Remote sensing in landscape ecology

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The Allerton Park workshop essentially defined landscape ecology as a field of study that cuts across multiple natural and social sciences (Wu, 2013). The report on the workshop (Risser et al., 1984) highlighted landscape ecology to have a core focus on spatiotemporal patterns that exist in the landscape and to be highly inter-disciplinary. A key focus of the field is on spatial heterogeneity, including how it emerges and evolves, how this spatial heterogeneity influences processes, and how humans manage the landscape. Scale and scaling issues were also emphasised in the report. In particular, it was highlighted that the relationships between ecological processes and the spatial patterns in a landscape are not confined to a particular scale and so there is often a desire to study over a range of scales. It was also recognised that there was a need to acquire, manage, and use large data sets. This pointed to the need for adequate computing facilities and also awareness of the potential of remote sensing as a source of relevant spatiotemporal data and Geographical Information Systems (GIS) as a tool to allow landscape ecology to progress (Risser et al., 1984). These various issues clearly indicate that remote sensing and allied technologies are viewed as an important component of the subject. Indeed, remote sensing is seen as a foundation of landscape ecology (Wickham and Riitters, 2019). Now, 40 years after the workshop, the key aim here is explore recent trends in the use of remote sensing in landscape ecology.

Uses of remote sensing in landscape ecology

Wiens (2008) commented on the vast progress made in the first 25 years since the workshop. In particular, it was noted that remote sensing was offering data at levels that would have been unimaginable at the time of the workshop in 1983. Additionally, the associated toolbox for analysing geospatial data sets had vastly expanded to help address key questions of interest (Wiens, 2008). Technological developments in remote sensing and GIS have continued and were highlighted in a later editorial in this journal by Risser and Iverson (2013). It is now 40 years since the Allerton Park workshop, and the place and role of remote sensing in landscape ecology has continued to evolve. These developments are evident in the content published in *Landscape Ecology* since the last relevant commentary by Wu (2013).

As expected, the core focus of recent articles in the journal that used remote sensing remains on spatial patterns and issues of heterogeneity with scaling issues often of considerable interest (Frazier, 2014; Luan et al., 2018; Egerer et al., 2020; Rudge et al., 2022; Mondal and Jeganathan, 2022; Gann and Richards, 2023). Many articles have made use of Landsat sensor data (Moris et al., 2022; Hopkins et al., 2022) notably taking advantage of the relatively long time series of data that has now been formed (Zhao et al., 2015; Bost et al., 2019; Jung et al., 2020; Fisher et al., 2021; Yu et al., 2021). But numerous other sources of image data have been used. These include images from major space agency programmes such as the sensors carried on-board the Sentinel satellites (Mercier et al., 2021; Rasanen et al., 2021) as well as imagery from MODIS and ASTER sensors (Mondal and Jeganathan, 2022). There has also been growth in other sources of data. One major growth area has been the use of sensors carried on unoccupied aerial vehicles (UAVs) or drones which offer considerable flexibility for focused data acquisition (Egerer et al., 2020; Duffy et al., 2021; Borja-Martinez et al., 2022; Rudge et al., 2022; van Blerk et al., 2022). Use has also been made of data from fine spatial resolution commercial satellites such as WorldView-2 (Gann and Richards, 2023). While much of the research has used relatively conventional optical multispectral sensors, there have been studies taking advantage of developments in remote sensing technologies. These include studies that exploit the rich spectral information content that is available through hyperspectral sensing (Donovan et al., 2023).

Other parts of the electromagnetic spectrum have also been used, including active radar systems (Betbeder et al., 2017). Studies have also exploited the potential of LiDAR and hence expanded from 2D to 3D (Kedron et al., 2019; Hall et al., 2022). The addition of a temporal dimension is also possible and even global scale studies can now be undertaken at a fine temporal resolution (Pazur et al., 2021). In addition, the research community has gained from parallel developments in other subject areas. For example, advances in machine learning (Portelli, 2020; Stupariu et al., 2022; Theron et al., 2022), formation of new data streams such as citizen science (Callaghan et al., 2019), developments in positioning technology (Hadjikyriakou et al., 2020), and access to relevant and often free geo-data (Mercier et al., 2021; Piedallu et al., 2023) many of which are systematically collected in space and time (Santos et al., 2016). Moreover, the generation of a plethora of mapping software (Rudge et al., 2022) and provision of algorithmic code act to reduce the technical skill set required by researchers (Buettel et al., 2018). From these various developments it is evident that the subject is vibrant and remains interdisciplinary with much still to gain from development elsewhere, such as in engineering and computer science (Gann and Richards, 2023).

