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A Framework for Assessing 3D Landscape Connectivity

Amy E. Frazier, Wenxin Yang, Morgan Rogers

Abstract

Historically, landscape connectivity assessments have almost exclusively relied on two-dimensional (2D) representations of the landscape, where any vertical heterogeneity–such as tree height–is collapsed into a 2D pixel representing only the land cover type. In reality, species make movement and behavior decisions based not only on land cover but also the three-dimensional (3D) height and structure of objects on the surface of the earth, including trees, shrubs, and buildings. With the rise in availability of 3D datasets from lidar, radar, sonar, and structure from motion, there are new opportunities to incorporate the vertical dimension into general landscape ecology approaches and movement ecology. However, landscape connectivity has received less attention, likely because there is not yet a comprehensive framework for conceptualizing the many ways in which connectivity can be represented and measured in 3D. Here we present a framework for conceptualizing and measuring 3D connectivity across the three paradigms commonly employed in landscape ecology: the patch-mosaic, graph-based, and gradient surface models. For each of these three models, we outline how 3D connectivity can be conceptualized and measured using existing metrics as well as areas where new metrics are needed to fully realize the potential of 3D data in landscape and movement ecology.

Introduction

Landscape connectivity is the degree to which the spatial configuration of the environment facilitates or impedes biological flows, and it is often interpreted in the context of organisms moving or dispersing within and between habitat patches (Tischendorf and Fahrig 2000). Landscape connectivity is critical for species migrations, nesting, breeding, and foraging as well as increasing individual fitness by supporting reproduction (Fahrig et al. 2022). The importance of connectivity is highlighted in many of the targets established in the Kunming-Montreal Global Biodiversity Framework, but measuring, monitoring, and reporting connectivity can be challenging (Frazier et al. 2024).

Historically, landscape connectivity assessments have almost exclusively relied on two-dimensional (2D) representations of the landscape, where any vertical heterogeneity–such as tree height–is collapsed into a pixel of land cover type. In reality, species that actively locomote make movement and behavior decisions based on land cover or habitat as well as the three-dimensional (3D) structure of objects on the surface of the earth, including trees, shrubs, and built structures (Gámez and Harris 2022; Russo et al. 2023). For species that rely on passive locomotion, these same 3D objects may also provide barriers or influence the flows of wind and water. While research is still in the early stages, incorporating 3D elements into landscape assessments is already uncovering critical ecological relationships that traditional 2D land cover data fail to capture. For instance, studies have found that the height, volume, surface area, and spatial configuration of 3D built structures influence aerodynamics that shape migratory flight paths (Liu et al. 2021), impact acoustic transmissions crucial for animal communication (Warren et al. 2006), and generally affect species presence in some areas (Choi et al. 2021; Rogers 2022). Similarly, 3D vegetation structure has been positively correlated with biodiversity and ecosystem health (Huang et al. 2014; Beninde et al. 2015; Skidmore et al. 2021). Therefore, there is ample motivation for extending assessments of landscape connectivity into the vertical dimension.

The rise in availability of 3D datasets from lidar, radar, sonar–including satellite born lidar from NASA's GEDI mission–and optical methods like structure from motion (SfM) from drone imagery and even overlapping Planet scenes (Frazier and Hemingway 2021) has created opportunities to incorporate the vertical dimension into general landscape and movement ecology approaches (Kedron et al. 2019; Liu et al. 2020; Lepczyk et al. 2021). However, connectivity has received less attention (Casalegno et al. 2017), partly because there is not yet a comprehensive framework for conceptualizing the many ways in which connectivity can be represented and measured from 3D landscape representations. Without an organizing framework, it is difficult to build on existing work, compare findings across species and locations, or assess change over time. The lack of an organizing framework also prevents replication studies and ultimately hinders standardized reporting for global conservation targets (Frazier et al. 2024).

This perspective offers a framework for conceptualizing and measuring 3D connectivity across the multiple data paradigms that are common in landscape ecology. First, we review how landscapes are conceptualized and modeled in the patch-mosaic, graph-based, and gradient surface models. We then demonstrate how connectivity can similarly be conceptualized and modeled across these three paradigms when the vertical dimension is introduced. Lastly, we discuss opportunities for future research contributions. Importantly, this perspective is not focused on topography (e.g., digital elevation model), which is also sometimes considered a 2.5 or 3D landscape element, as much work in landscape ecology has already addressed these data models. Instead, we focus specifically on incorporating 3D landscape elements (e.g., trees, buildings, etc.) into connectivity assessments.

