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METHODOLOGICAL DEVELOPMENTS IN LANDSCAPE ECOLOGY AND RELATED FIELDS (M-J FORTIN, SECTION EDITOR)

Remote Sensing's Recent and Future Contributions to Landscape Ecology

Morgan A. Crowley [1] · Jeffrey A. Cardille [1]

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Abstract

Purpose of Review The purpose of this article is to review landscape ecology research from the past 5 years to identify past and future contributions from remote sensing to landscape ecology.

Recent Findings Recent studies in landscape ecology have employed advances made in remote sensing. These include the use of reliable and open datasets derived from remote sensing, the availability of new sources for freely available satellite imagery, and machine-learning image classification techniques for classifying land cover types. Remote sensing data sources and methods have been used in landscape ecology to examine landscape structure. Additionally, these data sources and methods have been used to analyze landscape function including the effects of landscape structure and landscape change on biodiversity and population dynamics. Lastly, remote sensing data sources and methods have been used to analyze historical landscape changes and to simulate future landscape changes.

Summary The ongoing integration of remote sensing analyses in landscape ecology will depend on continued accessibility of free imagery from satellite sources and open-access data-analysis software, analyses spanning multiple spatial and temporal scales, and novel land cover classification techniques that produce accurate and reliable land cover data. Continuing advances in remote sensing can help to address new landscape ecology research questions, enabling analyses that incorporate information that ranges from ground-based field samples of organisms to satellite-collected remote sensing data.

Keywords Landscape ecology · Remote sensing · Multi-scale · Open access · Data fusion · Machine learning

Introduction

In the last 5 years, landscape ecologists have continued their seminal focus on the relationships of pattern and process [1], addressing questions of landscape structure, landscape function, and landscape change [2]. For example, recent studies have analyzed landscape structure by examining urban green cover, rangeland distribution, wetland extent [3–6], fragmentation of forests [7], land cover and land use [8–10], and heterogeneity of urban and agricultural landscapes [11–14]. For relating landscape structure to ecological processes, studies have focused on habitat and resource selection by plants and animals [15–18], forest dynamics and structure [19], and pollination on agricultural lands [20, 21]. For analyzing the movement across landscapes, analyses have explored movement related to corridors and connectivity [22–27] and movement of species populations related to metapopulation dynamics using genetics to track reproduction and population dispersal across generations [28, 29]. For quantifying landscape change, recent studies have used landscape history to analyze disturbances such as fire and their impacts on landscape structure over time [30–33]. By analyzing prior landscape changes, other landscape ecologists have also worked towards predicting changes in landscape structure and evaluating potential impacts through system feedbacks and potential changes in land planning by using simulation models [34–53, 54••, 55, 56•].

Many of these studies in landscape ecology have relied on contributions from the field of remote sensing. Since the launch of the satellite Landsat-1 MSS in 1972, a variety of remote sensing platforms (e.g. satellite, aerial) have collected

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✉ Morgan A. Crowley
morgan.crowley@mail.mcgill.ca

[1] Department of Natural Resource Sciences, McGill University, 21,111 Lakeshore Road, Sainte-Anne-de-Bellevue, Québec, Canada

data in the form of image observations. Each sensor gathers imagery at a pre-defined spatial resolution, which denotes the ground measurement that each pixel represents in an image. Spectral resolutions vary based on the wavelength intervals that the sensors are collecting reflectance of the sun on the earth's surface. The temporal resolution of a given remote sensing platform is derived from its orbital path and speed, which determines the satellite's revisit rate for collecting a new image in the same location. Sensors currently in operation include optical sensors from NASA's Landsat program, optical and synthetic aperture radar (SAR) sensors from the European Space Agency Copernicus constellation, and many other public and privately owned airborne and spaceborne systems. Researchers are able to choose their remote sensing sources based on their research questions, whether they use sources such as unmanned aerial vehicles (UAVs), active sensors like light detection and ranging (lidar), field-based spectroscopy, cross-boundary satellites [38–41]. Users can preprocess images to correct for atmospheric interferences caused by haze, clouds, or angle of the sun [42–44]. By comparing imagery and ground-based measurements, users can classify land cover types (e.g., forests, wetlands, development) to analyze the landscape structure [45–48]. Freely available remote sensing data from satellite sensors with large spatial coverage has become available in the last 10 years [49–53, 54•]. For example, in 2008, the free and open Landsat data policy was implemented, and in 2014, the first sensor from the European Space Agency's open-access Copernicus mission was launched [49–53, 55]. With increasing data availability for large-area coverage and medium spatial resolution sensors like Landsat and Sentinel, there has been a dramatic increase in research using satellite data in the last 5 years [52].

