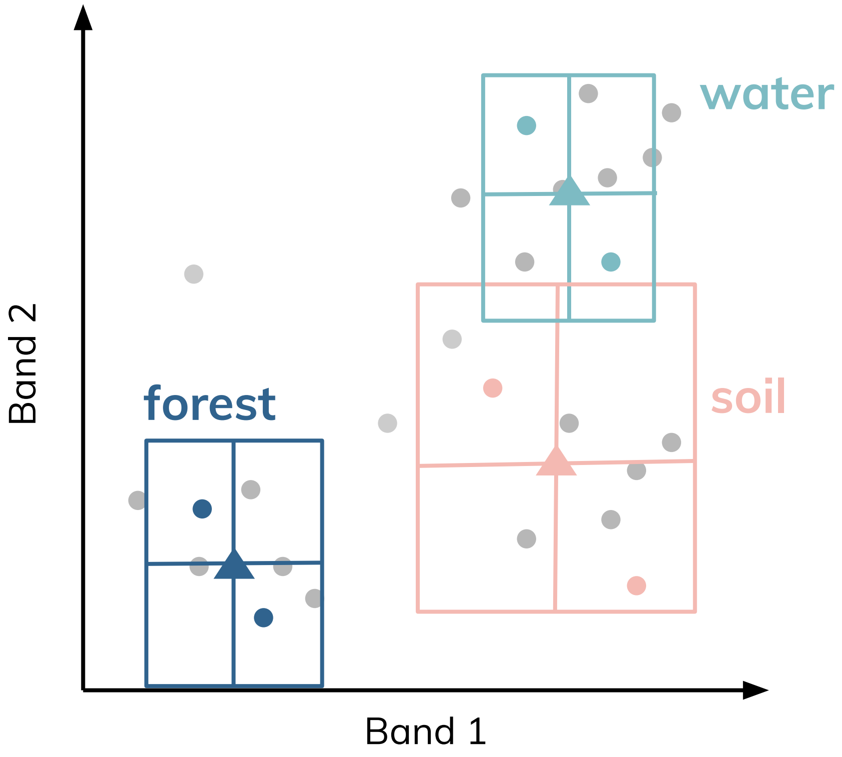
Supervised classification

- Find means and standard deviations for each group based on known points



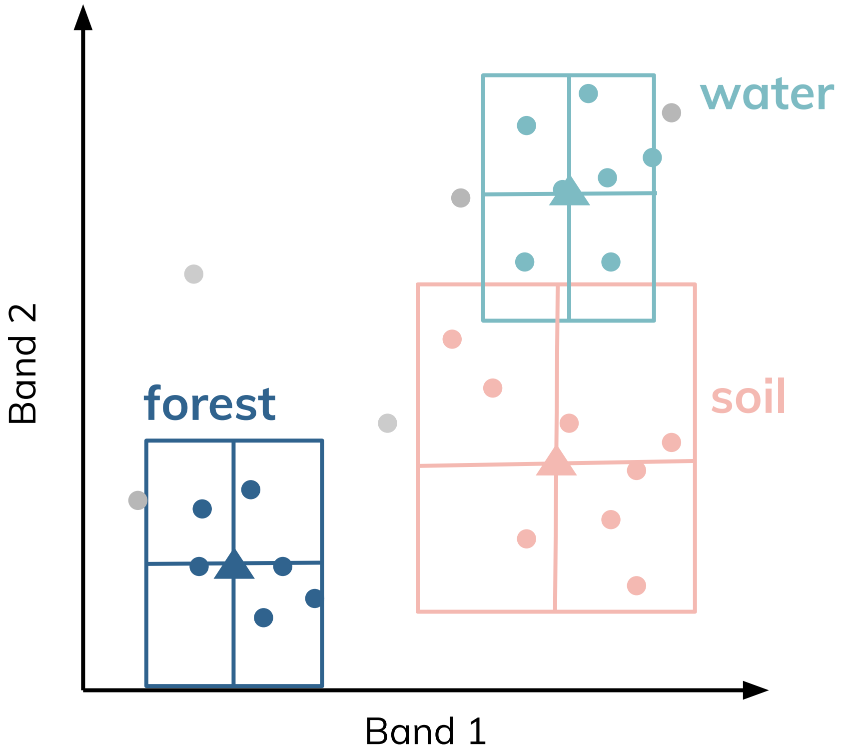
Supervised classification

- Find means and standard deviations for each group based on known points



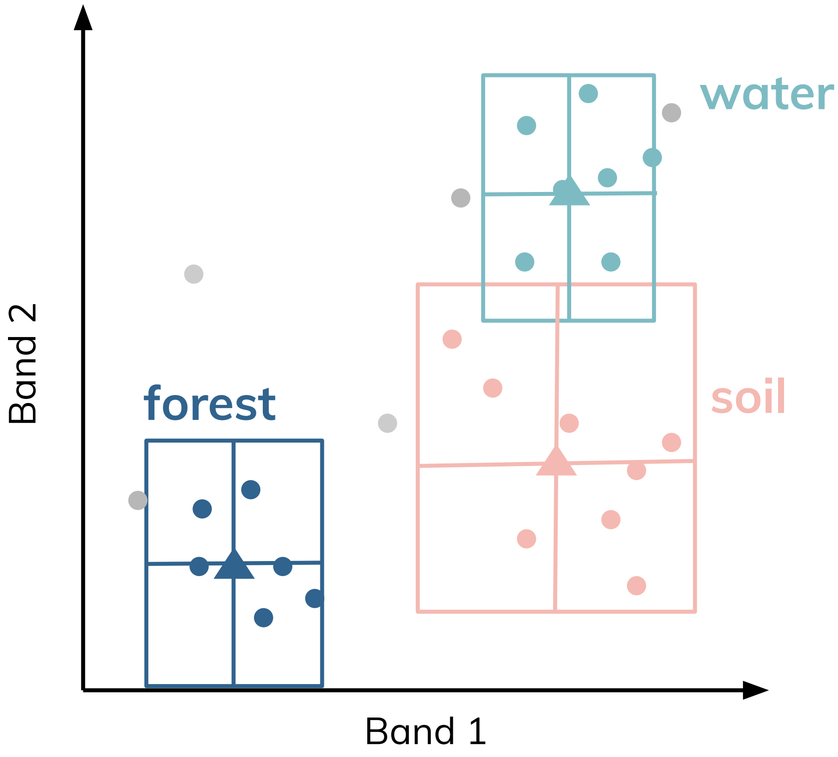
Supervised classification

- Find means and standard deviations for each group based on known points
- Assign points to groups



Parallelipiped

- Find means and standard deviations for each group based on known points
- Assign points to groups