Established paradigms for measuring landscape connectivity

Landscapes can be conceptualized and modeled in many ways, which in turn dictate how the composition and configuration of landscape elements, including connectivity, are represented and measured. In landscape ecology, three general paradigms have been established (Fig. 1): (1) the patch-mosaic, (2) graph-based, and (3) gradient surface models. While these three models are not mutually exclusive and share certain data elements (see following section), they provide an established framework for situating families of connectivity metrics and imagining how these metrics can be extended into 3D.

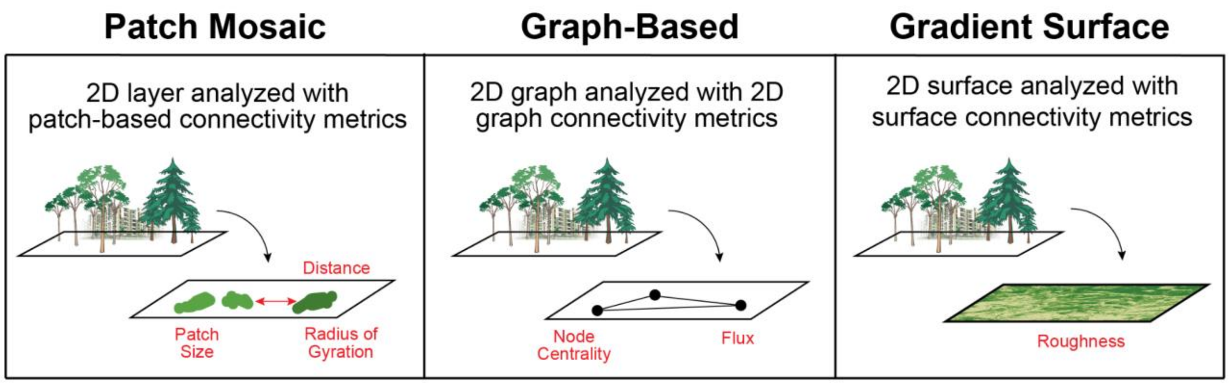

Figure 1. Approaches for measuring landscape connectivity using the patch-mosaic, graph-based, and gradient surface paradigms in landscape ecology. In each case, the landscape has historically been represented as a two-dimensional data model (vector, raster, or graph, depending on the paradigm) to which metrics are applied based on that data model. Examples of metrics for each paradigm are given in red text.

In the patch-mosaic model, land covers or objects are represented as discrete, structural patches (Forman and Godron 1981), and metrics are computed on individual patches or groups of similar patch types, called classes. Developed in the 1980s, the patch-mosaic model describes landscape structures as a mosaic of discretely delineated homogenous areas (Forman and Godron 1981). The PMM has dominated landscape analyses (McGarigal et al. 2009; Frazier and Kedron 2017), and in it, connectivity is typically assessed according to the spatial arrangement of land cover patches and whether that arrangement will facilitate or impede movement and dispersion (Fig 1a). Common patch-based, landscape metrics for connectivity include patch area, cohesion, proximity, and radius of gyration (Yang et al. 2024). A limitation of all patch-mosaic metrics is that they treat the background matrix as homogenous and do not account for the quality of the intervening space between patches (Frazier et al. 2024). Therefore, most patch-based connectivity metrics measure the facility of movement or dispersion between patches based solely on distance, without accounting for what an individual might encounter in the intervening area.

The graph-based paradigm (Fig. 1b) emerged from graph theory, and in it, landscapes are represented as a set of nodes (i.e., habitat patches) and links that join pairs of nodes according to structural or functional distances (i.e., via dispersal) (Urban and Keitt 2001). As their original applications in landscape ecology were for connectivity (Minor and Urban 2008), many have clear ecological meaning for connectivity including the strength and directionality of potential flows (Estrada and Bodin 2008), provided they are based on clear and robust ecological knowledge. The metrics are also relatively simple to compute with existing software (Yang et al. 2024) and many are applied for landscape connectivity including node degree, betweenness centrality, and integral index of connectivity, or IIC (Pascual-Hortal and Saura 2006; Estrada and Bodin 2008; Yang et al. 2024). More mathematically involved metrics, such as ProtConn (Saura et al. 2018), are based on graph networks but also include patch-based attributes such as patch area, setting them apart from metrics based solely on the topological configuration of the graph (e.g., betweenness centrality) (Yang et al. 2024).

