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Three-dimensional digital mapping of ecosystems: a new era in spatial ecology

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Three-dimensional digital mapping of ecosystems: a new era in spatial ecology

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1 **Three-dimensional digital mapping of ecosystems: a new**
2 **era in spatial ecology**

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22 **Abstract**

23 Ecological processes occur over multiple spatial, temporal and thematic scales in three-dimensional
24 ecosystems. Characterising and monitoring change in 3D structure at multiple scales is challenging
25 within the practical constraints of conventional ecological tools. Remote sensing from satellites and
26 crewed aircraft has revolutionised broad-scale spatial ecology, but fine-scale patterns and processes
27 operating at sub-metre resolution have remained understudied over continuous extents. We introduce
28 two high-resolution remote sensing tools for rapid and accurate 3D mapping in ecology – terrestrial
29 laser scanning and structure-from-motion photogrammetry. These technologies are likely to become
30 standard sampling tools for mapping and monitoring 3D ecosystem structure across currently under-
31 sampled scales. We present practical guidance in the use of the tools and address barriers to
32 widespread adoption, including testing the accuracy of structure-from-motion models for ecologists.
33 We aim to highlight a new era in spatial ecology that uses high-resolution remote sensing to
34 interrogate 3D digital ecosystems.

35

36 **Keywords:** digital ecology, ecosystem science, remote sensing, 3D mapping, terrestrial laser
37 scanning, structure-from-motion photogrammetry

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46 **Introduction**

47 Understanding how ecosystems vary in space and time underpins land- and seascape management, but
48 to be effective, accurate and comprehensive information must be captured across multiple scales. Our
49 knowledge of ecosystems represents decades of observations by ecologists using field equipment like
50 quadrats, to capture biological information, and theodolites or satellite positioning systems (e.g. GPS)
51 to record habitat topography. Direct observation field techniques capture detailed habitat information
52 but are labour and resource intensive, resulting in trade-offs between three types of scale: spatial,
53 temporal and thematic, and their components of resolution and extent [1,2]. For example, an
54 abundance survey of all macro-organisms to species level (high thematic resolution and extent) with
55 sampling at 1 m intervals (high spatial resolution) cannot feasibly cover an extent of 1 km² (limited
56 spatial extent) or if it does, would take a very long time (limited temporal resolution). The
57 impracticality of conventional methods for spatially or temporally continuous sampling has led to an
58 average difference of 5.6 orders of magnitude between the extent represented and extent actually
59 sampled in ecological studies, necessitating interpolation or extrapolation with the risk of over-
60 leveraging data [3].

61 Disruptive remote sensing technologies to rapidly record detailed, spatially-referenced biological and
62 physical information are now accessible to the field ecologist. These techniques overcome some of the
63 logistical challenges and trade-offs of direct observation field sampling and extend the scales of
64 remote sensing capability. This review considers tools able to capture three-dimensional (3D)
65 ecosystem data at finer scales than can be achieved with more familiar remote sensing from satellites
66 or crewed aircraft. We present an introduction to two of the most powerful and accessible high-
67 resolution 3D mapping techniques, which hold enormous potential for the rapid collection of
68 ecologically relevant, spatially continuous data at multiple scales: terrestrial laser scanning and
69 structure-from-motion photogrammetry (figure 1). Uptake of these new technologies varies widely
70 across disciplines and user groups, and there is a strong case for their increased adoption in ecology.
71 Our primary audiences are ecologists, environmental managers and other interested parties who have
72 limited or no experience with these high-resolution remote sensing tools. We direct more experienced

73 users to our analysis of the accuracy of structure-from-motion photogrammetry models at scales and
74 contexts relevant to ecological studies, addressing a key barrier to uptake. Our aim is to shed light on
75 powerful and increasingly user-friendly tools, encourage innovative and novel analytical approaches,
76 and highlight the new era of 3D digital spatial ecology.

