Developing landscape-scale forest restoration targets that embrace spatial pattern

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Abstract

Context  Forest restoration plays an important role in global efforts to slow biodiversity loss and mitigate climate change. Vegetation in remnant forests can form striking patterns that relate to ecological processes, but restoration targets tend to overlook spatial pattern. While observations of intact reference ecosystems can help to inform restoration targets, field surveys are ill-equipped to map and quantify spatial pattern at a range of scales, and new approaches are needed.

Objective  This review sought to explore practical options for creating landscape-scale forest restoration targets that embrace spatial pattern.

Methods  We assessed how hierarchy theory, satellite remote sensing, landscape pattern analysis, drone-based remote sensing and spatial point pattern analysis could be applied to assess the spatial pattern of reference landscapes and inform forest restoration targets.

Results  Hierarchy theory provides an intuitive framework for stratifying landscapes as nested hierarchies of sub-catchments, forest patches and stands of trees. Several publicly available tools can map patches within landscapes, and landscape pattern analysis can be applied to quantify the spatial pattern of these patches. Drones can collect point clouds and orthomosaics at the stand scale, a plethora of software can create maps of individual trees, and spatial point pattern analysis can be applied to quantify the spatial pattern of mapped trees.

Conclusions  This review explored several practical options for producing landscape scale forest restoration targets that embrace spatial pattern. With the decade on ecosystem restoration underway, there is a pressing need to refine and operationalise these ideas.

Keywords  Restoration · Scale · Reference · Benchmark · Point pattern analysis · Hierarchy theory · Landscape pattern analysis · Drone · UAV

Background

Forest restoration plays an important role in global efforts to slow biodiversity loss and mitigate climate change. Supported by the United Nations Decade on Ecosystem Restoration (www.decadeonrestoration.org; Strassburg, 2021), the scale of forest restoration...
continues to grow. Increasingly, projects seek to restore entire landscapes in place of bespoke interventions and plantings. The trillion trees initiative (1T.org), for example, aims to conserve, restore, and grow one trillion trees by the year 2030. If such ambitious projects are to fulfill their aspirations of carbon abatement and biodiversity restoration, they need to be guided by objective targets with appropriate ecological context.

Traditionally, the conditions that existed prior to disturbance formed the basis of most restoration targets (Jackson and Hobbs 2009; Hall 2010). The 2004 primer on ecological restoration (Society for Ecological Restoration, 2004) reflected this practice, recommending that a reference ecosystem—a representation of a native ecosystem that is the target of ecological restoration (Gann et al. 2019)—be developed using historical information including descriptions of the site prior to damage, historical aerial photography and paleoecological evidence, as well as contemporary ecological knowledge. However, several recent reviews have challenged the role of historical information in restoration targets (Harris et al. 2006; Jackson and Hobbs 2009; Higgs et al. 2014; Hobbs 2018), with issues including ecological drift between historical records and present-day ecosystems, accelerated ecological change caused by anthropogenic climate change, and a limited understanding of the impact of pre-European cultures on ecosystems. For these reasons, Higgs et al. (2014) concluded that while historical information gives context to the disturbance regimes, succession pathways, and range of variability prior to restoration, historical conditions alone are not appropriate restoration targets.

More recently, the Society for Ecological Restoration standards have formalised the use of an “appropriate local native reference ecosystem”, informed by observations from intact ecosystems close to restoration sites, as the foundation of restoration planning (McDonald et al. 2016; Gann et al. 2019). This dynamic reference concept (Hiers et al. 2012) reflects ecological shifts in response to environmental changes, addressing a key issue with the use of historical references. Still, the use of a contemporary local reference ecosystem has not gone unchallenged. Many have suggested that local reference sites are inflexible and unattainable for many projects (Hobbs 2017; Evans and Davis 2018; Higgs et al. 2018a,b), views refuted by advocates of the approach (Aronson et al. 2018; Gann et al. 2018). The theoretical foundation for using local reference sites has also been challenged, because as with historical reference sites, modern conditions may be unsuitable targets in the face of rapid climate change (Wardell-Johnson et al. 2015). In addition, the relatively recent disruption of indigenous land management practices may have led to different ecosystems than existed historically, for example, where modern-day fire suppression in western United States has resulted in considerably higher stem densities than those that existed historically (North et al. 2022). Nevertheless, many restoration projects, including those in regulatory and ecosystem accounting contexts, require measurable targets and assessment criteria. After considering their suitability in terms of practicality and past, current, and future disturbances, an intact reference landscape remains the best place to derive appropriate criteria.