The gradient surface model was introduced in response to the limitations of the patch-mosaic model for capturing fine-scale heterogeneity across continuous landscapes (McGarigal and Cushman 2005; Cushman et al. 2010). Gradient landscapes can be represented through any continuous variable (e.g., NDVI), but there are no discrete patches from which to compute traditional landscape metrics, so metrics capturing the variation in surface heterogeneity from the field of surface metrology have been adapted for landscapes (McGarigal et al. 2009). These surface metrics have their root in microscopy and molecular physics (Stout 1994), with many derived from frequency-based, aspatial recombinations of the surface measurements, which means they are not always ecologically-relevant indicators of the spatial arrangement of natural landscapes (Kedron et al. 2018).

Extending representations from 2D to 3D

Connectivity analyses across the three paradigms described above have almost exclusively relied on 2D representations of the landscape through rasters (single or multi-band) and vectors (e.g., points, lines, polygons), both of which can store attributes such as land cover type. In practice though, most land cover data for landscape ecological analyses are eventually formatted as rasters. From these rasters, groups of contiguous land cover pixels can be extracted to patch mosaics through connected components labelling. Alternatively, a graph can be constructed from the patch mosaic (or directly from a vector). Gradient surfaces, which aim to capture more heterogeneity than discrete classifications by representing landscapes via 2D rasters with continuous data values, are also represented by 2D rasters.

Recent technological developments have made it easier to capture 3D representations of landscape elements, facilitating the extension of established concepts into the vertical realm. These modern forms of 3D data are being derived directly from 3D sensors such as lidar, radar, and sonar, which are active remote sensing techniques that measure the return of pulses of radiation (light, radio, and sound waves, respectively) and translate the time it takes for the signal to return into distance to the object. 3D data can also be derived indirectly from 2D optical sensors (i.e., cameras) where overlapping images are captured and photogrammetric techniques are applied via the ‘structure from motion’ workflow (Westoby et al. 2012) to reconstruct the 3D positions of objects based on the camera and scene geometry. From both 3D and 2D sensors, accurate locations of objects in 3D space can be generated in the form of point clouds (Sun et al. 2011; Iglhaut et al. 2019). Structure from motion has been widely used with drone imagery, including underwater investigations of coral reefs (Lepczyk et al. 2021). From both the 3D and 2D sensors, resulting point clouds can be classified according to the type of object they represent (e.g., building, tree, ground), providing complementary land cover information to the structural/height information.

While 3D point clouds can be analyzed in their raw form, more often they are converted into raster format for easier handling. The most computationally efficient method is to collapse the point clouds into a raster, where cell values represent the height (z-value) of the detected objects in a particular class (e.g., buildings, trees). These rasters are akin to a digital surface model (DSM) or a canopy height model (CHM), which subtracts the DEM from the DSM to provide relative heights above ground. These data products are sometimes considered 2.5D since they include vertical measurements. The CHM is ideal for 3D landscape investigations because it relativizes the ground height, allowing analyses to focus on the height and form of structures without confounding those measurements with elevation.

Collapsed 2.5D rasters are a simple way to represent 3D height/structure as a data model, but only a single value can be stored in each cell. To capture more of the vertical heterogeneity, the point cloud can be ‘sliced’ at different vertical thresholds to produce multiple, 2.5D raster layers that represent height or structure of different object types at various elevations above ground. We refer to this data model as ‘2.5D Stratified’. These multiple layers are particularly useful in, for example, an urban environment with both skyscrapers and shorter buildings to understand the environment encountered by high-flying versus low-flying birds (Casalegno et al. 2017; Kedron et al. 2019). In marine environments, the multi-strata approach can help better understand the association between fish distributions in the water column and seascape structure, a high priority for fisheries management and marine protected areas (Lepczyk et al. 2021). More frequently spaced ‘slices’ capture more of the vertical heterogeneity while larger spacing between slices may be useful to capture relationships in specific strata. Lastly, the data can remain in a 3D format either as a raw point cloud, segmented into 3D vector objects (or a polygon mesh), or voxelized into a 3D grid (Bakx et al. 2019).

