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REVIEW

Unsupervised Intelligent Framework for Earth Science Remote Sensing Applications Based on Clustering Algorithms

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ABSTRACT

Archives of Earth observations have grown and continue to grow in volume, modality, and temporal density, providing unprecedented access for monitoring the Earth system and exacerbating the paucity and high cost of quality labels. This is a review of unsupervised intelligent methods for Earth science remote sensing based on clustering algorithms and capable of analyzing data in a scalable, interpretable manner under domain shift. We begin by summarizing the remote sensing data properties that make it difficult to learn unsupervised, and they are: high-dimensionality, mixed-pixels, sensor-specific noise, spatial autocorrelation, non-uniform time series, heterogeneous across sensors. We next list key clustering families that are applied in remote sensing, including centroid-based and medoid-based, probabilistic mixtures, density-based, hierarchical, graph clustering, spectral clustering, subspace/low-rank models of hyperspectral data, fuzzy clustering to ambiguity, and deep clustering using self-supervised representation learning. On these algorithmic mammoths, we introduce end-to-end patterns of framework design, i.e., preprocessing, harmonization, sampling, and tiling on a scale of archive computations, spatial-context synthesis with super pixels and regularization, multi-modal fusion with shared latent spaces and spatiotemporal clustering with consistency and drift management. Lastly, we also talk about application areas like stratifying land-covers, grouping of hyperspectral materials, discovering SAR regimes, hazard surveillance, and analyzing climate-hydrology regimes with the focus on not analyzing by labels but by stability tests, uncertainty reporting, and process-based validation. The review summarizes practical advice and presents open dilemmas to effective, operational unsupervised intelligence for Earth observation.

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1. Introduction

One of the most significant observational pillars of Earth system science is remote sensing, which allows to monitor continuously the land surface, oceans, cryosphere, and atmosphere of a broad range of spatial scales and long-term intervals [1,2]. Over the last ten years, the Earth observing (EO) ecosystem has become increasingly rich in capability and variety: multispectral and hyperspectral imagers can now give spectrally finer detail; synthetic aperture radar (SAR) can now sensibly monitor all-weather, day-and-night with sensitivity to surface roughness and moisture; thermal sensors can now provide data reflecting energy balance and evapotranspiration; the LiDAR can now provide measurements of structure in 3D form; multi-temporal analysis has become the norm of business rather than the exception [3–6]. These breakthroughs have opened new possibilities to observe and learn about the environmental transformation, including urbanization and deforestation, as well as drought dynamics, shore processes, glacier melting, and the effects of hazards. However, they too have brought a conceptual bottleneck: the scale, speed and diversity of EO data are now much greater than the rate at which high-quality, task-relevant labels and hand-crafted learning materials can be generated.

This bottleneck has been increased by many modern remote sensing processes relying on supervised learning. Although supervised deep learning has demonstrated a high level of performance in segmentation, classification, and object detection, it usually assumes a large amount of labeled data that is representative of the scenario in which the model will be used. This is often not the case in applications of earth science. Labels are costly as they can only be interpreted by experts, conducted in the field, or cross-referenced with other related items (e.g., land-cover categories), and are subjective or changing (e.g., land-cover categories). In addition, the remote sensing data are defined by large domain variations among geography, seasons, illumination, atmospheric conditions, sensor types, and geometries of acquisition. A model that was trained in one area or time can degenerate in a different area or time because of the variation of phenology, soil background, structure of materials used in the built environment, or sensor calibration. Cases with the fewest labels are those most critical to decision support, such as floods, wildfires, volcanic eruptions, landslides, extreme storms, and so forth. These facts encourage a complementary paradigm that intelligent systems will be able to acquire structure in data with little or no human annotation and will be responsive to changes in condition [7,8].

Such systems can be approached through unsupervised learning and clustering, more specifically. The basic idea behind clustering is to cluster observations such that observations in the same cluster are closer to each other than to observations in other clusters. This general concept is consistent with a lot of remote sensing tasks: finding repeated spectral-textural patterns; dividing a scene into homogeneous units; classifying large collections of archives in ways that can be interpreted; finding non-normal observations that could be indicative of an anomaly or a new phenomenon; and making intermediate representations that can be used to make downstream maps and analyses. Clustering may serve as either a goal (e.g., unsupervised stratification of a land cover) or, also, as a method to encourage the use of weak supervision and active learning by offering pseudo-labels, prototypes, or data divisions [9,10]. Significantly, clustering may be incorporated throughout the processing pipeline: at pixel-level clustering of hyperspectral images to segmented region clustering, at patch-level clustering of scenes, and at trajectories and seasonal pattern clustering.

Although the concept of clustering is simple, it is not trivial to do good clustering in Earth science remote sensing. EO data are high-dimensional and noisy and similarity is not often well represented using a generic Euclidean metric in raw pixel space [11]. The complicating factors in cluster formation are mixed pixels, sensor noise, atmospheric effects, speckle in SAR, cloud contamination and missing observations. Contextual effects: neighboring pixels are correlated and significant patterns are usually localized in continuous regions as opposed to discontinuous spots. Circumstantial conditions are also important: most Earth system variables experience seasonal cycles or extreme disturbance regimes, multi-year trends, and they can be as informative as instantaneous reflectance or backscatter. In multi-sensor environments, observations cannot be so simply compared and strong alignment or fusion approaches need to be used. Lastly: applications in earth science require interpretability and scientific correctness: clusters are preferably expected to map to such meaningful physical or ecological states, or at least any reproducible stratification and hypothesis generation is required[12].

These issues have resulted in a broad range of clustering-based methods in the remote sensing literature, ranging from classical algorithms, graph-based and more recent deep clustering methodologies. Conventional methods, including k-means, Gaussian mixture models, hierarchical clustering, and fuzzy c-means are still very popular because they are simple and scalable. Density-based methods (e.g., DBSCAN variants) are more suitable for the shape of irregular clusters and also identify outliers, whereas spectral and graph clustering methods allow a principled approach to the inclusion of neighborhood structure and non-linear similarity[13]. In the case of hyperspectral imagery, subspace and low-rank models can solve the curse of dimensionality and the existence of correlated bands[14]. However, more recently, the field of representation learning has transformed the clustering paradigm: autoencoders, contrastive learning and encoders based on transformers can generate embeddings where semantically meaningful clusters are more readily dissimilar, and clustering pipelines that simultaneously learn features and cluster assignments have become possible. Such techniques are now used together with spatial regularization, multi-scale context aggregation, and self-supervised training on large archives, in the field of Earth observation.

The concept of an unsupervised intelligent framework goes beyond the choice of a clustering algorithm. Clustering is not the entire pipeline as used in remote sensing practice, and has to be ingested with data, preprocessed, feature constructed, model selected, scaled, and validated. An example is in preprocessing, where one can have radiometric calibration, atmospheric correction, speckle filtering, cloud masking, topographic normalization, co-registration, and resampling across resolutions. The design of features can be spectral indices, texture descriptors, morphological profiles or learned representations of self-supervised models. Spatial information can be injected using super pixels or object-based image analysis (OBIA), neighborhood graphs, Markov random fields or post-process smoothing and merging of regions. Time-series embeddings, seasonality-aware distance or online drift-adaptable clustering may be needed to do multi-temporal analysis. The operational components have to be efficient to operate on large mosaics and archives, resilient to diverse data quality and easy to understand to facilitate scientific interpretation and decision-making[15,16].

One of the major challenges of unsupervised remote sensing is the evaluation[17,18]. The quality of clustering is ambiguous in nature unlike supervised problems where the performance can be compared against ground truth labels: two different partitions can be valid depending on the scale and the purpose of the application, as well as the similarity concept used. The usual measures of internal validation (e.g., silhouette score, Davies-Bouldin index) are sometimes informative but not very scientifically useful, particularly in spatially structured or high-dimensional data. External validation demands labels that might not be available or that may be reliable only partially. Consequently, models tend to be assessed by proxy supervision (small labelled subsets, human inspection), stability tests (initially and perturbation resistance to other models), or physics and process-based sanity checks (e.g., seasonality consistency, known spectral physical correlations). Creation of more effective evaluation procedures is critical in the process of transitioning evidence-of-concept clustering experiments to valid Earth science processes. As illustrated in **Figure 1**, the integration of clustering within an end-to-end framework helps address the challenges posed by heterogeneous data sources, domain shifts, and the absence of labels.

The review is on clustering as a research paradigm in the construction of unsupervised intelligent designs in Earth science remote sensing projects. We do not model clustering graphically: clustering is not modeled as an algorithmic step that interacts with representation learning, spatial-temporal modeling, multi-sensor fusion, and human-in-the-loop refinement. The review highlights the methodological decisions that have a direct impact on the performance in practice - distance measures and embeddings, scalability strategies, resistance to noise and domain shift, and cluster interpretation and validation mechanisms. We also point out how clustering may be useful to various scientific goals, such as stratification to sample and field campaigns, regime and pattern discovery in climate and hydrology, unsupervised segmentation in mapping, and novelty detection in hazards and rapid response[19,20].

