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REVIEW ARTICLE

A review of methods for scaling remotely sensed data for spatial pattern analysis

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Abstract
Context Landscape ecologists have long realized the importance of scale when studying spatial patterns and the need for a science of scaling. Remotely sensed data, a key component of a landscape ecologist's toolbox used to study spatial patterns, often requires scaling to meet study requirements.
Objectives This paper reviews methods for scaling remote sensing-based data, with a specific focus on spatial pattern analysis, and distills the numerous approaches based on data type. It also discusses knowledge gaps and future directions.
Methods Key papers were identified through a systematic review of the literature. Trends, developments, and key methods for scaling remotely sensed data and spatial products derived from these data were identified and synthesized to detail the general progression of a science of scaling in landscape ecology.
Results Upscaling both continuous and categorical data can oversimplify data, creating challenges for spatial pattern analysis. Object-based and neighborhood approaches can help, and since patch boundaries are more likely to align with objects than pixels, these may be better options for landscape ecologists. Many downscaling methods exist, but these approaches are not being widely employed for spatial pattern analysis.
Conclusions A diverse range of scaling methods are available to landscape ecologists, but work remains to integrate them into spatial pattern analysis. Moving forward, advances in computer science and engineering should be explored and cross-disciplinary research encouraged to further the science of scaling remotely sensed data.

Keywords Scaling methods · Upscaling · Downscaling · Heterogeneity · Spatial patterns · Remote sensing data

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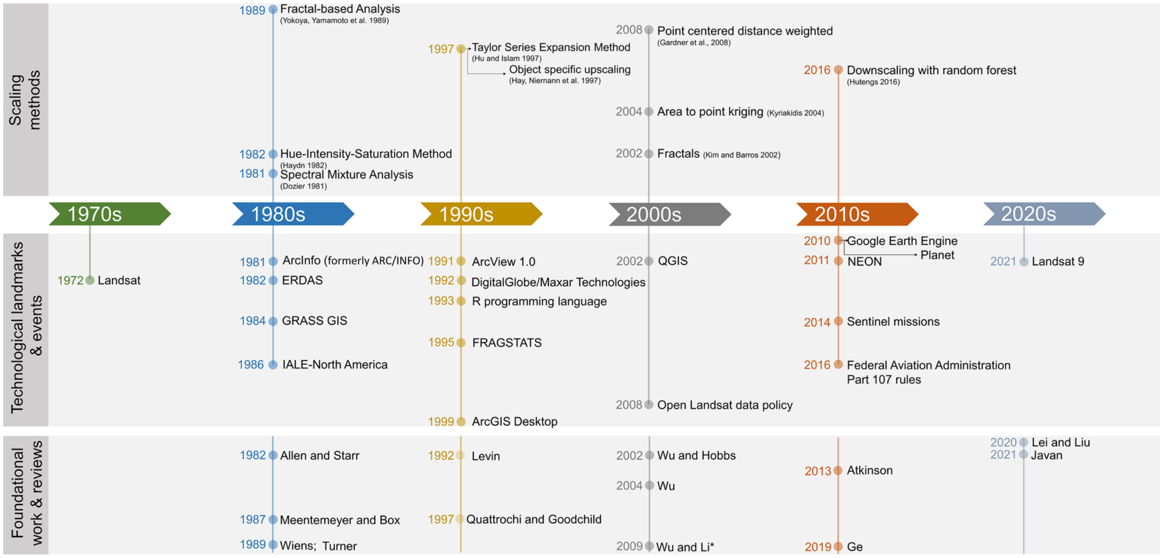

Fig. 1 Selected milestones contributing to the progression of the science of scaling. Milestones are grouped under foundational work and reviews, technological landmarks and events, and scaling methods. These milestones are not intended to be all-inclusive. IALE-North America—North American Regional Association of the International Association for Landscape Ecology; NEON—National Ecological Observatory Network; FAA—Federal Aviation Administration. The FAA's Part 107 rules regulate drone pilot certification and operating requirements (Frazier and Singh 2021). *Indicates a review paper

Introduction

Spatial pattern analysis is a cornerstone of landscape ecology that has fostered unprecedented developments in both theory and practice (Wu et al. 2002). The wide availability of remote sensing data, particularly with the opening of the archives such as Landsat (Zhu et al. 2019), has made it increasingly easy for researchers to quantify spatial patterns in landscapes (Frazier and Kedron 2017). However, the remote sensing data that form the basis for many spatial pattern analyses are captured at a fixed resolution, prompting researchers to change the scale (resolution) of the data in order to match observational or modeling objectives.

Ecologists have long recognized the biases associated with translating information across scales (Meentemeyer and Box 1987; Turner et al. 1989a, b; Levin 1992; Jelinski and Wu 1996), and much work in landscape ecology has focused on how changing the scale of a dataset (grain and extent) impacts derived spatial patterns, using both categorical (Turner et al. 1989b; Saura 2004; Wu 2004) and continuous data (Frazier 2016). Findings have shown that landscape pattern analysis is highly sensitive to grain, or spatial resolution (Turner et al. 1989a, b; Wu et al. 2002; Hall et al. 2004; Wu 2004), and a mismatch between the grain of the process and the pattern may produce incorrect conclusions (Galpern and Manseau 2013). Foundational, theoretical work (e.g.,(Allen and Starr 1982; Turner et al. 1989a; Wiens 1989; Levin 1992)) along with technological advances including the Landsat missions starting in 1972 and ArcGIS Desktop in the late 1990s, allowed for many different methods for scaling spatial data to emerge (Fig. 1). These and other studies promoted scaling issues to the front of the research agenda in landscape ecology through the 1990s and early 2000s, prompting Wu and Hobbs (2002) to identify scaling as one of the top research priorities for the discipline, and it continues to be an important topic in the field (Lang 2008; Zhang et al. 2014; Chambers et al. 2016; Ke et al. 2017; Li et al. 2017; Kedron et al. 2018; Lang et al. 2019).