When adjacent native ecosystems are an appropriate source of reference information, a logical next step is to conduct ecological surveys within a landscape near the restoration project that shares similar environmental conditions (e.g., soil, slope, aspect) (Durbecq et al. 2020). Survey data can then be averaged and extrapolated to produce area-based targets such as the number of stems to be planted or the total number of hectares of a given vegetation type be restored—common forest restoration targets (FAO and WRI 2019; Castro et al. 2021). Unfortunately, these targets overlook spatial pattern and variability within landscapes (Hiers et al. 2016). Whether it’s the spacing of trees within a forest stand, or the patterns formed by patches of similar vegetation, the spatial patterns formed by vegetation are some of the most recognisable characteristics forests. Spatial patterns are also linked to ecological processes: broad-scales vegetation patterns can be related to disturbance regimes and soil properties (Turner and Gardner 2015), and stand scale pattern among trees can be related to competition, facilitation, and dispersal (Ben-Said 2021).

Because spatial pattern is important for ecosystem structure and functioning, many publications have advocated the inclusion of landscape scale (Bell et al. 1997; Reif and Theel 2017; Mansourian 2021) and stand scale (Reynolds et al. 2013; Hessburg et al. 2015; Gatica-Saavedra et al. 2017) spatial pattern in restoration targets. However, with several notable exceptions defining reference spatial patterns of...
conifer forests in western United States (e.g., Sánchez Meador et al. 2011; Larson and Churchill 2012; Churchill et al. 2013; Wiggins et al. 2019), multiscale pattern observations from reference landscapes are rarely included in restoration planning and monitoring. In a review investigating which indicators are used to assess forest restoration success, Gatica-Saavedra et al. (2017) suggested that “future assessments would benefit greatly by inclusion of [stand scale] spatial pattern analysis.” A possible reason for the gap between what has been advocated in literature and restoration practice may be confusion around which conceptual frameworks, data sources, and analytical tools are available to observe and analyse forest pattern across multiple scales.

A multi-disciplinary approach is needed to address the challenges of landscape restoration (Suding 2011; Perring et al. 2018; Mansourian 2021), and assessing spatial pattern is no different. The disciplines of landscape ecology, remote sensing, and plant ecology have developed tools and frameworks capable of assessing the spatial patterns of vegetation across a range of scales. Landscape ecologists have long grappled with the challenge of delineating the components of landscapes (Wu and Li 2006; Turner and Gardner 2015). Hierarchy theory, for example, interprets landscapes as nested decomposable entities, and has been used for landscape stratification (Wu 1999; Wu and Li 2006). The remote sensing community have been measuring forests since the launch of the first Landsat mission in the 1970s (Cohen and Goward 2004), and new satellites and analyses have produced global high-resolution maps of forest classes within landscapes—the pattern of which can be assessed with landscape pattern analyses widely used in landscape ecology. Apart from some success measuring larger trees in open savannas (Brandt et al. 2020), satellite resolution is still too coarse for individual tree surveys in forests. Airborne sensors do provide sufficiently high resolution, albeit at a cost too high for most projects and monitoring programs. In the last decade, drones have been developed that can survey large areas (1–100 ha) at resolutions not feasible with satellites, at a fraction of the cost of airborne platforms. These datasets can produce spatially resolved individual tree scale maps of forest stands (Almeida et al. 2019, 2021; Belmonte et al. 2020). Finally, plant ecologists have embraced the challenge of understanding the spatial arrangement of trees at the stand scale, with spatial point pattern analysis offering a suite of techniques to statistically describe the spatial patterns among individual trees (Velázquez et al. 2016).