Each of these three formats (i.e., 2.5D collapsed, 2.5D stratified, and 3D) can be considered within the three paradigms discussed above to produce a framework for the various ways that 3D connectivity can be conceptualized and measured in landscape ecology (Fig. 2a-i). In the sections below, we walk through each data form across the three paradigms to show how connectivity measurements would be operationalized. We demonstrate where existing methods and metrics for computing connectivity in 2D can be extended to these higher-dimensional representations, and we identify cases where new methods, metrics, and software will need to be developed or adapted from other fields.

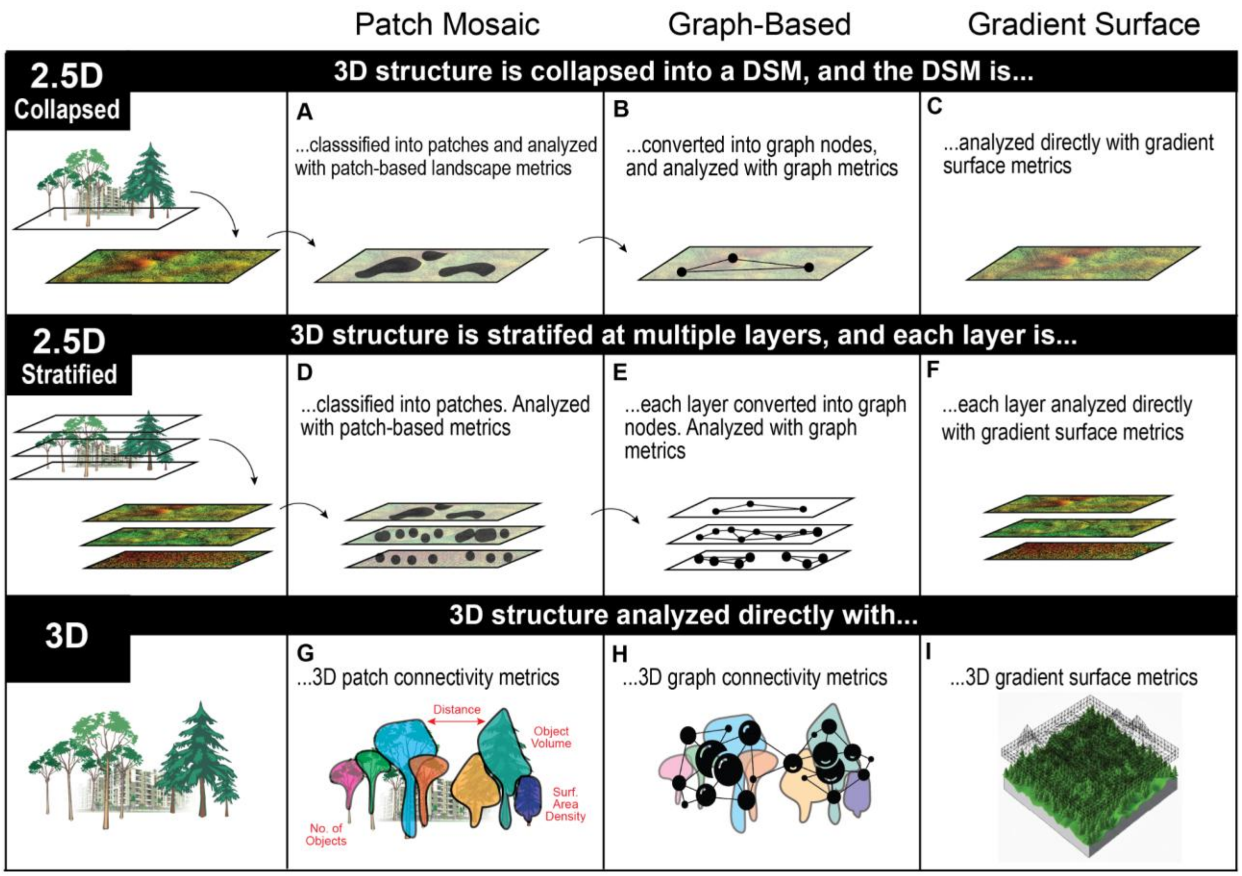

Figure 2. A matrix of the ways in which 3D landscape information can be represented and analyzed according to the three main conceptual paradigms in landscape ecology: the patch mosaic model (left column), graph-based model (center column), and gradient surface model (right column). Each paradigm can be applied to 2D raster data derived from a single stratification/collapsation of a 3D landscape (top row), 2.5D raster data derived from multiple stratifications of a 3D landscape (center row), or 3D (x,y,z) data models that have not been collapsed into rasters, such as point clouds, meshes, or 3D objects (bottom row).