Reasons for the continued use of remote sensing in landscape ecology

The situation outlined above reflects strongly on the foundations provided by the Allerton Park workshop but also on key trends in remote sensing since 1983. Over this period, the key attributes of remote sensing that make it attractive for use in ecology (Lechner et al., 2020) have been enhanced. Indeed, trends since 1983 point to three somewhat inter-related reasons for the continued use of remote sensing in landscape ecology. These reasons are: (1) the research community is getting more of it, (2) it is getting easier to use it, and (3) it is often free or inexpensive.

At the time of the Allerton Park workshop in April 1983 the research community had access to a limited range of remotely sensed data sets. At that time, researchers were essentially constrained to data acquired by airborne systems such as aerial photography and multispectral scanners together with only limited options for satellite sensor imagery, notably from Landsat sensors and the NOAA AVHRR. There is now a lot more remotely sensed data available, and it is more in many dimensions. For example, Landsat sensors have been in continuous operation since the summer of 1972. Much effort has been expended to ensure data continuity (Wulder et al., 2019), with broadly similar data available across the entire time period but also some major enhancements. Crudely, the spectral, spatial, temporal and radiometric resolutions of key Landsat sensor data have been enhanced. So not only is it possible to use broadly similar spectral bands over time, the data have been improved in a variety of ways allowing increasingly detailed characterisation of the Earth's surface. This is further expanded by development of other satellite missions such as the constellation of Sentinel satellites. These too provide a wide range of data sets in optical to microwave wavebands which are free and openly available via Copernicus.

A wide variety of other satellite systems are available offering different features. For example, recent Gaofen satellites carried a hyperspectral sensor, the Defence Meteorological Satellite Programme provides nighttime lights imagery and the third generation of Meteosat satellites provides imagery of approximately one third of the planet's visible disc every 5 minutes. Large commercial constellations such as those operated by Planet or Capella Space offer high cadence data, allowing multiple observations per-day. The stream of data from spaceborne LiDAR systems such as GEDI flown on the International Space Station opens the door to routine study in 3 dimensions, or 4 if the temporal dimension is exploited (Duncanson et al. 2022). Airborne systems also continue as a valuable data source. Airborne hyperspectral data have, for example, been used to acquire data at different spatial resolutions to study issues of scale (Dai et al., 2022). There have also been major developments in methods to aid the use different data sets especially if containing complementary information. This includes work on fusing hyperspectral and LiDAR data (Asner et al., 2007) or to combine different data sets to get the best from each. For example, super-resolution analyses allow the formation of data series with fine spatial and temporal resolution (Li et al., 2020). In essence, it is now possible to work at spatial scales ranging from the sub-pixel to global and at a variety of temporal and spectral resolutions.

It is much easier to use remote sensing now than it was in 1983. Today there is easy access to imagery over the internet. User friendly satellite data archives for a vast array of satellite systems, including commercial systems, are available. Moreover, resources such as Copernicus not only make access to imagery simple, but also provide analysis-ready data and even data products so that specialist knowledge on extracting information from the remotely sensed data is sometimes no longer necessary. Tools for information extraction have also developed and are also often openly available for free. For example, there has been parallel development of methods for use with remotely sensed data. Classifiers, for example, have been developed from basic statistical techniques used in the 1980s through methods suited to multi-source data (Peddle et al., 1994) to machine learning methods such as random forests, support vector machines and various types of neural network (Maxwell et al., 2018). Many of these methods are also available for free, notably as R packages or other resources for use in a variety of free and open source tools (Rocchini et al., 2013; 2021). In addition, there is also sometimes no need to physically handle data sets as resources such as Google Earth Engine allow cloud based processing of a wide variety of data sets for a vast array of applications (Gorelick et al., 2017; Zhao et al., 2021). Finally, good practice advice aids extraction of relevant information from remotely sensed data for popular applications (e.g. Penman et al., 2016).