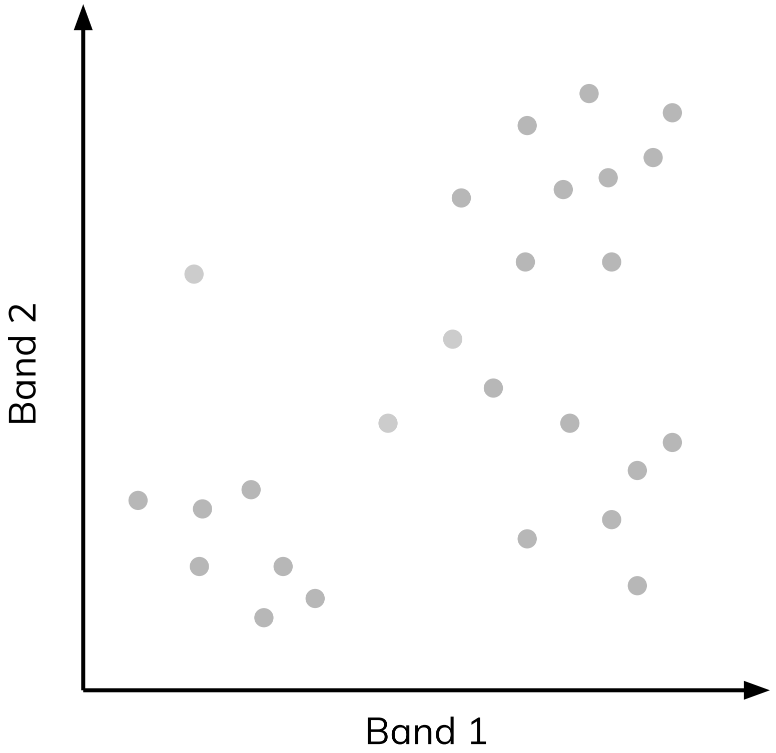
Pros

- fast/easy
- More realistic than just using the mean

Cons

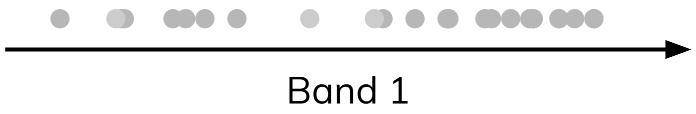
- Unclassified pixels
- Overlapping classes

Supervised classification



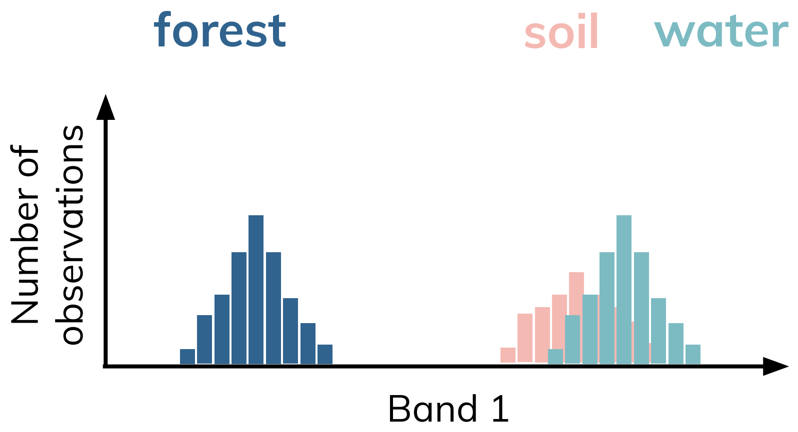
Supervised classification

Unknown pixels:

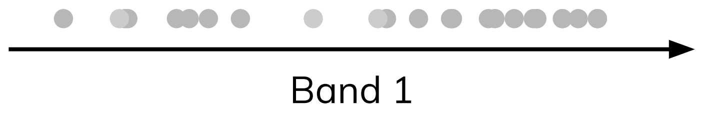


Supervised classification

Known pixels:

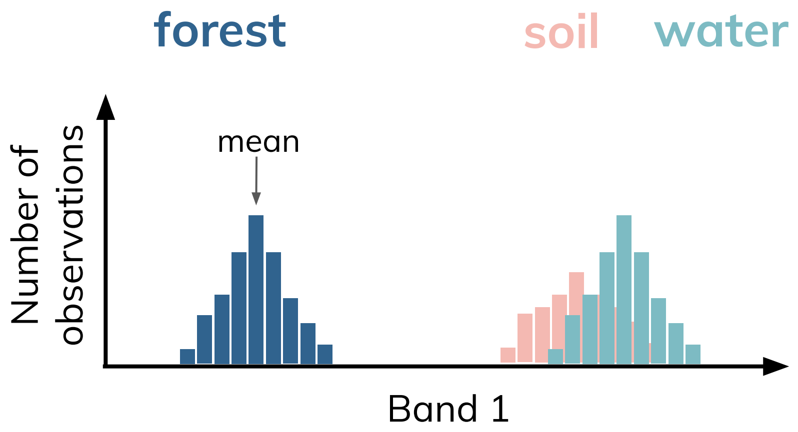


Unknown pixels:

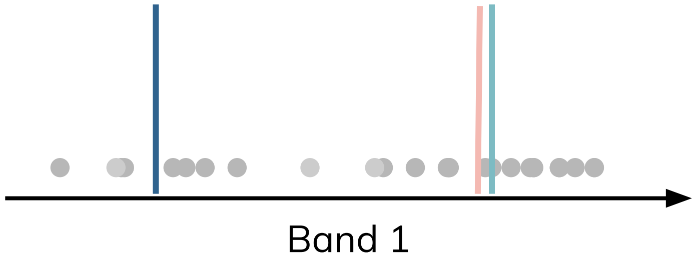


Supervised classification

Known pixels:



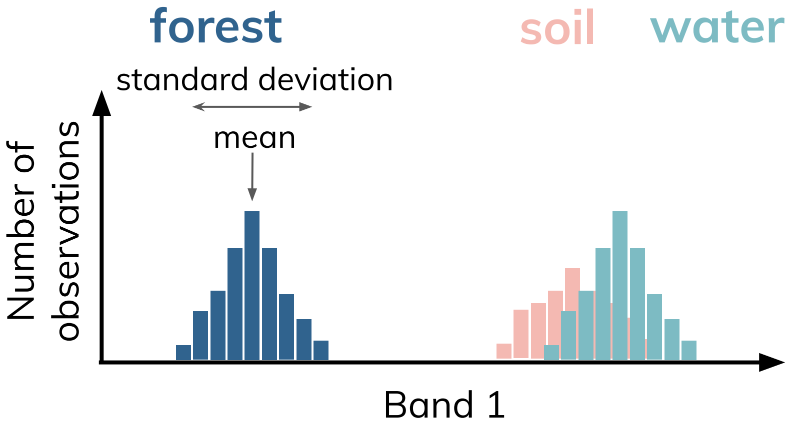
Unknown pixels:



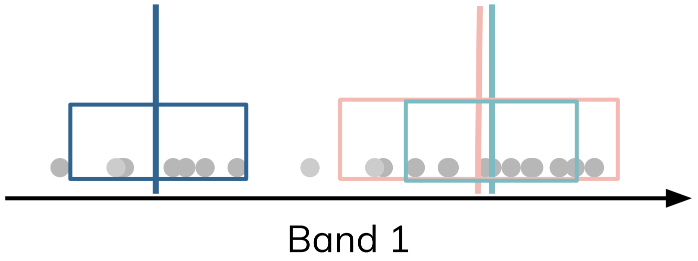
minimum distance to mean

Supervised classification

Known pixels:



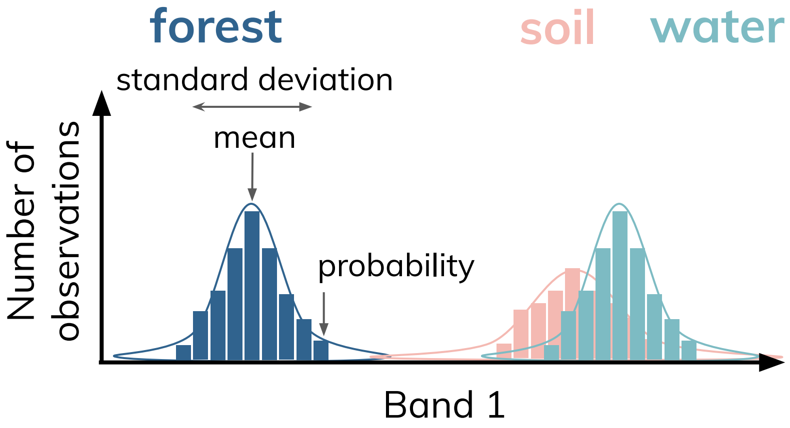
Unknown pixels:



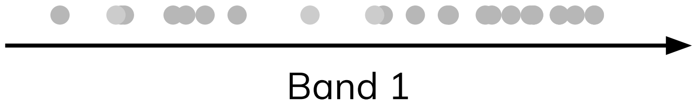
parallelipiped

Supervised classification

Known pixels:



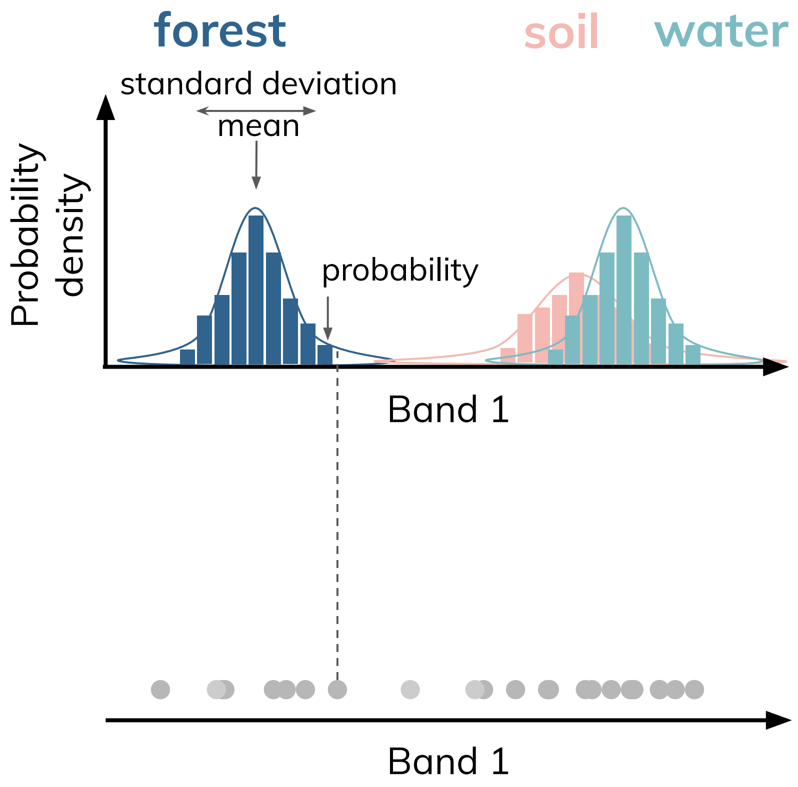
Unknown pixels:



Supervised classification

Known pixels:

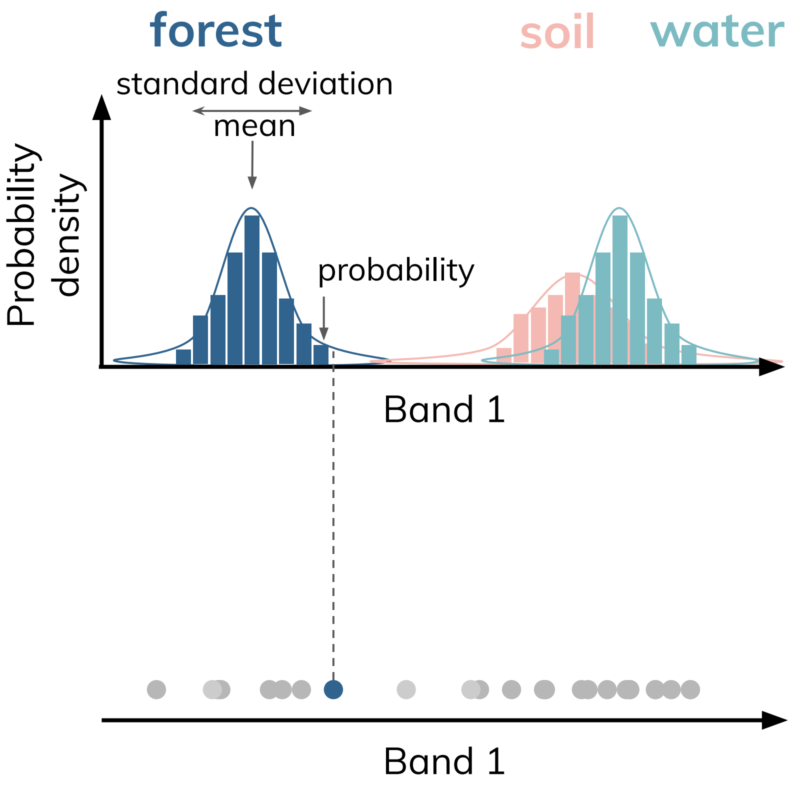
Unknown pixels:



Supervised classification

Known pixels:

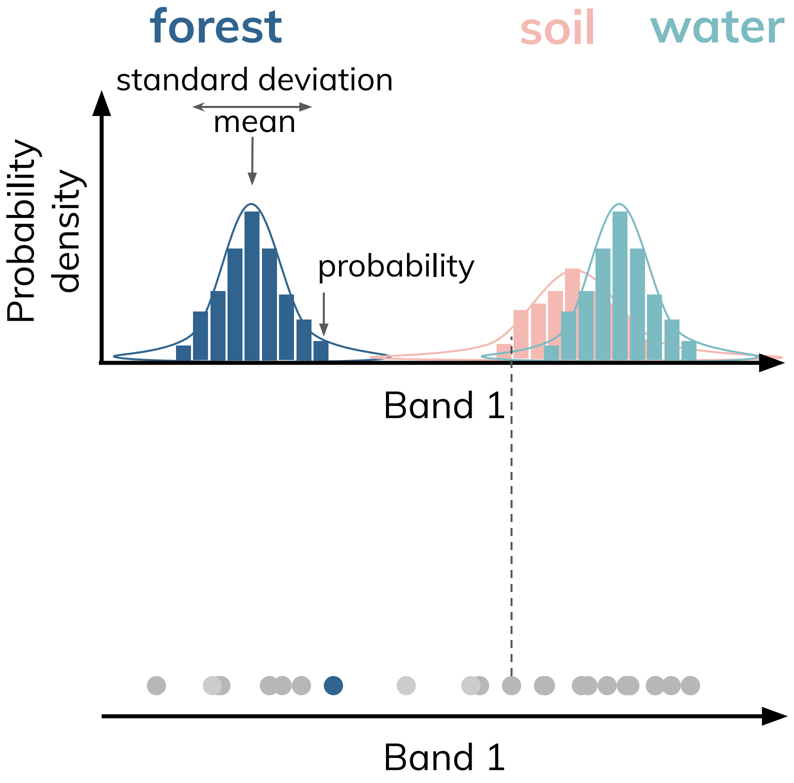
Unknown pixels:



Supervised classification

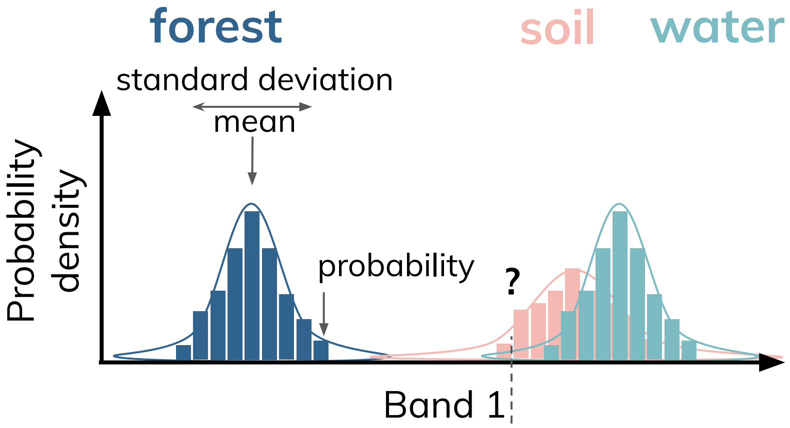
Known pixels:

Unknown pixels:

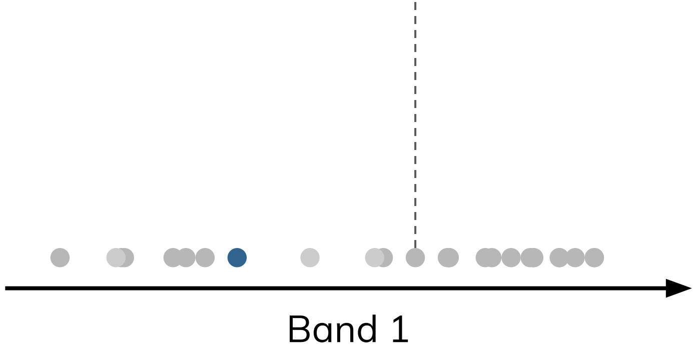


Supervised classification

Known pixels:

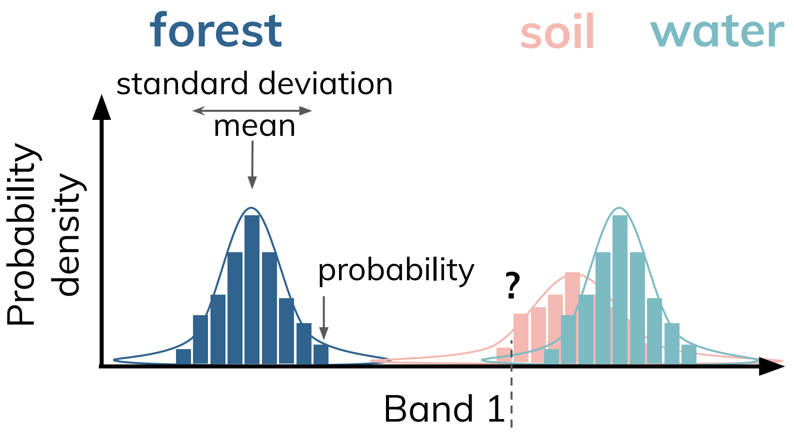


Unknown pixels:



Supervised classification

Known pixels:

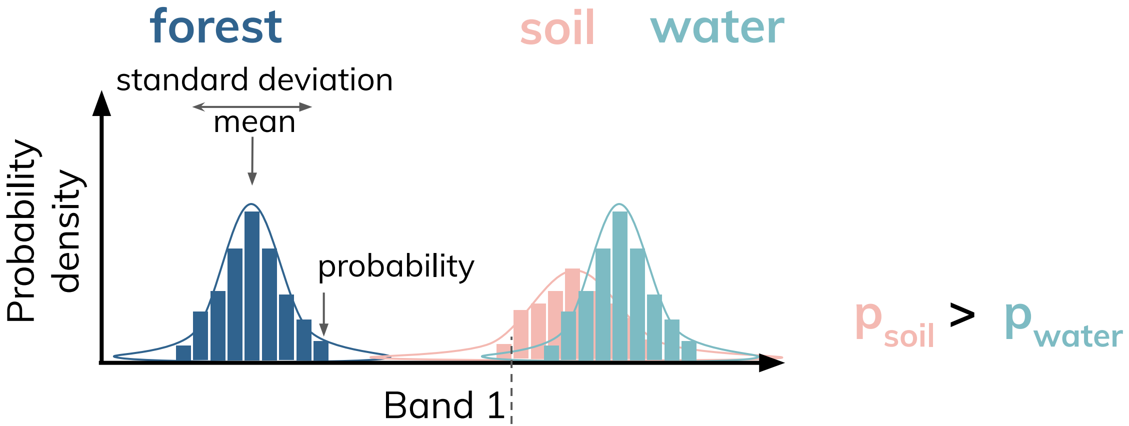


p_{soil} > p_{water}

Unknown pixels:

Supervised classification

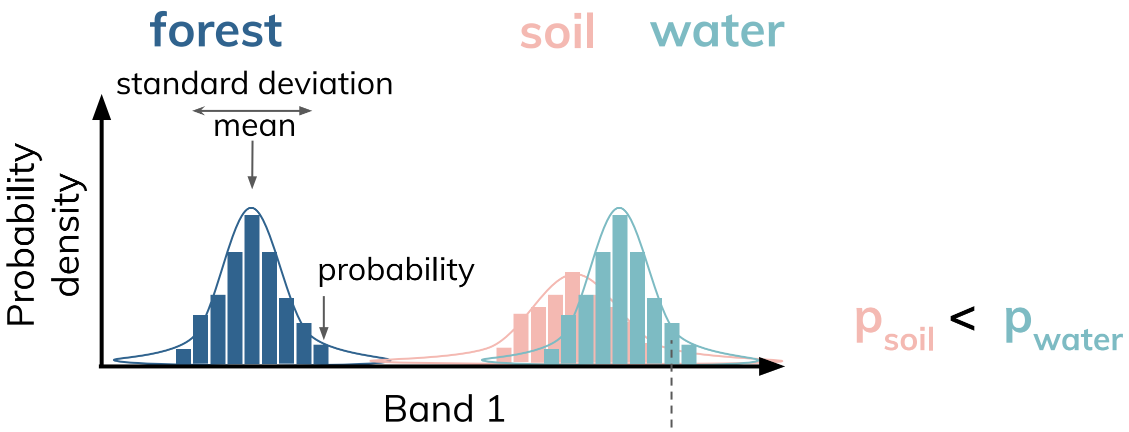
Known pixels:



Unknown pixels:

Supervised classification

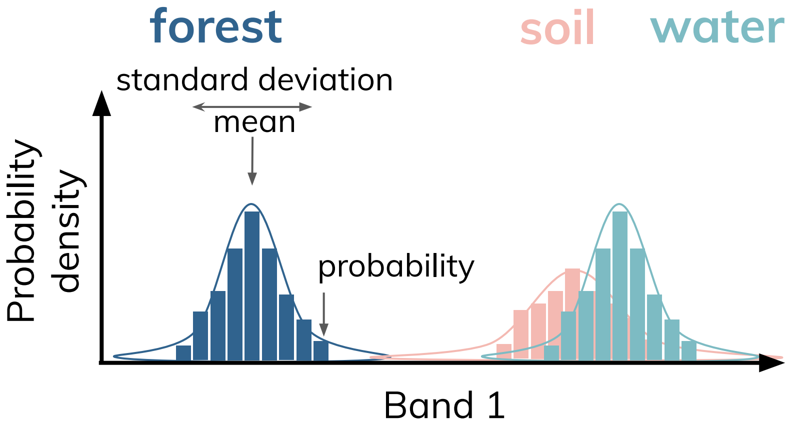
Known pixels:



Unknown pixels:

Maximum likelihood

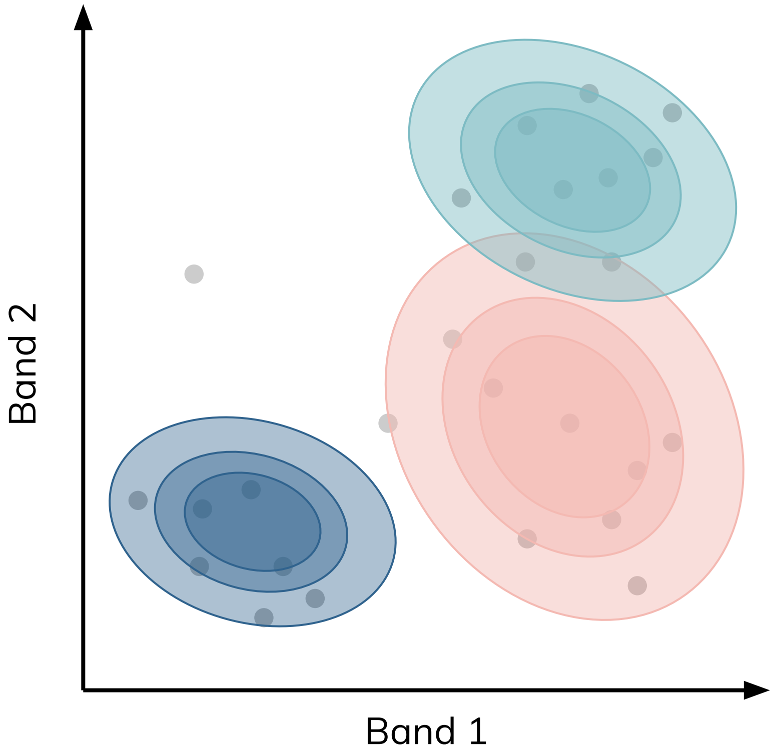
Known pixels:



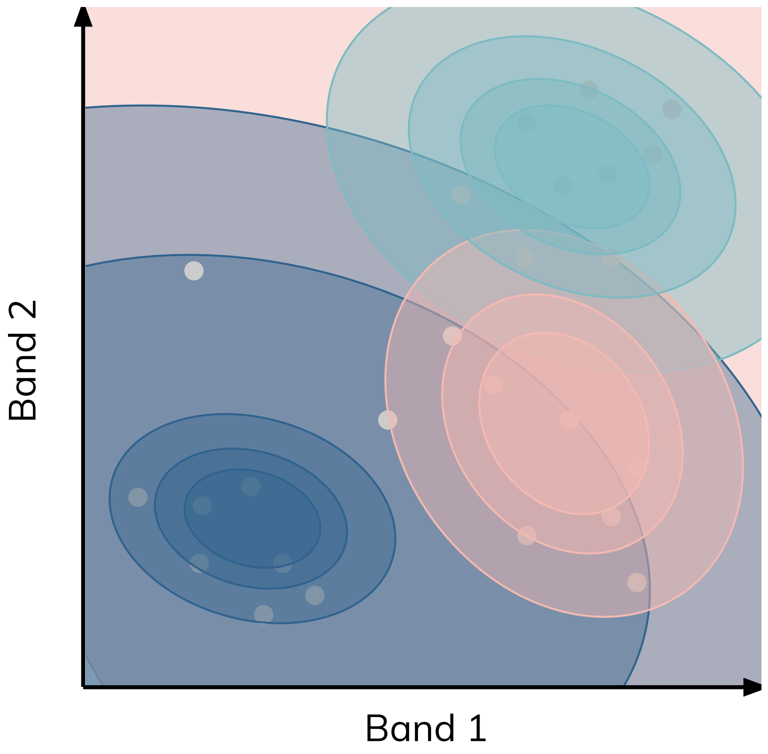
Unknown pixels:

maximum likelihood

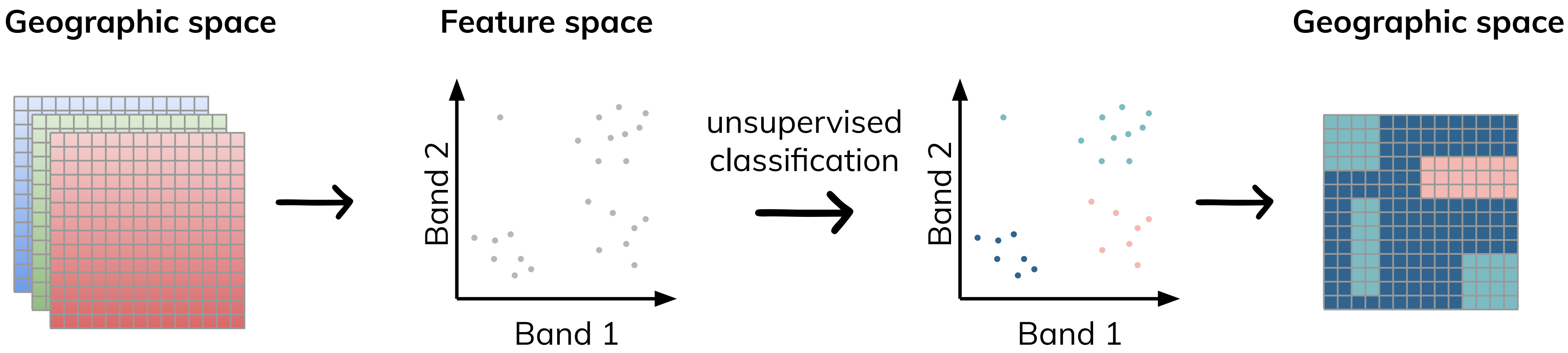
Maximum likelihood



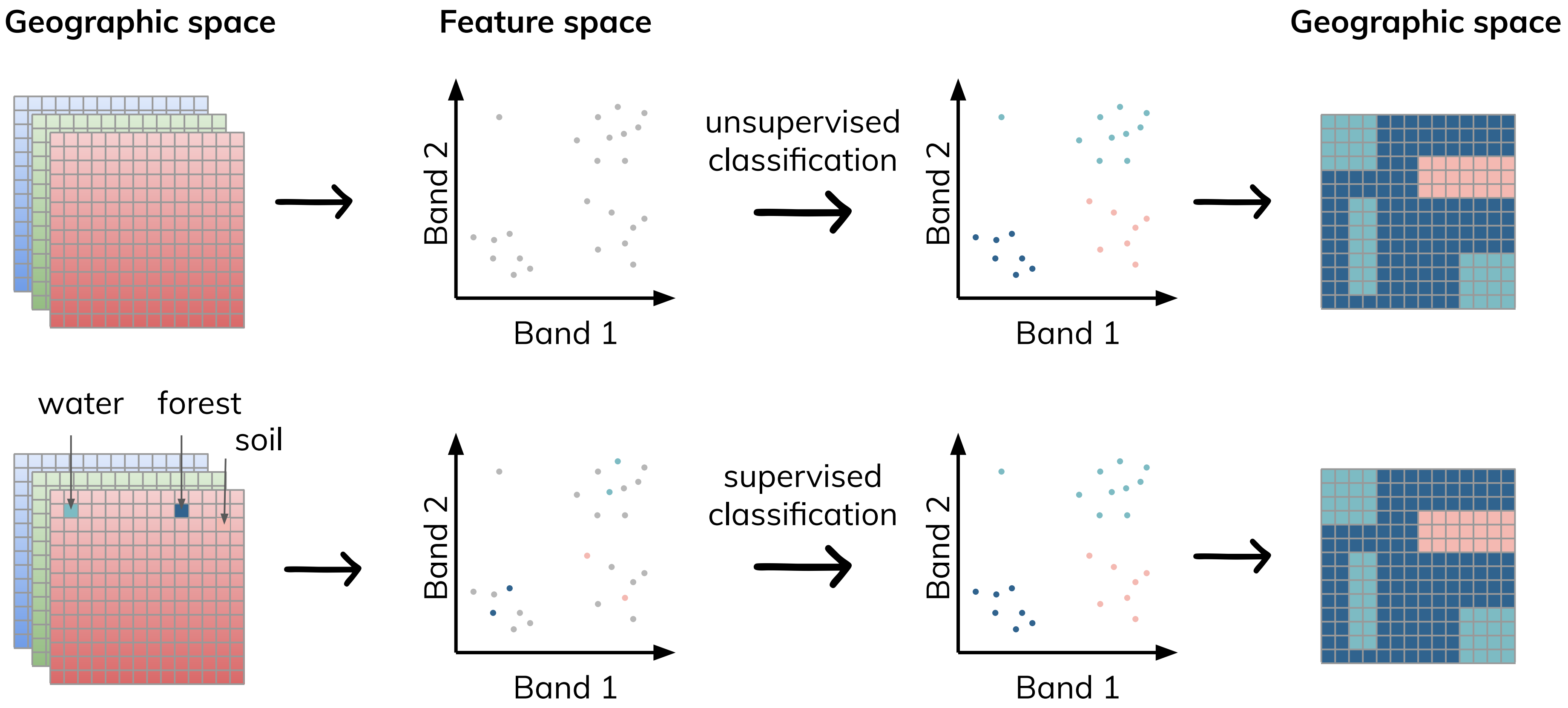
Maximum likelihood



(un)supervised classification



(un)supervised classification



Classification approaches

Unsupervised	Supervised

Classification approaches

Unsupervised	Supervised
• Algorithm identifies groups of pixels with similar spectra	• Algorithm identifies groups of pixels with similar spectra

Classification approaches

Unsupervised

- Algorithm identifies groups of pixels with similar spectra
- User assigns meaning to resulting classes

Supervised

- Algorithm identifies groups of pixels with similar spectra
- User provides examples for desired groupings

Classification approaches

Unsupervised

- Algorithm identifies groups of pixels with similar spectra
- User assigns meaning to resulting classes
- Bulk of analyst's work comes after the classification process

Supervised

- Algorithm identifies groups of pixels with similar spectra
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Classification approaches

Unsupervised

- Algorithm identifies groups of pixels with similar spectra
- User assigns meaning to resulting classes
- Bulk of analyst's work comes after the classification process
- Pros:
  - No prior knowledge of area required
  - Human error is minimized
  - Relatively fast/easy
  - Unique spectral classes are produced
- Cons:
  - Spectral classes may not represent features on the ground
  - Does not consider spatial relationships
  - Can be time-consuming to interpret
  - Spectral properties may vary over time/images

Supervised

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Unsupervised

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- Pros:
    - Spectral classes represent features on the ground
    - Training areas are reusable
- Cons:
    - Information classes may not match spectral classes
    - Difficulty and coast of selecting training sites