This article explores how these tools and techniques can be employed together to produce landscape-scale forest restoration targets that embrace spatial pattern. We start by briefly discussing hierarchy theory as a means of conceptualising reference landscapes as nested sub-catchments, patches, and individual trees. Then we describe how patches can be delineated with GIS and remote sensing products, and how the spatial patterns of these patches can be quantified with landscape pattern analysis. We go on to describe how individual tree crowns can be delineated with drone-based remote sensing, and how the spatial patterns of these trees can be quantified with spatial point pattern analysis. Given that restoration budgets can be constrained, we emphasise practical and cost-effective tools and techniques throughout, including publicly available data sources and software. Although we discuss forests here, the ideas are equally relevant to savannas and other sparsely treed ecosystems.

Hierarchy theory—a framework to simplify reference landscapes as nested hierarchies of sub-catchments, patches, and trees

Hierarchy theory was originally used to describe the observation that complex systems are often hierarchical in nature (Simon 1991) and has been adopted as a conceptual framework in landscape ecology (Wu 1999). In hierarchy theory, the strength of the interactions among entities is used to define each level (Lischke et al. 2007), with the individual entities in each level sometimes referred to as holons. For a given focal level, the levels above set the constraints, where the levels below constitute the component parts. In the case of forested landscapes, the lowest level could be considered the individual tree, then forest patches, then ‘integrated flow systems’ (Wu and David 2002), referred to as sub-catchments here (Fig. 1). While these hierarchies do not necessarily reflect the complexity of interactions in ecosystems (Wu and David 2002), they help to simplify the composition of landscapes. In practical terms, understanding the spatial pattern of reference landscapes requires the
delineation of the entities within a reference landscape, then the analysis of their spatial pattern.

Mapping sub-catchments and forest patches

If the hierarchical levels of a forested landscapes are taken to be the sub-catchment, the vegetation patch, and the individual tree, the first step in characterising the pattern of reference systems is to define the boundaries of the entities at each level. At the highest level, catchments and sub-catchments can be approximated with catchment boundary maps. For example, the HydroATLaS dataset (Linke et al. 2019) provides a global high-resolution database of catchments and waterways. Decisions need to be made around which stream order or sub-catchment size corresponds to repeated landscape units or holons (e.g., first, second or third order streams), after which the delineation of the sub-catchment could be conducted within a GIS.

The next level down is the forest patch: a basic framework in landscape ecology (Forman and Godron 1981; Turner and Gardner 2015). A common input for patch delineation is land-cover products derived from satellite imagery. An early application of satellite remote sensing was to predict land-cover types, namely the use of Landsat to predict land cover in North America (Anderson 1976). Modern satellites offer increased spatial resolution which has improved land-cover classifications, and the accessibility of these products is also improving. For example, the Copernicus global land service offers a global 100 m resolution product (Tsendbazar et al. 2020), which can be accessed online (lcviewer.vito.be). More recently, the European Space Agency released WorldCover, a global 10 m land cover product based on Sentinel-1 and Sentinel-2, also accessible online (https://viewer.esa-worldcover.org/worldcover/). These options provide a practical tool to group patches of similar vegetation (e.g., evergreen broadleaf, shrubland, deciduous broadleaf etc. using the Copernicus global cover product). At the jurisdictional level, more detailed land cover maps are often available. However, most land-cover products are susceptible to inaccurate classifications—mainly due to the amount of within class variability and between class similarity (Ustin and Gamon 2010)—and require field validation.

Land cover maps provide information about forest cover type at the pixel level, but further analysis is required to define patch boundaries from land-cover rasters. Patches can be mapped with contiguity rules, where the number of adjacent cells of the same class is compared to a given threshold (Turner and Gardner 2015). For example, the four-neighbour rule, where pixels of the same class that are touching horizontally or vertically are included in a patch, or the eight-neighbour rule, where pixels touching diagonally are also included in a patch. While the contiguity rules are straightforward, they are sensitive to the minimum mapping unit (pixel size) of the input raster: finer grain generally leads to the delineation of emergent properties such as connectivity, that emerge from interactions of landscape components.
more patches (Turner and Gardner 2015). Contiguity rules also ignore the reality that landscapes comprise a range of patches at different scales depending on the question being asked (McGarigal and Marks 1995). A more functional approach to delineating patches incorporates the habitat requirements of focal animal species. For example, PatchMorph (Girvetz and Greco 2007) requires an input raster layer with cells defined as either suitable or unsuitable habitat, before thresholds for density (number of cells within a neighbourhood), gap thickness (areas of unsuitable habitat within suitable habitat), and spur thickness (narrow areas of habitat that extend beyond patches) are defined, based on species characteristics. The outputs of a range of these variables can be stacked to approximate the habitat connectivity for the focal species. The FragPatch software (Kilheffer and Underwood 2018) has developed a similar approach tailored to fragmented landscapes. Both methods produce patch mosaics relevant to species habitat requirements and could be useful when restoration aims to provide habitat for a particular species.