However, despite recognition of the importance of scale and a plethora of studies testing the impacts of scale on spatial patterns, questions persist about which methods to use in different contexts (Ge et al. 2019), particularly for the remote sensing (and remote sensing-derived) data on which many spatial pattern analyses rest. When data that have been scaled are subsequently used for spatial pattern analysis, it adds an additional layer of complexity (loss of rare land cover types, sensitivity of patterns to grain size, etc.). Even with gradient surface models (McGarigal et al. 2009) and hybrid approaches to characterize landscapes, measuring landscape patterns that accurately characterize ecological processes at multiple scales continues to challenge landscape ecologists.

With the increased volume of remote sensing data being produced daily and the growing need to rescale these data for modeling in landscape ecology, it is an opportune time to review the choices for scaling and how those choices impact subsequent analyses. The objective of this review is to survey methods for scaling remotely sensed data for spatial pattern analysis with a specific focus on two broad categories of scaling: upscaling and downscaling. Within each of those categories, we detail methods for scaling the two data types most commonly used in spatial pattern analyses: continuous data and discrete/categorical data. Through a systematic review of the literature, we summarize the trends and developments used within the discipline for scaling data for spatial pattern analysis. Key papers were identified for this article through a systematic review of the literature using keywords and keyword combinations such as, "scaling" + "technique", "scaling" + "remote sensing," "downscaling," "upscaling" and others. Journal databases including *Landscape Ecology*, *Remote Sensing of Environment*, *International Journal of Remote Sensing*, the *ISPRS Journal of Photogrammetry and Remote Sensing* as well as Google Scholar were all exhaustively searched until relevant papers were no longer identified. Scaling techniques were categorized and theoretical and methodological developments, persistent issues, and gaps were identified from roughly 200 core papers. We synthesize scaling options and develop a conceptual decision tree for researchers. Finally, we propose future research directions and highlight other disciplines that landscape ecologists might consult when seeking to scale data. We begin by clarifying scale concepts and defining how we use the terms 'scale' and 'scaling' in this review. For the sake of brevity, we have chosen to use the term remote sensing to also include remote sensing-derived datasets.

Scale concepts and terminology

Definitions and term usage

Across the sciences, the term "scale" has been used to describe many similar but subtly different concepts. Schneider (2009) notes the Oxford English Dictionary offers 15 different definitions of scale. The term is used several different ways even within ecology and landscape ecology, and these variations complicate discussions (Wu 2007). Therefore it is important to define the terms as they are used in each situation (Schneider 2009). Here, we use the term "scale" to refer to *the spatial scale of a measured variable*, which determines the minimum resolvable area, or resolution. The term "fine scale" is used to refer to detailed maps and "coarse scale" for maps with larger pixel sizes and/or less detail.

A distinction must also be made between the terms "scale" and "scaling". To "scale" something is the verb form and means to change the size while maintaining the same proportions. This verb form is often referred to as "scaling", which should not be confused with the term scaling as it is used in the physical sciences to describe a manifestation of the underlying dynamics and geometry relating key processes over broad ranges (Brown et al. 2004). Hereafter, we adopt the first definition and define scaling as *a change of the spatial size of the measurement unit*. We focus specifically on spatial scaling while recognizing that temporal, and organizational scaling are important concepts in landscape ecology. We are interested in the observational scale, which is the scale at which measurements are made or sampling is conducted and is distinct from intrinsic scale, which is the scale at which a pattern or process operates. We focus on scaling remotely sensed data, and do not review other geospatial data as they fall outside the scope.

General methods and data types

Methods for scaling remotely sensed data are generally classified as either "upscaling" or "downscaling" (Fig. 2). Upscaling involves coarsening the resolution by aggregating a larger number of smaller units into a smaller number of larger units. Upscaling assumes the existence of an aggregate property. Downscaling involves disaggregating data from a larger unit into multiple smaller units to make the resolution finer.