Computing Connectivity with 3D Data

2.5D Collapsed: Across all three paradigms, computing connectivity metrics with 2.5D collapsed data (Fig. 2, top row) is akin to computing traditional metrics except that the attribute being assessed is height or structure instead of land cover. As mentioned above, if the points are classified, then separate 2.5D collapsed rasters can be created for building height and tree height, for example. In the patch-mosaic and graph-based models, the patches (or nodes) represent contiguous pixels of a certain height/structure (or range). For example, the Cotton-headed Tamarin (*Oedipomidas oedipus*) spend much of their life above ground and tend to remain around 5-30 m above ground (Neyman 1977; Mittermeier et al. 2013). Therefore, an ecologically relevant approach may be to collapse all forest pixels with heights ranging from 5-30m into 'habitat' and then analyze how that habitat is connected across those key elevations. Similarly, sharks spend different stages of their life histories at different ocean depths (shallow nurseries as juveniles and deeper waters offshore as adults), which could be collapsed to capture the current connectivity in these critical habitats. Once the patches are segmented, the same sets of connectivity metrics used for traditional 2D assessments in the patch-based and graph-based models can be used here (Keeley et al. 2021; Yang et al. 2024).

For gradient surfaces, the surface metrology metrics gain ecological relevance when applied to 2.5D collapsed height information instead of continuous land cover, potentially creating new applications for these metrics. For example, the surface metric *summit density* (*Sds*) represents the number of local peaks per area. When computed for a tree height surface, *Sds* holds ecological relevance since tree height scales with tree size, indicating areas where larger trees are clustered that could signal habitat for certain species, carbon sequestration benefits, or even overall community organization (Lutz et al. 2013). For connectivity, surface metrics that have previously held little value for landscape ecology may now offer key insights. For instance, the *core fluid retention index* (*Sci*) and *valley fluid retention* (*Svi*) indices are derived from the amount of void space at different ranges of the height distribution (histogram) (Kedron et al. 2018). These metrics could be used to represent the amount of 'air space' across a landscape that might be utilized by birds, for instance, to connect between habitat areas. Ecologically, surface metrics have been difficult to interpret when applied to land cover, but they are already receiving more attention when applied to 2.5D collapsed rasters of height information (LaRue et al. 2025). Extending these foundations to connectivity assessments is an exciting opportunity area.

2.5D Stratified: With stratified data (Fig. 2, middle row), each layer can be analyzed using the same metrics and approaches as with the collapsed data, but the approach provides greater vertical resolution. For example, instead of just one layer representing forest canopy at a certain height, four strata could be created to represent the forest floor, understory, canopy, and emergent layer. Similarly, a coral reef could be partitioned vertically to capture structural complexity at different levels to guide restoration efforts (Vida et al. 2024). Connectivity within each of these layers can then be assessed to understand how different species that inhabit each layer may move through it, such as ungulates in the forest floor, amphibians in the understory, apes in the canopy, and birds in the emergent layer. The strata approach has been used to compare greenspace connectivity at different heights in an urban area (Casalegno et al. 2017), but many other applications can be envisioned.

With stratified layers, there is also an emerging opportunity to compute connectivity *across* the different strata. For instance, gorillas spend much of their time on the forest floor, but they also use the understory and canopy to forage, sleep, or escape danger. Therefore, a gorilla may traverse multiple strata during a day. There is very little, if any, research and metrics available for assessing connectivity across vertical strata. However, this can be done in the patch-based and graph-based paradigms by computing Euclidean distance between the patches or nodes in different strata and then applying the typical connectivity metrics from these approaches. For instance, the Probability of Connectivity metric (Saura and Pascual-Hortal 2007) is a graph-based measure that captures the probability that two individuals, randomly placed in the landscape, are in connected habitat areas. The metric incorporates a dispersal probability, which often takes the form of a negative exponential decay based on physical distance. Using the Euclidean distances between a node in Strata A and a node in Strata B, it is possible to measure the probability of connectivity between layers. More creatively, a non-physical measure of distance could be used (Frazier 2019), such as similarity of the horizontal heterogeneity of the two strata. Cross-strata connectivity metrics can be further parameterized using species-specific movement data gathered from the literature or GPS trajectories, allowing terms within the connectivity to be weighted accordingly.