While patch mosaics are foundational to landscape ecology and the assessment of landscape pattern, alternatives exist that may better capture relationships between pattern and processes. One approach is to use graph theory, where landscapes are depicted as a network of nodes (patches) joined by edges (Urban and Keitt 2001; Baranyi et al. 2011). Patch mosaics can be translated to graphs using the Conefor Seninode software package (Saura and Torné 2009). Gradients are another popular alternative to patch mosaics, where continuous rather than categorical maps are created. Gradient inputs include percent tree cover—as opposed to categorical forest cover—now available in global forest cover products (Hansen et al. 2003; Kobayashi et al. 2016).

Landscape pattern analysis—evolving techniques to quantify the pattern of vegetation patches

The most widely used landscape pattern analyses are the landscape metrics available within the FRAGSTATS software package (McGarigal and Marks 1995). Landscape metrics include patch level metrics such as area and perimeter, class level metrics such as the number of patches per class and the patch area distribution, and landscape level metrics such as the total number of patches and largest patch within a mosaic (Kupfer 2012). While FRAGSTATS has popularised the adoption of landscape metrics, they can also be applied using other software such as the landscape metrics R package (Hesselbarth et al. 2019). Because landscape metrics can be calculated with land-cover maps and freely available software, they are a simple approach for quantifying the spatial pattern of reference vegetation patches.

In a special issue exploring landscape pattern analysis, Costanza et al. (2019) pointed out that the use of landscape metrics continues to grow despite the criticism of several review articles (Li and Wu 2004; Kupfer 2012; Lausch et al. 2015; Frazier and Kedron 2017; Gustafson 2019). Limitations include a lack of relationship between metrics and real-world ecological processes, inaccuracies in the mapping of patches or patch classes that misalign with ecological processes, the scale dependency of metrics, and the inability of categorical patch mosaics to capture variable ecological processes. Several improvements and alternatives have been suggested to address these issues. The most straightforward changes involve altering patch metrics to make them more ecologically relevant, with Kupfer (2012) suggesting that core area could replace patch size (where a buffer is removed from the edge of patches), and least cost distance could replace nearest neighbour distance (where resistance between patches is calculated). Other approaches involve using different input data, including gradients and networks, to assess spatial pattern. Surface metrics have been developed to calculate the spatial pattern of gradient datasets (McGarigal et al. 2009), which can be calculated in FRAGSTATS and the GEODIV R package (Smith et al. 2021). Frazier and Kedron (2017) pointed out that while surface metrics may better reflect ecological attributes in some cases, gradients suffer from the same correlation and redundancy issues as landscape pattern analyses that rely on patch mosaics. Novel approaches to assess landscape spatial pattern were also explored in the same special issue (Costanza et al. 2019), which include information theoretical metrics (Nowosad and Stepinski 2019), transiograms (Zhai et al. 2019), and agglomeration curves (Brooks and Lee 2019).

In addition to pattern analysis, emergent properties of reference landscapes that arise from interaction between the landscape and its organisms can also be quantified. Connectivity—defined as the flow of organisms and material across space and time (Keeley...
et al. 2022)—is a key emergent property that has been advocated as a means of assessing restoration success (Tambosi et al. 2014; Volk et al. 2018). Many measures of connectivity exist (Kindlmann and Burel 2008), and several of the analytical tools and depictions of landscapes discussed here were developed to assessing connectivity. When landscapes are depicted as patch mosaics, nearest neighbour and buffer analyses can be used as proxies for connectivity (Moilanen and Nieminen 2002). Additionally, the species-specific patch delineation methods discussed above map functional connectivity for a given species (Girvetz and Greco 2007). When landscapes are depicted as spatial networks with graph theory, indexes of connectivity can be calculated based on the characteristics of connections between nodes and edges (Pascual-Hortal and Saura 2006; Saura et al. 2011). And when landscapes are depicted as gradients, continuous landscape resistance maps can be created on a species-specific basis, and least cost paths can calculate connectivity for given species (Cushman et al. 2006).