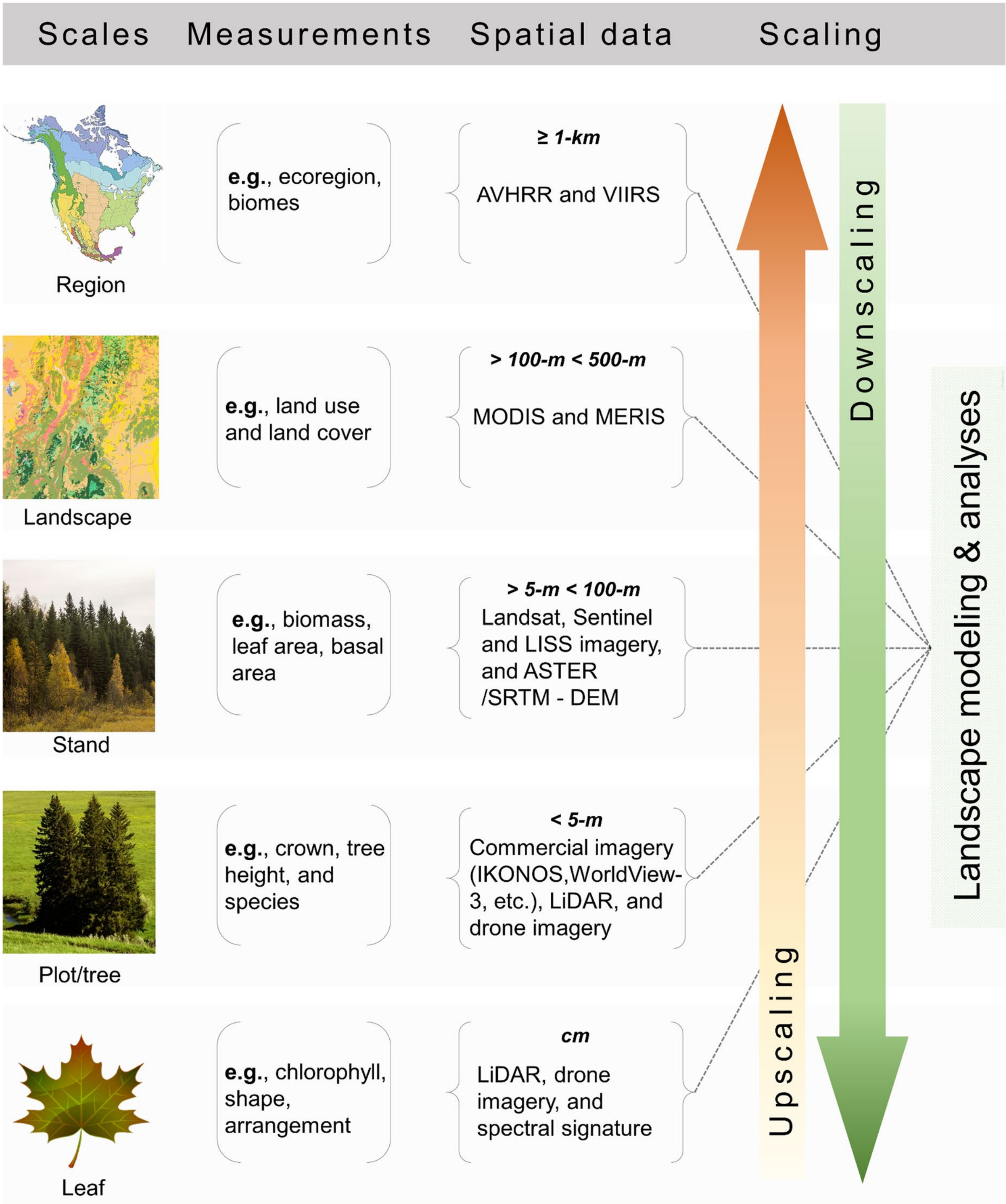

Fig. 2 A schematic of upscaling and downscaling with examples of feature scales, typical imagery and data types for representation, and common metrics extracted from the data. *ASTER* Advanced Spaceborne Thermal Emission and Reflection Radiometer, *AVHRR* Advanced Very High Resolution Radiometer, *DEM* Digital Elevation Model, *LiDAR* Light Detection and Ranging, *LISS* Linear Imaging Self Scanning, *MERIS* Medium Resolution Imaging Spectrometer, *MODIS* Moderate Resolution Imaging Spectroradiometer, *SRTM* Shuttle Radar Topography Mission, and *VIRS* Visible Infrared Imaging Radiometer Suite

Both upscaling and downscaling are commonly performed using remote sensing-based data to change the scale for analysis. Some researchers also recognize a third category –sidescaling– in which the resolution is maintained (Ge et al. 2019). Sidescaling is typically employed when obtaining area-to-area predictions and is not discussed further in this review.

For both upscaling and downscaling, the type of data being scaled determines which methods are appropriate. Two data types are commonly used for spatial pattern analysis in landscape ecology. The first type is continuous data, such as remote sensing reflectance values, vegetation indices, or digital elevation models (DEMs). These data vary continuously over the landscape and can be directly used to compute gradient surface metrics (McGarigal et al. 2009; Kedron et al. 2018) or they can be thresholded into discrete categories for patch-based analyses (Arnot et al. 2004; Frazier and Wang 2011). While this review focuses on optical data, the same scaling principles can be applied to the products of point cloud data (LiDAR, etc.) that landscape ecologists use. The second, more common, type of data used in spatial pattern analysis are categorical data, such as land use and land cover (LULC) maps. These datasets are typically derived from remote sensing reflectance bands, but the pixels have been reassigned to thematic class codes. These datasets are used directly to compute traditional patch-based landscape metrics. The data type and scaling method can have a number of different impacts on the spatial patterns derived from them, and these impacts are the focus of the review below.

Upscaling

Upscaling continuous data

Upscaling continuous data can be relatively straightforward since values can be numerically summarized within the larger unit. The most basic approaches use descriptive statistics (e.g., mean, median) to re-assign the set of values within the larger aggregate pixel to a single value, which may be categorical, (e.g., Riitters et al. 1997) (Fig. 3), while others simply use the central pixel (Bian and Butler 1999) or a random pixel (He et al. 2002) as the output value. A comparison of the impacts of mean and central pixel resampling on spatial pattern metrics found that, while mean aggregation filters out small patches, it produces more stable results for certain landscape metrics than other approaches (Raj et al. 2013), while central pixel resampling can substantially magnify small effects. Mean aggregation was also used in a study examining scaling effects on gradient surface metrics. Results indicated that mean aggregation led to non-linear changes in metric values with resolution, suggesting that some amount of information loss occurs during the aggregation process (Frazier 2016). In short, while simple, numerical upscaling approaches are easy to use, they can impact spatial pattern analysis by oversimplifying the data resulting in data loss, eliminating rare or small patches, and magnifying small effects.

To overcome the loss of heterogeneity that occurs with simple numerical methods, neighborhood-based (focal or moving window) approaches have been used

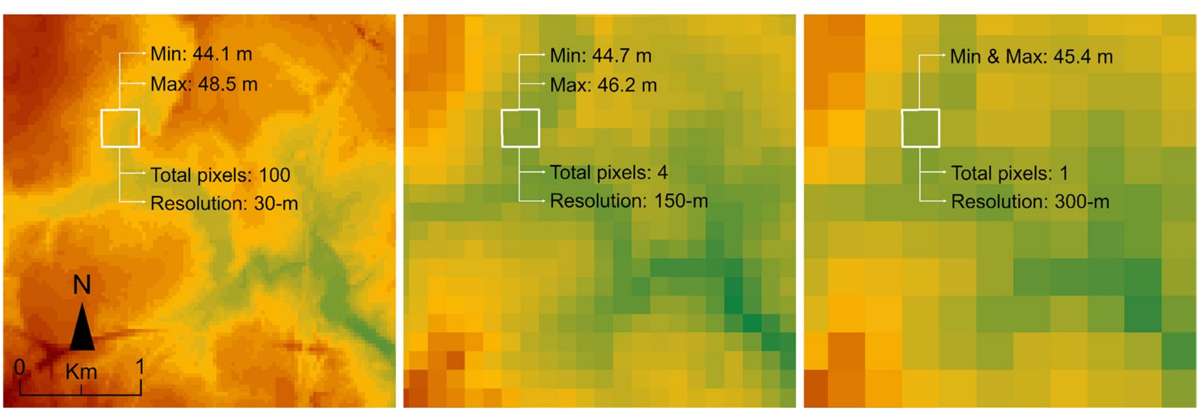

Fig. 3 Upscaling of a digital elevation model (DEM) using the mean of the input cells to generate a coarser resolution raster. Minimum and maximum values change as input cells of the DEM are upscaled from 30-m to 150-m and 300-m