77

78 **Remote sensing in ecology**

79 Remote sensing from satellite and crewed aircraft has revolutionised spatial ecology with diverse
80 applications that continue to grow as technology advances in capability, accessibility and familiarity.
81 Passive earth observation from satellites has enabled global-scale mapping and monitoring of land
82 cover, ecosystem function and climatic variables [4], and now offers metre-resolution daily imagery
83 of anywhere on the globe, presenting new opportunities for ecology, conservation and management
84 [5]. Active spaceborne sensors have facilitated the study of broad-scale (km to global) ecosystem
85 structure [6], enabling estimation of global ocean bathymetry [7] and continuous global topography
86 [8]. The ICESat-2 laser altimetry mission will have ecosystem characterisation applications through
87 mapping heights of ice, vegetation canopy and freshwater bodies [9], as well as unanticipated
88 potential for nearshore bathymetric mapping [10].

89 Remote sensing from crewed aircraft provides similar data products to satellite sources at higher
90 resolution over smaller extents. Airborne laser scanning has become a widely used tool for
91 characterising 3D habitat structural complexity and exploring organism-habitat relationships [11,12].
92 Bespoke or repeat airborne laser scanning surveys are uncommon in academic research due to high
93 operating costs of crewed aircraft, and compatibility issues pose challenges for the analysis of existing
94 available data [13].

95 Satellite and crewed aircraft remote sensing is irreplaceable for continuous mapping at up to global
96 extents. However, the technique becomes logistically inappropriate when detailed information is
97 required across smaller spatial extents (metres to hectares) or shorter time periods (hours to weeks)
98 due to limits of data resolution, accuracy or cost. For 3D mapping at these scales, recent technological

99 advances have led to the emergence of high-resolution (millimetre to centimetre), rapidly deployable
100 remote sensing tools that include terrestrial laser scanning and structure-from-motion photogrammetry
101 (figure 1) [14–16]. Advancement in sampling technology drives an ever-expanding range of questions
102 we can ask about the natural world, and the ability to accurately map ecosystems in three or more
103 dimensions is changing the way we study their ecology and management [11,13,17].

104

105 **High-resolution remote sensing tools for spatial ecology**

106 Terrestrial laser scanning and structure-from-motion photogrammetry both generate accurate, high-
107 resolution digital 3D models of the environment in the form of a point cloud (figure 1). A point cloud
108 is simply a collection of individual points with X, Y and Z coordinates describing their 3D position.
109 Additional attributes can be added to each point to provide information such as colour or other local
110 statistic. From point clouds, other topographic data products like mesh models and rasters can be
111 generated for additional analyses (figure 1). Although their outputs appear similar, terrestrial laser
112 scanning and structure-from-motion photogrammetry generate point clouds in different ways,
113 resulting in differences in the point cloud characteristics. For an overview of data collection steps
114 using these two techniques see figure 2.

115

116 *Terrestrial Laser Scanning*

117 Using the same principles as airborne laser scanning, terrestrial laser scanning is a high-precision
118 ground-based survey technique used extensively in civil engineering. It is an active remote sensing
119 approach that builds an accurate model of the surroundings by emitting millions of laser pulses in
120 different directions and analysing the reflected signals [18]. Data collected using calibrated laser
121 scanning equipment have intrinsic precision and real-world scale.

122 Terrestrial laser scanning is conducted from a set of discrete stations using a tripod-mounted
123 instrument, collecting data radially from a low elevation (generally < 2 m). This results in a reduction

124 in both point density and angle of incidence to the ground with increasing distance from the scanner,
125 and sectors of missing data behind obstructions like trees. Regions with low point density are filled by
126 merging data from multiple scanning stations (figure 2), introducing a low level of quantifiable error.
127 Data extent, resolution and coverage must be balanced with the survey time needed, especially in
128 complex ecosystems like forests where many stations are required for comprehensive coverage of a
129 large extent. Terrestrial laser scanning typically penetrates through fine-scale features like vegetation
130 to record points on internal surfaces (e.g. branches) and the ground, as the independent laser pulses
131 can travel through small gaps. Compared to crewed airborne systems, terrestrial laser scanning offers
132 higher resolution, more accurate data from a near-ground perspective, with lower operating costs and
133 responsive deployment capability, but across a more limited survey extent.