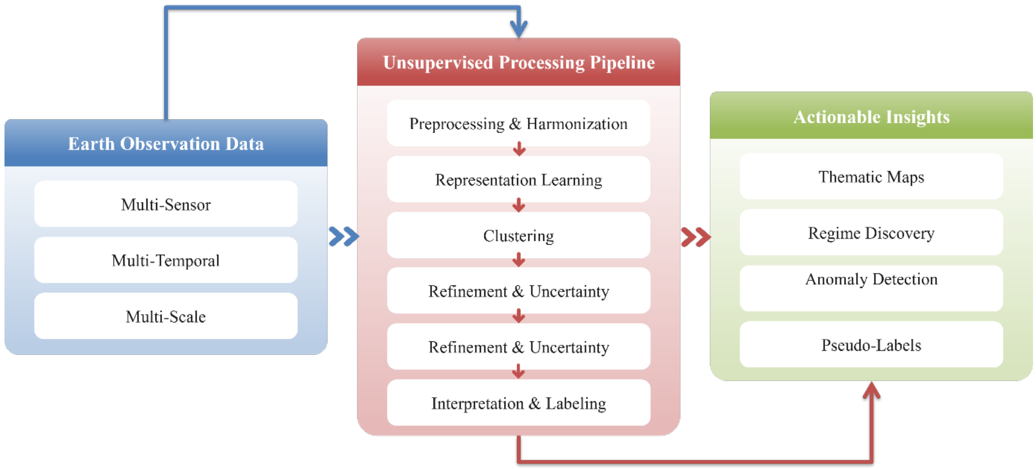

Figure 1. Conceptual overview of clustering-based unsupervised intelligence in Earth observation, from data ingestion to actionable insights.

In this review, we define an "unsupervised intelligent framework" as an end-to-end pipeline that integrates data harmonization, representation learning, clustering, spatial-temporal regularisation, validation, and product generation into a single cohesive system. Unlike conventional unsupervised pipelines that treat clustering as an isolated algorithm applied to pre-processed features, an intelligent framework is explicitly designed to handle scale and data imperfections, to remain robust under domain shift across geography, seasons or sensors, to prioritise interpretability through prototypes and uncertainty maps, and to support operational deployment with versioning and reproducibility. Accordingly, it answers not only which clustering algorithm works, but also how to build a repeatable, scalable, and scientifically interpretable system for Earth observation [21].

The article has threefold contributions. To begin with, we do a synthesis and divide clustering algorithm and remote-sensing-aligned adaptation into a single taxonomy, bridging substantive classical clustering methods with recent advances in deep clustering. Second, we put forth an intellectual hypothesis reference architecture of unmonitored intelligent EO pipelines, defining typical modules, and setting patterns of designs that are repeated per modality and context of use. Third, we address analysis and deployment issues that receive less attention, such as determining how to optimize cluster utility with no labels, avoiding or guaranteeing reproducibility and spatial-temporal leakage, and scaling approaches to contemporary EO archives without loss in interpretability [22–24].

The rest of the paper is organized in the following way. Section 2 defines the type of remote sensing data and generates clustering issues in the Earth science fields with special focus on the constraints that influence algorithm and pipeline development. In Section 3, the evaluation of families of algorithms based on clustering of EO data and the required adaptation involves the ability of spatially aware, high-dimensional, and deep clustering methods. Section 4 gives the design of end-to-end unsupervised intelligent frameworks, which include preprocessing, feature learning, multi-modal and spatiotemporal integration, and viable deployment patterns. Section 5 reviews the representative applications and gives information on the evaluation method, robustness, and scalability. Section 6 ends with unresolved issues and prospects for more trustworthy, interpretable, and functional unsupervised intelligence to monitor the Earth systems.

2. Remote Sensing Data Characteristics and Problem Formulation

2.1. Earth Observation Modalities, Products, and Observational Geometry

The range of sensing modalities and the fact that the signals measured are indirect manifestations of surface or atmospheric states characterize Earth science remote sensing [25]. Optical multispectral sensors are optical sensors that measure reflected radiance in a small set of bands, and they can be used to map vegetation, water, soil, and urban objects worldwide over long time periods [26]. Hyperspectral instruments build upon this and sample the spectrum with a fine resolution, allowing more discriminative characterization of materials and biochemical properties, but being more sensitive to noise, redundancy, and atmospheric effects [27]. Synthetic aperture radar offers active illumination in the microwave, and it is able to measure backscatter based on the roughness, dielectric, and structural properties of the surface and provide strong measurements even when covered by clouds and at night without speckle and intricate geometrical interactions with moisture [4]. Thermal infrared sensing is associated with the land surface temperature and emissivity, which are important in studies of energy balance, the estimation of evapotranspiration, and urban heat islands [28]. LiDAR is a 3D structure that compensates for 2D imagery because it measures the vertical distribution of surfaces and vegetation using return waveforms or discrete returns [29]. Passive microwave measurements can provide data about soil moisture, snow, sea ice, and precipitation, with less desirable fine-scale detail, but of great value in all-weather operation [30].

In addition to modality, EO data are spread across processing levels that denote more correction and abstraction [31]. Products of lower levels maintain the original geometry and radiometric characteristics of measurements, and at higher levels, they might be atmospherically corrected, orthorectified, reprojected, and gridded, with or without retrieval models or data assimilation. These changes are noteworthy to unsupervised learning since the clustering implicitly presupposes comparability between samples. Comparability in remote sensing is based on harmonization decisions, such as the atmospheric correction algorithms, radiometric normalization of the sensors, and resampling of spatial resolutions. Observational geometry also adds to the concept of similarity since the sun-sensor angles in optical data and the incidence angle in SAR affect recorded values at constant surface conditions. The distance structure can be dominated by differences in phenology and illumination, and acquisition geometry when the multi-temporal records are examined, unless these differences are suitably considered.

2.2. Fundamental Data Characteristics: High Dimensionality, Noise, and Mixed Observations

The remote sensing data is often present in high-dimensional spaces where physically significant variability is confounded with nuisance variables. As an example, hyperspectral imagery can contain hundreds of bands that are highly correlated and, therefore, the curse of dimensionality occurs where distances lose their information and clusters become hard to partition. Even multispectral data may act as high-dimensional data, with indices, textures, multi-scale features, or time stacks added to it. Silence and non-existence are everywhere. Cloud cover, haze, and aerosol scattering affect optical imagery and regeneration artifacts can be left behind even after a correction. SAR measurements contain multiplicative speckle noise as well as possibly having layover and shadow effects on complex terrain. Thermal measurements are close to emissivity assumptions and atmospheric profiles. Throughout modalities sensor calibration variations, striping, and compression artifacts can cause structured errors which are generated as spurious clusters [32–35].

One of the unique problems of EO is that observations are frequently combinations of sub-pixel components. Mixed pixels will be formed when there is more than one type of land cover in the sensor footprint, when the vegetation is sparse, or when land-water boundaries exist [36]. The same can be said of course-resolution passive microwave data, whereby footprints can contain non-homogeneous surfaces, and in LiDAR whereby returns are a vertical combination of canopy and ground [37]. Mixed observations make methods of clustering ambiguous: a pixel can be a legitimate member of many semantic categories, and forcing hard boundaries can cause unstable boundaries [38]. This encourages soft clustering models and uncertainty-sensitive allocations, in particular where the outputs will be to assist in developing scientific meaning or downstream mapping.

2.3. Spatial Structure, Scale Effects, and the Role of Context

Remote sensing images are not a set of independent samples, but rather a spatial field characterized by great autocorrelation and multi-scale structure [39]. Neighboring pixels tend to be similar in property and objects of interest like agricultural fields, city blocks, wetlands or burn scars cover adjacent space. Consequently, clustering without respect to spatial context can tend to chop objects up into salt-and-pepper designs, especially when the noise in a given modality is large, or when the within-class variance of objects is large in a given image. On the other hand, excessively effective spatial smoothing of fine but significant features such as narrow riparian strips or early disturbances may be eliminated. The key factor is the effect of scale: the sort of granularity of the clusters required in global stratification versus local segmentation, coarse climate regimes and finer habitat mapping, and pixel and object-based analysis. Spatial resolution alters the statistical composition of data and the definition of similarity can be changed; multi-resolution harmonization and scale-consistent evaluation are imperative.

Context is also semantic. In certain circumstances, urban impervious areas such as bare soil might have identical spectral characteristics, whereas spatial structure and neighborhood composition are able to distinguish them. Similarly, snow, clouds and bright sand could be spectrally identical in some bands, but spatial texture, elevation and temporal persistence can be used to give other information. The smart unsupervised structures often thus tend to be a fused approach of clustering with context representations, be it in constructed texture features, graph neighborhoods, super pixel groupings or deep encoders, which amalgamate data between receptive areas [16].

2.4. Temporal Dynamics and Non-Stationarity in Earth System Observations

Numerous earth science applications are by definition temporal and clustering frequently has to work on sequences rather than snapshots [40]. Phenology of vegetation, farm cycles, snow patterns and melting, the activity of lakes, and urbanization bring about typical temporal markers. The hazards that include floods and wildfires are associated with sudden transitions and then recovery patterns. Climate-related variables can be interannual and long-term. The time series of temporal sampling is patchy because of the cloud cover, cycles in orbit, and sensor failures, which cause partial and imbalanced time series. These properties make the definition of similarity difficult since two places might be similar in a pattern of seasons but lag in time or may be similar in some periods and separate in events.

It is the non-stationarity that is especially strong in EO [41]. The distributions of observed data changes also vary among seasons, different regions of varying ecological or geological environments, among sensors with varying spectral response, and different calibration histories. Discontinuities may also occur even among sensors of similar types when their processing algorithms are changed, or the version of a product is changed. In the case of unsupervised clustering, these shifts may result in clusters that are indicative of conditions of acquisition, as opposed to surface processes. Representations that account for nuisance variability and focus on dynamics, and adaptive or continual strategies that can accommodate concept drift without disrupting prior learned structure, are then frequently useful to spatiotemporal clustering.

In summary, as seen in **Table 1**, both data characteristics pose particular challenges that the clustering technique must address, i.e., dimensionality reduction of hyperspectral data or mixed membership of land-cover transition.

Table 1. Remote sensing data characteristics and their implications for clustering performance in Earth science applications.