Classification approaches

Unsupervised

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- **Bulk of analyst's work comes before the classification process**
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    - Spectral classes represent features on the ground
    - Training areas are reusable
- Cons:
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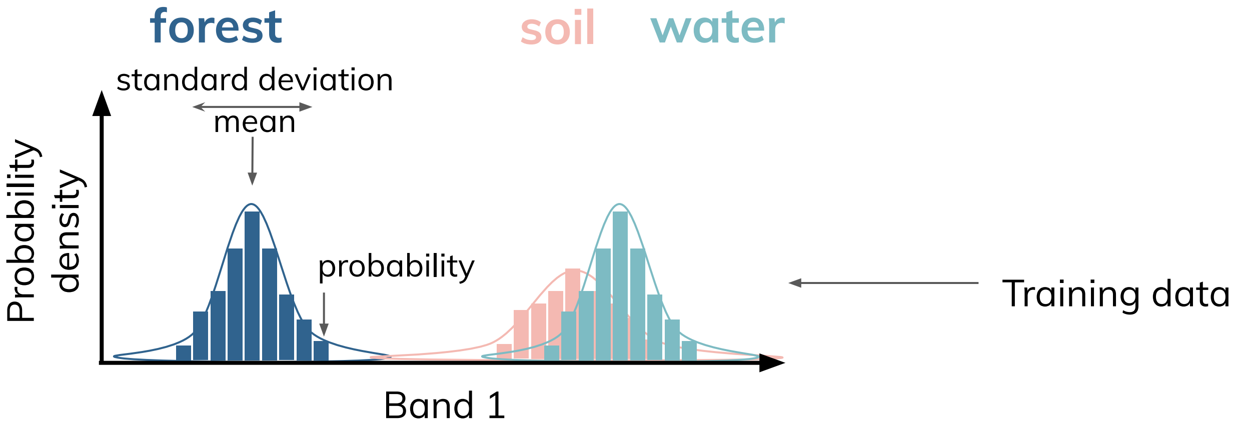
    - Difficulty and coast of selecting training sites

Maximum likelihood

Known pixels:

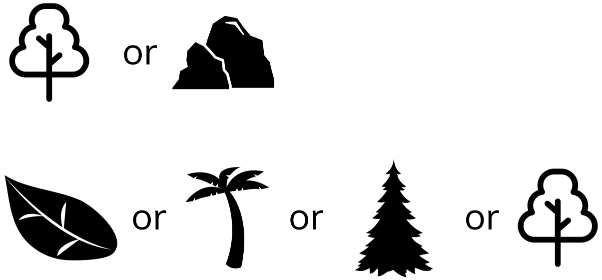


Unknown pixels:

maximum likelihood

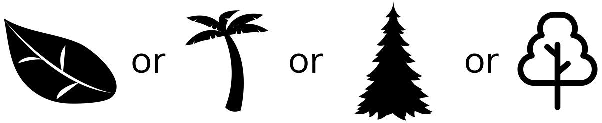
Supervised classification: training data

Classification scheme:



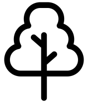
Supervised classification: training data

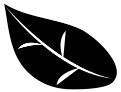
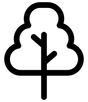
Classification scheme:



Does the resolution match your scheme? (spatial/temporal/spectral/radiometric)

Supervised classification: training data

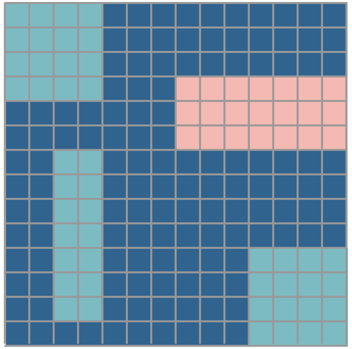
Classification scheme:  or 

 or  or  or 

Does the resolution match your scheme? (spatial/temporal/spectral/radiometric)

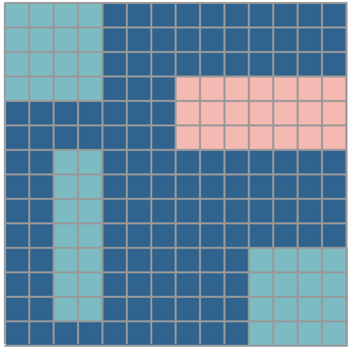
Does your training data capture the heterogeneity of each class?

Testing how we did!



How accurate is this map?

Testing how we did!



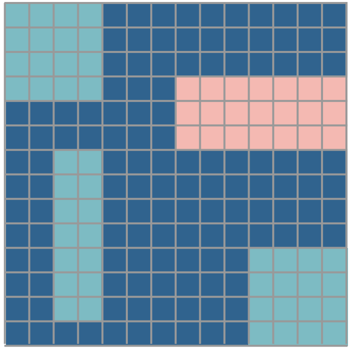
How accurate is this map?

"True answer"

Our guess based on remote sensing data

	forest	soil	water
forest			
soil			
water			

Testing how we did!



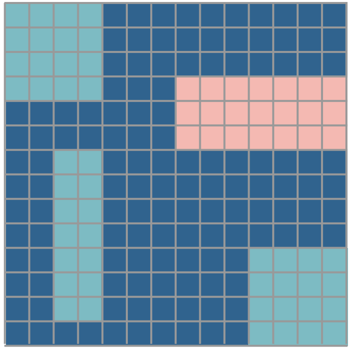
How accurate is this map?

"True answer"

Our guess based on remote sensing data

	forest	soil	water
forest	25	0	0
soil			
water			

Testing how we did!



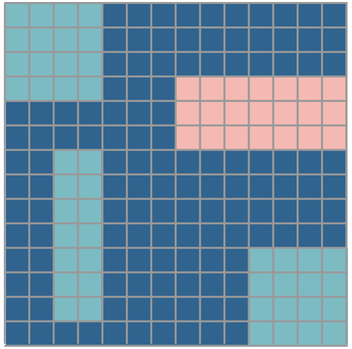
How accurate is this map?

Our guess based on remote sensing data

"True answer"

	forest	soil	water
forest	25	0	0
soil	0	12	0
water	0	0	18

Testing how we did!



How accurate is this map?

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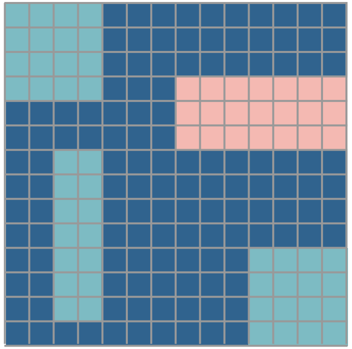
Accuracy = sum of correct matches ÷ total number of cells

Testing how we did!