A limitation of cross-strata metrics is that since the layers are discontinuous, any metrics measuring cross-strata connectivity can only take into account the distance (physical or otherwise) between the layers, without information on the characteristics or quality of the intermediate landscape. The strata approach simplifies the 3D morphology of the height/structure included in each layer, and so is limited in capturing vertical dispersal or movement within strata, which can be problematic if the strata are coarse. In the cotton-headed Tamarin example above, if a single strata were to include all heights from 5-30m, some areas may still not be directly reachable given the species' jumping abilities. Defining and collecting more finely-spaced strata can help fill these gaps, as can placing strata in ecologically meaningful places across the canopy, but the ecological information needed to guide these decisions is often unknown. While issues of scale in connectivity studies have been thoughtfully addressed (Calabrese and Fagan 2004), studies testing optimal strata spacing and placement would be particularly useful for informing 3D connectivity analyses at this early stage (Fig. 3), particularly to determine whether optimal strata spacing is species specific, or whether there are general spacings that can be used for multi-species studies (e.g., as for horizontal dispersal in connectivity metrics (Minor and Lookingbill 2010)).

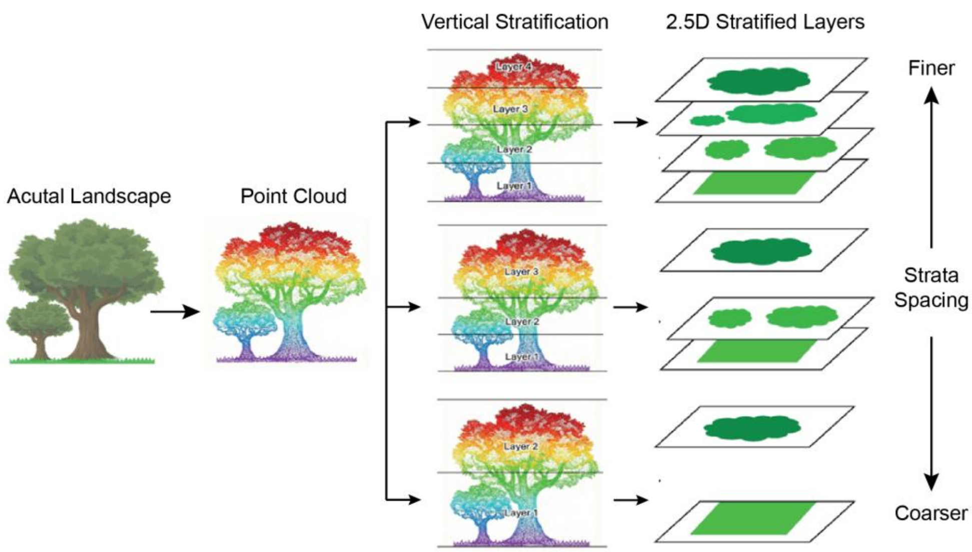

Figure 3. Example of how a single landscape can be stratified into multiple, 2.5D layers.

3D: The limitation of discontinuous strata is overcome in the fully 3D data models (Fig. 2, bottom row). For the patch-mosaic model, the raw point cloud or voxels are segmented into discrete, 3D spatial objects, which occupy space and volume. While this process can be computationally intensive, and segmentation often requires human assistance, the resulting objects can be analyzed as 3D objects. A set of 3D landscape metrics for spatial objects has been developed that includes derivations of object volume and surface area (Kedron et al. 2019; Liu et al. 2020).

Computationally, these metrics are more expensive than their 2D counterparts, but they can capture actual vertical relationships such as true, Euclidean distance between two objects in 3D space.

For 3D graph-based approaches, the objects are abstracted into nodes, and a 3D network (or a 3D embedding into a 2D network) can be constructed. In landscape ecology, 3D graphs have seen limited, if any use, but there is opportunity to learn from other fields, including neuroscience (Gleeson et al. 2007) and cell biology (Zitnik et al. 2024), where these models are being used to understand cellular structures and connections between brain regions. With 3D graphs and embeddings, it is possible to better capture the layered architecture of ecosystems and to better understand how changes in one layer could cascade to other layers through connections. For instance, modeling a forest via a 3D graph/embedding could provide predictions regarding the pathways that pests might spread from the soil, through the understory, to the canopy, providing land managers with insights into where the next, most likely invasion paths will be.