Data Characteristic	Typical Source(s)	Why It Matters for Clustering	Common Mitigation in Unsupervised Frameworks
High dimensionality and band correlation	Hyperspectral, feature stacks	Distance concentration and unstable partitions in raw space	Dimensionality reduction, denoising, learned embeddings
Mixed pixels and gradual transitions	Moderate/coarse resolution optical, passive microwave	Hard labels are ambiguous; boundaries become noisy	Soft/fuzzy assignments, uncertainty mapping, object-based units
Sensor- and geometry-dependent radiometry	Optical BRDF/illumination, SAR incidence angle	Clusters can reflect acquisition conditions instead of surface states	Normalization, harmonization, angle correction, invariant features
Noise and artifacts	SAR speckle, striping, clouds/haze	Spurious micro-clusters and fragmented maps	Filtering/denoising, masking, robust distances, spatial regularization
Spatial autocorrelation and multi-scale structure	Most imagery	Independent-sample assumption fails; salt-and-pepper outputs	Superpixels/OBIA, graph clustering, CRF/MRF or smoothing refinement
Irregular temporal sampling and missingness	Optical time series (cloud gaps), multi-sensor fusion	Similar dynamics may be misaligned or partially observed	Temporal embeddings, masking-aware models, seasonality-aware distances
Domain shift across geography/season	Global EO	Clusters drift; prototypes lose transferability	Self-supervised pretraining, adaptive/continual clustering, stratified sampling

2.5. Multi-Sensor and Multi-Modal Fusion as a Clustering Problem

The science of the Earth systems is becoming more dependent on the use of complementary observations. Data taken by optical methods can be the greenness of the vegetation, and SAR can be the canopy structure and moisture sensitivity; thermal data can be the surface temperature and stress; LiDAR can be the vertical structure, and the passive microwave can give all-weather hydrologic information [42–45]. Fusion can introduce robustness and disambiguate classes that cannot be separated in a single modality, but it brings about alignment and comparability problems. Some differences might be between spatial resolution, revisit frequency, and geolocation accuracy between sensors, and observations do not necessarily occur contemporaneously. The modes of modalities are not the same as they are inherently different, i.e., naively concatenating the features can overweight some of the sensors or increase the noise.

In a non-supervised model, multi-modal clustering can either be set up as one where modalities share a common latent space, or co-clustering of modalities, where consensus across modalities informs the division [46]. The scientific question is in interaction with the fusion strategy. As an example, in cases when the interest is in finding regimes of surface moisture and structure of vegetation, SAR and optical can be considered as two complementary views of one latent state. Divergence between modalities can be informative instead of unproductive when the aim is to detect the inconsistencies, which signal change or anomaly. These considerations encourage clustering schemes that can reflect common structure as well as modality-specific variation especially in scenarios where they act over large geographies as well as long periods of time.

2.6. Problem Formulations for Clustering in Remote Sensing

There are various forms of clustering in remote sensing that vary in the definition of a sample, the space of representations, and the desired output. In hyperspectral analysis, unsupervised stratification of land-cover and preliminary partitioning of a scene, pixel-wise clustering considers each pixel observation as a single sample and is popular. Nevertheless, pixel-based methods are vulnerable to noise and the spatial discontinuity particularly in high-resolution images. Rather, samples are defined by object-based formulations as segments, superpixels or geographically meaningful units, which aggregate pixel statistics in each object [47]. This can make it stronger and easier to interpret, but it adds the issue of reliance on the quality of segmentation and can ignore fine structures that do not coincide with segments.

Scene categorization is performed by patch- or tile-based clustering, which is also applied to large archives to cluster them into semantic category clusters. Each sample is a local context window and it encodes texture, patterns and multi-scale structure. Samples can be time-series vectors, a phenological description, learned sequence embeddings in a spatiotemporal context, and the objective is to cluster trails into regimes. More complicated models are graph-based clustering on spatial neighborhoods, in which the edges indicate adjacency or similarity, and clustering is a partition of a graph and not a partition of independent points. The similarity measure is the focal modeling option in all the formulations. Similarity in remote sensing will have to strike a compromise between sensor physics, sensor scale, and context, and is often better defined in a learned embedding space than the raw measurement space [48].

2.7. Desiderata for an Unsupervised Intelligent Framework in Earth Science

A remote sensing intelligent architecture of Earth science needs to meet the demands, which are not limited to creating compact clusters. It must exhibit partitions that are stable under perturbations of reasonable degree, e.g., modest perturbations in preprocessing, sampling, or initializing, since unstable clusters are hard to interpret scientifically, and hard to operate upon. It must be semantically grounded, either by matching clusters or known categories where feasible or by allowing post hoc interpretation by analyzing prototypes, by attributing features, or by comparing to external data, like elevation or climate normals or land management limits. The domain shift robustness is crucial, as the variability of the Earth system and sensor variations exists as such; a framework that groups mainly according to region-specific artifacts has weak scientific value [49].

Scalability is also of the essence. Movable EO archives demand algorithms, whose tasks can be accomplished on billions of pixels and long record series, usually with bad tiling, distributed computing, or streaming representations. Meanwhile, the structure must maintain spatial coherence and should not introduce tile-based artifacts of tile-based processing. Lastly, the framework must support the downstream application, such as weak supervision, active learning, anomaly screening, and change analysis. When interpreted more literally, clustering is sometimes most useful because it receives the labeling load by grouping data into meaningful clusters that can be inspected, labeled, combined, or refined by the scientist, effectively transforming unsupervised structure discovery into a practicable intervening step between unprocessed EO data and useful Earth science products [50]. Collectively, these desiderata—stability, semantic grounding, robustness, scalability, and downstream utility—distinguish an unsupervised intelligent framework (defined in Section 1) from a conventional clustering pipeline that optimizes only for internal cluster quality metrics.

3. Clustering Algorithms for Unsupervised Remote Sensing Intelligence

3.1. Overview and Design Considerations in the Remote Sensing Context

The computational heart of most unsupervised intelligent systems is the clustering approach, as it transforms a model of remote sensing measurements into discrete or soft groupings that can be interpreted, mapped, or utilized as pseudo-labels [51]. The geometry of the feature space, lack of spatial and temporal coherence, noise and missingness, and necessity of spatial and temporal coherence all have a profound influence on the practical behavior of clustering algorithms during Earth observation. Remote sensing also often deals with highly correlated variables, non-Gaussian probability distributions with heavy tails, sampling bias due to clouds, orbit effects, and land-bin ocean mask, as opposed to many commonly used machine learning benchmarks. As a result, the choice of algorithm is often not explained by the theoretical properties, but also by the ability to scale to large arcs, resilience to the artifacts, and the ability to add domain restrictions like adjacency, smoothness, or multi-modal alignment. The section is a review of significant families of clusters and highlights the alterations and hybridization that can put them to effective use in Earth science remote sensing.

3.2. Partitional Clustering: Centroid-Based Methods and Their Variants

The centroid-based clustering is still popular in remote sensing because of its conceptual simplicity and economical nature in computations [52]. The canonical approach divides the samples into a fixed number of clusters by minimizing intra-cluster dispersion, usually under Euclidean distance. In multispectral space and a variety of derived feature spaces, this gives rapid stratification of large scenes, allowing for first-group things to be explored through grouping or to build pseudo-labels that allow weak supervision. Raw Euclidean distance in measurement space is, however not a good proxy of semantic similarity, as it is affected by the effects of illumination and atmospheric residues in addition to the scaling peculiar to the sensor. Consequently, centroid-based techniques are often combined with the initial preprocessing, e.g., standardization, dimensionality reduction or application of physically motivated indices and textures that are more consistent with surface characteristics.

Centroid-based clustering is commonly used in hyperspectral imagery, once the spectra have been projected into a lower-dimensional subspace, where the redundancy and noise are minimized [53]. Similar concepts can be used in time-series contexts: they can use temporal profiles which can be either summarized to form features of a seasonal profile or encoded into compact representations and clustered. In pipelines that are running mini-batch and streaming versions are popular since they can obtain large archives in a series of steps and still compute relatively accurate centroids. The biased emphasis of centroid-based procedures in remote sensing is their propensity to give prominence to approximately spherical clusters within the selected feature space, which may wrongly project complicated category manifolds and may split heterogeneous land-cover typologies into multiple clusters that mirror intra-class variation instead of different classes.

3.3. Medoid-Based and Robust Partitional Approaches

In cases where noise, outliers or non-Euclidean distances are of interest, the medoid-based formulations are desirable since the cluster representatives are real samples and not arithmetic averages [54]. It applies to SAR and other modalities in which a distribution can often be heavy-tailed and in multi-modal fusion in which similarity can be based on kernels or learned metrics. Medoid-based methods may be more resistant to outliers, as well as offer more interpretable prototypes, because every cluster can be represented by an actual observation, which can be visualized and examined. Their primary limitation is computational cost that increases as the number of samples increases, inspiring approximate nearest-neighbor search and subsampling methods when used with large remote sensing data.

A strong variant of clustering is also reflected in loss functions and trimmed objectives, which under-represent the extremes. Practically, robustification is usually carried out implicitly by using representation learning and denoising, though explicit goals of robust clustering can be helpful in cases where preprocessing is noisy, or where there are artifacts, whose patterns are outliers to centroid estimation, like thin clouds, sensor striping, or residual speckle [55].

3.4. Probabilistic Mixture Models and Soft Assignment

Probabilistic clustering has an intuitive approach to the treatment of mixed pixels and uncertainty that mix following a mixture distribution [56]. The most commonly used are Gaussian mixture models, commonly estimated through expectation maximization, and produce soft assignments, which are membership probabilities. Soft assignment in remote sensing is useful where transitions between land-covers are smooth, sub-pixel mixture is prevalent, or the aim is to label specific areas of uncertainty at boundaries. Mixture models can also be used to support strategies with the selection of models and can be extended to accommodate prior information, including the preference for some covariance structure or a set of constraints that implement spectral correlations.