Remote sensing systems can be expensive but that need not mean the imagery acquired is costly to users. For example, Landsat 8 cost approximately US$ 1 billion but the imagery is so useful to so many that it more than pays for itself (National Research Council, 2013). Indeed the value of the imagery to many is one of the reasons behind the opening up of the whole Landsat sensor data archive, making the data available to everyone for free (Zhu et al., 2019). Similarly other satellite data sets such as those from MODIS and Sentinel are freely available to all. Other sources of remotely sensed data can also be inexpensive. UAV based sensors put the researcher in control of the data acquisition and effective use can be made of inexpensive systems. Even data from commercial systems can be relatively inexpensive, especially if the data already archived and the test site small. The costs of activities such as ground data collection to inform image analyses can also be reduced by increasing use of crowdsourcing, with citizens often contributing for free (Fritz et al., 2017).

Prospects of remote sensing in landscape ecology

Remote sensing is likely to continue to play a major role in future research in landscape ecology. Satellite remote sensing systems, for example, are set to evolve further. This ranges from incremental advances associated with the continuation of the Landsat satellites with Landsat Next in development through new opportunities associated with the enhanced set of wavebands it will offer to the exploitation of data from completely new satellites such as Hotsat. The latter should offer relatively fine spatial resolution thermal infrared imagery providing the opportunity to expand the study of the thermal environment. There are many other satellite systems in development that should provide new data streams (e.g. video). Increasing use may be made of data from unusual sources. For example, vehicular dashcams and CCTV offer a rich source of local environmental information beyond their planned application (Morris et al., 2013: Boyd et al., 2022). The use of these different but often complimentary data streams may be enhanced by developments in techniques for the analysis of multi-modal data. Parallel developments in other diverse areas from artificial intelligence through quantum sensing and computing through to citizen science may also benefit studies that use remotely sensed data, especially if current challenges can be addressed (Basiri et al., 2019; Yuan et al., 2020; Claramunt and Lotfian, 2023). Developments in other forms of sensing, such as of sound and smell, may also help ensure richer characterisation of the environment. Current trends, such as the transition from change detection to near real time environmental monitoring (Woodcock et al., 2019) may be enhanced further by technological advances such as increased on platform data processing.

The various exciting developments and opportunities may also come with some new challenges. These may range from methodological problems to concerns on ethical and legal issues. Also, while the requirement for specialist remote sensing expertise may be reduced, it is unlikely to disappear. For example, while UAVs have revolutionised much research activity some specialist knowledge may be useful. Much work with UAVs has, for example, focused on relatively simple applications such as target detection. However, if this extends to richer assessments, such as the biochemical and biophysical characterisation of vegetation, then there are issues a non-expert may not be aware of that could substantially degrade a study if not addressed. Detailed characterisation of vegetation by remote sensing requires care on key issues such as the planning of flight lines and timing of image acquisition especially with regard to the angular geometry between the Sun, target and sensor that modulates the spectral response. Also the spectral and radiometric properties of sensors carried on UAVs are a concern and impact greatly on issues such as estimation of a vegetation index and the radiometric calibration of the images that is often an essential pre-processing task (Coburn et al., 2018). The fine spatial detail of imagery obtained from sensors carried by UAVs has been a virtue in many studies, but could turn into a vice. For example, amateurs may not realise that spatially degrading the extremely fine spatial resolution imagery acquired could enhance the data for popular applications. It would, for example, act to reduce intra-class spectral mixing that could reduce the accuracy of some analyses. Specialists in remote sensing and other subject areas will, therefore, remain important to landscape ecology. Continued inter-disciplinarity will help ensure that landscape ecology can maximally gain from remote sensing.

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References

Asner, G.P., Knapp, D.E., Kennedy-Bowdoin, T. et al. (2007) Carnegie airborne observatory: in-flight fusion of hyperspectral imaging and waveform light detection and ranging for three-dimensional studies of ecosystems. Journal of Applied Remote Sensing, 1: p.013536.