Literature Review

In this review, we examine recently published manuscripts from landscape ecology that have been made possible through advances in remote sensing. We outline recent developments in remote sensing and landscape ecology, highlighting important developments from each field to illuminate their current and approaching potential. To achieve this, we employed a systematic review of highly cited literature related to landscape ecology and remote sensing for the last 5 years, from 2014 to 2019. We identified recently published manuscripts that apply remote sensing methods in landscape ecology using Web of Science. We sorted the manuscripts by overall citation count in order to identify the most prominent contributions made within this field. We terminated our exhaustive literature search after identifying all 172 manuscripts meeting the search criteria (e.g., "landscape ecology" & "remote sensing"). The 172 manuscripts were categorized by landscape ecology research themes: landscape structure, landscape change, landscape function. For each landscape ecology theme, we identified remote sensing data sources and analyses most frequently used in landscape ecology by analyzing the author keywords (Table 1). Eleven publications were removed that were unrelated to landscape ecology or remote sensing. Additional recently published manuscripts were also incorporated into the review. Once we identified recent contributions of landscape ecology, we projected future research opportunities for landscape ecology by identifying other advances in remote sensing that might also be relevant to landscape ecology, as determined from the most frequently cited manuscripts from remote sensing in Web of Science from 2014 to 2019.

Recent Advances in Remote Sensing

Explosion of Data Diversity and Availability

The first decades of landscape ecology were characterized by a relatively data-poor setting, with only a few satellites potentially providing data and practical limits to analysis. For example, early studies in the 1970–1980s typically analyzed only one Landsat image at a time because they were expensive, had to be shipped on tapes from receiving stations, and took weeks to analyze on computers of the time period. In the last 10 years, this framework has been overturned, with hundreds of thousands of images freely available for analysis from multiple public and free remote sensing platforms [49, 51–53, 54••, 55, 56•, 57•, 58]. These new or improved platforms include those on large satellites like Landsat-8 and Sentinel-2, on airplanes, on unmanned aerial vehicles (UAVs), via small/micro/nanosatellites, and through ground-based sensor systems. Some example sensors include passive multi-spectral optical (i.e., collecting ground reflectance along the optical light spectrum divided into three to ten segments), actively collected synthetic aperture radar (SAR) (collecting return rates of wavelengths from multiple, pulsating microwave beams), thermal sensors (i.e., heat detection), hyperspectral sensors (i.e., collecting ground reflectance of the sun at ten or more segments of the light spectrum), and actively collected lidar (i.e., collecting return rates of wavelengths from a single, pulsating laser) [59–69]. Meanwhile, atmospheric noise in data is decreasing. For example, "analysis-ready" imagery and data cubes are now available for Landsat imagery, which enables users to spend less time preprocessing imagery [70, 71]. Whether launched by private companies or public agencies, remote sensing sources are increasing in spatial, spectral, and temporal resolutions of the observations [72, 73].