Taken together, there are a wealth of analyses available to determine the pattern of reference vegetation. The choice of landscape pattern analysis will depend on project requirements and the nature of the reference vegetation. Landscape metrics that have been around since the 1980s might provide some guidance about the size and configuration of patches of a given vegetation type, but the ecological meaning of these metrics is not necessarily clear. When the connections between habitats is of interest, for example, when restoring vegetation to facilitate the movement of threatened fauna, graph theory might be more appropriate. And when the relationships between observed patterns and processes are of interest, gradient methods might better capture subtle dynamics. Finally, emergent properties, such as connectivity, can be derived to produce more holistic measures of pattern.

Drone-based remote sensing—new methods to map the location of trees

We previously discussed options to delineate reference landscapes into their component sub-catchments, and these sub-catchments into their component forest patches. While patch mosaics allow the assessment of landscape pattern, they also provide a stratification tool to assess the spatial pattern of the next level down: individual trees. In the following section, we review ecological, remote sensing and restoration literature to demonstrate how drones can be used to produce individual tree scale maps within defined forest patches. We focus on the measurement of structure and composition, attributes often measured when assessing restoration success (Gatica-Saavedra et al. 2017).

Forest structure is often assessed in terms of the size and frequency of trees, traditionally measured with field surveys of stem diameter. While spatial pattern can be incorporated into these surveys with the addition of spatial information, namely GPS, this adds considerable time to data collection. Drone surveys regularly cover more than 5 hectares and produce spatially resolved remote sensing products including point clouds and rasters. To map structure at the individual tree scale, researchers have focussed on detecting treetops and segmenting tree crowns from both point clouds and canopy height models (Fig. 2a). Several tree detection and segmentation algorithms are available within open-source software such as the lidR package (Roussel et al. 2020) and treeseg (Burt et al. 2019). Zaforemska et al. (2019) evaluated the performance of the four segmentation algorithms available within lidR as well as the adaptive mean shift point cloud algorithm (Xiao et al. 2016), using a point-cloud collected over a mixed species woodland as input. They found that the adaptive mean shift algorithm performed best overall, a similar finding to a comparisons of algorithms applied to airborne LiDAR (light detection and ranging) (Aubry-Kientz et al. 2019). They noted that the
performance of raster-based models is highly species dependent, with pine trees performing better due to their single local maxima. As such, tree segmentation accuracy depends on both the choice of algorithm and the environment, and validation against field data is required.

Although the majority of 3D tree detection and segmentation research has used specialised LiDAR systems, the same algorithms can also be applied to point clouds generated with structure from motion algorithms applied to widely available RGB (red–green–blue) survey data. Mayr et al. (2018), for example, used a drone-mounted consumer-grade RGB camera to generate a canopy height model, then segmented individual tree polygons with an inverse watershed segmentation. Similarly, Belmonte et al. (2020) detected individual trees using photogrammetric data collected with a multispectral sensor, generated a dense point-cloud using structure from motion, then segmented individual trees using the Li et al. (2012) algorithm. While the use of structure-from-motion is appealing due to the lower cost and complexity of consumer and professional-grade drones, the low canopy penetration of this approach makes it best suited to more open forests.

Tree detection and crown segmentation produces maps of tree location and crown area, but not DBH (Diameter at Breast Height)—which can be required to calculate established metrics such as diameter distribution. To address these requirements, some developments have been made toward calculating DBH with drone-derived datasets. One approach is to model DBH by developing allometric relationships between stem diameter, crown size and tree height, which has been demonstrated at the global scale (Jucker et al. 2017). However, at the local scale, studies have found these relationships to be less reliable (Luck et al. 2020; Levick et al. 2021; Rudge et al. 2021). Another approach is to directly measure tree stems at 1.3 m above ground level with LiDAR enabled drones (Reitberger et al. 2009), although these approaches rely on very dense point clouds to accurately measure DBH (Puliti et al. 2020), so would require intensive measurement of small areas at the expense of broader spatial scales. Taken together, the unreliable crown to DBH allometric relationships and the high point requirement for direct measurement show that there are no widely accepted methods to measure DBH with drone-based data. In the future, drone derived crown attributes such as crown area and height might become a suitable replacement for DBH as a proxy for tree size.