Basiri, A., Haklay, M., Foody, G. et al., (2019) Crowdsourced geospatial data quality: Challenges and future directions. International Journal of Geographical Information Science, 33:1588-93.

Betbeder, J., Laslier, M., Hubert-Moy, L. et al. (2017) Synthetic aperture radar (SAR) images improve habitat suitability models. Landscape Ecol 32: 1867–1879. https://doi.org/10.1007/s10980-017-0546-3

Borja-Martínez, G., Tapia-Flores, D., Shafer, A.B.A. et al. (2022) Highland forest's environmental complexity drives landscape genomics and connectivity of the rodent Peromyscus melanotis. Landscape Ecol 37: 1653–1671. https://doi.org/10.1007/s10980-022-01428-6

Bost, D.S., Reilly, M.J., Jules, E.S. et al. (2019) Assessing spatial and temporal patterns of canopy decline across a diverse montane landscape in the Klamath Mountains, CA, USA using a 30-year Landsat time series. Landscape Ecol 34: 2599–2614. https://doi.org/10.1007/s10980-019-00907-7

Boyd, D.S., Crudge, S., Foody, G. (2022) Towards an automated approach for monitoring tree phenology using vehicle dashcams in urban environments. Sensors, 22: p.7672.

Buettel, J.C., Ondei, S., Brook, B.W. (2018) A practical method for creating a digital topographic surface for ecological plots using ground-based measurements. Landscape Ecol 33: 9–18. https://doi.org/10.1007/s10980-017-0598-4

Callaghan, C.T., Bino, G., Major, R.E. et al. (2019) Heterogeneous urban green areas are bird diversity hotspots: insights using continental-scale citizen science data. Landscape Ecol 34: 1231–1246. https://doi.org/10.1007/s10980-019-00851-6

Claramunt, C., Lotfian, M. (2023) Geomatics in the era of citizen science. Geomatics, 3:364-366.

Coburn, C.A., Smith, A.M., Logie, G.S. et al., (2018) Radiometric and spectral comparison of inexpensive camera systems used for remote sensing. International Journal of Remote Sensing, 18:39:4869-90.

Dai, J., Vaughn, N.R., Seeley, M. et al. (2022) Spectral dimensionality of imaging spectroscopy data over diverse landscapes and spatial resolutions. Journal of Applied Remote Sensing, 16: p.044518.

Donovan, M.K., Alves, C., Burns, J. et al. (2023) From polyps to pixels: understanding coral reef resilience to local and global change across scales. Landscape Ecology, 38:737-752.

Duffy, J.P., Anderson, K., Fawcett, D. et al. (2021) Drones provide spatial and volumetric data to deliver new insights into microclimate modelling. Landscape Ecol 36: 685–702. https://doi.org/10.1007/s10980-020-01180-9

Duncanson, L., Kellner, J.R., Armston, J. et al. (2022) Aboveground biomass density models for NASA's Global Ecosystem Dynamics Investigation (GEDI) lidar mission. Remote Sensing of Environment, 270: p.112845.

Egerer, M.H., Wagner, B., Lin, B.B. et al. (2020) New methods of spatial analysis in urban gardens inform future vegetation surveying. Landscape Ecol 35: 761–778. https://doi.org/10.1007/s10980-020-00974-1

Frazier, A.E. (2014) A new data aggregation technique to improve landscape metric downscaling. Landscape Ecol 29: 1261–1276. https://doi.org/10.1007/s10980-014-0066-3

Fisher, A.G., Mills, C.H., Lyons, M. et al. (2021) Remote sensing of trophic cascades: multi-temporal landsat imagery reveals vegetation change driven by the removal of an apex predator. Landscape Ecol 36: 1341–1358. https://doi.org/10.1007/s10980-021-01206-w

Fritz, S., Fonte, C.C. and See, L. (2017). The role of citizen science in earth observation. Remote Sensing, 9: p.357.

Gann, D., Richards, J. (2023) Scaling of classification systems—effects of class precision on detection accuracy from medium resolution multispectral data. Landscape Ecol 38: 659–687. https://doi.org/10.1007/s10980-022-01546-1

Gorelick, N., Hancher, M., Dixon, M. et al. (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment, 202: 18-27.