Emergence of Massive-Throughput Analysis Platforms

Open and free high-capacity analysis software and programs have greatly altered the potential for accessing and analyzing

Table 1 The thematic coding structure of this literature review. Each manuscript was categorized by landscape ecology theme and example keywords were extracted that related to remote sensing data sources and methods. In this table, the keywords are ordered by most frequently used for each landscape ecology theme. Landscape structure is the spatial arrangement of landscape elements, such as land cover types and forest patches. Landscape change refers to the changes in the landscape structure over time and space. Landscape function is the interactions between landscape structural elements, whether through ecological processes or energy flows, such as the interactions between animal migration routes and forest connectivity

Theme (no. of manuscripts)	Data sources (no. of manuscripts)	Remote sensing methods (no. of manuscripts)
Structure (88)	lidar (15)	canopy-height model (8)
	Landsat (14)	classification and regression tree (8)
	citizen science (6)	digital elevation model (6)
	airborne laser scanning (ALS) (4)	normalized difference vegetation index (NDVI) (6)
	hyperspectral data (4)	clustering (4)
	Unmanned aerial vehicle (UAV) (4)	random forest machine learning (4)
	aerial photography (2)	segmentation (4)
	airborne remote sensing (2)	spatiotemporal (4)
	AVIRIS (2)	support vector machine (SVM) (4)
	GeoEye-1 (2)	3D urban form (2)
	Google Street View (2)	aggregation (2)
	high-resolution satellite data (2)	image processing (2)
	historical imagery (2)	land cover classification (2)
	IKONOS (2)	maximum entropy classifier (2)
	land surface temperature (2)	multi-scale (2)
	MODIS (2)	object-based image analysis (OBIA) (2)
	PhenoCam dataset (2)	spectral unmixing (2)
	RapidEye (2)	spectral variable selection (2)
	participatory science (2)	structure-from-motion (SFM) (2)
	TerraSAR-X (2)	tree species classification (2)
	Shuttle Radar Topography Mission (SRTM) (1)	
Change (42)	Landsat (7)	spatiotemporal (3)
	MODIS (2)	change detection (1)
	participatory mapping (2)	landscape accuracy metric (1)
	historical map (1)	NDVI (1)
	lidar (1)	OBIA (1)
	multi-source satellite images (1)	random forest machine learning (1)
	PhenoCam (1)	segmentation (1)
	time series (1)	
Function (46)	lidar (4)	enhanced vegetation index (EVI) (2)
	land surface temperature (2)	NDVI (2)
	airborne remote sensing (1)	change detection (1)
	AVIRIS (1)	differenced normalized burn ratio (1)
	citizen science (1)	digital elevation model (1)
	microsatellites (1)	downscaling (1)
	MODIS (1)	maximum entropy classifier (1)
	National Land Cover Dataset (NLCD) (1)	random forest machine learning (1)
	participatory mapping (1)	radar (1)
	WorldView-2 (1)	VIIRS (1)

time series of imagery and combining data from different remote sensing sources to better understand landscape structure [51, 52, 56•, 57•]. Most notably, the cloud-based storage and processing platform, Google Earth Engine, was first released in 2010 to increase accessibility to remote sensing and geospatial data using Google servers. Prior to this, the only option for many landscape ecologists wishing to use remotely sensed data was to download individual images and analyze them on local computers or networked clusters [54••, 56•]. Cloud-based platforms facilitate aggregation of remotely sensed observations of a landscape collected on different dates into a temporally ordered data “stack” or “cube.” Changes in landscape structures due to natural and human disturbances can then be quantified over time [74–78]. Combining remote sensing observations from different sensors can also provide multi-scale views (i.e., varying spatial and temporal resolutions and extents in time and space) (Table 2) [54••, 56•, 79–81]. Recent studies have combined observations from multiple remote sensing sources such as the USGS's Landsat satellite and NASA's MODIS satellite [82–85]; Landsat and synthetic aperture radar (SAR) [86]; airborne laser scanning (e.g., lidar) and digital aerial photogrammetric data (e.g., aerial photographs) [87, 88]; unmanned aerial vehicles (UAVs) and digital aerial photogrammetric data [89]; UAV, aerial, and satellite [90]; lidar and Landsat [91, 92].