to capture a greater amount of the surrounding information during the aggregation process. The theoretical basis for using focal windows is that the digital value given to a pixel results not just from the ground sampling area of that pixel but also from objects in neighboring pixels (Cracknell 1998; Jensen 2016). Galpern and Manseau (2013) used a focal window approach to upscale continuous resistance surfaces representing movement impedances in order to match the grain of analysis to the true functional grain of the organism. The authors showed that focal windows could increase accuracy when identifying the relative importance of landscape features influencing connectivity, but that accuracy ultimately depended on the numerical operator employed (e.g., min, mean, max), as these operators performed differently depending on the spatial patterns in the landscape.

The moving window data aggregation (MWDA) method (Graham et al. 2019) is a more recent approach that uses focal windows to compute variability in continuous rasters and then use that heterogeneity as the basis for aggregation to a coarser resolution. The authors show that MWDA can capture information about the landscape spatial structure that is lost when using a direct aggregation approach, and that the method is particularly useful in landscapes where there is spatial autocorrelation in the environmental predictor variables (e.g. fragmented landscapes) and when the process scale is small relative to the aggregated resolution.The MWDA method is available as an R package (grainchanger.r).

Variance has also been incorporated into upscaling/aggregation through object-based methods. The object-specific upscaling (OSU) method was designed to reduce scaling errors by dividing a scene into homogeneous regions called objects and using those objects to guide aggregation (Hay et al. 2001). OSU defines multiscale spatial thresholds based on progressively increasing windows where the spectral variance of image objects are scale-dependent. These scale-dependent measures are then used as weighting functions to determine the upscaled values (Hay et al. 1997). A multiscale extension of OSU uses hierarchical sampling and evaluates each pixel in relation to coarse grain objects (Hay et al. 2001). More recently, object-based segmentation coupled with Moran's I has been used to translate higher resolution training data for coarser resolution land cover classifications (Bihamta Toosi et al. 2020).

Fractals represent another approach for upscaling continuous data. Fractals are self-similar shapes that repeat their fundamental patterns at ever increasing or decreasing scales. They can be used to translate information across scales by informing a scaling transfer model that corrects for scaling effects based on the fractal relationship between approximate and exact pixel measurements (Gupta et al. 2000; Wu et al. 2015). Wu et al. (2015) use fractal theory to develop a relationship between image spatial resolution and leaf area index (LAI), which is a continuous vegetation index computed directly from remote sensing reflectance measurements. Their results showed that the fractal-based scaling model performed well in estimating LAI and evaluating the scaling bias.

Upscaling categorical data

When upscaling categorical data, majority rules aggregation (MRA) is a common choice, especially for LULC data. MRA assigns the LULC comprising the majority of the contributing pixels to the aggregate pixel (Benson and MacKenzie 1995; Moody and Woodcock 1995). The similar random rule-based (RRB) method randomly selects a class from the fine-scaled pixels and assigns it to the coarser map, maintaining cover type proportions but disaggregating categories and changing spatial patterns (He et al. 2002). Since MRA ignores proportions and assumes within-pixel values are homogenous, small effects can be substantially magnified (Holt et al. 1996). In other words, aggregating fine-scaled, mixed pixels could result in over or underrepresentation of a phenomenon, pattern, or class and rare or sparse land covers may be eliminated (Xu et al. 2020). MRA can distort land cover type proportions and frequently produces clumpy landscapes, while RRB can produce disaggregated spatial patterns (He et al. 2002; Raj et al. 2013).

Aggregation methods like MRA and RRB do not incorporate an understanding or measure of ecological processes, which some have argued makes them unsuitable for upscaling data that will ultimately be used for ecological analysis (Graham et al. 2019). Saura (2004) examined the effects of MRA on forest fragmentation indices by comparing aggregated values to actual sensor measurements and found that MRA tended to produce more fragmented patterns compared to actual sensor readings. Garcia-Gigorro and Saura (2005) also used an MRA filter to aggregate categorical data but compared it to a point-spread function (PSF), in which surrounding pixels provide a weighted contribution to the aggregate value. The authors found the PSF aggregation better mimicked the way in which the sensor captured the data and so fragmentation indices computed from PSF-scaled rasters had lower errors.

The point-centered distance-weighted moving window (PDW) method also attempts to overcome the limitation that MRA and RRB do not consider the relative proportion of each land cover type by using a weighted sampling net to maintain proportions when upscaling or downscaling (Gardner et al. 2008). First, the center point of the pixel in the map to be created is located and recorded in real dimensions. Then, the geometry of the sampling net is determined by the number of points and the distance between the points. Finally, the normalized frequency distribution of land cover types obtained from the data sampled at each point in the net is used, and the cover type of the rescaled map is randomly selected from the normalized frequency distribution of cover types (Gardner et al. 2008). Spatial autocorrelation can be included when using PDW, making it more robust compared to central pixel resampling and MRA (Raj et al. 2013).

Downscaling

Downscaling is usually a more difficult challenge than upscaling because it requires allocating coarser data, where there is little information about the spatial distribution of values, to finer scales, where values must be spatially distributed. Due to the lack of within-grain information, robust downscaling often requires stochastic or probabilistic approaches.

Downscaling continuous data

Resampling

The most basic form of downscaling continua is resampling, or downsampling, where a larger pixel is partitioned into smaller units, and the value from the larger is allocated to the smaller units (Fig. 4). When no a priori information for how the values should be distributed spatially at the smaller scale is available, downsampling often assigns the value from the larger pixel to all of the smaller pixels. Downsampling in this manner does not actually change pixel values and can falsely suggest a higher level of heterogeneity is present. Scale-related findings must be cautiously interpreted in these instances (Frazier et al. 2021), and oversight can be difficult to detect and misleading in ecological modeling studies (Sillero and Barbosa 2021). Bilinear and cubic convolution approaches can also be used in the absence of a priori information to interpolate pixel values at the finer resolution that fall between pixel centers in the coarser image. Depending on the method, interpolated values may contain uncertainties and biases that can propagate into spatial pattern analyses. Despite these drawbacks though, resampling continues to be widely used when researchers need to downscale data.

