

Improving the Spatial Scale of Impact Assessment: Analyzing and Applying the Regionalized LC-IMPACT Methods

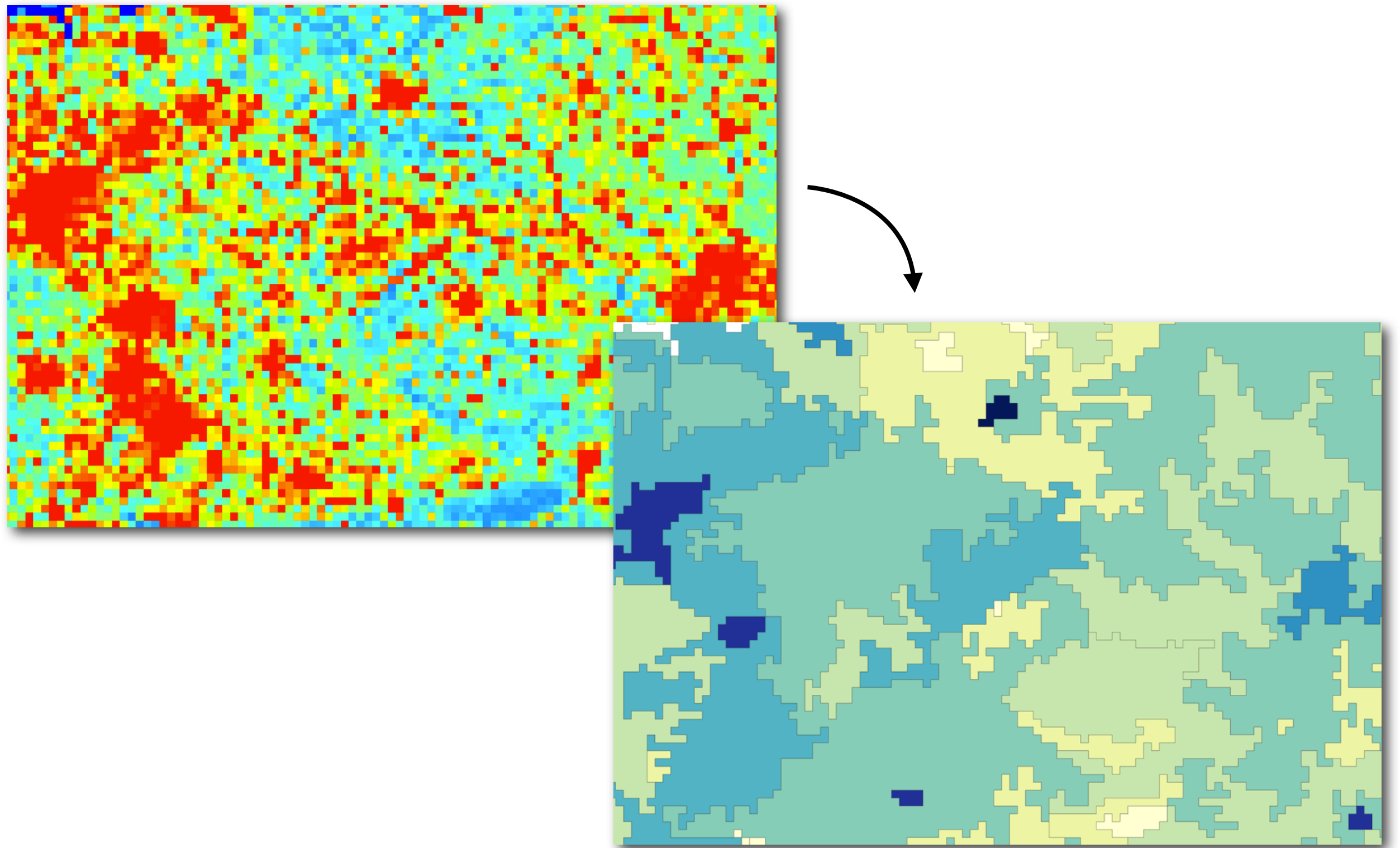
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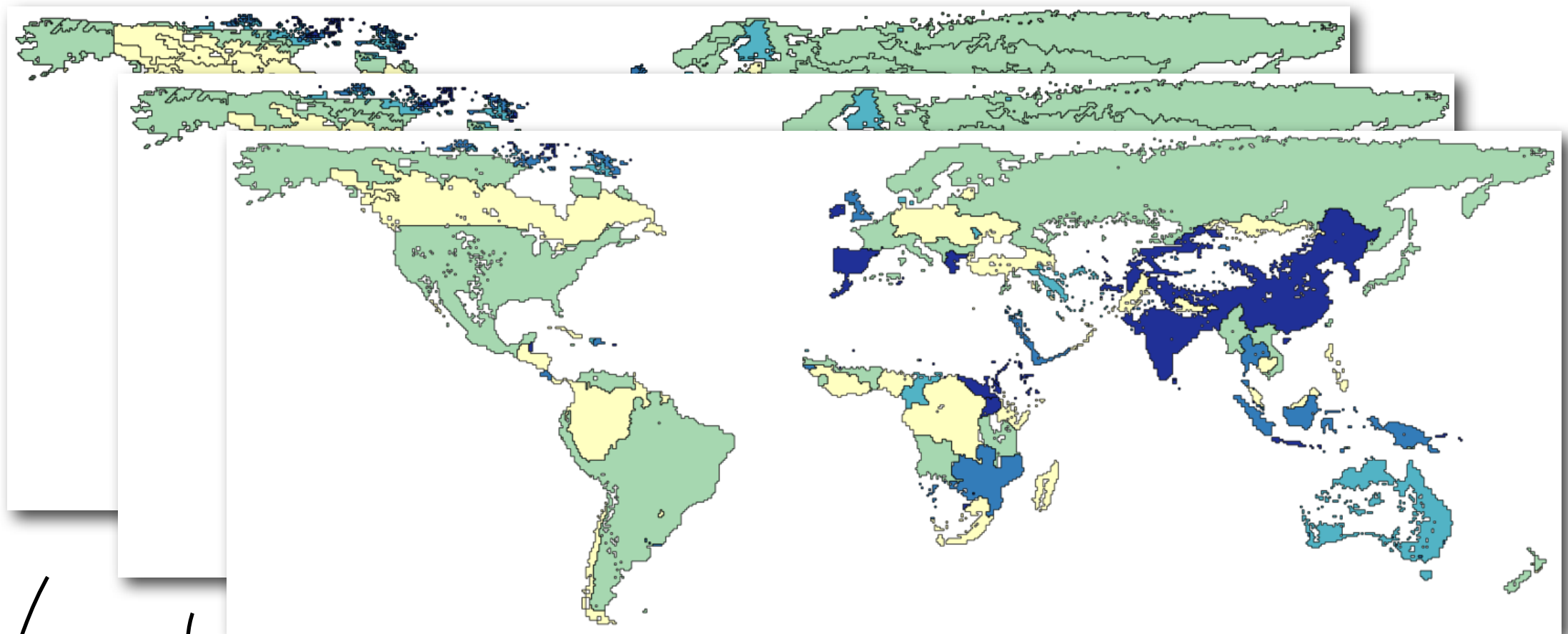
Simplification



This presentation is about improving and applying the systematic method to choose the spatial scale of impact assessment published in [Mutel et al](#) to the regionalized impact assessment methods developed in the [LC-IMPACT project](#).