However, Gaussian mixtures are not compatible with remote sensing data in which clusters are not necessarily elliptical and where noise is not Gaussian [57]. High-dimensional covariance estimation is unstable and is similar to high-dimensional linear parametric estimation. It is common to have high-dimensional covariance estimation unless covariance is dimensionality reduced/regularized. The simplicity of probabilistic models can be easily lost in a multi-temporal and multi-modal model environment, which encourages the use of simplified forms or latent variable models that decouple common structure and sensor-dependent variability. The probabilistic view can also still be beneficial even when the assumption of a mixture is not perfect due to a tendency to promote uncertain outputs, and allows the use of downstream Bayesian decision-making in earth science applications.

3.5. Density-Based Clustering and Outlier-Aware Grouping

The density-based approaches consider clusters as continuous high-density areas of the sample that are separated by low density. This point of view is best adapted to the remote sensing situations when cluster shapes are irregular, and anomalies occur, which is also scientifically significant. A common way to treat such noise points or small clusters is by outliers to convective inversion points in SAR, directly viewed materials in hyperspectral, image desaturant residues, across algorithm parameters, and by considering these noise points as a rare land-cover type, a dense scattering regime, an anomaly in family spectral profile, or a noise point. Density-based schemes can thus play two roles in unsupervised schemes, not only in clustering common patterns, but also in screening the abnormalities that can be of interest [13].

One of the challenges with persistent Earth observation is that data density differs between regions and seasons, and what is thought to be dense will depend on scale and the representation chosen [58]. High-resolution imagery can result in a large number of samples per common surface, and a rare surface can be underrepresented. Density-based methods may fail when different densities vary dramatically between clusters, which may combine sparse but meaningful clusters with background noise. A typical application of density-based clustering is often applied to practical remote sensing deployments that have been trained on an embedding that equalizes density structure, geographically stratified by acquisition condition, or stratified by geography.

3.6. Hierarchical Clustering and Multi-Scale Structure

Hierarchical clustering is also appealing to Earth science due to the natural and human systems that have a nested structure in many cases [59]. The categories of land cover may be sorted based on large classes of physiognomics to small subtypes; climate regimes may be sorted into macro-regions and further sorted by either seasonality or extremes, and urban form may be seen at the neighborhood, district, and metropolitan levels. Hierarchical techniques generate dendrograms that can be explored at any number of granularities, allowing the analyst to choose a cluster resolution that is suitable for a scientific question.

Nevertheless, naïve hierarchical clustering is not very scalable to large sample sizes, so it cannot be used directly on large EO scenes. The application of hierarchical clustering to aggregated units such as super pixels, spatial tiles, or cluster prototiles based on a step-one partitioning is thus a common practice in remote sensing. An additional problem is that hierarchical methods are also sensitive to linkage criteria and distance definition, both of which may give qualitatively different trees. Hierarchical clustering is most valuable in unsupervised intelligent models in the presence of strong representations, in the sense of being viewed as a multi-scale exploration tool and not necessarily an important single partition [60].

3.7. Graph-Based and Spectral Clustering with Spatial Awareness

Graph-based techniques are critical to the field of remote sensing since they offer a direct way to embrace the structure of the neighborhood and non-linear similarity. Clustering can be described as a graph partitioning problem by building a graph, where the nodes, which are pixels, superpixels, or patches, are connected by the similarity or adjacency. Formulations of spectral clustering and normalized cut are especially applicable to image segmentation as they can encourage partitions that are coherent as well as boundary respecting, particularly when edge weights indicate feature similarity as well as spatial proximity [61].

Practically, spectral methods are limited in power, both by the cost of computation and by the graph construction. Tens of millions of pixels can be contained in a large EO scene, which is impractical to represent as a complete graph. K-nearest neighbor approximations, sparse affinity approximations, and superpixel-level graphs are thus prevalent. Also, a variety of kernels and neighborhood radii can influence the ability of the graph to record meaningful surface transitions or merely replicate spatial autocorrelation. In the case of SAR and hyperspectral data, cases of instability may be mitigated by computing graph weights in a denoised or reduced-dimensional space. The graph-based method is especially useful in multi-modal contexts, where neighborhoods across modalities can be used as edges, and in spatiotemporal contexts, when graphs can be used to relate observations across time to impose a form of time consistency [62].

Table 2 categorizes the major clustering families, comparing their strengths, limitations, and typical use cases in remote sensing.

Table 2. Summary of clustering algorithm families for remote sensing, highlighting strengths, typical limitations, and common applications.

Algorithm Family	Representative Methods	Strengths in EO Settings	Typical Limitations	Example Remote Sensing Uses
Centroid-based (partitional)	k-means, mini-batch k-means	Scales to massive archives; easy to implement	Assumes convex/spherical clusters; sensitive to feature scaling	Archive stratification, pseudo-labeling, coarse land-cover grouping
Medoid-based/robust	k-medoids, trimmed clustering	More robust to outliers; interpretable prototypes	Higher compute cost; needs efficient nearest-neighbor	Noisy modalities, prototype selection for expert review
Probabilistic mixtures	GMM, Bayesian mixtures	Soft assignment; uncertainty; mixed pixels	Covariance estimation hard in high-dim; shape assumptions	Soft land-cover regimes, subpixel ambiguity analysis
Density-based	DBSCAN/HDBSCAN	Non-convex shapes; natural outlier detection	Varying density across regions; parameter sensitivity	Anomaly screening, rare surface regime discovery
Hierarchical	Agglomerative, divisive	Multi-scale partitions support taxonomy exploration	Poor scalability without aggregation	Regime hierarchies, eco-region subtyping
Graph/spectral	Spectral clustering, normalized cuts	Incorporates adjacency; segmentation-like outputs	Graph construction and eigendecomposition scale poorly	Spatially coherent segmentation, object boundary-aware clustering

Table 2. *Cont.*

Algorithm Family	Representative Methods	Strengths in EO Settings	Typical Limitations	Example Remote Sensing Uses
Subspace/low-rank	Sparse subspace, low-rank models	Handles hyperspectral structure; denoises while clustering	Compute-heavy; parameter tuning	Hyperspectral material clustering, endmember candidate grouping
Fuzzy/possibilistic	Fuzzy c-means	Models mixed membership and transitions	Sensitive to scaling; may need regularization	Ecotones, shoreline mixing, burn severity gradients
Deep clustering	AE + clustering, SSL embeddings + k-means	Learns representations; improves semantic grouping	Risk of learning artifacts; compute and reproducibility challenges	Multi-modal clustering, scene/patch grouping, scalable pseudo-labeling

3.8. Subspace and Low-Rank Clustering for Hyperspectral and High-Dimensional Data

The high-dimensional remote sensing data is often close to low-dimensional manifolds or subspace unions, as spectral variation is often caused by a small number of material and illumination factors [63]. Subspace clustering algorithms take advantage of this structure and assume that each sample is described by a combination of other samples, with sparsity or low-rank constraints, and subsequently derive clusters based on affinity relationships between them. These methods have found specific application in hyperspectral analysis, where the classes can be separated by distinct subspaces and where linear mixing models can be physically justified.

Denoising and dimensionality reduction can also be done with low-rank models, which can enhance the stability of clustering [64]. The techniques can be used in Earth science contexts to distinguish significant spectral variability, noise, and atmospheric residuals. They also have drawbacks, such as sensitivity to parameter values and large computational requirements when applied to large scenes, so most of the time they are applied to large scenes by spatial subsampling, patch-wise processing, or approximate solvers. Although a full subspace clustering is infeasible, the same principle of clustering-enhancing low-dimensional structure is applied to hybrid (combining low-rank denoising and manifold learning) frameworks in which clustering algorithms are then applied that are less expensive to compute.

3.9. Fuzzy Clustering and Uncertainty-Aware Partitions

Fuzzy clustering provides each sample with degrees of membership of clusters, and this is conceptually parallel to mixed pixels and smooth transitions so common in remote sensing [65]. Fuzzy partitions use natural boundaries instead of strict ones, and therefore represent ecotones, urban-rural gradients, shoreline mixing, and partial severity of burns. This is useful in earth science since uncertainty is not just a bother, but it may indicate truly ambiguous physical conditions or constraints of the spatial resolution of the sensor.

In intelligent systems, fuzzy clustering is also very convenient as an intermediate step, as membership maps can be used to further refine, draw attention to areas that are to be manually evaluated, or give pseudo-labels that are soft and pseudo-labeled in a semi-supervised manner. Nevertheless, fuzzy techniques are prone to scaling and initialization, and they again use a significant distance measure. Therefore, their practical usefulness will generally be hinged on feature normalization, well-embedding features, and, when feasible, spatial regularization, which will stop noisy membership variations at pixel resolution [66].

3.10. Deep Clustering and Representation Learning for Earth Observation

Deep clustering methods solve one of the bottlenecks of remote sensing clustering: the discrepancy between the raw space of measurement and the semantic similarity [67]. Deep models can convert the clustering problem to a problem where more effective standard algorithms can be solved by learning an embedding of the discriminative structure, and the invariant one. In the form of autoencoders, the method is trained to reassemble its inputs into compressed forms, and the application of clustering in the latent space can act as an alternative to the training goal, or be combined with it. Autoencoders have been applied in EO to reduce dimensionality reduce hyperspectral data, denoise SAR, as well as learn compact patch and scene descriptions. However, reconstruction goals may maintain variability in nuisance, and this encourages the application of self-supervised learning.