Development of Algorithms for Large-scale Image Classifications

A primary focus of remote sensing research is to develop methods for converting remotely sensed data into a meaningful description or picture of what is actually on the ground. This is referred to as "classification" of the remotely sensed data. Several recent advances have greatly improved algorithms used in classification [54•, 56••, 93]. For example, object-based image classifications group neighboring pixels into objects and classify the objects based on their shape, size, color, texture (spatial variation), and context (neighboring or ancillary information) [94, 95]. Machine/deep learning approaches (e.g., convolutional neural networks, random forests) are automated classification algorithms that rely on minimal user interference when classifying imagery [59, 63, 72, 96–101]. Additionally, time-series analyses have been used to map land cover changes by stacking images from multiple sources and identifying disturbance patterns and deviations from expected values [69, 74, 102–113]. This allows the rapid detection of landscape change and disturbances like forest loss and fires. Time-series analyses have created reliable global-scale landscape change datasets that are freely available for subsequent analyses [114–118]. For example, a regularly updated forest cover dataset including landscape changes and drivers of changes is available annually for the entire globe [119, 120]. Additionally, the World Resources Institute's Global Forest Watch initiative detects forest changes globally in near real time [121]. Other recent studies have used time-series analyses, machine learning, and object-based image analyses to analyze land surface temperatures and identify urban heat islands [122], to provide increased data to support forest inventory efforts [66], to map landscape changes related to climate change [123], to inform precision agriculture [124], to monitor air pollution [125], to quantify colored dissolved organic matter in lakes [126], to quantify aboveground biomass [127], and to track urbanization [128].

Advances in Landscape Ecology Using Remote Sensing

Landscape ecologists use remote sensing for three principal reasons: (1) to quantify landscape structure based on classified imagery; (2) to identify landscape change and its impact and make future predictions using statistical models; and (3) to quantify landscape function. Landscape structure is the spatial arrangement of landscape elements, such as land cover types and forest patches. Landscape change refers to the changes in the landscape structure over time and space. Landscape function is the interactions between landscape structural elements, whether through ecological processes or energy flows, such as the interactions between animal migration routes and forest connectivity.

Quantifying Landscape Structure

Remote sensing observations provide the potential to map and analyze landscape structure at a variety of spatial and temporal grains and extents. Landscape ecologists analyze both raw

Table 2 In the first column, we identified possible scale requirements (both spatial and temporal grain and extents) for landscape ecology research. In the second column, we named presently available remote sensing sources that meet those scale requirements. In the third column, we present example studies that use those sources in their analyses. Landsat is a satellite mission from the USGS consisting of multiple sensors that have been launched since 1972, including the Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI). MODIS (Moderate Resolution Imaging Spectroradiometer) is a sensor from NASA that is mounted on two satellites, Terra and Aqua. Sentinel-2 is a European Space Agency mission consisting of two satellites, Sentinel-2A and Sentinel-2B. Planet Labs is a satellite company that has multiple satellites in orbit, including Dove, RapidEye, and SkySat. Unmanned aerial vehicles (UAVs or drones) are useful for mapping small extents at a fine resolution with a mounted sensor on board

Scale required	Best sensors at required scale	Example studies
Fine spatial grain	10 cm–1 m ("Planet Labs" satellites, UAV, airplane)	[38, 45, 48, 93, 183]
Fine temporal grain	Every ~5 days at 10–60 m (Sentinel-2), and daily at 250 m (MODIS)	[67, 69, 78, 95, 112]
Large spatial extent	Global and daily at 250 m (MODIS)	[69, 78, 83, 95]
Long temporal extent	1972 to present, every 16 days at 30–60 m (Landsat MSS, TM, ETM+, OLI)	[53, 91, 106, 122, 132]

remote sensing data and remote sensing-derived maps to quantify landscape structure. For example, by harmonizing airborne lidar and satellite imagery, researchers were able to quantify structural connectivity and identify patches that were most important for landscape-level conservation in Alberta, Canada [129]. Landscape ecologists have extracted landscape-based information using a variety of remote sensing spectral vegetation indices (e.g., tasseled cap, leaf area index, normalized difference vegetation index (NDVI)) [130–132]. In Finland, researchers combined data collected by citizen scientists (e.g., landowners, students, recreationalists) with lidar-derived forest measurements to quantify landscape structure [133]. Additionally, landscape structure has frequently been quantified using open-source toolboxes designed to process remote sensing data [134–137]. The wide range of applications employing landscape-scale analyses has been made possible from the increasing availability of remote sensing sources and advances in imagery analyses (Table 3).