For gradient surfaces, the original surface metrics from mechanical engineering and manufacturing were designed to identify ideal bearing surfaces for holding lubricant (Stewart 1990). When they were adapted for landscape ecology (McGarigal et al. 2009), these metrics were applied to 2D and 2.5D representations, including DEMs and maps of continuous values like NDVI, rather than 3D surfaces. This imperfect translation created the difficulties mentioned above in assigning ecological relevance to many surface metrics (Kedron et al. 2018). Now that 3D landscape representations are more widely available, there is an opportunity to revisit the relevance of surface metrology metrics for landscapes, as a recent study of structural diversity across macrosystems has shown (LaRue et al. 2025) In particular, landscape ecologists should examine how metrics based on the bearing area curve can capture the full landscape structure including crown shapes and branch angles, with potential applications for movement and turbulence patterns in both land and sea.

Resistance-based approaches to connectivity

Resistance-based approaches, including least-cost path analysis (LCPA) and circuit theory among others, deserve specific mention because they are widely used for modeling landscape connectivity and identifying movement corridors (Adriaensen et al. 2003; McRae et al. 2008; Zeller et al. 2012; Diniz et al. 2020) but do not fall neatly into any of the paradigms defined above. While fundamentally based on graph theory, their inputs usually include a gradient surface, namely a resistance layer that represents the relative cost of movement or flow through the landscape. Therefore, 3D landscape information can be integrated in several ways. Since resistance layers are commonly derived from expert-based knowledge, 3D landscape information can be considered directly during this process (e.g., higher resistance values can be assigned to building height classes that exceed flight height ranges (Liu et al. 2021)). When the resistance layer is constructed using weighted overlay techniques, studies have used 2D collapsed height rasters of vegetation and buildings to compute a suite of 3D structural metrics, which are then weighted and combined into resistance layers (Kong et al. 2021). Lastly, the resistance layer can be empirically informed through species distribution models (SDM), which model habitat stability as a function of biological observations and environmental predictors. Here, either collapsed or stratified 2.5D rasters of height/structure can be included as environmental predictors in the SDM (Choi et al. 2021). However, it is important to note that the species observations that are critical for SDMs should also have 3D attributes to maximize these relationships.

It should be noted that current conceptualizations of resistance approaches assume horizontal movement and do not consider multiple vertical movement modes. For example, arboreal taxa may exhibit multiple modes of vertical movement including climbing vertically, moving laterally, or ascending/descending (e.g., via jumping). To capture these different modes, resistance rasters could be parameterized separately for each defined vertical stratum and used to generate stratum specific connectivity outputs. To the best of our knowledge, such an approach has not yet been applied to resistance layers and represents an emerging opportunity alongside patch and other gradient and graph based frameworks using a stratified approach.

Discussion and Conclusions

The uptick in availability of 3D datasets has created new opportunities for rethinking how landscape connectivity can be approached. In this Perspective, we outline a framework for computing structural connectivity across the patch-mosaic, graph-based, and gradient surface paradigms in landscape ecology, laying out nine different ways in which '3D' data can be manipulated and considered for connectivity measurements (Fig. 2). These nine ways are not meant to be exhaustive but rather structure how landscape connectivity assessments may be conducted and compared. As more 3D connectivity research emerges, we urge researchers to be explicit about the way in which 3D data models are being incorporated into metrics and how those decisions might impact any findings.

While the illustrative examples provided were small scale, there are many applications where these concepts can be applied at landscape scales. For example, quantifying the 3D connectivity of flammable vegetation across both urban and wildland environments could help better predict fire spread, which is of growing concern in many ecosystems around the world. In forested environments that harbor vulnerable arboreal species, 3D connectivity could be assessed at large scales to identify optimal locations to build canopy bridges to facilitate movement and dispersal while keeping species in their preferred habitat. In marine environments, 3D connectivity could be used to better understand nutrient flows and habitat linkages to optimize the network of marine protected areas worldwide. More generally, the incorporation of vertical landscape structure and 3D connectivity is especially relevant for understanding general species movement processes, including the behavioral and functional needs of organisms, which are the focus of movement ecology. These topics are of growing importance as climates shift, driving large-scale species migrations, and coupling the structural concepts put forth here with functional connectivity needs is a natural next step.

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