Forest composition refers to the array of organisms within an area (McDonald et al. 2016), and field surveys of composition usually focus on the species, life form, or functional type of each tree within a plot. These surveys are not necessarily spatially resolved and are often used to calculate aggregate diversity indices (i.e., species richness or the Simpson’s Diversity Index). To produce individual tree scale maps of forest composition using drone data, researchers have applied a range of analytical methods to segment trees then ascribe them to a class (such as species or functional type) (Fig. 2b), mostly using orthomosaics collected with consumer-grade drones with RGB cameras. Because the difficulty in classifying individual trees varies between environments and research questions (e.g., classifying spectrally distinct species isolated from other trees would be a simpler task than spectrally similar species in a highly diverse closed forest), the following does not focus on reported accuracies, but discusses the available options in broad terms.

One approach to calculating individual tree scale composition from drone data is to first segment crowns before classifying segments with statistical machine learning methods. Crowns can be segmented using the individual tree crown segmentation methods discussed above, or with geographic object-based image analysis (GEOBIA) (Blaschke 2010), which groups similar pixels into segments. For example, De Luca et al. (2019) applied a large-scale mean shift algorithm to segment images, then used random forest and support vector machine algorithms to classify segments, all within the open source Orfeo Toolbox (Grizonnet et al. 2017). Similarly, Onishi and Ise (2021) used the slope of a canopy height model to segment individual tree crowns, then applied a convolutional neural network algorithm to classify species. Reversing the order, Nevalainen et al. (2017) conducted pixel-level classification of species within a Pine and Spruce Forest using a range of methods including random forest, before detecting individual trees using an RGB derived 3D point cloud. Where statistical machine learning methods are well established, deep learning is a relatively new approach to classifying tree species from drone-based remote sensing imagery [reviewed in dos Santos et al.
(2019) and Diez et al. (2021)]. While much of the deep learning literature has applied semantic segmentation methods which classify individual pixels, there are a growing number of studies classifying individual tree crowns. As with statistical machine learning methods, this can be done by first segmenting crown areas from canopy height models, before applying deep learning classification algorithms. For example, Fujimoto et al. (2019) extracted crown segments from a photogrammetry derived canopy height model, which were then used for training and classification with the ResNet architecture (He et al. 2016). Likewise, Natesan et al. (2019) extracted crown segments from a digital surface model using an iterative local maxima filter and watershed segmentation algorithm, which was also applied within a ResNet architecture. These studies both achieved high accuracies, although the accuracy of this approach is strongly dependent on the accuracy of the original crown segmentations.

Instance segmentation is an emerging deep learning technique that allows for both segmentation and classification of individual tree crowns without the need for a separate crown segmentation step. One popular architecture for instance segmentation is mask Region-based Convolutional Neural Networks (Mask R-CNN) (He et al. 2017). Ferreira et al. (2020) applied Mask R-CNN to an RGB orthomosaics to segment and classify species of Amazonian palm trees. They found that the mask R-CNN approach resulted in higher accuracy than traditional semantic segmentation (CNN). Likewise, Chadwick et al. (2020) used mask R-CNN to segment tree crowns of regenerating conifers in the Rocky Mountains, although species were not classified. It is interesting to note that applications of instance segmentation, which represents the forefront of computer vision, has been restricted to RGB data—available with widely accessible consumer-grade drones. As a result, advanced analytics might enable the accurate classification of trees using relatively affordable, accessible hardware.

Despite these promising results, significant challenges stand in the way of widespread adoption of these methods to survey reference vegetation. As outlined in Kattenborn et al. (2020), these issues include the irregularity and complexity of natural vegetation, the need for extensive reference datasets, and the wall-to-wall (as opposed to single targeted images) nature of raster outputs derived from drone surveys. Technical barriers also exist, as deep learning software currently requires considerable specialised knowledge. Some of these challenges can be addressed, but deep learning classification of drone survey data is still unlikely to be accessible for most restoration ecology applications at present. However, high accuracy rates together with the development of new pre-trained models and user-friendly interfaces suggest that these methods are set to become the preferred choice for drone-based composition surveys.