Future Prospects

Advances in methods for quantifying landscape structure will mirror advances made in remote sensing for image classification due to the direct relationship between a landscape's surface cover and its structure. As data diversity and availability continue to grow, information from remote sensing data seems poised to make novel advances within landscape ecology in the near future. For example, opportunities exist for increasing landscape-scale analyses focusing on biomass analyses and vegetation structure using data from the recently launched and future active sensors (e.g., NISAR, GEDI, BIOMASS, MOLI, SAOCOM1A, ICESat-2, ALOS-4, TanDEM-L, RADARSAT Constellation Mission) [138]. Additional opportunities will be created to use the finer spatial and temporal resolutions that will be provided by future optical satellites that are being built (e.g., Landsat 9, Sentinel constellation). While many landscape ecology studies take advantage of remote sensing observations collected by aerial and satellite sources, future studies can use observations from novel data sources like UAVs and microsatellites (i.e., small satellites from companies like DigitalGlobe and Planet) for very high spatial resolution observations of fine-scale landscape features [139], hyperspectral sensors for greater spectral sensitivity when using raw remote sensing values in landscape ecology models [140], and synthetic aperture radar (SAR) sensors and lidar sensors for reconstructing three-dimensional landscape structure and analyzing connectivity [141–143]. Landscape structure can be quantified by using feature extraction techniques and machine-learning classifiers to improve the accuracy of image classifications [80, 144, 145]. By quantifying landscape structure on a cloud-based processing platform like Google Earth Engine [57•], large-area landscape ecology structural analyses become more tenable and it will no longer be necessary to download new imagery to personal computers.

Quantifying Landscape Change

Landscape ecology studies use remote sensing images from multiple collection dates to identify landscape change, to analyze their impacts on populations, and to predict future landscape change. Satellite-based time-series data (whether from one sensor or many) provide observations spanning multiple decades of landscape change such as cumulative forest cover decline, recovery of forest species from disturbances, degradation of forest patches, and land-use change [130, 132, 146–152]. Researchers applied a temporal trend analysis of Landsat TM time-series imagery and vegetation indices from 1987 to 2010 to map gradual and abrupt forest decline and regrowth in Québec, Canada, and inform land management policy [132]. Another study integrated multi-source imagery from NASA's Landsat MSS, TM, ETM+, the Russian KATE-200 satellite camera, and satellite Keyhole imagery to identify regions for management by evaluating the relationship between oasis changes and landscape structure in an arid region of China from 1963 to 2010 [148]. Remote sensing data has also been incorporated into existing landscape ecology simulations to model stochastic dynamics of landscape structure elements, and in turn, landscape function. For example, landscape ecologists have used remote sensing-based data to predict rates and patterns of urban expansion over time [153], to quantify landscape structure and ecosystem service changes in urban areas [154, 155], and to simulate changes in soil organic carbon due to changing climate [156]. Observations from remote sensing platforms enable landscape ecologists to reconstruct landscape history for analyzing landscape changes and to inform predictive models for landscape changes.

Future Prospects

As the temporal revisit rate of satellite image observations gets shorter, landscape ecologists will be able to see landscape changes as they happen in near real time, whether they are persistent (e.g., fire), ephemeral (e.g., floods), or gradual (e.g., forest degradation) [157–159]. Increased data frequency will be useful for analyzing landscape changes at daily or monthly resolutions rather than only annual resolutions. Additionally, by accessing publicly available near-real-time global datasets that map land cover changes using cloud-based platforms like Google Earth Engine, landscape ecologists will be able to perform their own analyses more rapidly without developing their own image classification protocols. Multi-temporal landscape analyses of the same landscape or analyses comparing different landscapes will become increasingly accessible by employing data fusion methods to combine observations from multiple sensors and weighing the evidence from each

Table 3 A review of novel remote sensing techniques that were applied in landscape ecology studies and some results that contributed to the field of landscape ecology