Two-step methodology

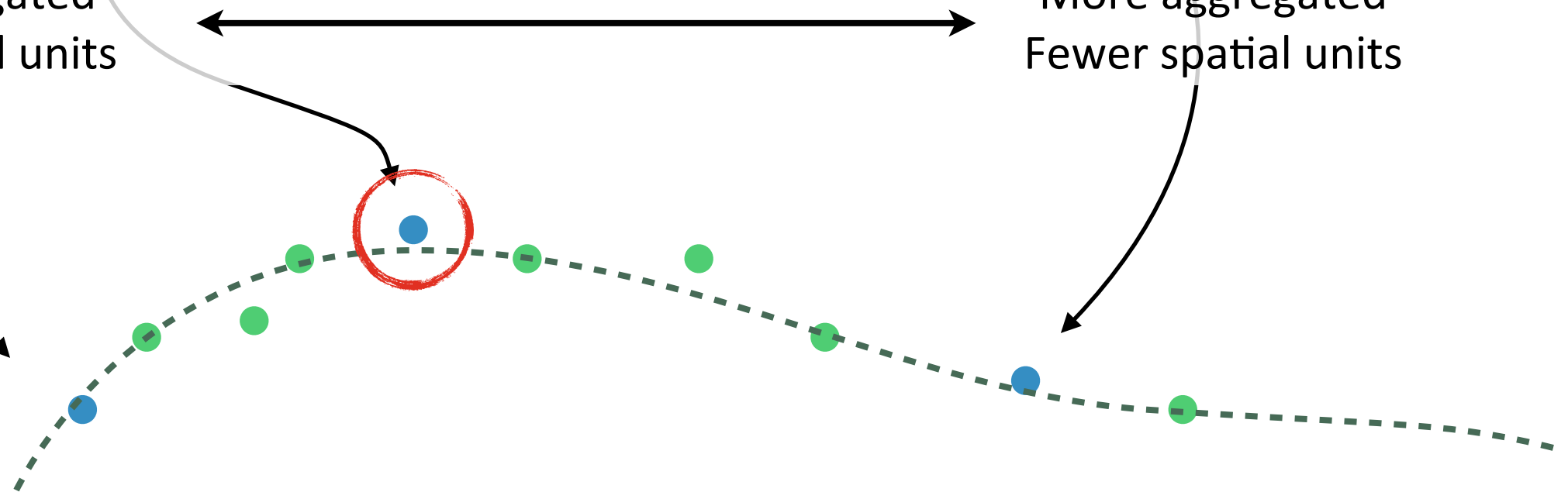
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Less aggregated
More spatial units

More aggregated
Fewer spatial units

2



3

The basic technique is to apply a discretize the continuous surface of characterization factors at a number of levels of aggregation, to generate a set of candidate maps (step one). These candidate maps are then evaluated using some metric, and the candidate map that minimizes or maximizes the metric is chosen as the “best” spatial scale.

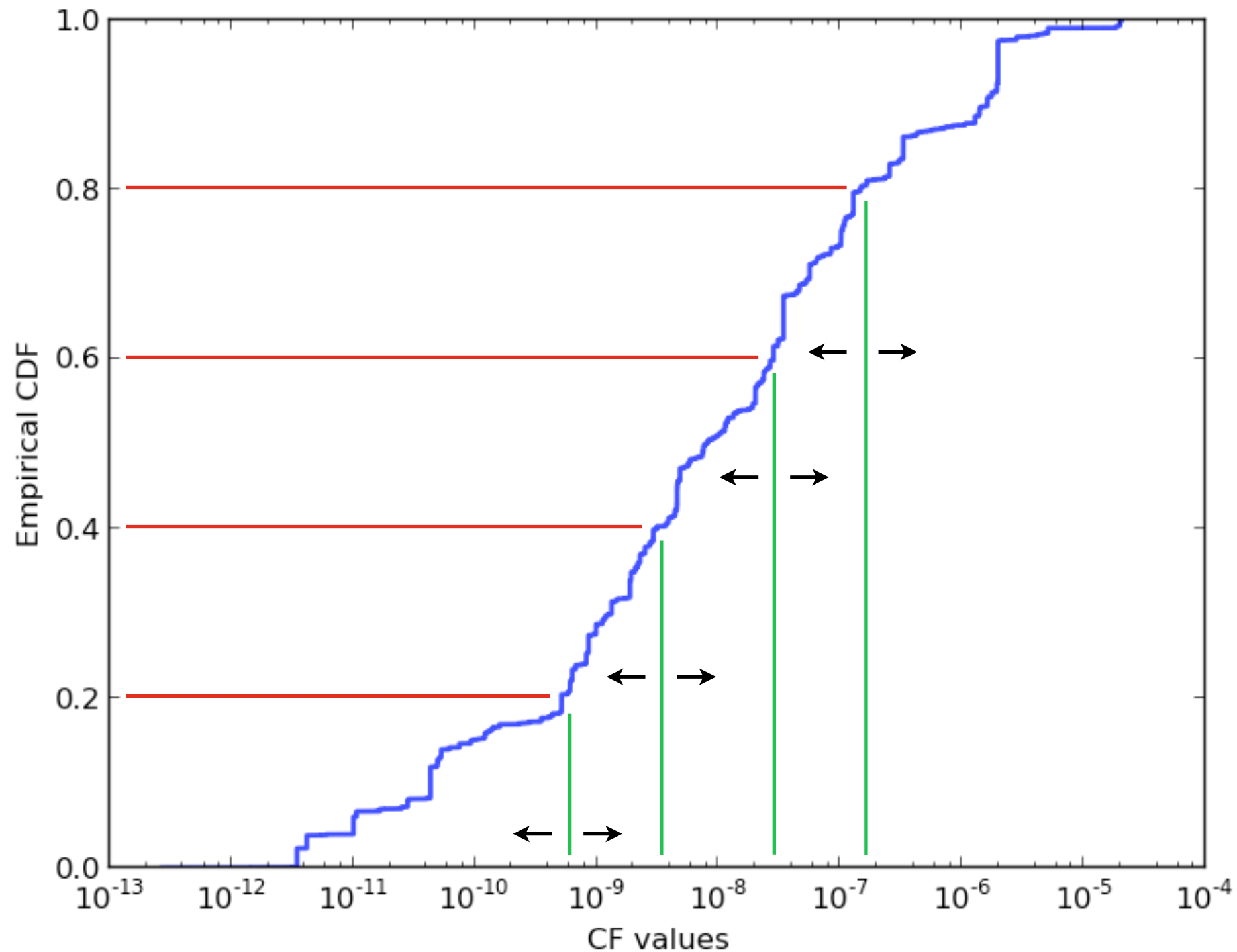
CF spatial aggregation

- Why simplify?
 - Need polygonal areas for LCA matrix math
 - Indicate appropriate spatial resolution to LCI dataset developers
 - Improve CF signal-to-noise ratio
 - Allows generation of CF uncertainties

There are (at least) four reasons to simplify raster or otherwise disaggregated CF maps. First, it allows us to use our normal matrix-based LCA math (because we have a set of spatial units). Second, it tells inventory developers what spatial scale they need to think about for their datasets. Third, it helps interpretation and understanding by improving the signal-to-noise ratio. Finally, it gives us automatic generation of characterization factor uncertainties.

Better discretization

- Equal-width binning



The earlier approach ignored spatial relationships and simply binned the CF data based on the empirical CDF. The bins lines can be adjusted as a sensitivity check. Note that this is equal width in data percentages, not data ranges.