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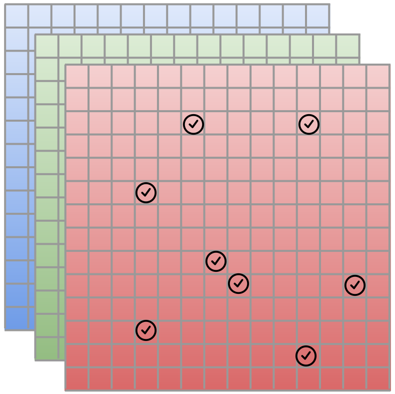
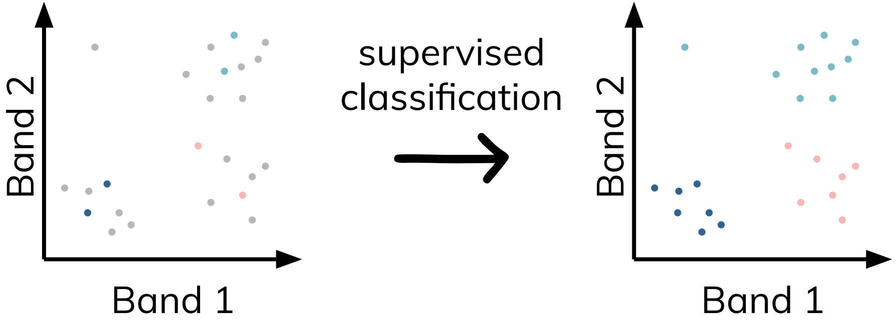
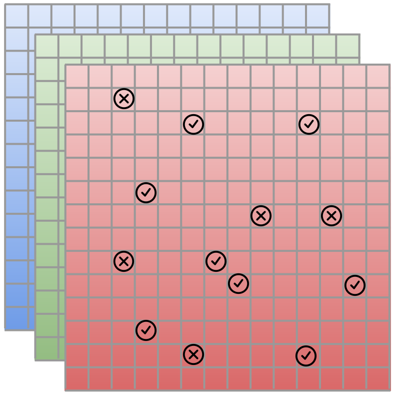


training:



Testing how we did!



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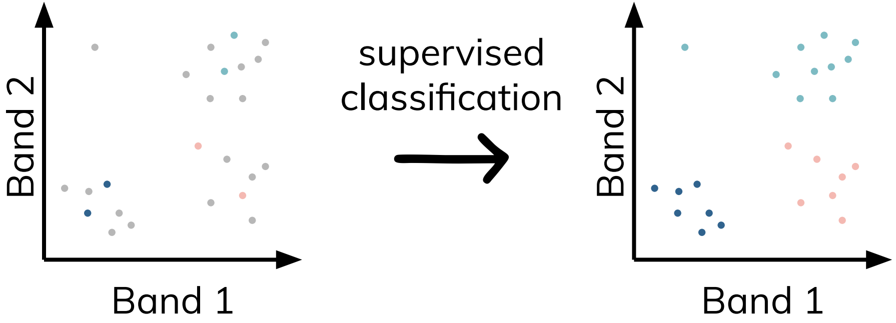


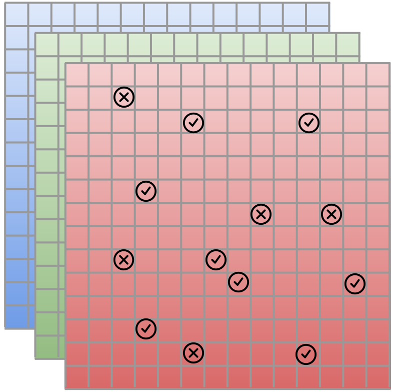
testing:

"True answer"

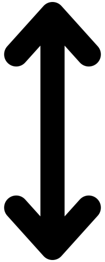
Our guess based on remote sensing data

	forest	soil	water
forest			
soil			
water			

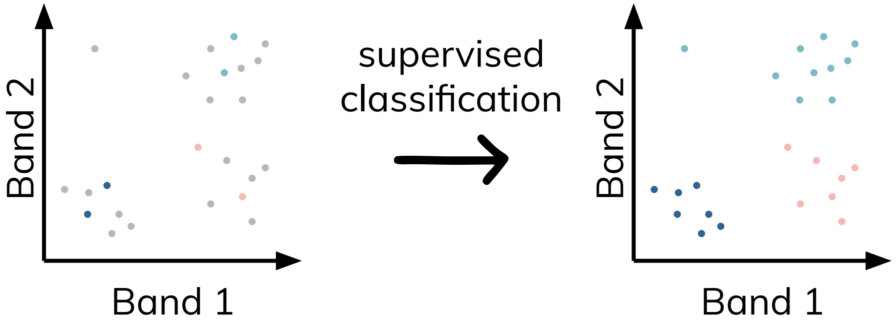
Testing how we did!



training:



testing:

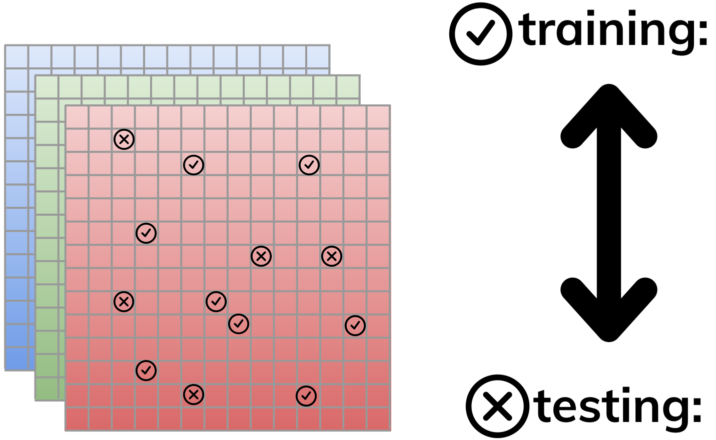


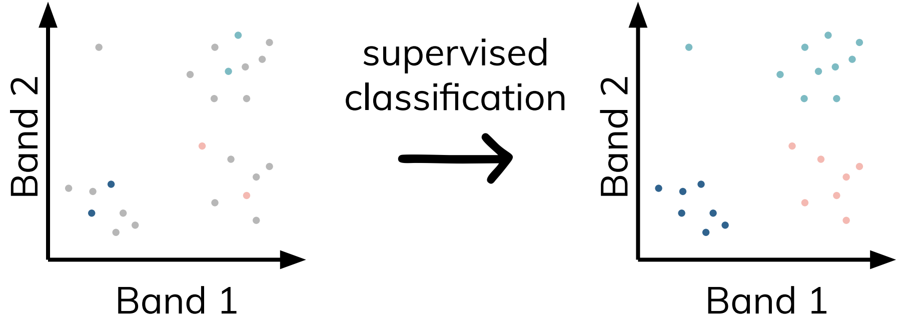
"True answer"

Our guess based on remote sensing data

	forest	soil	water
forest			
soil			
water			

Cross-validation





"True answer"

Our guess based on remote sensing data

	forest	soil	water
forest			
soil			
water			

Big ask!

ESCIs due December 2