Spatial point pattern analysis—statistical methods to describe tree pattern at the stand level

By allowing restoration practitioners to visualise the spatial patterns of trees within forest patches, the individual tree maps produced with drone-based remote sensing could become valuable resources in their own right. Still, generalising and comparing these results is difficult without quantifying the patterns using spatial statistics. Spatial point pattern analysis has been applied to study spatial associations in plant ecology [see Velázquez et al. (2016) and Ben-Said (2021) for reviews], making it suited to quantify the spatial patterns among trees surveyed with drones. Spatial point patterns can be analysed with open-source software, namely the Spatstat (Baddeley et al. 2015) R package and the Programita (Wiegand and Moloney 2004, 2013) software. This software can characterise attributes of tree spatial pattern like dispersion, which quantifies the degree of randomness in the spacing of trees. A random pattern describes a situation where the probability of finding a tree is independent of its proximity to other trees, an over-dispersed (regular) pattern describes a situation where the probability of finding a tree reduces with proximity to another tree, and an under-dispersed (aggregated, clumped) pattern describes a situation where the probability of finding a tree increases with proximity to another tree (Dale 2000).

Spatial point patterns are unlikely to be homogeneous across a given forest patch, because pattern is influenced not only by interactions among trees (referred to as second order effects), but also underlying environmental gradients (referred to as first order effects), such as soil water content and topography (Fig. 1). Fortunately, spatial point pattern analysis can be applied to assess changes in the spatial pattern of trees associated with environmental gradients. Wiegand and Moloney (2013) offer two approaches
to this problem: mapping the intensity of a pattern within an observation window then comparing this pattern to underlying heterogeneity or applying statistical tests to examine the relationships between patterns and covariates. Efforts to scale up the pattern observed in vegetation surveys to the patch scale could be informed when similar patterns are observed within a given patch class, or when pattern can be predicted by environmental covariates.

More sophisticated applications of spatial point pattern analysis can also reveal the complex spatial patterns that would be expected in natural forests. For example, bivariate and multi-variate patterns can reveal whether certain classes of plants, such as functional types, form clusters (Wiegand and Moloney 2013). Likewise, quantitative marks, such as DBH or crown size, can reveal how tree sizes relate to one another (Pommerening and Särkkä 2013)—an emerging topic in LiDAR remote sensing (Lin and Wiegand 2021). Spatially explicit ecological indices can also be calculated, including the individual species area relationship and the spatially explicit Simpson’s Diversity Index (Shimatani 2001; Shimatani and Kubota 2004). These indices allow not only the calculation of the frequency of individuals within a given area (e.g., diversity scores), but also how trees of different classes are arranged in space.

While the spatial patterns observed in reference systems could help to guide more ‘natural’ arrangements in tree planting, perhaps more relevant over the long-term are the pattern-process relationships that govern the development of different point patterns. To take one example, clustering among smaller trees and regular spacing among larger trees can provide evidence of density dependent mortality, caused by an increase in competition as trees grow: the so-called honeycomb rippling model (Wiegand et al. 2006). In a restoration context, understanding how density-dependent mortality is expected to impact stem densities is relevant to predict tree mortality as restoration matures. To take another example, observed spatial point patterns have been linked to the seed dispersal characteristics of different tree groupings. Seidler and Plotkin (2006), for example, found significant relationships between seed type and the size of clusters; trees with ballistic (e.g., explosive pods) seeds were tightly aggregated in small clusters, and at the other end of the spectrum, trees dispersed by larger animals (e.g., fruits) had the largest clusters. For initial planting, understanding restoration trajectories, and guiding interventions, assessing how process links to spatial pattern in the stands of reference ecosystems would be instructive.