134 Falling costs and improved portability have increased the accessibility of terrestrial laser scanning to a
135 wide variety of users [15,18]. Custom built versions have lowered costs even further [19], although
136 the equipment and software required is still expensive compared to structure-from-motion
137 photogrammetry, and may be prohibitively so for some users. Early adoption of terrestrial laser
138 scanning for natural sciences was concentrated in the fields of geography and geoscience [18,20].
139 More recently it has seen application in ecology [13], particularly in forest ecology where the below-
140 canopy perspective complements airborne data collection. Applications include quantifying biomass,
141 growth and 3D structure of forest vegetation [15,21–24], non-destructive estimation of above ground
142 grass and mangrove biomass [25,26], assessing vegetation water content [27], studying cave-dwelling
143 bat and bird colonies [28,29], mapping freshwater habitats [30] and exploring the relationships
144 between organisms and fine-scale topography [31,32].

145

146 *Structure-from-motion photogrammetry*

147 Structure-from-motion photogrammetry is a low-cost machine vision technique that enables the
148 reconstruction of a detailed 3D model from a set of overlapping two-dimensional digital photographs
149 [33]. The camera may be handheld or pole-mounted for small scenes, while drone-mounted cameras

150 are commonly used to capture larger extents [34]. Commercial adoption of structure-from-motion is
151 increasing as a low-cost, flexible survey tool, but questions remain over best practices for producing
152 repeatable and high quality outputs.

153 With structure-from-motion photogrammetry, the geometry of a scene is reconstructed from the
154 relative positions of thousands of common features detected in multiple photographs taken from
155 different vantages. Structure-from-motion is a passive remote sensing technique because photographs
156 capture reflected light from an external source like the sun. While a basic model can be generated
157 entirely automatically, manual input into the processing stage is required for accurate outputs.
158 Structure-from-motion models have no inherent real-world scale, so known coordinates or distances
159 must be incorporated to generate scale. There is greater opportunity for error introduction with
160 structure-from-motion compared to terrestrial laser scanning, and uncertainty in data outputs varies
161 widely and unpredictably within [35] and among studies [36]. For example, error can be introduced
162 through camera lens distortion, poorly focused images, movement of features in the scene, and
163 imprecision in manual processing stages. Care must be taken to minimise the propagation of error
164 through the model construction pipeline [36]. Structure-from-motion generates more homogenous and
165 comprehensive data coverage compared to terrestrial laser scanning in less time, because the camera
166 is moved around the scene, often using an aerial platform. However, multiple images of a point on a
167 feature are needed to calculate a position, so internal surfaces of complex features (e.g. branches of a
168 dense bush or coral), shaded surfaces and moving features (e.g. blades of grass in the wind) are less
169 likely to be captured or positioned accurately. Structure-from-motion tends to return a generalised
170 outer surface of such features, lacking finer details.

171 The algorithms used for structure-from-motion are computationally demanding but falling costs of
172 computer processing power and affordable, user-friendly software are making this technique
173 increasingly accessible (see [36] for popular software options). As with terrestrial laser scanning,
174 structure-from-motion saw early adoption in geography and geoscience [33]. Ecological applications
175 include modelling forest and vegetation structure and biomass [25,34,37,38], and quantifying fine-
176 scale habitat topography and structure [14,39–41]. Recently there has been particular interest in

177 underwater structure-from-motion for measuring and mapping 3D habitat complexity in coral reef
178 systems [42–44].