Hadjikyriakou, T.G., Kassara, C., de Roland, LA.R. et al. (2020) Phenology, variation in habitat use, and daily activity patterns of Eleonora's falcon overwintering in Madagascar. Landscape Ecol 35: 159–172. https://doi.org/10.1007/s10980-019-00940-6

Hall, J.S., Plisinski, J.S., Mladinich, S.K. et al. (2022) Deforestation scenarios show the importance of secondary forest for meeting Panama's carbon goals. Landscape Ecol 37: 673–694. https://doi.org/10.1007/s10980-021-01379-4

Hopkins, L.M., Hallman, T.A., Kilbride, J. et al. (2022) A comparison of remotely sensed environmental predictors for avian distributions. Landscape Ecol 37: 997–1016. https://doi.org/10.1007/s10980-022-01406-y

Jung, M., Scharlemann, J.P.W., Rowhani, P. (2020) Landscape-wide changes in land use and land cover correlate with, but rarely explain local biodiversity change. Landscape Ecol 35: 2255–2273. https://doi.org/10.1007/s10980-020-01109-2

Kedron, P., Zhao, Y., Frazier, A.E. (2019) Three dimensional (3D) spatial metrics for objects. Landscape Ecol 34: 2123–2132. https://doi.org/10.1007/s10980-019-00861-4

Lechner A.M., Foody G.M., Boyd, D.S. (2020) Applications in remote sensing to forest ecology and management. One Earth, 2: 405-12.

Li X., Foody G.M., Boyd, D.S. (2020) SFSDAF: An enhanced FSDAF that incorporates sub-pixel class fraction change information for spatio-temporal image fusion. Remote Sensing of Environment, 237:111537.

Luan, X., Buyantuev, A., Baur, A.H. et al. (2018) Linking greenhouse gas emissions to urban landscape structure: the relevance of spatial and thematic resolutions of land use/cover data. Landscape Ecol 33: 1211–1224. https://doi.org/10.1007/s10980-018-0661-9

Maxwell, A.E., Warner, T.A. and Fang, F., (2018). Implementation of machine-learning classification in remote sensing: An applied review. International Journal of Remote Sensing, 39: 2784-2817.

Mercier, A., Hubert-Moy, L., Baudry, J. (2021) Sentinel-2 images reveal functional biophysical heterogeneities in crop mosaics. Landscape Ecol 36: 3607–3628. https://doi.org/10.1007/s10980-021-01331-6

Mondal, S., Jeganathan, C. (2022) Effect of scale, landscape heterogeneity and terrain complexity on agriculture mapping accuracy from time-series NDVI in the Western-Himalaya region. Landscape Ecol 37: 2757–2781. https://doi.org/10.1007/s10980-022-01533-6

Moris, J.V., Reilly, M.J., Yang, Z. et al. (2022) Using a trait-based approach to asses fire resistance in forest landscapes of the Inland Northwest, USA. Landscape Ecol 37: 2149–2164. https://doi.org/10.1007/s10980-022-01478-w

Morris, D.E., Boyd, D.S., Crowe, J.A. et al. (2013) Exploring the potential for automatic extraction of vegetation phenological metrics from traffic webcams. Remote Sensing, 5: 2200-2218.

National Research Council, 2013. Landsat and beyond: Sustaining and enhancing the Nation's Land Imaging Program. The National Academies Press, Washington D.C.

Pazúr, R., Price, B., Atkinson, P.M. (2021) Fine temporal resolution satellite sensors with global coverage: an opportunity for landscape ecologists. Landscape Ecol 36: 2199–2213. https://doi.org/10.1007/s10980-021-01303-w

Peddle, D.R., Foody, G.M., Zhang A. et al. (1994) Multi-source image classification II: An empirical comparison of evidential reasoning and neural network approaches. Canadian Journal of Remote Sensing, 20:396-407.

Penman, J., Green, C., Olofsson, P. et al. (2016) Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative.