Machine learning

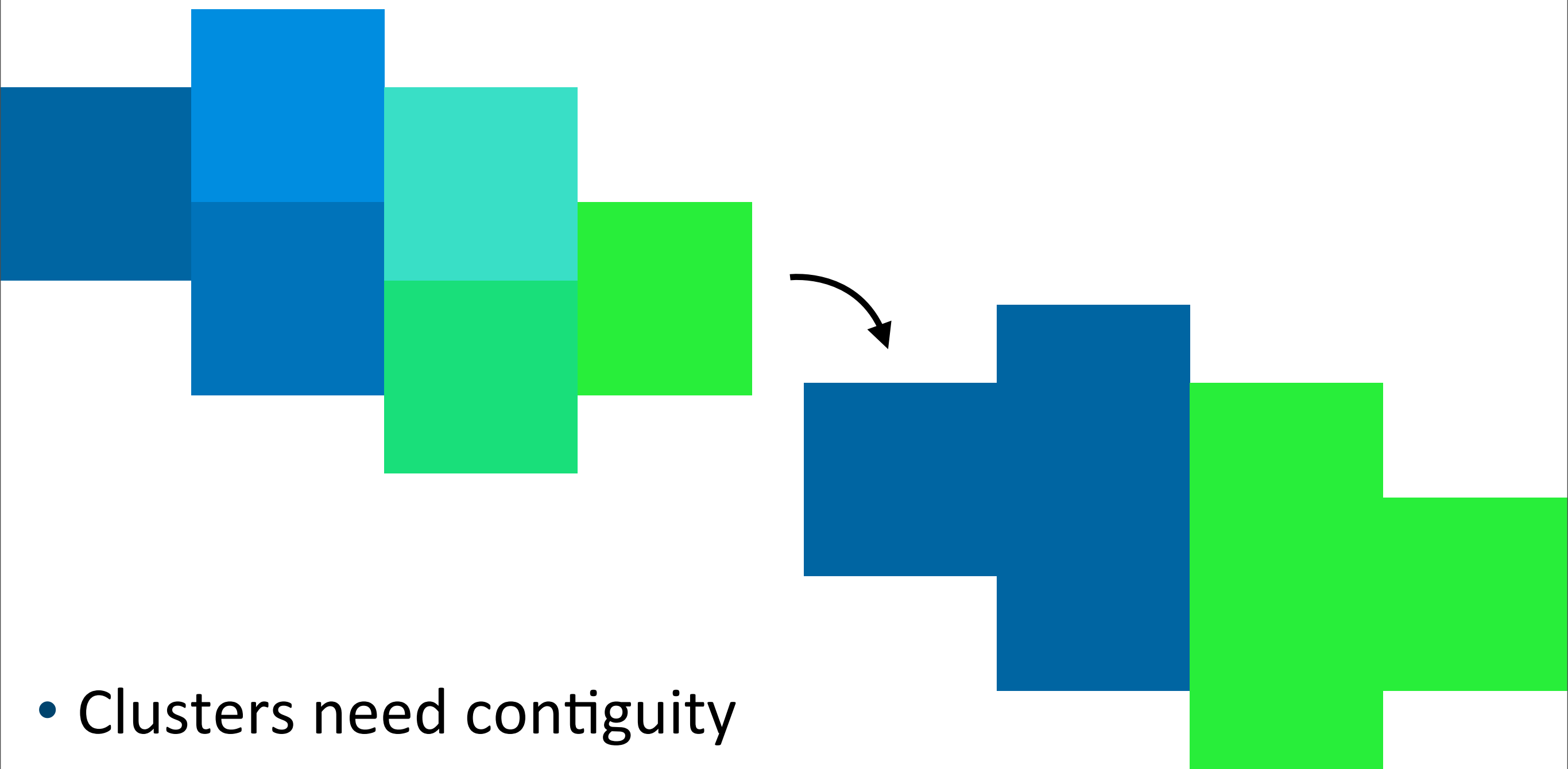


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6

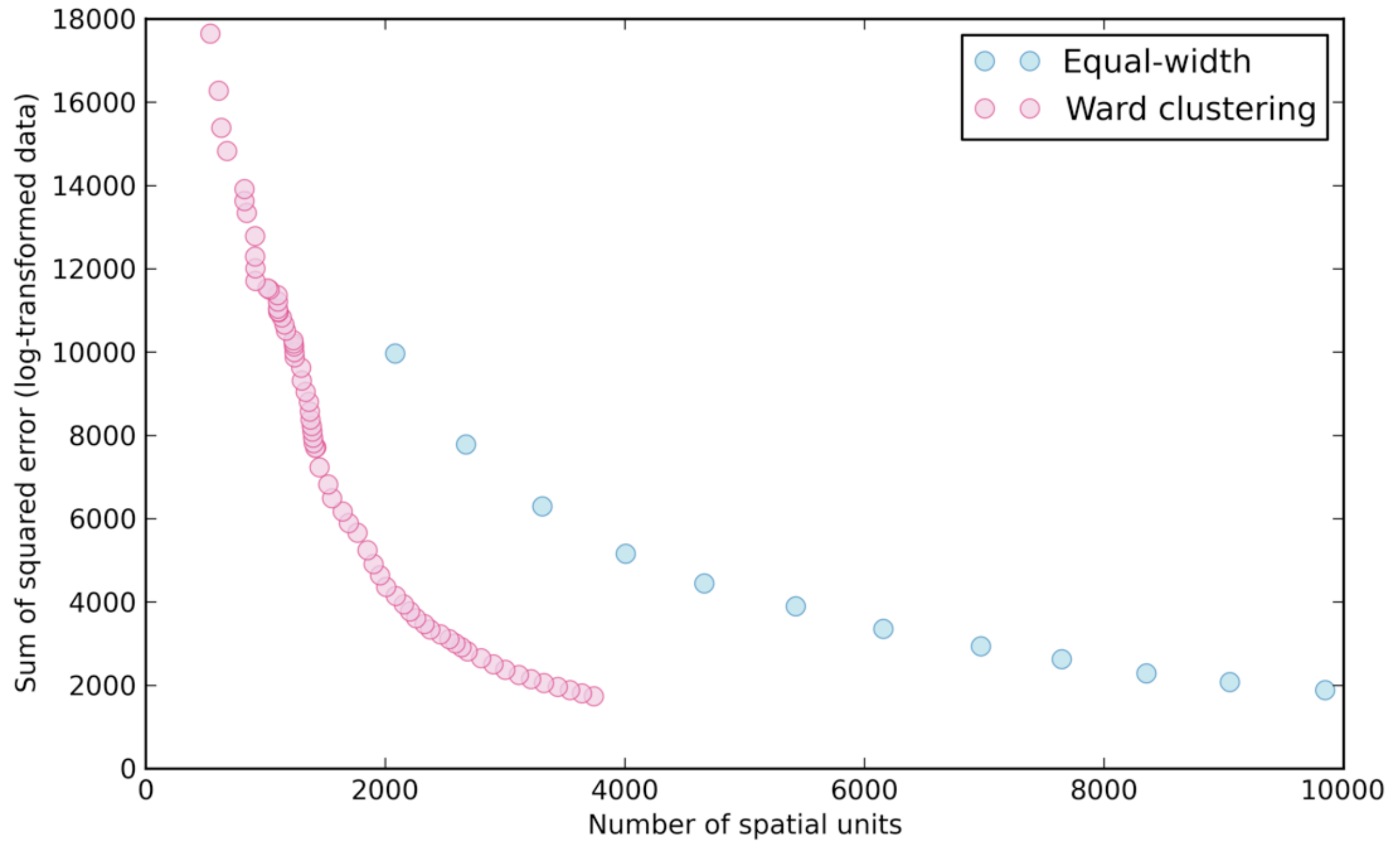
However, we can do better by borrowing techniques from the machine learning community.