Self-supervised learning is now one of the most popular approaches to constructing EO representations in an unlabeled fashion [68]. It is possible to solve contrastive learning, masked reconstruction, and predictive objectives in remote sensing by taking advantage of the spatial context, temporal continuity, multi-view augmentations, and cross-sensor correspondences. Embeddings can be learned, then clustering can be used to get semantic clusters, and the assignment of clusters can be used as pseudo-labels to cycle new representations. Transformer-based encoders and multi-scale convolutional networks have gone further to enhance the ability to incorporate the use of context, which is critical in disambiguating spectrally similar surfaces. The difficulty here, though, is making sure that embeddings are scientifically meaningful and not restricted to the trivial collections induced by acquisition artifacts or geography. In the case of Earth science, deep clustering structures are hence becoming more comprehensive in the use of constraints that promote spatial regularity, temporal regularity, and cross-domain generalization.

3.11. Spatial Regularization, Structured Priors, and Physically Informed Constraints

Explicit mechanisms, which make spatial or temporal smoothness, are often useful in remote sensing clustering [69]. To introduce structured priors, it can be introduced with the introduction of clustering by morphological filtering, region merging or conditional random field refinement. Instead, they can be added directly to clustering goals via a penalty on discontinuities in labels between adjacent pixels or graph Laplacian regularization can be added. Such techniques minimize salt-pepper noises and even set the clusters with adjoining physical features, enhancing readability and map functionality.

Physically informed constraints are another advancement in unsupervised systems in the direction of intelligence [70]. In earth science, similarity is not simply statistical, it is also determined by process understanding. Expectations that can be captured using constraints include smooth seasonal change, consistency of energy balance, or even realistic bounds of the variables retrieved. Although it is not computationally feasible to achieve fully physics-based unsupervised clustering, it is possible to partially use physical priors to reduce spurious clusters and make scientifically realistic clustering. Temporal regularization may be applied in multi-temporal scenarios to avoid clustering and capture the effects of transient noise in the observation and produce stress on enduring modalities or transient change events.

3.12. Scalability, Approximation, and Practical Algorithm Selection

Another common aspect of remote sensing is the necessity to strike a balance between methodology sophistication and scalability [48]. Numerous of the beautiful clustering models fail to be effective when they are applied to global mosaics, dense time series or even dense time series of multi-sensors. Due to this, operational structures are usually based on approximations, including tiling, prototype-based clustering, mini-batch optimization and hierarchical aggregation where local learning of fine-scale clusters is performed followed by aggregation into global categories. Scalable graph building can be done using approximate nearest-neighbor techniques and large-scale embedding code-sharing and clustering can be done using distributed computing environments.

The choice of algorithm in practice is then based on the scientific goal of the application and the limitations of its use. Scalable centroid-based clustering on robust embeddings can be adequate when the aim is to speedily stratify to sample, or in initial exploration. Graph-based or spatially regularized methodologies are more suitable when the task is of a segmentation-type mapping, that is boundaries are important. In cases where there is a combination and uncertainty at the center stage, probabilistic or fuzzy techniques provide benefits. In cases where the semantics are complicated and raw distances cannot be trusted, deep representation learning with clustering is usually necessary. Through these options, the main concept is that performance-based clustering in Earth science is impossible to be isolated from representation, context, and validation and must be considered as part of a complete unsupervised intelligent system, not as a single algorithmic procedure [71].

4. Unsupervised Intelligent Frameworks: End-to-End Pipeline Design

4.1. From Algorithms to Systems: Why an End-to-End Framework Matters

Clustering is not commonly used as an independent feature in Earth science remote sensing [72]. Studies have found the utility of cluster outputs not just to be dependent on the selection of the algorithm but also on the order of upstream and downstream actions that determine the distribution of the data, the space of representations, or the interpretation of the outcomes. An unsupervised intelligent architecture, by contrast, focuses on the design of systems: it combines data preparation, representation learning, clustering, refinement, and validation into an intelligible pipeline capable of being reliably executed over large regions, several sensors, and long durations of time. Such a systems perspective is significant in that remote sensing data are vulnerable to numerous nuisance effects that can take over the clustering structure unless removed. It is also significant in the sense that Earth science applications normally demand results that are spatially consistent, time-varying, and scientifically interpretable. A theory that yields clusters of points mathematically compact yet non-congruent with physical processes or ease of map use will not aid scientific discovery or operational decision-making. **Figure 2** depicts the reference architecture of an unsupervised framework, outlining the core stages from data ingestion and preprocessing to clustering, refinement, and productization.

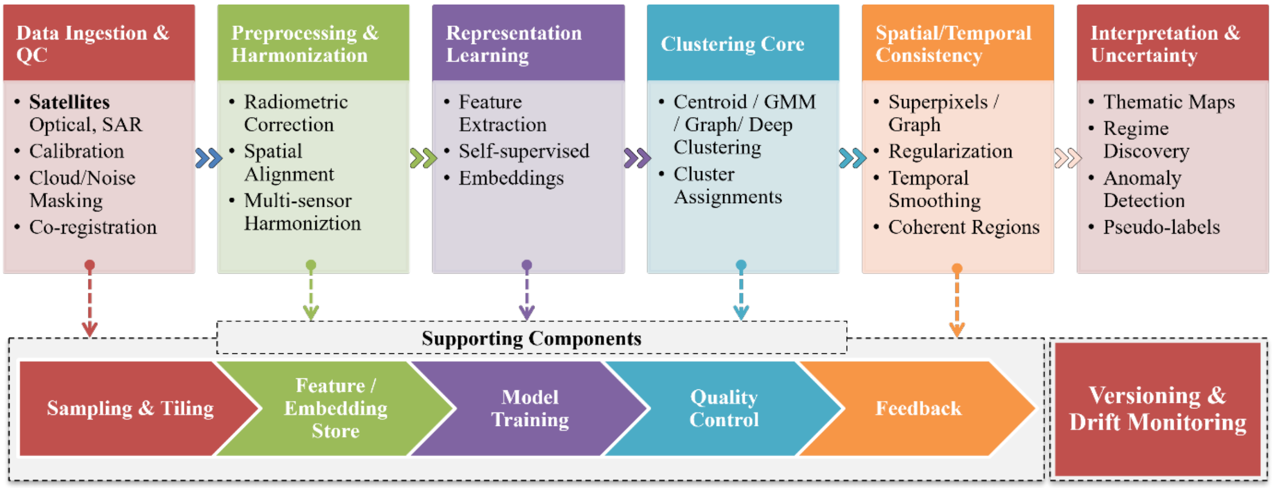

Figure 2. Reference architecture of an end-to-end unsupervised intelligent framework, illustrating key pipeline modules and their interconnections in Earth observation clustering.

Table 3 shows the core modules of an unsupervised intelligent framework, detailing the key design choices and potential failure modes.

Table 3. Reference architecture of an end-to-end unsupervised intelligent framework for earth science, including data preprocessing, clustering core, spatial/temporal integration, and productization.

Pipeline Module	Inputs // Outputs	Design Choices	Failure Modes to Watch	Typical Outputs
Data preparation & QC	Raw/Level-1/2 // harmonized stacks	Calibration, correction level, masking, co-registration	Product-version discontinuities; cloud/leak artifacts	Cleaned tiles, masks, uncertainty flags
Sampling & scaling strategy	Archives // training/fit subsets	Stratified vs. uniform sampling; tiling/overlap; prototypes	Rare regimes under-sampled; tile boundary inconsistency	Representative subsets, global prototypes
Representation construction	Measurements // features/embeddings	Handcrafted indices/textures vs. SSL embeddings; multi-scale	Embeddings dominated by acquisition conditions	Feature vectors, latent embeddings
Clustering core	Embeddings // assignments (hard/soft)	Family choice; k selection; distance metric	Over/under-clustering; instability to init	Cluster labels, membership probabilities
Spatial/temporal consistency	Assignments // coherent maps	Graph regularization; superpixels; temporal smoothing	Oversmoothing removes small targets; drift is misread as change	Region maps, transition maps
Interpretation & refinement	Clusters // semantics	Prototypes, cluster naming/merging, expert-in-loop	Post hoc bias; semantic mislabeling	Labeled cluster catalog, prototype gallery
Productization & monitoring	Maps/time series // operational outputs	Versioning; drift detection; update policy	Cluster ID instability across releases	Stable products, change logs, alerts

4.2. Data Ingestion, Harmonization, and Preprocessing as Foundations of Unsupervised Learning

The front of an unsupervised model starts with data ingestion and harmonization; the raw observations are converted into similar units that can be compared with each other and clustered. In optical data, radiometric calibration, atmospheric correction, and cloud and shadow treatment can be further steps in this step. In the case of SAR, it involves radiometric calibration, speckle mitigation, terrain correction, and the incidence angle effects are taken into account carefully. Emissivity assumptions, retrieval uncertainties, and footprint effects. Coarse-resolution products: Thermal and passive microwave products must be considered with respect to emissivity assumptions, retrieval uncertainties, and footprint effects. LiDAR processing can include waveform decomposition, ground normalization, and obtaining structural measures. There are modalities both at inter-modes where co-registration and resampling are required, and at sampling scales in multi-sensor fusion, resampling kernel selection, and target grid resolution may affect the structure of spatial texture and value distribution [73].

The geometry of the feature space on which clustering is taking place is influenced by harmonization decisions [74]. Preprocessing differences between sensors or product versions may also be systematic, and this results in cluster boundaries. Equally, normalization decisions may either increase or decrease those variables that are most significant in the disaggregation of physical states. In the case of multi-temporal analysis, it is necessary to preprocess the data consistently across time to eliminate artificial shifts that simulate change. Since the unsupervised techniques do not have labels to adjust such problems, preprocessing is not just a handy factor but a type of structural determinant of the clustering results. To this end, more advanced frameworks tend to have formal quality checks, uncertainty indicators, and masking mechanisms such that clustering is done on those observations whose reliability is known, and the similarity of physical meaning.