The study of ecotones within reference landscapes is another application that could help to disentangle relationships between tree spatial pattern and different ecological processes. In alpine regions, the study of tree spatial pattern in treelines (an ecotone that marks the upper limit of tree-growth), has revealed nuanced relationships between pattern and processes. Globally, increased air temperatures are expected to result in a higher density of trees within treelines (MacDonald et al. 1998), but this broad process has been modulated by local abiotic and ecological factors at finer scales. Elliott (2011), for example, found that treelines with a random spatial pattern were more responsive to climatic shifts, because random patterns indicate that vegetation is not reliant on facilitation. Elliott (2011) also pointed out the importance of boulders in creating microsite conditions within treelines. Studies have also found that trees are more clustered on south facing slopes in the northern hemisphere (Elliott and Kipfmüller 2010; Dearborn and Danby 2020), potentially due to die-back on the harsher north facing slopes. Point patterns have also been used to illustrate how competitive interactions among trees relate to environmental conditions, with Wang et al. (2021) demonstrating that competition was only present in less harsh conditions. Bader et al. (2021) offered a categorisation of treeline patterns and their potential relationship to process: discrete ecotones can indicate damage or stress; diffuse ecotones indicate mortality caused by environmental heterogeneity, stochastic processes, or seed-limited colonisation; and those containing islands (clusters) indicate environmental heterogeneity, clonal reproduction and positive feedbacks with tree cover or microclimate. Applying these insights to a restoration planning context, the analysis of ecotones within a reference system could help to disentangle the impact of global processes such as temperature and rainfall, from local processes such as competition and facilitation—relevant when designing interventions aimed at emulating the spatial pattern of reference ecosystems.

Finally, while the above approaches help to draw relevant links between static spatial point patterns and ecological processes, inferring complex, dynamic processes from static patterns is still difficult (Velázquez
et al. 2016; Ben-Said 2021), because several process could be responsible for the same pattern. To better understand the processes driving observed patterns, Velázquez et al. (2016) recommended the application of dynamic, individual-based models [e.g., the Heterofo (Wergifosse et al. 2020) and canopyshotnoise (Pommerening et al. 2021) packages]. By allowing the assessment of the relative influence of different biotic and abiotic processes over longer time horizons, these models could further inform decisions around which restoration interventions will lead to spatial patterns of trees similar to those observed in reference areas.

Limitations

This review has explored a range of data sources, hardware, and analytical tools that could be applied to develop restoration targets that incorporate the spatial pattern observed in reference landscapes—from the landscape to the individual tree scale. But this framework is not comprehensive nor is it prescriptive, and several limitations remain. Firstly, there are theoretical issues with the reference ecosystems concept, such as its relevance in the face of accelerating climate change. Suitable references may be non-existent for many restoration projects, and when they are available, emulating the spatial pattern may not be feasible when there is extensive substrate change. The landscape pattern analysis discussed also relies on accurate land-cover classifications, which may be unavailable, or classes might misalign with relevant levels of vegetation organisation. Practical constraints also hamper operational drone-based tree surveys, including the high barrier to entry, licensing requirements, the cost of hardware and flight regulations. Finally, inherent limitations exist within the spatial point pattern analysis framework, and specific pattern-process relationships may be difficult to establish when several processes are responsible for a single pattern. These issues need to be considered when applying this type of framework in the establishment of restoration targets.

Conclusion

Whether it’s the spacing of trees seen from the ground, or the mosaic of patches seen from above, vegetation in remnant forests can form striking patterns. These patterns also relate to important ecological processes like competition and disturbance. If restored forests are to emulate the values of remnant forests, they need to be guided by clear targets that recognise the spatial patterns of remnant ecosystems—a thorny problem in patchy and heterogenous landscapes. Drawing on landscape ecology, remote sensing and plant ecology, this review explored practical options available for developing landscape scale forest restoration targets that embrace spatial pattern, based on observation made within intact reference ecosystems. Hierarchy theory provides an intuitive way to stratify reference landscapes into nested hierarchies of sub-catchments, vegetation patches and trees. Vegetation patches can be delineated with publicly available mapping products based on satellite data or hierarchical patch delineation methods. The spatial patterns formed by these patches can then be revealed using landscape pattern analysis. Drone surveys can produce spatially resolved maps of individual trees within these patches—including information about tree size and composition. Finally, spatial point pattern analysis can quantify the spatial patterns formed by these trees, helping to inform restoration activities by relating pattern to ecological processes while allowing the scaling-up of pattern among individual trees, through the forest hierarchies to the landscape level. Encouragingly, many of these approaches are cost effective and intuitive, reducing the barriers to adoption by restoration practitioners. While limitations remain, the rise of landscape restoration and the importance of spatial pattern presents a legitimate need to refine and operationalise these ideas to improve real world restoration targets.

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