Ward hierarchical clustering



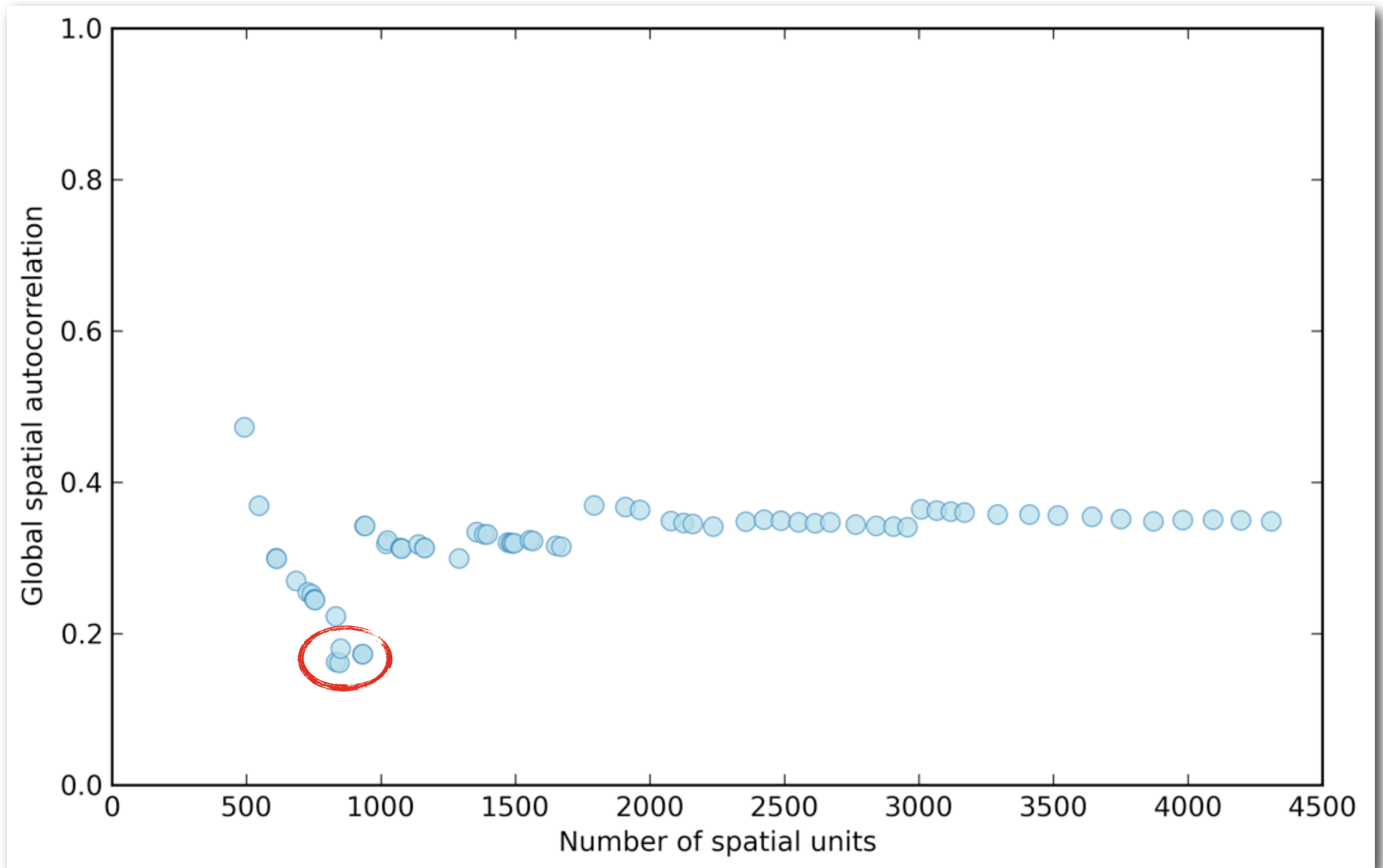
- Clusters need contiguity
- Use variance minimization to choose new clusters

Ward clustering is better



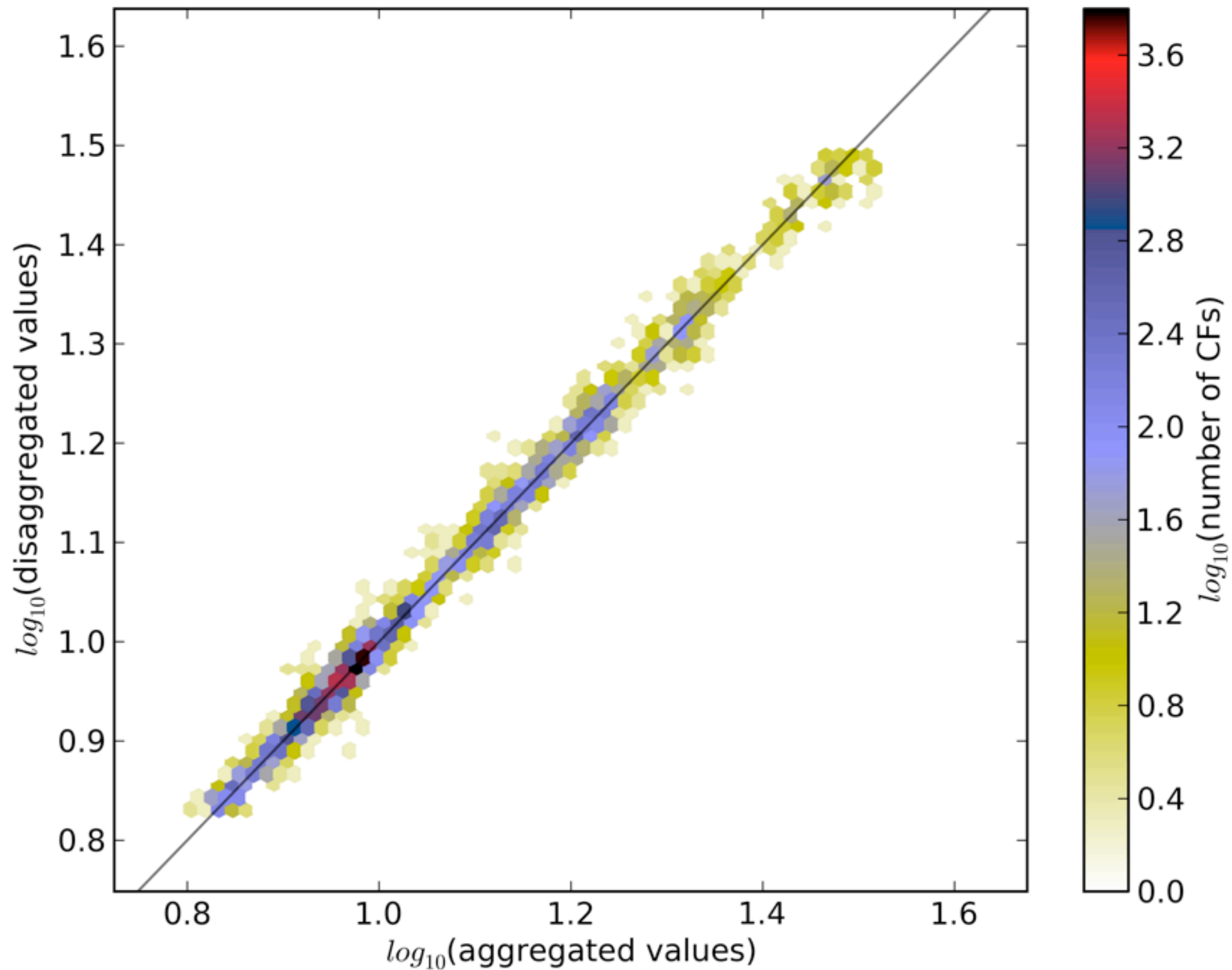
Ward hierarchal clustering is much better than equal-width binning.