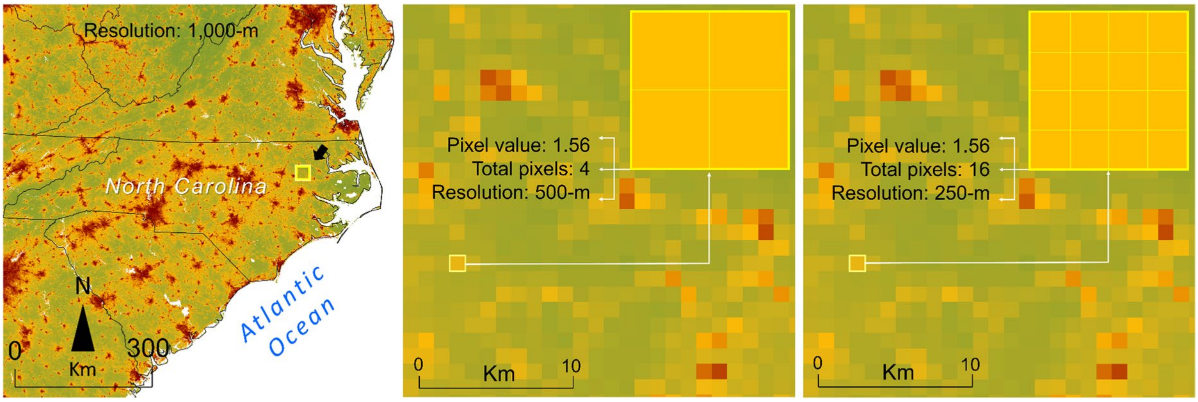

Fig. 4 Downsampling of 1-km Visible Infrared Imaging Radiometer Suite (VIIRS) data to 500-m and 250-m via resampling. As resolution becomes increasingly fine, minimum and maximum values of pixels do not change but the number of columns and rows increases within the image, as does data volume

Image Fusion

Image fusion combines images from multiple datasets to produce an output that is more informative at fine scales than any of the individual inputs. Image fusion can function for downscaling when spectral information from a finer resolution is combined with coarser-scale spatial information. Sometimes called 'pansharpening', early fusion methods recalculated the hue, intensity, and saturation of each pixel at the finer scale based on correlations between the multispectral and panchromatic bands (Haydn et al. 1982; Gillespie et al. 1987). Spectral distortions and spatial artefacts were common with pansharpening, prompting a series of improvements (Ranchin et al. 2003; Nencini et al. 2007; Shah et al. 2008; Pardo-Iguzquiza et al. 2011; Golibagh Mahyari and Yazdi 2011). More recently, deep learning algorithms have been used (Huang et al. 2015; Azarang and Ghassemian 2017; Yang et al. 2017; Seo et al. 2020), and in some cases the trained learning network has been shown to generalize well to images from different satellites without the need for retraining (Yang et al. 2017). Deep learning methods have a greater computational demand and sometimes require higher-level machine learning expertise by the user. Bayesian-based methods have also been explored, but can be limited due to the difficulty identifying an appropriate statistical model for image representation (Pandit and Bhiwani 2021). Developing efficient pansharpening approaches remains an active research area (Kaur et al. 2021). Other types of image fusion include Kalman filtering (KF), which is a recursive algorithm for integrating disparate remotely sensed data by minimizing the mean of the squared errors (Welch and Bishop 2006. KF integrates observations and their uncertainties, does not require explicit parameter tuning, and hence is well-suited for large extent applications.

Methods based on Taylor series–an expansion of a function into an infinite sum of polynomial terms– have also been used for image fusion downscaling. The Taylor expansion assumes that most functions are smooth over the range of interest, so a polynomial can be fit to approximate it. In remote sensing, Taylor series expansion methods (TSEM) model the relationship between surface properties, such as radiance or surface fluxes and heterogeneity and variance/covariance functions, and applies these relationships to aggregate or disaggregate map features (Hu and Islam 1997). TSEM has been refined for nonlinear functions and to correct scaling bias (Gao et al. 2001; Garrigues et al. 2006). A recent iteration of TSEM is the physical scaling method (PSM), which uses contexture and radiative transfer theory (Tian et al. 2003). TSEM is conceptually straightforward, but computations can be arduous, and TSEMs can be unwieldy with many variables (Pelgrum 2000; Malenovský et al. 2007; Wu and Li 2009).

Despite the large body of research on image fusion for downscaling, these techniques have been used sparingly in landscape ecology. Townsend et al. (Townsend et al. 2009) compared 15-m pansharpened Landsat images to 30-m images in an analysis of spatial patterns in protected areas and found that the pansharpened images produced lower classification accuracies, possibly due to noise introduced by the fusion process. Chen et al. (2020) used TSEM to attribute surface temperature anomalies to different LULC spatial patterns, but the application was not directly used for pattern analysis. Beyond these, pansharpening has been used in landscape ecology for estimating aboveground biomass (Doyog et al. 2021) and counting wildlife (Duporge et al. 2020). However, an opportunity exists to use the validated fusion methods described above for downscaling in order to increase the spatial resolution of data for spatial pattern investigations.

