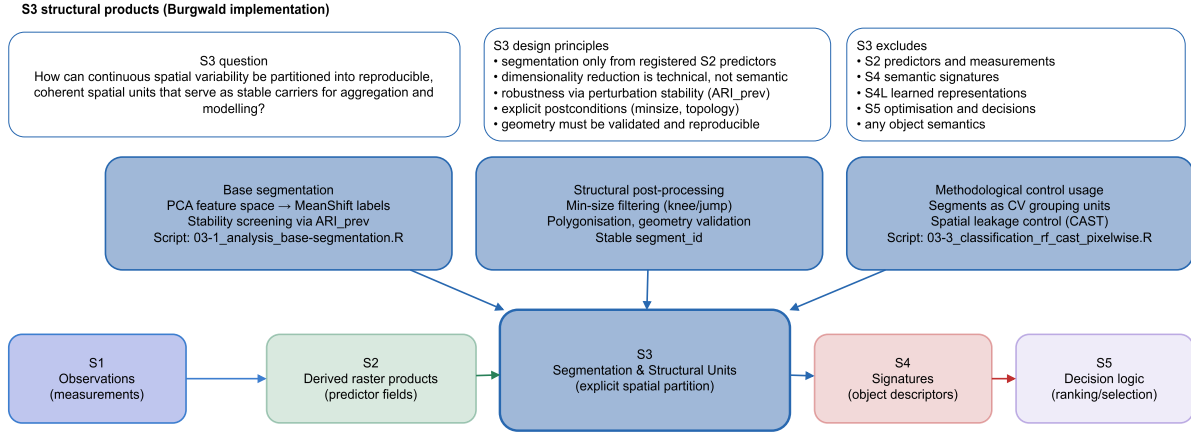# S3 — Structural Space

Segmentation and Stability-Controlled Structural Units

1 S3: Segmentation and structural spatial units

Burgwald decision stack — integrated conceptual and operational description

S3 structural products (Burgwald implementation)

1.1 Role of S3 in the Decision Stack

S3 denotes the layer in which spatially explicit raster information is transformed into discrete spatial units. These units are not semantic objects in a domain sense, but operational structural entities that define coherent spatial supports for aggregation, attribution, and downstream decision logic.

S3 introduces explicit spatial partitioning. Continuous pixel fields are converted into labelled regions that are internally homogeneous with respect to a selected feature space. The segmentation itself is treated as a structural representation, not as an interpretation of physical or ecological objects.

The guiding question of S3 is:

How can continuous spatial variability be partitioned into reproducible, spatially coherent units that serve as stable carriers for further analysis?

S3 deliberately excludes semantic interpretation. Derived physical predictors, classifications, and observational summaries belong to S2. Signatures and aggregated descriptors belong to S4. Learned representations are assigned to S4L. Ranking, optimisation, and decision logic belong to S5. Whenever a product assigns meaning, aggregates attributes, or supports explicit decisions, it has left the S3 domain.

Within the Burgwald workflow, S3 fulfils three structural functions. First, it provides stable spatial supports for aggregation beyond the pixel scale without introducing arbitrary neighbourhood definitions. Second, it externalises spatial boundary formation into an explicit, reproducible algorithmic process, improving auditability and reducing subjective bias. Third, it provides a geometric scaffold for auxiliary methodological purposes, such as stabilising spatial cross-validation by grouping samples via persistent segment identifiers.

1.2 Construction Principles and Epistemic Framing

Segmentation in S3 is derived exclusively from S2 feature layers. All transformations applied prior to segmentation — standardisation and dimensionality reduction — are treated as technical conditioning steps rather than as semantic modelling.

Segmentation parameters are not interpreted as physical process scales. Instead, parameter selection is framed as an operational control problem. The objective is to identify parameter regimes that generate internally consistent segmentations, are locally robust against small perturbations, remain computationally tractable, and provide reproducible structural partitions. This follows a general understanding of segmentation as a numerical clustering problem in joint spatial–feature space rather than a model of physical object formation, as originally formalised in the MeanShift framework[1] and later adopted widely in object-based image analysis and large-scale remote sensing workflows [2] [3].

This framing avoids circular justification: segmentation defines structure, and structure would otherwise be used to justify segmentation scale. Scale is therefore interpreted as a numerical stability property, not as an ontological statement about landscape objects or ecological entities.

Postconditions are applied to enforce basic structural constraints on the resulting partition, in particular minimum region size filtering and consistent polygonisation of the masked label raster.

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[1]Comaniciu, D., & Meer, P. (2002). *Mean Shift: A robust approach toward feature space analysis.* IEEE Transactions on Pattern Analysis and Machine Intelligence.

[2]Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1), 2–16.

[3]Drăguţ, L., Csillik, O., Eisank, C., & Tiede, D. (2014). Automated parameterisation for multi-scale image segmentation on multiple layers. *ISPRS Journal of Photogrammetry and Remote Sensing*, 88, 119–127.

The final product of S3 is a polygon layer with validated geometries and stable segment identifiers that serve purely as structural carriers.

1.3 Segmentation Pipeline and Feature Space Construction

The segmentation workflow operates on a transformed predictor space to reduce numerical dominance effects and redundancy.

Each predictor band is standardised to zero mean and unit variance:

$$z = \frac{x - \mu}{\sigma}$$

This ensures comparability across heterogeneous feature sources.

Principal Component Analysis is then applied to reduce dimensionality and collinearity while preserving dominant variance structure. PCA is used as a numerical conditioning step, not as a latent process model. The use of PCA as a conditioning step follows standard practice in high-dimensional remote sensing pipelines to stabilise distance-based clustering and reduce feature redundancy, without implying semantic latent factors or physical interpretability [4].