Forestry



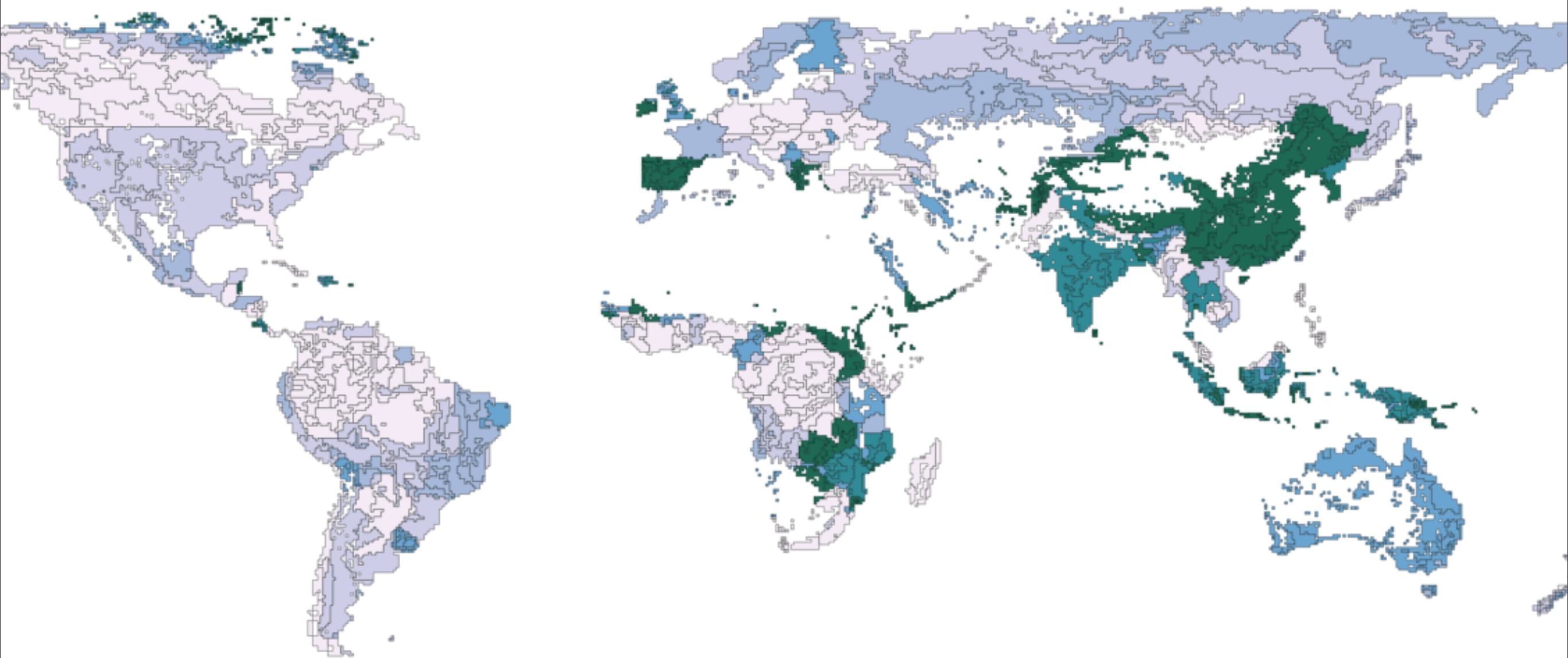
Here is an example for carbon fluxes from forestry. The metric chosen to evaluate the different candidate maps remains minimization of spatial autocorrelation, as in [Mutel et al.](#)

Forestry



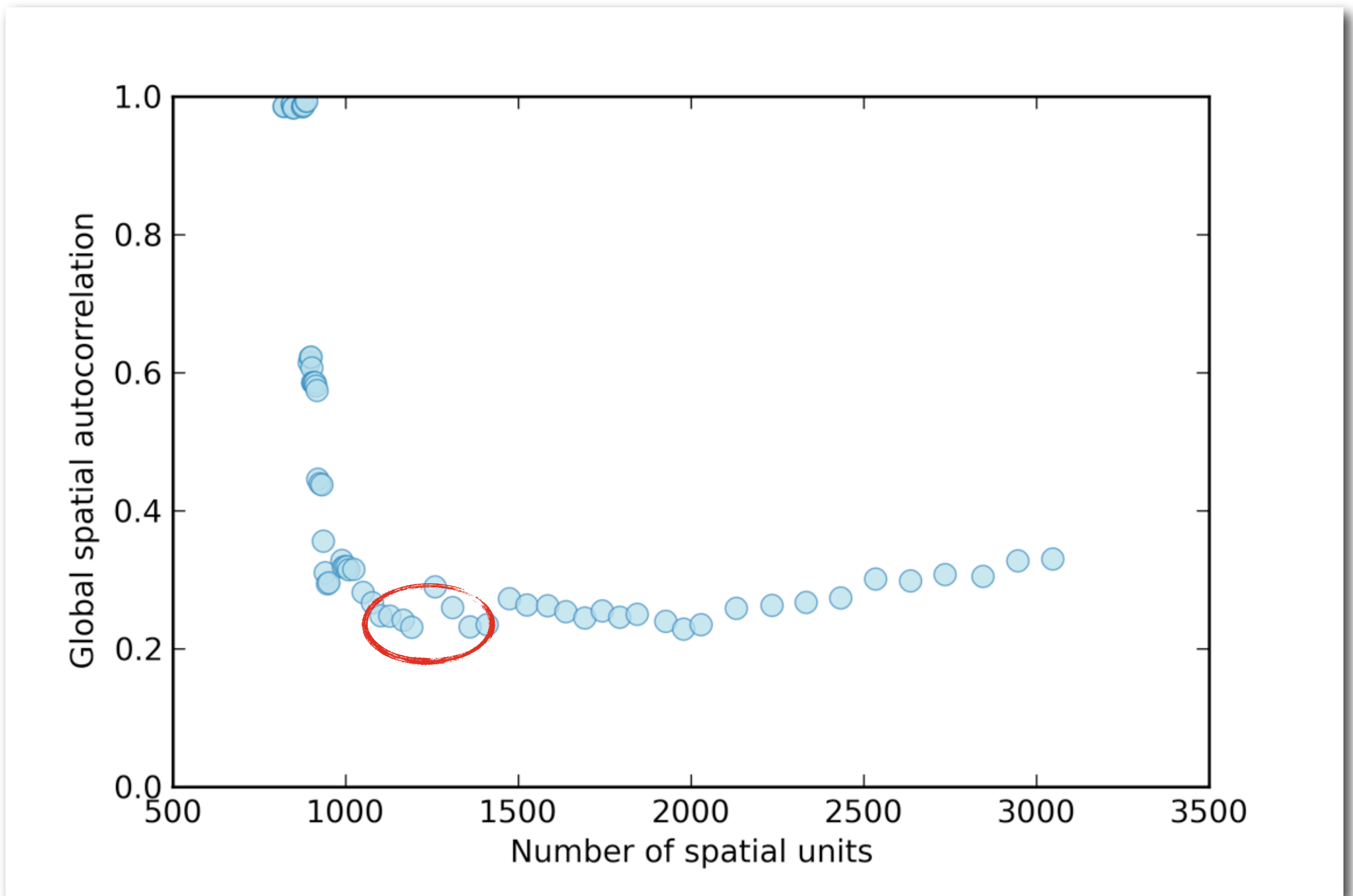
The clustered, or aggregated, CF values match quite well with the raw disaggregated values. Clustering seems to have found a good approximation of the underlying spatial scale of the impact assessment.