4.3. Sampling, Tiling, and Archive-Scale Computation

The current EO archives are so big that naive full-resolution clustering cannot be performed, particularly in the presence of long time series as well as several sensors. Unsupervised intelligent models are thus computational approaches that maintain statistical representativeness, and are not computationally demanding [75]. Spatial tiling is widespread, but it causes boundary effects, since clusters trained in isolation on tiles are not likely to be consistent. Frameworks solve this with either overlap regions, sharing of global prototiles, or two-stage approaches where tile-level clusters are calculated, followed by merging them with the cluster centroid or medoid in a second global clustering step. The strategies of sampling are also significant. Unless uniform random sampling is carried out, it can cause overrepresentation of dominant surfaces and underrepresentation of rare but scientifically important phenomena. The embedding and clustering phases are usually made to view different conditions by stratified sampling based on eco-region, land -water masks, elevation bands, or seasonal windows.

Sampling should also consider coverage and frequency of events in time when spatiotemporal clustering is needed [76]. Time-series clustering may be applied to individual per-pixel trajectories, but when done at scale, it may be achieved by compressing trajectories into embeddings and subsequently clustering a subset to learn prototiles that could be assigned efficiently to the entire archive. Such workflows have become possible using distributed computing environments and cloud-based EO platforms; however, the architecture is similar: the framework separates heavy representation extraction, followed by clustering and subsequent efficient assignment to generate dense maps. This is aimed at maintaining scientific fidelity and at the same time ensures that the pipeline can be rerun and extended as new data becomes available.

4.4. Representation Construction: From Physical Features to Learned Embeddings

Representation is the key to the success of raw EO measurements and clustering performance. Classical systems are based on physically driven characteristics of spectral indices, band ratios, texture measures, and morphology. Such characteristics store domain information and may lower the sensitivity to illuminations and atmospheric changes which makes distance-based clustering more significant. In the case of hyperspectral analysis, dimensionality reduction, redundancy, and noise are commonly removed by dimensionality reduction techniques like principal component projection or manifold learning. Log transforms as well as polarization ratios in SAR can stabilize the variance and can be used to improve the reflection to capture the scattering process. Spatiotemporal phenological descriptors, seasonal harmonics or event-based summary statistics can transform irregular trajectories to fixed-length vectors, which can then be clustered [77].

More recently, unsupervised frameworks are becoming more based on learned representations. Autoencoders and denoising models are able to compress data and reduce noise and self-supervised learning is able to generate embeddings that focus on invariances and context. Self-supervised objectives are commonly formulated in remote sensing to utilize data structures with either spatial context as a supervisory cue or multi-temporal continuity, or to match patches between tuned sensors. Embeddings learned can be calculated at the pixel, patch, object or time-series level, and the granularity of embedding can tend to control the type of clusters formed. The subtle spectral differences can be segregated by fine-grained embeddings, at the price of segregating semantic classes, or the semantic clusters can be more interpretable as a result of coarser context-sensitive embeddings, at the cost of blurred local transitions. One important framework choice is thus the desired extent of interpretation which must inform representation design as it must inform the choice of clustering algorithm [78].

4.5. Spatial Context Integration and Object-Centric Pipelines

The addition of spatial context may be applied at any stage and before, throughout, or after clustering [76]. Pre-clustering integration Pre-clustering integration is usually achieved by segmentation or super pixel generation, which quantizes imagery into homogeneous blocks and alleviates noise by combining pixel attributes. One must note that this is especially useful in high-resolution optical images in which variability inside classes is strong and object contours have meaning. The descriptors of segments are then grouped into object-based pipelines which create groups that match fields, neighborhoods or more geomorphic units more naturally than pixel-based clusters. This method also minimizes the burden of computation by minimizing the sampling, and inherently imposes spatial coherence.

Spatial context can be represented during clustering via neighborhood graphs, spatially weighted distances or regularised objectives that penalize inaccuracies in labels along the perimeter area between neighboring samples [79]. These kinds of strategies are vital where the objective is similar to segmentation in which the map-like results have to be continuous and decipherable. The refinement processes involved in post-clustering integration may include smoothing, region merging and correcting boundaries. All of these are not cosmetic steps that can transform patchy pointwise assignments to consistent regions that can be scientific or interpreted, but they can also allow uncertainty analysis, by detecting boundaries and transition regions. These integration strategies are modality and application dependent as e.g., too much smoothing can cause the small but immaterial details to be hidden in hazard mapping and too little can result in unusable maps in land-cover stratification.

4.6. Multi-Modal Fusion Frameworks and Latent Space Alignment

Multi-sensor frameworks have to answer two questions that are related to each other the way modalities should be aligned and the definition of similarity between them [80]. The early fusion method builds up a composite feature in the joint space and clusters together which is helpful when the modalities are aligned and of similar magnitude. Nonetheless, early fusion is fragile in cases where a single modality is overpowering variance or in cases where a data loss may take place. Late fusion clusters by per-modal encoding and also later reconciles partitions, which can retain modality-specific organization but can fail to capture common latent states that only become evident when signals are interacted with.

One common tradeoff, which is to find a common latent representation in which modalities are mapped to a shared embedding space [81]. In the absence of supervision, alignment may be promoted via cross-modal reconstruction, mutual agreement between representations of co-located samples, or cross-objective contrasting the representation of co-registered samples. Clustering may then be done in the common space to derive partitions that combine complementary physical information. In the case of Earth science, the usefulness of such frameworks is in the fact that classes and regimes that are ambiguous in single-modality descriptions, like the distinction between vegetation structural differences that are equivalent in optical and SAR images, or the definition of moisture regimes where passive microwave is more robust in the presence of clouds, are clarified by them. The danger is that faulty alignment may result in clusters that mirror sensor artifacts or registration faults, and this is the reason quality flags, uncertainty modelling, and meticulous co-registration are essential elements of multi-modal unsupervised system design.

4.7. Spatiotemporal Frameworks: Time-Series Embeddings, Consistency, and Concept Drift

The framework should be explicitly represented in time when the goal under consideration is to find regimes, trajectories, or change processes. One of these groups' temporal characteristics was calculated at each site, including the seasonal amplitude, the timing of peak occurrence, and trend indices. This can be interpreted and is usually useful when studying phenology and climate variability, although it may have difficulty with intermittent sampling and event dynamics. A second method learns time-series embeddings with sequence models or time classifiers and clusters in embedding space. This has the capability of capturing complex dynamics and may be combined with masking measures to deal with missing observations. In change-oriented applications, differences or directions in relation to a baseline can be clustered, so that differences or pathways can be grouped according to the type of disturbance or a recovery pathway [82].

The temporal consistency may be realized through measurement with time change of graph connections among observations, addition of cannulization within a consistent graph which encourages smooth transition, or evolving cluster maps in which fresh data is appended and adjustments to prior graphs occur. Concept drift is a necessary condition of Earth system monitoring; distributions change due to climate change, sensor constellations change over time, and land cover changes as well. Unsupervised structures that are to be used in long-term mode thus enjoy the advantage of constant learning plans, in which representations and cluster prototypes can be progressively changed without disastrous re-assignment. The scientific objective is to enable remarkable environmental change to come into a successful cluster change without experiencing spurious changes through processing updates or season fluctuation. One of the challenges of remote sensing spatiotemporal unsupervised intelligence is the ability to achieve this balance [83,84].

4.8. Refinement, Interpretation, and Human-in-the-Loop Intelligence

The key characteristic of intelligent unsupervised structures is the ability to identify and analyze clusters in such a manner that they relate to scientific sense [85]. Since clustering is by definition not identifiable and may generate several plausible partitions, it is important to use post-clustering interpretation. Numerous frameworks enable interpretation to be performed through deriving prototypes, summarizing cluster statistics and projecting clusters back into geographic space in order to analyse spatial patterns and correspond with established environmental gradients. The robustness of regimes and sensitivity to preprocessing are also analyzed using cluster stability analysis, and artifacts and robust regimes. Clusters of Earth science interpretation cluster maps are usually compared to independent datasets of elevation, climate normals, soil maps, or field observations, thus basing clusters on process knowledge.

Another application of human-in-the-loop refinement is to give a practical transition between unsupervised grouping and operational products [86]. Analysts are able to examine clusters, combine or separate them and place them into semantic labels that are associated with known categories. The uncertainty measures may direct this process by pointing out dubious areas or the active sampling methods may emphasize the boundaries of clusters and the infrequent groups to sample. More to the point, the human interaction should not compromise the unsupervised learning, on the contrary, it can formalize a workflow wherein clustering systematizes data, professionals can present specific feedback, and the protocol refines the presentations and partitions. These workflows have the benefit of reducing labeling overheads without compromising scientific control of the definition of categories, especially in situations where the definition is changing or when local context is important.

4.9. Deployment and Reproducibility: From Research Pipelines to Operational Workflows

An unmonitored intelligent architecture needs to be implementable, replicable and open to become useful in practice[87]. Deployment entails the decision of where the computation will take place, e.g., cloud-based processing of global products or edge processing of rapid response. It is also concerned with engineering choices related to tiling, memory allocations, and access patterns of data, and whether a pipeline will be able to execute in a routine. Reproducibility: One deletes preprocessing steps and model settings, random seeds and product versions are explicitly reported and versioned, as any of these factors can change cluster results. In the case of earth science, reproducibility is also associated with spatial and temporal leakage of evaluation, as well as with making sure that the clusters that are being reported are due to a generalizable structure and are not due to a peculiarity of a local region or time interval.

The operational workflows also need to be monitored and updated. With the incoming data, the framework has to choose whether to assign the new data to old clusters, renew prototypes, or enlarge the set of clusters to fit new phenomena. These options are directly related to scientific interpretation: stability promotes temporal comparability, and adaptivity promotes sensitivity to new regimes. A sound unsupervised structure will ensure these trade-offs are explicit and have tools to record changes, quantify uncertainty, and convey cluster meaning to the end user. In this regard, the design of pipelines is not an implementation fact, but a scientific tool that dictates how the information on remote sensing is transformed into knowledge[88].