Interpolation

Interpolation inferrs a downscaling solution through a model but does not resolve it through the production of new, fine resolution data (Atkinson 2013). This is in contrast to the use of the term interpolation to predict between sparsely distributed points. Bilinear or bicubic interpolation samples nearby pixels to estimate the values for finer resolution pixels. Another, more advanced example is spatial area-to-point (ATP) kriging, which predicts values on a scale smaller than the original data (Kyriakidis 2004; Yoo and Kyriakidis 2006; Goovaerts 2006). Since it is not possible to measure remote sensing on a strictly point scale, the punctual semivariogram required for ATP kriging must be estimated through a de-regularization or deconvolution procedure (Kyriakidis 2004; Yoo and Kyriakidis 2006; Goovaerts 2006). Other kriging methods include downscaling cokriging for image sharpening (Pardo-Igúzquiza et al. 2006), geographically weighted ATP regression kriging, which considers spatial autocorrelation (Jin et al. 2018), and multiscale geographically weighted regression kriging, which is a hybrid of multiscale geographically weighted regression (MGWR) and ATP kriging (Yang et al. 2019). Geographically weighted ATP regression kriging has been used to downscale temperature data when studying species' range shifts (Platts et al. 2019), and bilinear interpolation has been used to downscale projected climate data to study climate change impacts on tree species (Attorre et al. 2011). Landscape metrics have been used to aid ATP residual kriging by providing supplemental information on the density of land cover patches (Liu et al. 2008), but studies using ATP kriging to downscale data prior to computing spatial pattern metrics are lacking.

Super-resolution mapping

Super-resolution mapping, sometimes called subpixel mapping (SPM), attempts to resolve the spatial distribution of land covers from a continuous raster of land cover proportions. SPM techniques are often applied to data that have been generated through spectral unmixing (i.e., spectral mixture analysis; (Keshava and Mustard 2002)). Many SPM methods rely on fundamental theories of maximum spatial dependency to guide the placement of sub-pixels (Li et al. 2014), with others incorporating training models and ancillary data such as histograms, transition probabilities, and variograms into algorithm development (Boucher et al. 2008; Wang et al. 2016). More recently, machine learning and deep learning methods have been implemented to resolve high resolution spatial information in images (Nigussie et al. 2011; Yu et al. 2013; Zhang et al. 2016; Ling and Foody 2019). However, these approaches do not always outperform simpler methods (Sharifi et al. 2019), and they can be computationally intensive.

Spatial pattern metrics have been used to inform SPM algorithms, similar to ATP residual kriging (described above). Su (2019) used the scale-invariant concept of fractals to guide a Hopfield neural network for SPM. Despite much progress related to SPM in the image processing and pattern recognition communities in the past decade though, these techniques have not been widely applied in landscape ecology, perhaps due to the computational complexities and lack of a universal method (Frazier 2015). More research may also be needed on the upper and lower limits of scaling in SPM (Ge et al. 2019) before the techniques can be widely applied in ecological investigations. One example of their use for spatial pattern analysis is from Muad and Foody (2012), who used SPM to delineate lakes and evaluate their shape characterization (area, perimeter, compactness). SPM provided results that closely matched the ground data, but the authors found it did not outperform interpolation downscaling techniques (bilinear and bicubic).

Downscaling categorical land cover data

Landscape ecologists frequently work with remote sensing data that have already been transformed into categorical land cover classes. Land cover data such as the National Land Cover Database, Coordination of Information on the Environment, Copernicus, GlobeLand30, and others are often produced from satellite sensors where the nominal scale is fixed. When finer scale data are needed, statistical downscaling techniques can be used to translate relationships between the coarser-grained categorical data and finer-grained covariates (e.g., climate, landforms, human activity, etc.) to produce fine-grained predictions (Atkinson 2013). Relationships between the response variable and covariates are typically modeled using regression (Dendoncker et al. 2006), with advanced techniques using generalized additive modeling with constrained optimization (Hoskins et al. 2016) or integrating geostatistics via block-to-point kriging to include an estimation of uncertainty (Poggio et al. 2013).

An alternative approach researchers have adopted when seeking to downscale data is to downscale the landscape metric values themselves, rather than the land cover raster from which they were derived. While this approach does not technically downscale remote sensing pixels, these techniques are an important research area of landscape ecology. These techniques rest on the empirical evidence that many landscape metrics exhibit consistent and robust scaling relationships across a range of spatial grains or extent (Turner et al. 1989a, b; Wu 2004). These relationships between metric and scale often follow a power law relationship (Frazier et al. 2021), and this function can be extrapolated to predict the data at finer scales (Saura and Castro 2007; Argañaraz and Entraigas 2014; Frazier 2014). Success has been variable though (Frazier 2015) because coarse-graining the land cover rasters, which is required to derive the scaling function, introduces statistical biases. Researchers are working to overcome these biases, but a universal method is not yet available.

Discussion and synthesis

This review highlights the plethora of upscaling and downscaling methods for remote sensing data that are available to landscape ecologists. Several summary points emerge. First, with upscaling, the oversimplification of results is a persistent challenge with both continuous and categorical data. The underlying heterogeneity and landscape structure can be lost during aggregation, and rare categorical classes may disappear entirely, which ultimately impacts the accuracy of spatial pattern analyses performed on the data. Oversimplification is more likely to occur when using basic methods, such as mean or central pixel resampling, whereas neighborhood approaches such as MWDA are designed to better preserve the spatial structure of underlying heterogeneity. Since heterogeneity ultimately drives the spatial patterns measured across a landscape, preserving heterogeneity during upscaling or downscaling should be the primary consideration for landscape ecologists.

The review found that object-based approaches can overcome some of the challenges with precision and accuracy that result from pixel-based techniques. These object-based approaches present an interesting dilemma for landscape ecologists though. Since patch boundaries are more likely to align with spatial objects than individual pixels, these approaches may be viable options for upscaling and downscaling when the aim is ultimately to compute spatial pattern analyses. However, object-based approaches are designed to collapse inter-pixel heterogeneity based on spatial and spectral similarity, so it is important to ensure that the scale of the original image dataset being upscaled is finer than the observational scale at which the phenomenon of interest presents. Otherwise, identified objects may not represent homogenous patches, and upscaling will simply increase uncertainty.

Regarding downscaling, resampling is the most basic technique to implement, but it does not actually change pixel values and can therefore falsely suggest a higher level of heterogeneity is present. More advanced interpolation, fusion, and sub-pixel mapping methods have been developed by the remote sensing community, but landscape ecologists do not appear to be utilizing these techniques to improve the spatial resolution of datasets prior to computing spatial pattern analyses. When downscaling categorical land cover data, regression-based approaches that correlate covariates to land cover are common, however, care must be taken to ensure that the variables used in downscaling are not also used in any ancillary analyses with the downscaled data, otherwise collinearity is likely.