Forestry



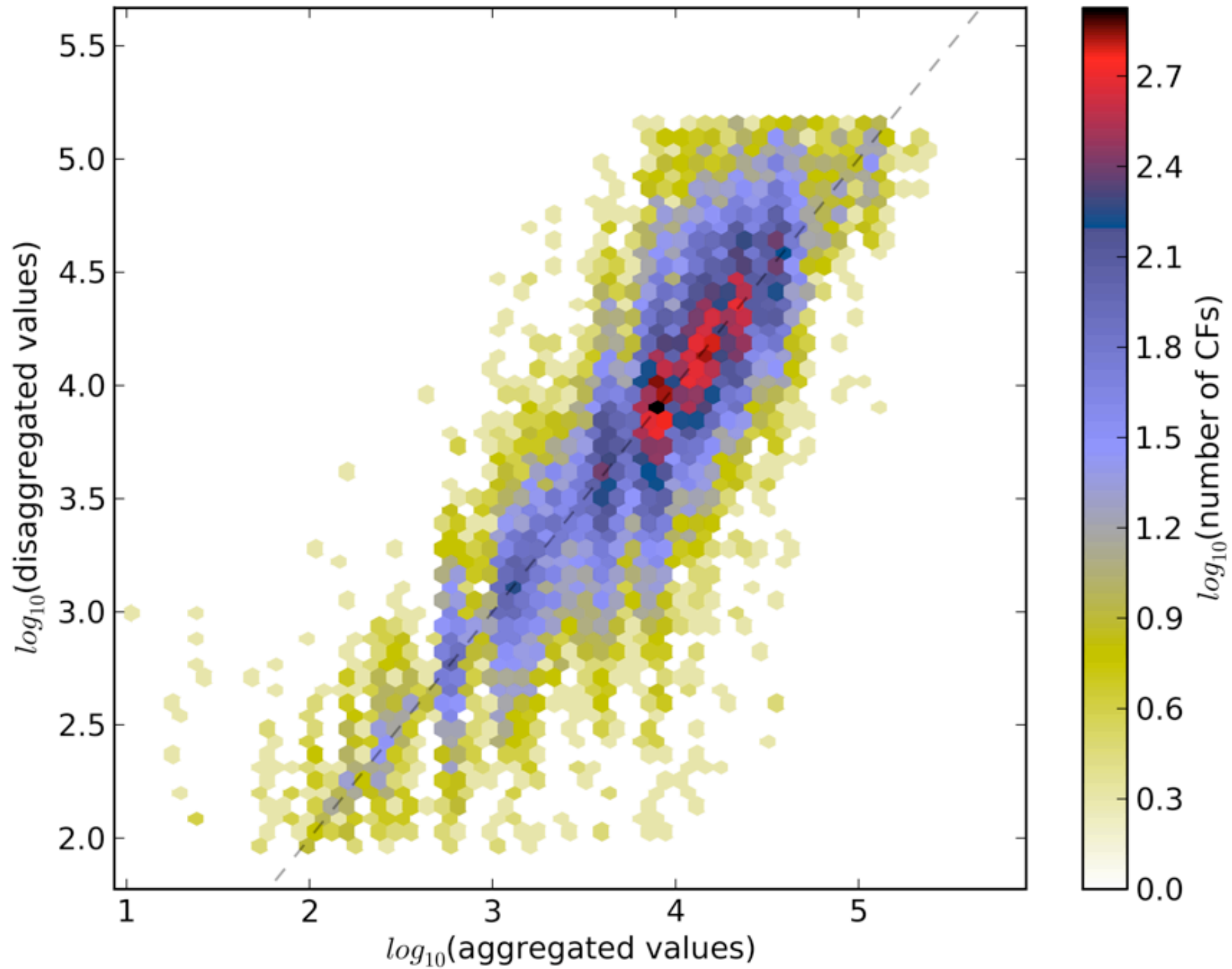
A map of the chosen “best” spatial scale. This map shows us that clustering has found a strong dependence on country-level data.

Noise



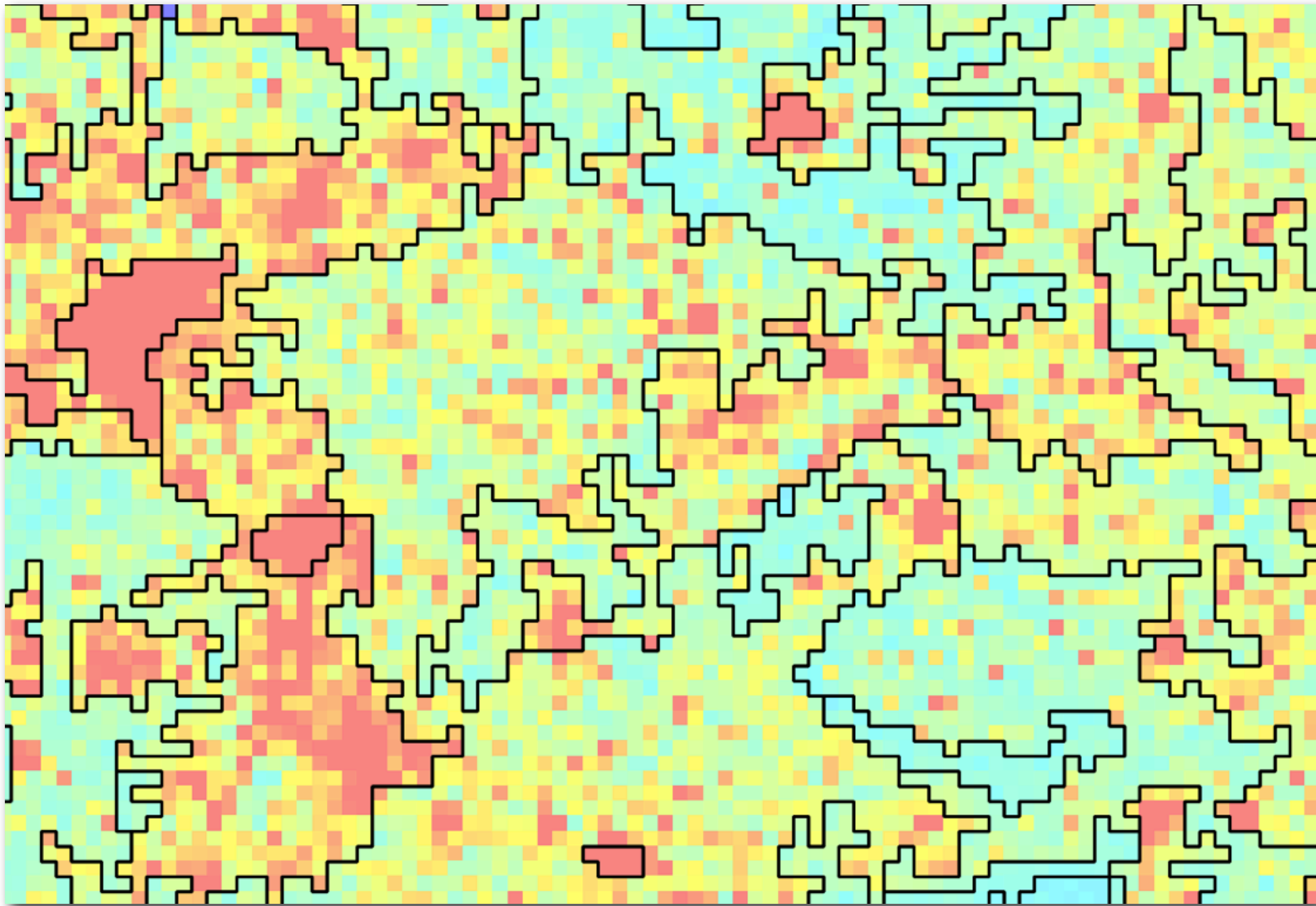
With noise (in this case, the characterization factors for 2000-hz, averaged over the day), we get a similar minimization of spatial autocorrelation. We default to the smallest number of spatial units if there is a large minimized area.