Remote sensing advance	Use in landscape ecology	Research finding	Reference
Regional airborne lidar data	Quantified structural habitat connectivity and simulate changes	Identified most important patches for landscape conservation in Alberta, Canada	[129]
Multiple data sources with varying spatial and thematic resolution	Predicted seasonal land surface temperatures	Determined strong predictors of land surface temperatures to include percent of impervious surfaces, percent of tree canopy from spring to fall, and vegetative-based indices from summer to fall	[131]
Multiple data sources from ground observations and airborne lidar	Quantified aboveground forest biomass and vegetation structure	Identified spatially explicit biodiversity indicators for bird habitats for 41 different species in boreal forest regions	[133]
Refining spatial resolution from remote sensing sources	Examined landscape surface metrics at a higher spatial resolution to assess scale-dependent relationships	Found that map accuracy for data aggregation of sub-pixel remote sensing classifications was dependent on spatial heterogeneity of the landscape	[136]
Synthetic aperture radar (SAR) data sources	Calculated resistance maps for habitat connectivity	Found that SAR-based maps explained more of the species abundance for forest beetles than aerial photograph-based maps	[141]
Active (lidar) and passive (AVIRIS) aerial sensors	Modeled vegetation structure and historical land use	Determined that topography and substrate type impacted vegetation distribution, and grazing intensity/ranges predicted vegetation patterns on Santa Cruz Island, USA	[142]
Data fusion of imagery from multiple spaceborne sources	Mapped and quantified spatiotemporal landscape mosaic patterns	Found that water use, land development policies, urbanization, and agricultural technological advances caused oasis conversions in arid regions of China from 1962 to 2010	[148]
Multiple data sources from ground samples and MODIS time-series data	Quantified the temporal and spatial patterns of land-use regime shifts	Identified that regime shifts were caused by livestock/pasture privatization and installment iron fences in Qinghai-Tibetan Plateau using oral histories and GIS data	[150]
Multi-temporal satellite analysis	Quantified land cover change and calculated landscape composition and configuration	Found that an abandoned mine landscape was less heterogeneous with fewer dense conifer patches and more bare patches than a comparison protected site over 20 years in the Northwest Territories, Canada	[160]
High-resolution radar and lidar data	Mapped vegetative structure and modeled dispersal barriers of population structure using Circuitscape connectivity software	Determined that higher elevations in the Amazon rainforest were related to larger genetic distances between macaw individuals due to mountain ridges limiting gene flows	[182]
Multiple data sources from ground observations and remote sensing–derived land cover data	Identified relationships between land cover classes and reptile roadkills using a hotspot analysis	Identified hotspots of amphibian/reptile deaths near arable land, suburban areas, and vineyards using freely available remote sensing data in eastern Austria	[184]
Satellite time-series data	Analyzed multi-temporal landscape mosaic patterns	Identified changes in coverage and pattern of six dominant tree species in Saskatchewan, Canada	[185]
Long-term remote sensing time-series dataset	Compared models for calculating landscape connectivity between scenario models and a 25-year surface water time series	Found that scenario-derived connectivity models were less effective than remote sensing–derived time series for identifying important areas for connectivity in south-eastern Australia	[186]

classification [54••, 129, 160–162]. Such analyses have been previously difficult for landscape ecology due to data collection limitations and financial costs of imagery. However, open-access satellites provide multi-scale views for free [37, 163]. Robust predictive models that are able to include remote sensing classifications derived from multiple sources or classifications with continuous values (e.g., forest quality on a continuous scale rather than discrete classes) will be useful for incorporating future data sources more readily into existing landscape ecology models.