Considerations when scaling data for spatial pattern analyses

The many scaling methods available can quickly overwhelm researchers, particularly when considering the varying levels of complexity that characterize the different methods. Choosing the most appropriate method often requires considering the scale of any ecological patterns and processes, discrepancies between the data and the process of interest, uncertainties and biases in datasets, and limitations in computer processing, software availability, and programming familiarity. Just as there is no quintessential scale from which to study ecological phenomena, there is similarly no single method conducive for scaling remote sensing data in all ecological contexts. A visual, decision-tree guide is provided to aid researchers in selecting the most appropriate technique for their data (Fig. 5). Below, we walk through several considerations that may be important for spatial pattern landscape analyses.

Much like species richness and abundance are the central tenets of species diversity, patch richness and abundance are similarly important for landscape diversity. The elimination of small or rare patches in a dataset can drastically alter one or both of these measures, leading to biases in spatial pattern metrics, and inaccuracies in subsequent pattern-process relationships. Therefore, researchers must be particularly cognizant of how a scaling algorithm might alter patch richness and abundance. In situations where the upscaled resolution will be larger than the size of individual patches and it is important to maintain small or rare patches or values, researchers should avoid using methods that select a single value (e.g.,

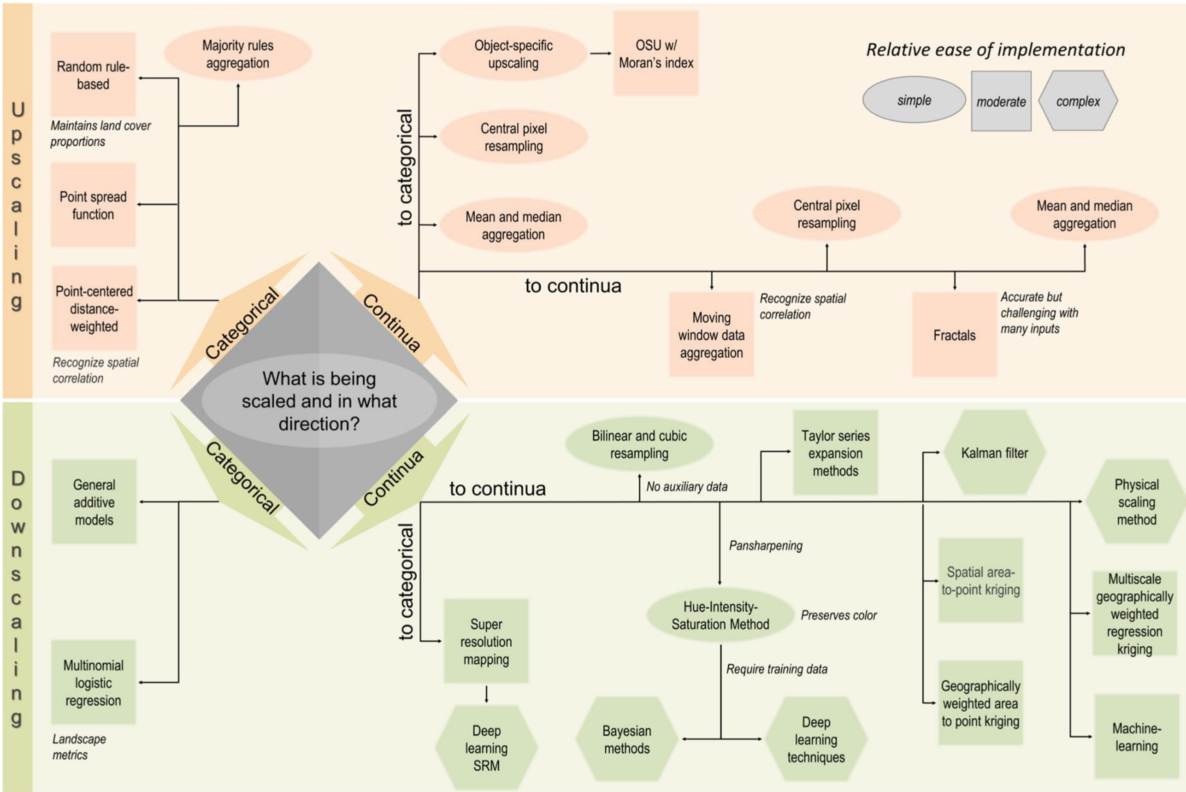

Fig. 5 Guide for selecting methods for scaling remotely sensed data for spatial pattern analysis. Additional information about each method can be found in the text as well as in Table 1 of the Supplementary material

min, max, central pixel, etc.). Instead, methods that closely maintain the original distribution of values, such as MWDA, are a better option for preserving the original heterogeneity of the landscape. An exception is when the land cover/patch type of interest is known to be characterized by the min or max value. In cases where this land cover/patch type should be prioritized, then the appropriate descriptive statistics can be used. When upscaling categorical data, majority and random rule-based methods are more likely to eliminate small or rare land covers compared to the point-centered distance-weighted method. However, if priority is placed on maintaining the largest or most dominant patches, then MRA, RRB, or central pixel resampling methods are likely sufficient. If preserving land cover type proportions and spatial information and patterns are the priority, RRB outperforms MRA (He et al. 2002).

Researchers must also consider the methodological limitations of each technique, including assumptions that underlying processes are scale independent or linear, and whether additional data are needed (Gao et al. 2015). The extent to which a method is robust to nonlinearity should be considered, including selecting methods that are suitable for nonlinear relationships. As advanced computational techniques such as machine learning and deep learning are adopted for rescaling, researchers should understand how these functions operate so that they may correctly parameterize models. Platforms like Google Earth Engine (GEE) are making it easier for researchers to perform these advanced computational techniques on large datasets, but it is important to understand how these platforms handle scale. For instance, scale in GEE must be specified by the user when exporting imagery or performing analyses, and the GEE user guide explicitly notes, "understanding how Earth Engine handles scale is crucial to interpreting scientific results obtained from Earth Engine."