Spatial complexity



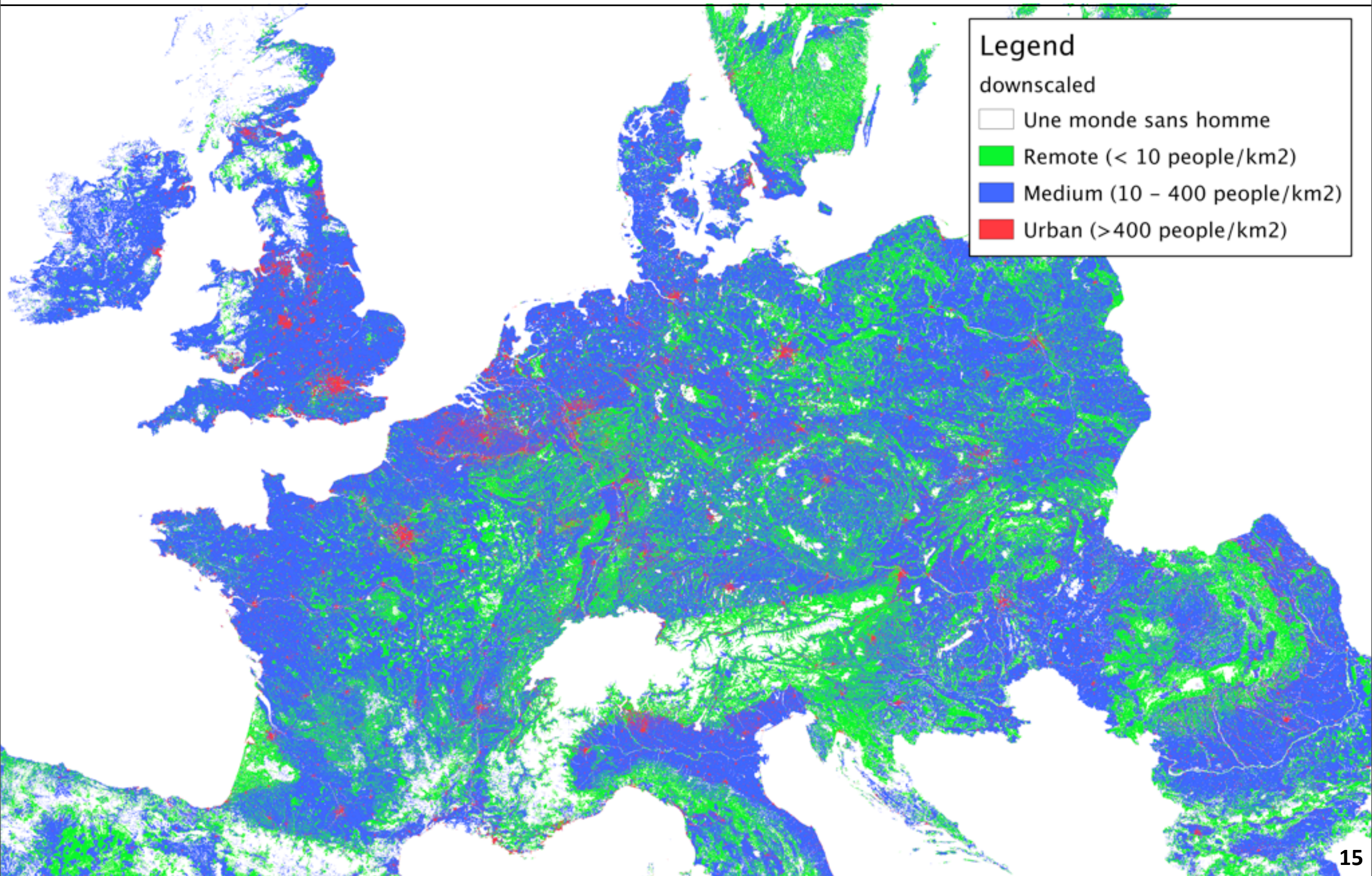
However, this spatial scale has a large error.

Spatial complexity



The chosen “best” spatial scale has spatial units which contain highly variable disaggregated data.