Segmentation is performed using OTB LargeScaleMeanShift in joint spatial–feature space. Three parameters jointly control the partition: spatial bandwidth (`spatialr`), feature-space bandwidth (`ranger`), and minimum region size (`minsize`). These parameters regulate spatial coherence, similarity tolerance, and fragment suppression. Their interpretation remains operational rather than physical.

1.4 Stability-Based Parameter Control

For each candidate parameter set, segmentation stability is evaluated through local perturbation screening. Rather than validating against external ground truth, internal consistency under controlled parameter variation is used as a robustness proxy. This operational notion of stability is closely related to cluster agreement analysis and resampling-based robustness testing in unsupervised learning[5] [6], and has been applied in spatial segmentation contexts to reduce sensitivity to arbitrary scale choices and parameter tuning[7] [8].

[4] Jolliffe, I., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A*, 374.

[5] Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of Classification*, 2(1), 193–218.

[6] Ben-Hur, A., Elisseeff, A., & Guyon, I. (2002). A stability based method for discovering structure in clustered data. *Pacific Symposium on Biocomputing*.

[7] Grady, L., & Funka-Lea, G. (2012). Multi-label image segmentation for medical applications based on graph-theoretic electrical potentials. *IEEE Transactions on Medical Imaging*, 31(3), 519–529.

[8] Maier, S. W., et al. (2018). Scale optimisation in object-based image analysis. *Remote Sensing*, 10(8).

Similarity between baseline and perturbed partitions is quantified using the Adjusted Rand Index (ARI), defined as:

$$\text{ARI} = \frac{\text{Index} - \text{Expected}}{\text{Max} - \text{Expected}}$$

The Adjusted Rand Index corrects raw partition agreement for chance coincidence and is widely used for cluster comparison, segmentation benchmarking, and robustness analysis in unsupervised settings[9] [10]. Values lie in the range $[-1, 1]$, with 1 indicating identical partitions.

For a parameter set, let a baseline segmentation be compared against K perturbed segmentations. For each perturbation $i \in \{1, \dots, K\}$, define

$$\text{ARI}_i = \text{ARI}(P_0, \ P_i),$$

where P_0 is the baseline partition and P_i is the partition obtained under the i-th perturbation. Stability is then summarised as

$$\text{ARI\_prev} = \frac{1}{K} \sum_{i=1}^{K} \text{ARI}_i$$

Here, K denotes the number of evaluated perturbations after removing the baseline configuration and applying deterministic subsampling.

A composite robustness score penalises unstable configurations:

$$\text{score} = \text{ARI\_prev} - 0.5 \cdot \sigma_{\text{ARI}}$$

with:

$$\sigma_{\text{ARI}} = \sqrt{\frac{1}{K-1} \sum_{i=1}^{K} (\text{ARI}_i - \text{ARI\_prev})^2}.$$

The perturbations are generated adaptively around the given base parameter triple:

$$s = \text{spatialr}, \quad r = \text{ranger}, \quad m = \text{minsize}.$$

Spatial perturbations apply:

$s \pm 1$ when $s > 3$.

Range perturbations follow:

[9] Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of Classification*, 2(1), 193–218.

[10] Steinley, D. (2004). Properties of the Hubert–Arabie adjusted Rand index. *Psychological Methods*, 9(3), 386–396.

$\Delta r = \max(0.005,\ 0.10 \cdot r)$ and

MinSize perturbations follow:

$$\Delta m = \max(5,\ 0.20 \cdot m), \qquad m_{\min} \geq 0.8 \cdot m.$$

Candidate perturbations are generated combinatorially and the baseline configuration is removed. To keep runtime bounded, the resulting set is reduced to a fixed maximum size by subsampling with a fixed random seed, ensuring run-to-run reproducibility under identical configuration.

To keep memory usage bounded and runtime predictable, ARI is computed on paired label value vectors derived from a fixed-size pixel sample. Label rasters may optionally be spatially downsampled using nearest-neighbour resampling via the configurable sampling factor `fac`; `fac = 1` preserves the original resolution, while fac > 1 activates deterministic spatial downsampling for large domains. In all cases, materialisation of large intermediate raster tables is avoided.

1.5 Interpretation, Contract, and Limitations

S3 always depends on the availability of at least one S2 feature layer, since a segmentation cannot be computed without a feature representation. In this sense, S3 is operationally downstream of S2. However, the assignment of products to S-layers is not identical to their execution order in the workflow: some S2 products may be generated later for practical reasons without changing their classification. The defining criterion remains whether a product represents a spatial partition or a derived measurement or descriptor.

Contract statement.

> S3 generates a reproducible spatial partition from continuous raster data. The resulting segments are used as stable spatial units for aggregation and further processing, but do not carry semantic labels, rankings, or decision logic.

The main limitation of the S3 approach lies in the dependence of the segmentation on scale selection and feature-space parametrisation. Different choices of spatial scale, feature composition, and bandwidth parameters can lead to different partitions, even when stability screening is applied. Stability reduces sensitivity to small perturbations, but it does not eliminate structural dependence on modelling choices.

ARI provides only a coarse measure of partition agreement and is insensitive to spatial morphology and topology. Feature-space bandwidth calibration remains empirical, and MeanShift segmentation remains sensitive to feature engineering. These limitations reflect a general property of spatial partitioning: segment boundaries are method-dependent rather than intrinsic properties of the landscape, a problem closely related to scale effects and the modifiable areal unit problem[11] [12].

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[11]Openshaw, S. (1984). *The Modifiable Areal Unit Problem*. Geo Books.
[12]Woodcock, C. E., & Strahler, A. H. (1997). The factor of scale in remote sensing. *Remote Sensing of*

Environment, 21(3), 311–332.