A way forward

Better incorporating heterogeneity into scaling

Scale and heterogeneity are inherently linked (Turner 1987; Allen and Hoekstra 1991; Kolasa and Pickett 1991; Dutilleul and Legendre 1993; Li and Reynolds 1995), and it is impossible to translate data across scales without either ignoring heterogeneity or dealing with it explicitly and effectively (Wu 2007). Most studies do not quantify or test the impact of heterogeneity on scaling results (Frazier 2015), leaving a dearth of understanding with regard to exactly how scaling impacts heterogeneity and vice versa. Certain techniques, such as MRA, will introduce different magnitudes of uncertainty into upscaled data based on the composition and configuration of the land cover classes (Frazier 2014; Frazier et al. 2021), and these aspects should not simply be ignored when rescaling data. At a minimum, the heterogeneity of the data being rescaled can be quantified and reported. Moving forward, researchers should explore the ways in which heterogeneity impacts scaling and continue to select and develop methods that deal explicitly with heterogeneity or minimize the change in heterogeneity.

This review highlighted how advances in artificial intelligence and deep learning are being leveraged to reduce the loss of heterogeneity and improve the accuracy of scaling methods. Research applying deep learning algorithms in remote sensing has grown increasingly mature (Ma et al. 2019), and improvements continue to be made that decrease processing time and requirements and better address heterogeneous and complex data. The fields of computer vision and signal processing continue to refine methods that can be applied to scaling. Examples include new spatial filtering approaches featuring nonlinear decomposition for pansharpening (Pandit and Bhiwani 2021), using dense blocks in deep networks to efficiently utilize shallow information for image fusion (Li and Wu 2019), and employing a Generative Adversarial Network with structural similarity, gradient loss functions, and concatenating images at each layer of the deep network to retain more information when fusing images (Fu et al. 2021). Keeping abreast of methodological developments in diverse fields will allow landscape ecologists to capitalize on innovations and state-of-the-art approaches to increase the accuracy and precision of scaling while minimizing processing demands.

Improving spatial resolution through new technologies

Advances in very high resolution commercial and personal remote sensing systems (e.g., Planet imagery and Uncrewed Aerial Systems (UAS), or drones, respectively) are rapidly increasing the bounds of remote sensing spatial resolution and creating opportunities to better understand the impacts of scaling. As these data become more prevalent and reliable, they can be used to bridge spatial scales and calibrate scaling models (Alvarez-Vanhard et al. 2021). Fusion methods, such as those developed using neural networks and deep learning (Song et al. 2018; Zhu et al. 2018; Jia et al. 2020) can be used to combine UAS data with coarser, satellite-derived data streams. However, research to date has focused mainly on calibration and measurement comparison rather than image fusion (Alvarez-Vanhard et al. 2021). Nonetheless, ecologists are already adopting UAS as a key tool for bridging gaps between satellite imagery and *in-situ* measurements (Revill et al. 2020; Thapa et al. 2021). As ecologists embrace UAS, their use may act as a catalyst for developing new downscaling methods and provide data that would otherwise be unavailable.

Open science frameworks to promote cross-disciplinary research

The push for reproducibility and openness in science, through platforms such as GEE and open source coding environments (Brunsdon and Comber 2020) may serve to further the science of scaling. Platforms like GitHub host a myriad of packages, scripts, and tutorials on scaling, potentially galvanizing novel and unconventional ideas. Increased accessibility may alleviate limitations in scaling science, such as lack of sufficient training data for machine learning. These platforms and environments can also reduce computational time and processing demands. Alternatively, the progression of scaling science may be impaired if increased access leads to neglecting the nuances of remote sensing data, mischaracterizing scale effects, and improperly scaling data.

Advancing the science of scaling requires cross-disciplinary research both in regards to theory and technology (Wu and Li 2009). Landscape ecologists can look to the fields of climatology, atmospheric science, computer science, and others to develop scaling approaches pertinent to their research. Questions surrounding implementing multiscale approaches, invariants of scale, and the ability to change scale may already be partially answered, but the answers are scattered across disciplines, and this lack of integration hinders knowledge production (Goodchild and Quattrochi 1997). Cross disciplinary collaboration may lead to novel methods of incorporating heterogeneity into scaling techniques, a universal method for developing scaling functions, and closing or shrinking additional knowledge gaps. A number of recent reviews in adjacent and germane fields have discussed scale and scaling remotely sensed data (e.g., in earth science (Ge et al. 2019), irrigation science (Ha et al. 2013), agronomy (Grunwald et al. 2015), geophysics/soil moisture (Peng et al. 2017)), providing ample opportunity to compare perspectives.

Conclusion

Remotely sensed data and derived products are key components of landscape analysis, but often need to be scaled to meet modeling or analysis assumptions. A plethora of scaling methods are available ranging from simple techniques with limited computational demands to more advanced methods that use deep learning algorithms. However, recognizing the advantages and limitations of different scaling methods as well as the differences between techniques is obligatory for landscape ecologists studying spatial patterns. Scale biases can add significant uncertainty and inaccuracies to an analysis. Neglecting these potential effects can complicate spatial pattern analysis and obfuscate results. We reviewed the methods available for upscaling and downscaling remote sensing data and identified the following key findings.

First, with both upscaling and downscaling, there is no single appropriate scaling method, and so there are always tradeoffs that must be considered. While a diversity of scaling methods are available to landscape ecologists, work remains to integrate these into spatial pattern analyses. Second, landscape ecologists must be particularly aware of how scaling impacts patch richness and abundance, as these pillars of landscape diversity will be impacted differently by different scaling methods (e.g., through the elimination of patches, promoting dominance of one class. etc.). Third, methods that preserve heterogeneity, such as moving window or object-based approaches, may ultimately be better suited for spatial pattern analysis, but more work is needed to understand how heterogeneity is impacted by scaling and vice versa. Fourth, the field can focus on leveraging technological advances in machine learning and deep learning and methodological innovations in computer vision and signal processing. Lastly, plenty of scaling techniques exist, but it appears many are not widely applied in landscape ecology. We can suggest more collaborations with remote sensing and signal processing scientists, but ultimately, the path forward is to ensure landscape ecologists know about the different options, understand the potential benefits of scaling data (particularly for downscaling), and feel comfortable determining an appropriate method.

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