Piedallu, C., Dallery, D., Bresson, C. et al. (2023) Spatial vulnerability assessment of silver fir and Norway spruce dieback driven by climate warming. Landscape Ecol 38: 341–361. https://doi.org/10.1007/s10980-022-01570-1

Portelli, R.A. (2020) Don't throw the baby out with the bathwater: reappreciating the dynamic relationship between humans, machines, and landscape images. Landscape Ecol 35: 815–822. https://doi.org/10.1007/s10980-020-00992-z

Räsänen, A., Manninen, T., Korkiakoski, M. et al. (2021) Predicting catchment-scale methane fluxes with multi-source remote sensing. Landscape Ecol 36: 1177–1195. https://doi.org/10.1007/s10980-021-01194-x

Risser, P.G., Iverson, L.R. (2013) 30 years later—landscape ecology: directions and approaches. Landscape Ecol 28: 367–369. https://doi.org/10.1007/s10980-013-9856-2

Risser, P.G., Karr, J.R., Forman, R.T.Y. (1984) Landscape Ecology: directions and approaches. Illinois Natural History Survey Special Publ. 2, Champaign, Illinois.

Rocchini D., Delucchi L., Bacaro G. et al. (2013) Calculating landscape diversity with information-theory based indices: A GRASS GIS solution. Ecological informatics 17:82-93.

Rocchini, D., Thouverai, E., Marcantonio, M. et al. (2021) rasterdiv—An information theory tailored R package for measuring ecosystem heterogeneity from space: To the origin and back. Methods in Ecology and Evolution 12(6):1093-102.

Rudge, M.L.M., Levick, S.R., Bartolo, R.E. et al. (2022) Developing landscape-scale forest restoration targets that embrace spatial pattern. Landscape Ecol 37: 1747–1760. https://doi.org/10.1007/s10980-022-01461-5

Stupariu, MS., Cushman, S.A., Pleşoianu, AI. et al. (2022) Machine learning in landscape ecological analysis: a review of recent approaches. Landscape Ecol 37: 1227–1250. https://doi.org/10.1007/s10980-021-01366-9

Theron, K.J., Pryke, J.S., Samways, M.J. (2022) Maintaining functional connectivity in grassland corridors between plantation forests promotes high-quality habitat and conserves range restricted grasshoppers. Landscape Ecol 37: 2081–2097. https://doi.org/10.1007/s10980-022-01471-3

van Blerk, J.J., West, A.G., Smit, J. et al. (2022) UAVs improve detection of seasonal growth responses during post-fire shrubland recovery. Landscape Ecol 37: 3179–3199. https://doi.org/10.1007/s10980-022-01535-4

Wickham, J., Riitters, K.H. (2019) Influence of high-resolution data on the assessment of forest fragmentation. Landsc Ecol 34: 2169–2182. https://doi.org/10.1007/s10980-019-00820-z

Wiens, J.A. (2008) Allerton Park 1983: the beginnings of a paradigm for landscape ecology?. Landscape Ecol 23: 125–128. https://doi.org/10.1007/s10980-008-9195-x

Woodcock, C.E., Loveland, T.R., Herold et al. (2019) Transitioning from change detection to monitoring with remote sensing: A paradigm shift. Remote Sensing of Environment, 238:111558.

Wu, J. (2013). Key concepts and research topics in landscape ecology revisited: 30 years after the Allerton Park workshop. Landscape Ecol 28: 1-11. doi:10.1007/s10980-012-9836-y

Yu, W., Zhou, W., Jing, C. et al. (2021) Quantifying highly dynamic urban landscapes: Integrating object-based image analysis with Landsat time series data. Landscape Ecol 36: 1845–1861. https://doi.org/10.1007/s10980-020-01104-7

Yuan, Q., Shen, H., Li, T. et al., (2020) Deep learning in environmental remote sensing: Achievements and challenges. Remote Sensing of Environment, 241: p.111716.

Zhao, S., Zhou, D., Zhu, C. et al. (2015) Rates and patterns of urban expansion in China's 32 major cities over the past three decades. Landscape Ecol 30: 1541–1559. https://doi.org/10.1007/s10980-015-0211-7

Zhao, Q., Yu, L., Li, X. et al., (2021) Progress and trends in the application of Google Earth and Google Earth Engine. Remote Sensing, 13: p.3778.