Understanding Landscape Function

Landscape ecologists can analyze landscape function of the study area by combining information derived from remote sensing with information from other sources into landscape ecology models. For example, satellite-derived ecosystem service indicators (e.g., water quality, soil moisture, and soil erosion) can be analyzed in combination with land cover information (e.g., wetland area) to estimate ecosystem service provisioning [164, 165]. Habitat classifications identifying population preferences and vulnerability related to landscape change, and primary productivity related to spatial distributions of species have been assessed using object-based classifications and random forest machine-learning algorithms of satellite data, vegetation structural observations provided by lidar data, and gross primary productivity values derived from the enhanced vegetation index [139, 143, 145, 166, 167]. By fusing spectral indices like NDVI with vegetative structural information provided by lidar and topographical information derived from SAR observations, human impacts on vegetation patterns and environmental gradients can be analyzed [142]. Research focusing on urban landscape ecology has analyzed remote sensing data like land surface temperature products to examine the relationship between land surface temperature and land cover/use [168–170]. By incorporating remote sensing data like the National Land Cover Database, NDVI, and Landsat 7 ETM+ observations with land surface temperatures, the urban heat island effect can be analyzed and used to predict future land surface temperatures [131].

Future Prospects

For analyzing landscape function, advances will be made in landscape ecology by using new remote sensing data sources and analyses to quantify interactions between landscape structure and ecological processes (e.g., land cover type and population movement). Calls have been made to shift habitat assessments from categorical indices (e.g., low, medium, and high) to continuous values (e.g., 0–100) to better evaluate impacts of landscape change on biodiversity and incorporate error quantification into landscape ecology models [115, 171•, 172]. This shift towards continuous values would capitalize on advances made in remote sensing for classifying gradients of sub-pixel land cover and forest quality, per-pixel confidences in classification, and data uncertainty measurements [147, 171•, 172–174]. New sensors like GEDI and continuous data such as forest quality can provide more functional information about the landscape in terms of species distribution, resource distribution, and three-dimensional habitat connectivity [175]. Landscape ecology studies that incorporate remote sensing images can also incorporate data from non-remote sensing sources like crowdsourcing, participatory research, and other existing geospatial datasets [54••, 56•, 176–178]. For example, landscape ecologists can incorporate geolocations of bird sightings collected by citizen scientists in eBird (eBird.org) in combination with vertical vegetative structure data from lidar to improve models analyzing species distribution or biodiversity. Additionally, the fusion of data and imagery from multiple sources can increase spatial, temporal, and spectral resolutions by updating the data cube with the finest resolution data available to better analyze landscape processes [54•, 112, 179–181]. For example, often genetic and metapopulation studies examine landscape changes that occur at scales finer than landscape changes captured by medium-resolution satellites like Landsat. Therefore, there is an opportunity to assimilate very high spatial resolution remote sensing data from microsatellites and UAVs or temporally fine-scale satellite time series to analyze metapopulation dynamics [182].

Conclusions

The advances that have been made in landscape ecology using remote sensing can inform future opportunities for integrating remote sensing in landscape ecology studies. Landscape ecology has made advances in quantifying landscape connectivity, using genetics to analyze metapopulation dynamics, examining multi-functional and social-ecological systems, simulating future landscape changes, and establishing landscape histories to inform and model future landscape changes. These advances have been made possible in part due to remote sensing including the production of reliable land cover datasets that use new data sources, time series of remotely sensed data and three-dimensional data, machine-learning classification techniques, and free data accessibility. Within landscape ecology, remote sensing images and analyses have been applied to construct multi-scale, multi-temporal, and multi-source landscape-scale analyses.

Upcoming data sources will be used to estimate functional attributes of a landscape such as interactions between landscape elements and ecological processes, which can then be integrated into existing landscape ecology models that relate landscape structure or landscape change to ecological responses like species diversity. Remote sensing–derived data can either inform the landscape structure and landscape change or the ecological responses, depending on research objectives and data availability. The fusion of remote sensing observations from multiple sources into data cubes can increase temporal and spatial resolutions without trading off spatial extent coverage. Near-real-time monitoring provided by open-access satellite sensors can provide landscapes pre and post-change at the time steps necessary to evaluate impacts on ecosystem processes. Ultimately, these advances in data sources at varying scales and resolutions from very high-resolution to large-area coverage enable landscape ecology analyses that can be produced more rapidly, for larger study regions, and for longer study periods.

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Compliance with Ethical Standards

Conflict of Interest Morgan Crowley and Jeffrey Cardille declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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