179

180 *Georeferencing*

181 Georeferencing is required to position 3D data generated using terrestrial laser scanning and structure-
182 from-motion in real-world space. Positions of equipment (e.g. laser scanner, drone) or identifiable
183 features (e.g. targets) are typically recorded using a survey grade Global Navigation Satellite System
184 (GNSS) with an accuracy of 1-3 cm. This stage can represent one of the largest sources of error in the
185 3D modelling processing pipeline. The influence of georeferencing error on terrestrial laser scanning
186 and small-extent structure-from-motion data (e.g. < 100 m²) can be minimised by incorporating it at a
187 late stage in processing, and with low weighting. However, with large scenes modelled with structure-
188 from-motion using drones, georeferencing using well-distributed ground control points must be
189 incorporated into the process at an earlier stage to provide scale, and prevent warping of
190 geometry [45]. With sub-centimetre-resolution 3D data, georeferencing error can be a limiting factor
191 for detection of fine-scale change in topography through time [32], and for estimating the accuracy of
192 survey techniques [46], demanding positioning technology with sub-centimetre accuracy (e.g. Total
193 Station).

194

195 **Accuracy of structure-from-motion models in ecological settings**

196 Structure-from-motion photogrammetry can achieve impressive accuracy, but the flexibility of the
197 technique makes it vulnerable to the introduction of error that is method and context specific. Most
198 assessments of accuracy in natural settings have been in the field of geoscience, with measurement
199 error varying from < 1 mm to over 3 m and somewhat dependent on the distance between camera and
200 surface [36]. The spatial scales of ecological patterns often include the very fine (< 10 cm), so an
201 estimate of the realistic achievable accuracy of structure-from-motion photogrammetry is crucial to
202 assess its usefulness to ecologists and environmental managers.

203 We compared structure-from-motion and terrestrial laser scanning models within three habitats (rocky
204 shore, honeycomb worm (*Sabellaria alveolata*) biogenic reef and saltmarsh) and at three ecologically
205 relevant scales (fine-scale: 25 m² with < 1 cm resolution, medium-scale: 2500 m² with < 2 cm
206 resolution, and broad-scale: 2500 m² with 5 cm resolution). Fine-scale photographs were collected
207 using a pole mounted camera (Canon EOS M, 22mm lens), while medium- and broad-scale
208 photographs were collected using a drone (DJI Phantom 3 Pro) flying at 25 m and 90 m altitude,
209 respectively. Terrestrial laser scanning data were used as “truth” because it is a commercially
210 recognised technique with known precision (6 mm at 50 m range), and the most accurate 3D mapping
211 technique we were aware of. Structure-from-motion and terrestrial laser scanning surveys were
212 conducted simultaneously using shared reference targets, to avoid the introduction of georeferencing
213 error. Survey and data processing protocols were designed to achieve maximum accuracy. Models
214 were compared as point clouds using the M3C2 algorithm implemented in the open source software
215 CloudCompare, designed for comparison of 3D point clouds from natural scenes containing surface
216 complexity at multiple scales [47,48]. Comparison of point cloud data avoided the introduction of
217 error by the more common approach of interpolating and averaging data to a raster format digital
218 elevation model (DEM) [46]. For detailed methods see electronic supplementary material, S1.

219 We found mean absolute distance (± 1 standard deviation) between structure-from-motion and
220 terrestrial laser scanner data ranged from 4 mm \pm 14 mm (fine-scale, rocky shore) to 56 mm \pm 111
221 mm (medium-scale, saltmarsh) (figure 3). In all cases, distances between the point clouds clustered
222 close to zero, indicating good average agreement, with positive and negative errors compensating
223 each other. The spread of measured distances varied, with fine-scale and stable substrate scenes
224 showing the least variation, while broad-scale and vegetated scenes showed the most (figure 3).

225 Visual inspection of model difference maps and cross-sections revealed that on average structure-
226 from-motion models were accurate, but as resolution decreased, sharp features became smoothed,
227 with cuboid reference objects being represented as mounds (electronic supplementary material, figure
228 S2). Similar results are reported in other studies, with high agreement between structure-from-motion

229 and terrestrial laser scanning at fine-scales of up to 1 m² [25,49] and centimetre-level accuracy at
230 broad scales (hectares) [46,50].