5. Applications and Evaluation of Clustering-Based Unsupervised Systems

5.1. Application Landscape and the Role of Clustering in Earth Science Workflows

Unsupervised systems based on clustering are used in Earth science remote sensing as standalone analytical systems and also as facilitating modules to larger pipelines of mapping and monitoring[89]. Clustering can be used in exploratory science to identify regimes, patterns, and transitional structures that are difficult to describe using preset labels. Clustering is able to deliver consistent stratifications that inform sampling, product generation and product quality control in the operational context, especially when there are sparse labels or even contested definitions. In all these contexts, the practical utility of clustering is found in the fact that it groups heterogeneous measurements together, summarizes large archives into a manageable form, and identifies anomalies or emergent states of affairs, which should be investigated further. These processes of the Earth system are too diverse to have a principal clustering formulation, but representation learning and integration of contexts decide what form of pattern is separable.

5.2. Land Cover and Land Use: Unsupervised Stratification and Map-Oriented Segmentation

Among the most frequent fields of application of unsupervised clustering have been land cover and land use, since it is almost natural to consider clustering similar surface reflectance, structure and seasonal behavior[90]. Clustering in multispectral optical imagery may produce early land-cover strata, which are then exploited further by the specialists to label downstream, which saves the expense of constructing supervised training sets and augments the representativeness of samples across eco-regions. Clustering is commonly used with object-based segmentation in high-resolution imagery in order to group the clusters into adjacent regions (e.g., agricultural fields, city blocks, forest stands). This design (with the reduction of pixel-level noise) and the unification of partitions with units (understandable by human beings) make maps more useful.

Ambiguity in label definition is also solved with the aid of unsupervised structures. Land-cover taxonomies differ by agency and product, and demarcations between land-cover classes, e.g., shrubland and grassland or barren and sparsely vegetated surfaces, can be fuzzy and context-dependent. Clustering may indicate substructures in broad classes and may indicate transitional gradients, allowing analysts to determine which scientific objective is better fulfilled by coarse regimes, fine subtypes, or soft memberships. Clustering can be used to reproduce phenological signatures that distinguish crop types, forest functional types or pasture dynamics better than single-date imagery, especially in changing illumination and atmospheric conditions when combined with multi-temporal data[91].

5.3. Hyperspectral Remote Sensing: Material Grouping, Subspace Structure, and Unmixing Support

Hyperspectral imagery is particularly highly clustered due to the dense spectral sampling, which is rich in surface composition [92]. Practically, clustering is employed to cluster spectra into material-like objects, to select putative endmembers, and to facilitate unmixing with clustering of pixels into spectrally consistent groups. Since hyperspectral data are frequently found in low-dimensional subspaces that represent mixtures of low-density material, subspace and low-rank clustering are directly useful, along with denoising and dimensionality reduction. The techniques assist in disentangling weak material variations and minimizing the effects of band correlation and noise.

The applications of the field include geology and mineral mapping, biochemical characterization of vegetation, water quality and contamination [93]. Clustering of outputs can be viewed in such instances as candidate material regimes, which are then compared to field measurements, spectral libraries, or other geologic map sources. The most important issue is that of semantic grounding: clusters can as easily represent instrument artifacts, atmospheric remnants, or even lighting effects as they can represent material variations. Effective models thus have a focus on detailed correction, strong embeddings and interpretive processes to match cluster prototypologies with familiar absorption characteristics or mixtures physically feasible.

5.4. SAR-Centric Applications: All-Weather Regimes, Texture, and Event Monitoring

The softness of SAR to surface roughness, moisture and structure renders it useful in unsupervised regime discovery and monitoring especially in cloudy areas or under high latitude [94]. Clustering of SAR backscatter and derived features has the ability to stratify wetlands, agricultural patterns, forest structure regimes, sea ice types and urban morphology. Unsupervised Clustering in flood mapping Unsupervised clustering may serve to define water-like scattering regimes as well as facilitate a quick screening process by pointing out anomalous low-backscatter areas compared to past baselines. The clustering technique has been used in cryosphere studies, isolating scattering patterns related to new ice, multi-year ice, conditions at the melting point, and damaged structures, and has been enhanced by time series which records transitions.

The major issue in SAR clustering is the complicated interplay between scattering, geometry and speckle noise [35]. Clusters without strong preprocessing and representation learning may be due to incidence angle gradients, speckle patterns or terrain effects and not surface processes. Combinations of temporal consistency and spatial regularization are thus prevalent which repress noise-induced fragmentation and prioritize lasting regimes. Multi-polarization and multi-frequency SAR additionally encourage multi-view clustering and multi-frequency latent alignment techniques that have the potential to gather the complementary scattering data and minimize the sensitivity to artifacts of any single channel.

5.5. Spatiotemporal Regime Discovery in Climate, Hydrology, and Ecosystem Dynamics

An important area of use of unsupervised systems based on clustering is the spatiotemporal regime discovery where the goal is to find regular patterns of dynamic variables, and not to provide labels to fixed categories [95]. Clustering may be applied in hydrology to classify basins or pixels on the basis of the seasonal runoff cycle, soil moisture cycle, drought cycle, or evapotranspiration cycle. Other applications of time series: Clustering time series of vegetation indices, solar-induced fluorescence, or proxies of canopy structure can be used to give an understanding of functional types, stress dynamics, and post-disturbance recovery as it applies to ecosystem science. Clustering can be used to address climate problems to discover repeating patterns of circulation or precipitation regimes, to divide patterns of extremes, or to stratify regions in terms of co-variability of variables.

In such circumstances, there is necessarily a temporal sense of similarity, and it often requires representations that specify phase, amplitude, and response of events. The schemes of having clusters of derived descriptors versus all the trajectories of descriptors versus clustering of learned embeddings differ, but the issue of science is the same: clusters need to reflect interpretable regimes that can be mapped onto physical drivers and are stable enough to compare them. It can be assessed by means of process-based tests of plausibility, correlation with known climatic gradients, or consistency with other independent measurements. Since the spatiotemporal clustering can potentially obscure the boundary between the detection of patterns and the generation of hypotheses, interpretability and uncertainty quantification are as important as the clustering partition [19].

5.6. Hazard and Rapid-Response Applications: Novelty, Anomaly, and Change-Aware Clustering

The importance of unsupervised structures has been identified in calamity surveillance as the possibility of recognizing change and novelty where labeled instances are limited and circumstances are extraordinary [96]. Disasters such as floods, wildfires, landslides, volcanic eruptions, and storm damage tend to occur in intricate landscapes in which training data of prior events may not port over very well. Scenes can be partitioned into common regimes, and then deviations found using clustering, or change vectors or time differences that indicate event impacts can be clustered. Clustering can be used in conjunction with historical archives to establish a baseline of normal variability and therefore, can be used to identify the real anomalies and the seasonal changes.

The applications are highly demanding in terms of robustness and readability since the decisions can be time-sensitive. Unsupervised outputs are seldom applied alone, and are typically combined with thresholding, expert examination, or downstream supervised refinement. An effective framework is usually able to give cluster maps and the corresponding measures of confidence such that the analysts may pay attention to apprehensive areas and inquisitive clusters. The scientific issue here is to guarantee that the novelty found is associated with actual physical change as opposed to acquisition variances, cloud contamination, or processing artifacts, which underlie the value of quality control and time-matching.

5.7. Datasets, Benchmarks, and the Limits of Standardized Evaluation

Methodological advances require benchmarking, which faces specific challenges in remote sensing standardization. Scenes are spatially correlated, and uninformed random cuts may give information between the training set and the test set via adjacent pixels. Time-series method evaluation also has similar leakage threats due to temporal persistence. Sensor and processing heterogeneity implies that a technique that works well on one dataset may not also work under new atmospheric conditions, land-cover structure, or imaging geometry. Consequently, the careful benchmark design is gradually becoming more focused on geographic and temporal transfer, multi-sensor assessment, and stress tests with missingness and noise [97].

Available datasets frequently emphasize classification and labeling, a subset of the unsupervised regime discovery objectives of clustering structures. The labels can either be crude or slipshod, and they might not match the substructures identified by clustering. This means that unsupervised remote sensing benchmarks should be taken seriously. They can be useful in making comparisons of representations and algorithmic stability, although they seldom present clear evidence of having scientific utility. The future of this field lies in the development of new evaluation protocols that are sensitive to domain changes, explicitly measure uncertainty, and relate cluster results to earth science variables and processes that are meaningful.

5.8. Evaluation without Labels: Internal Metrics, Stability, and Scientific Validity

One of the main issues in remote sensing clustering is that the quality of clustering cannot be quantified by a single objective measure particularly in the absence of labels [17]. Internal measures of validity help to measure compactness and separation in the feature space, but in high-dimensional contexts and when there is strong autocorrelation these measures are misleading, preferring partitions that are due to acquisition artifacts or noise-based structures. In the case of Earth science, assessment is normally based on stability analysis and scientific validity tests. Stability analysis looks at how the clusters behave when there is a change in initialization, subsampling, preprocessing variants or when there is only a small perturbation. Very sensitive clusters to such perturbations are probably not going to allow reproducible science or operational mapping.

Scientific validity test relates cluster patterns to autonomous facts. This may involve looking at geographic consistency and conformity to established environmental gradients, ensuring temporal consistency with seasonal cycles, or assessing whether cluster prototypes are physically realistic spectra or scattering properties. Additional grounding is made by comparison with ancillary datasets e.g., elevation, climate normals, soil maps, or land management boundaries. Notably, these checks are supposed to be in the form of hypothesis tests and not post hoc excuses: a cluster that purports to be the representation of a moisture regime ought to demonstrate the same relationship with precipitation, topography, or hydrologic setting. Such evaluation is in practice an iterative process, which informs the choices of being a good representation, tuning of parameters, and deciding whether clusters are meaningful at the scale of choice.