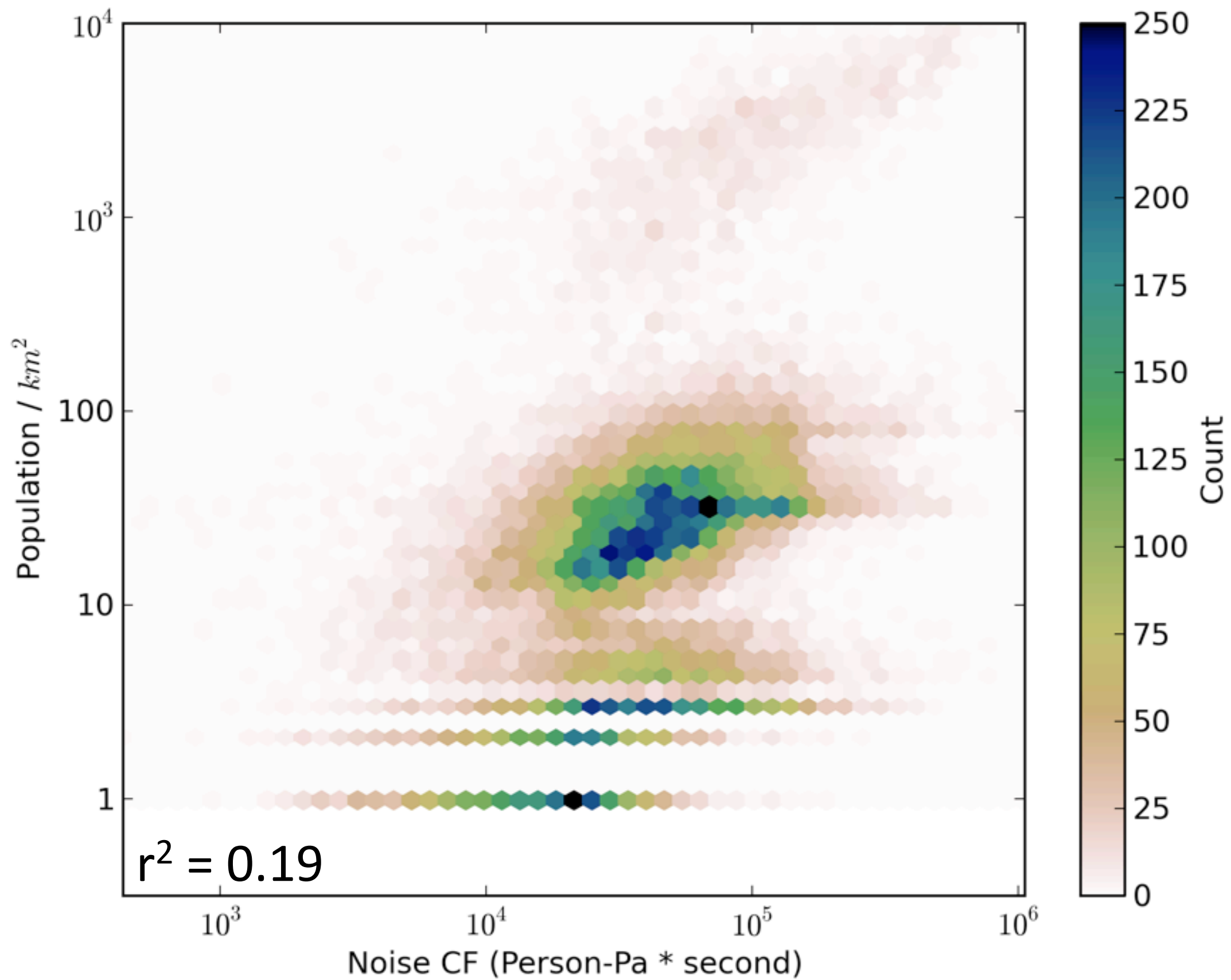
Archetypes



15

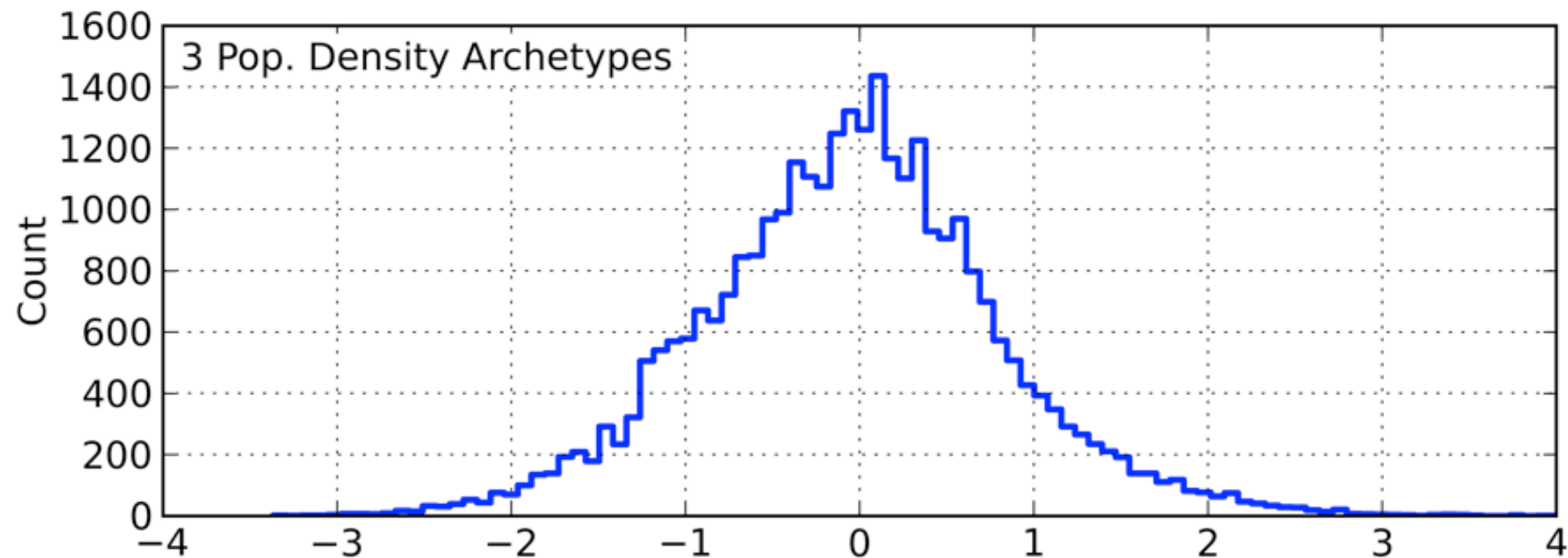
An alternative to GIS-based regionalization are so-called archetypes, which provide simple categories for inventory information. One proposed scheme is for three levels of population density. In many cases, these archetypes can also be represented as spatial layers. Population density data from [Gallego/EEA](#).

Population density correlation

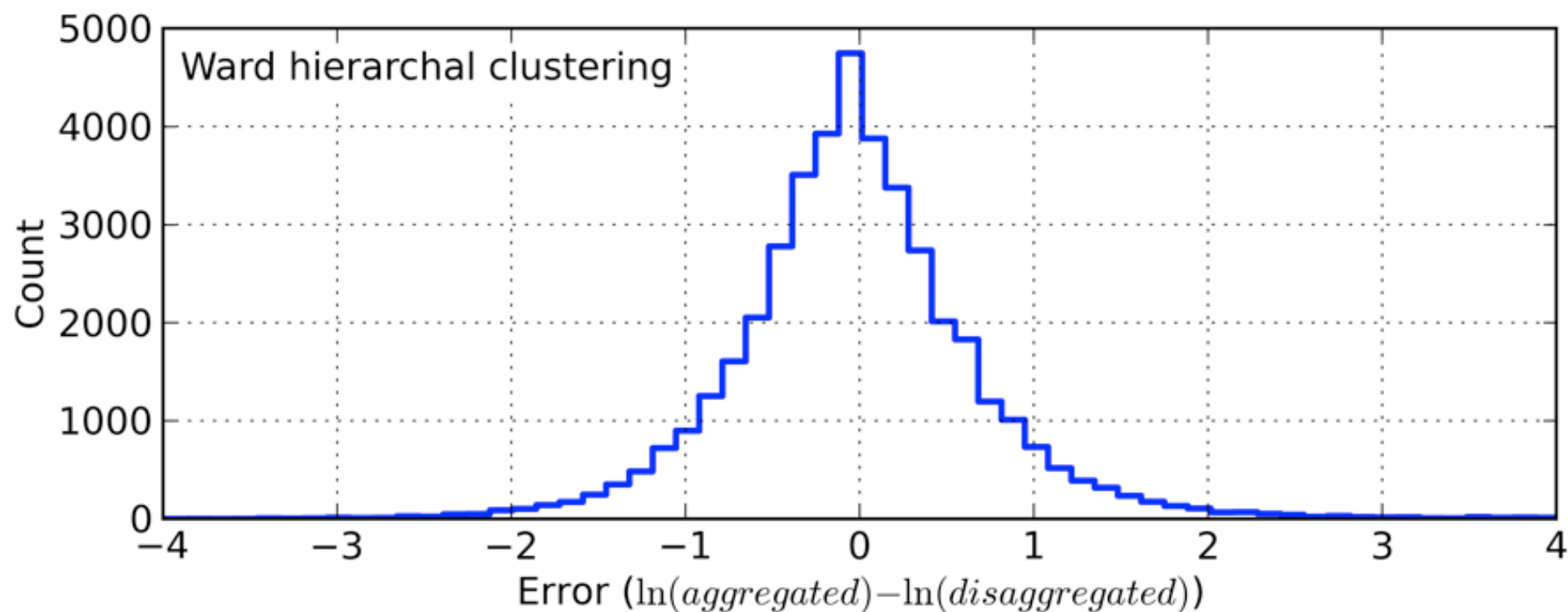


Noise CFs are correlated with population density, though not perfectly (other factors such as climate also play a role in CF generation).

Archetype error



Average $|\text{errors}|$: 0.53
Median $|\text{errors}|$: 0.66



Average $|\text{errors}|$: 0.38
Median $|\text{errors}|$: 0.52

Using an archetype-based approach introduces more and wider error, but may be acceptable if it allows a better match with inventory data. Ward clustering, by its very nature, produces very nicely distributed errors.

Raster data in LCA

- Benefits
 - No need for simplification
 - Can match inventory and impact assessment
- Costs
 - Software development
 - Complexity in understanding
- Fundamental question about what LCA is
 - What is “good enough”?

Another alternative may be the direct inclusion of raster data in LCIA methods or LCI datasets. This would increase software complexity but allow the direct use of the raw data. In my opinion, we have to ask ourselves what the real question is before we can try to answer it – what is good enough for LCA to provide decision support?

Conclusions

- Ward clustering is a **good** approach for generating candidate maps
- **Heterogeneity** of some regionalized LCIA methods poses challenges
 - Regionalization of foreground versus background?
- Work on advanced regionalized LCA **software** is ongoing in Brightway2 software tool
 - Scripts for LCIA autocorrelation also available

Thank you for your attention.



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bitbucket.org/cmutel/lcia-spatial-autocorrelation

Thanks to LC-IMPACT method developers for the data, and the people of the EU and Switzerland for funding my research.