Table 4 provides a toolbox for evaluating clustering outputs in remote sensing without dense labels, suggesting methods for assessing quality, stability, and scientific relevance.

Table 4. Evaluation toolbox for clustering-based remote sensing systems, detailing methods for assessing clustering performance without the need for dense labels.

Evaluation Dimension	What Is Assessed	Practical Method	What a Good Result Looks Like	Common Pitfalls
Internal quality (geometry)	Compactness/separation in representation	Silhouette, Davies–Bouldin, Calinski–Harabasz	Consistent improvement across runs/regions	Misleading in high-dim; rewards artifact-driven clusters
Stability & sensitivity	Reproducibility under perturbations	Multi-seed consensus; subsampling; preprocessing variants	Cluster structure persists; small variance in assignments	Overfitting to specific preprocessing; unstable k
Spatial coherence	Map usability and fragmentation	Region-size stats; boundary smoothness; object consistency	Coherent regions without erasing small features	Over-smoothing; tile seam artifacts
Temporal consistency	Regime persistence vs. drift	Transition matrices; seasonality checks; drift indicators	Expected seasonal cycles; meaningful event transitions	Confusing acquisition shifts with true change
Process/physics plausibility	Scientific validity	Correlate clusters with elevation/climate/soil; known relationships	Clusters align with drivers and constraints	Post hoc rationalization; confounders
Partial-label agreement	Alignment with limited truth	ARI/NMI/purity on small labeled audits	Strong agreement in multiple regions/times	Biased samples; labels not matching cluster granularity
Downstream utility	Value as pseudo-labels/features	Train a small supervised model using clusters; transfer tests	Improved generalization; reduced labeling effort	Leakage via spatial autocorrelation; cherry-picked tasks
Uncertainty usefulness	Reliability communication	Membership entropy; ensemble disagreement	Uncertainty peaks at boundaries/rare cases	Overconfident wrong assignments

5.9. Evaluation with Partial Labels: Proxy Supervision and Task-Based Validation

When there are limited labels, they can be utilized to assess clustering more explicitly, but the process should take into consideration the fact that such labels are partial and may be biased [98]. The method that has been commonly adopted is proxy supervision in which a limited number of expert-labeled samples are employed in quantifying the degree to which clusters conform to known categories. This aids external measures of inconsistency between cluster designations and designations, but the exegesis needs to factor in ambiguity in the definition of classes and sampling bias. The other is task-based validation, in which clusters are considered as features or pseudo-labels in a final supervised task having an independent evaluation set. In this paradigm, clustering is evaluated based on whether it leads to generalization or on the amount of labeling effort required and that might be more significant than quantifying alignment to one label taxonomy.

In the case of Earth science, geographic and temporal transfer tests tend to be used in combination with partial-label evaluation [99]. A clustering model that is performing well in a specific region and poorly in others may be overfitting that region. Likewise, a framework which succeeds in one season but fails abjectly in another might not have learnt the desired invariances. The task-based validation on domain shift together with uncertainty-aware pseudo-label selection is thus a feasible method to determine whether an unsupervised intelligent framework actually helps lessen dependence on dense labeling.

5.10. Robustness, Generalization, and Uncertainty Reporting

Robustness and generalization are not merely desirable features in remote sensing; however, they are the main determinants of success since the variability of the Earth system guarantees that the models will experience out-of-distribution conditions [100]. The clustering structures must be tested in geographical changes, seasonal changes, sensor models, and processing releases. Robustness is also connected with sensitive data loss, particularly of clouds in optical images and time series lapses. Uncertainty reporting augments the robustness assessment with the mechanism of reporting where assignments of clusters are sound and where they are vague. Boundary regions, mixed pixels, and new observations may be indicated by soft assignments, margin-based confidence measures or the ensemble consensus. This is useful in scientific interpretation and downstream decision-making, in which areas of uncertainty can initiate further data gathering or expert examination.

Uncertainty reporting can also be used as a monitoring tool in operational applications. When a framework starts generating large testing areas of low confidence assignments it can signify sensor anomalies, preprocessing alterations, or absolutely new environmental conditions. Associating uncertainty with data quality flags and known locations of domain shift is useful in identifying these cases [101]. An adult unsupervised system thus does not see uncertainty as a by-product, but rather as a primary output.

5.11. Efficiency, Scalability, and Practical Performance Reporting

The useful implementation of unsupervised systems based on clustering is subject to computational capability. It is also important that performance reporting in remote sensing should not be restricted to clustering quality but also should comprise the aspects of runtime, memory consumption and behavioral scaling as the size of the scene and the length of the archive grow. A variety of approaches prove infeasible even on continental mosaics or multi-year stacks which seem plausible on a small scale. Scalable frameworks that are successful tend to use rough clustering, prototype learning, distributed embedding extraction and effective assignment techniques. The impacts that these approximations have on the stability and interpretability of the cluster should also be reported in order to allow such a transparent comparison [13].

The issue of energy and compute is becoming more applicable, especially when dealing with deep representation learning on huge archives. Efficiency and timeliness are also related as far as Earth science is concerned. The monitoring process of hazards may need near-real-time results and climate regime analysis can afford slower throughputs provided it can represent more. Reporting of computational constraints, details of implementation, and reproducible configurations is clear which facilitates the translation of research methods to operational pipelines.

5.12. Reproducibility and Reporting Practices for Clustering-Based Remote Sensing Studies

Due to its sensitivity to preprocessing, representation options, and random starting point, clustering outcomes in particular make reproducibility practices particularly significant [71]. The preprocessing pipelines, masking strategies, feature normalization, embedding architectures, clustering hyperparameters, as well as random seeds should be reported in studies. They are also supposed to record the version of data sets and level of processing, as any variation in product production can change distributions. The concept of spatial and temporal splitting methods should be explained in such a way that prevents leakage and so that the results provided can be generalized and not due to spatial autocorrelation.

Moreover, Earth science also needs interpretability documentation in order to be reproducible [102]. It is also useful to provide prototypes of clusters, model patches or sample spectra and time series so that the reader may get an idea of what clusters are. Releasing cluster maps and uncertainty layers, and code and configuration files, is useful in making a meaningful comparison and reuse. Unsupervised intelligent frameworks are increasingly complex so this kind of reporting is essential in establishing trust in products produced by clustering, as well as in allowing cumulative development throughout the remote sensing community.

6. Conclusion

This review has discussed the clustering algorithms as the core part of constructing an unsupervised intelligent scheme in Earth science remote sensing. The fundamental driving force is similar in all modalities and all ways of use; the growing volume of Earth observation databases is becoming larger than metrics of high-quality labeling, and the Earth system itself shows rich domain length changes across geography, season, sensor mannerisms, as well as changing processing pipelines. Clustering provides a feasible and scientifically significant answer to these limitations by facilitating the discovery of structure, determination of regime, organization of the archive, and stratification under uncertainty without the need for dense annotation. Clustering is more than a grouping device when it is a part of an end-to-end system, that is, one that includes preprocessing, representation construction, spatial-temporal integration, and post-clustering interpretation.

One of the main points in the article is that performance clustering in the remote sensing field cannot be done without representation and context. Classical algorithms are still useful due to their simplicity and scalability, although the success of such algorithms is still largely dependent on feature design and normalization that can make physical similarities reflect in distances. Graph-based and spatially regularized models take into account the natural spatial structure of imagery, and can give more map-like results, whereas probabilistic and fuzzy models give a more natural means of expressing mixing and uncertainty. The self-supervised representation learning and deep clustering have increased the possibilities by pointing raw measurements towards embeddings with semantic groupings that are more disentangled and allowing unsupervised designs to work across modalities, scales, and the contents of complex scenes. These benefits are, however, only significant when paired with a keen eye on the nuisance factors, harmonization, and scientific interpretability, as the systems without supervision may just bundle acquisition artifacts but not Earth system processes.

Assessment is the main obstacle on the way to credible and comparable developments. In the absence of labels, common in-house measures are not enough, and may encourage partitions that are not scientific. This review thus puts emphasis on the stability analyses, uncertainty reporting, geographical and time-based transfer testing, and validation by other means of independent evidence, including known environmental gradients, process expectations, and additional datasets. In case there are partial labels available, the task-based validation under domain shift will offer a realistic way of determining whether clustering, in fact, lessens labeling burden as well as enhances generalization. Simultaneously, reproducible practices, such as the clear documentation of preprocessing, versions of data, hyperparameters, and splitting strategies, which do not cause spatial-temporal leakage, are key to creating confidence in the products obtained via clustering.

In the future, there are a number of research directions that can influence the future generation of unsupervised intelligent systems to observe the Earth. Greater transferable representations are likely to be offered by foundation-scale encoders and self-supervised training on large archives, but these will need to be adapted to EO physics, heterogeneity in multiple sensors, and spatiotemporal structure. The importance of continuing and online clustering will grow as constellations generate near-real-time streams and concept drift is created by climate and land-use change. More semantic grounding will be required, in the form of interpretable prototypes, physically informed constraints, structured priors, and so on, to encode clusters into useful Earth science information. Lastly, community development will be based on superior benchmarking and testing procedures that explicitly assess robustness among regions, seasons, and sensors and that regard uncertainty as a first-class product.

In short, clustering-based unsupervised intelligence does not even serve the purpose of supervised learning in remote sensing, but rather it provides a complementary paradigm that is well suited to the challenges of earth system observation: sparse labels, changing domains, heterogeneous sensors, and the scientific requirement of discovering rather than merely recognizing patterns. By considering clustering to be a sub-pipeline service, rich with respect to scalability, robustness, interpretability, and rigorous validation, researchers and practitioners will be able to transform the growing EO information universe into more stable maps, concise regime outlines, and more expeditious identification of breakages in environmental change.

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