231

232 **A case for increased adoption of 3D mapping techniques in ecology**

233 Terrestrial laser scanning and structure-from-motion photogrammetry offer rapid, detailed, continuous
234 extent 3D mapping of ecosystems. Relieving scale-dependence of sampling and easing trade-offs in
235 scale presents opportunities to ask new questions of the natural world and revisit classical paradigms
236 at new scales. The potential applications for high-resolution 3D mapping techniques are vast, and like
237 satellite remote sensing and airborne laser scanning, much of their value will likely only emerge once
238 techniques are firmly established as standard ecological tools. Unique insights are already being
239 generated, particularly in forest and coral reef ecosystems [51], whereas adoption has been slower in
240 other systems such as intertidal habitats. Multiscale topography plays a critical structuring role in the
241 intertidal zone by controlling environmental conditions and field time is constrained by tidal cycles,
242 making rapid 3D mapping tools valuable to intertidal field ecologists. In this section we identify and
243 discuss several themes of study in which emerging techniques have either already found innovative
244 and transformative applications or are likely to have high impact in the near future (figure 4).

245

246 *Understanding relationships between organisms and habitat structure*

247 Analyses of organism-habitat relationships can be hampered by our ability to quantitatively capture
248 the environment. This has resulted in a diversity of definitions, metrics and methods employed to
249 understand the mechanisms behind system-independent phenomena like habitat complexity-
250 biodiversity relationships [52]. The analysis of digital representations of 3D habitat structure to derive
251 system- and scale-independent metrics, like fractal dimension [53], or novel organism-centric metrics
252 [54], could lead to improved understanding by reducing the need to simplify 3D habitat structure (e.g.
253 to 2D profiles) to facilitate analysis [42,43,52,55,56].

254 Spatial patterning and the patchiness of species across a landscape can depend on topography at
255 multiple scales. In tidal flats and flood plains, elevation changes in the order of centimetres can
256 control species distributions, interactions and ecosystem services [14]. Understanding fine-scale
257 relationships can improve species distribution and habitat suitability modelling, a valuable
258 management tool, and lead to advances in organism-perspective landscape analysis. Terrestrial laser
259 scanning was used to estimate topographically-controlled foraging habitat suitability for the black
260 oystercatcher (*Haematopus bachmani*) and model how it may change under future sea-level rise [31].
261 Fine-scale topography and 3D structure can control other variables that can be modelled in finer
262 scales than ever before, like microclimate [57], soil pH [58] and hydrodynamic forces [59]. This can
263 enable quantification of environmental variables as continuous rather than categorical factors, which
264 may lead to alternative or improved interpretations of organism-environment relationships [60,61].

265

266 *Measuring and monitoring small, slow and complicated variation in 3D form*

267 Improved morphological descriptions of complex natural shapes can be made with comprehensive 3D
268 data, and variation in such shapes can be monitored through space and time at an organism-relevant
269 resolution. Using terrestrial laser scanning, researchers found that oysters, an ecosystem engineer, can
270 grow reef structure at a faster rate than current sea-level rise, with important management and
271 conservation implications [62]. Coral reef structure is difficult to quantify and previous methods
272 known to poorly capture detailed topography, like the chain-and-tape method, can now be replaced
273 with more repeatable structure-from-motion surveys with similar in-water effort [42,43]. Through
274 accurate feature modelling, terrestrial laser scanning can improve on traditional allometric equation
275 methods to estimate above ground biomass in trees (9.68% overestimation compared to 36.57–
276 29.85% underestimation) [63]. The low cost of operation and rapid deployment capability of
277 terrestrial laser scanning and structure-from-motion make them suitable for opportunistic pre- and
278 post-event change detection [64] and environmental impact assessment monitoring.

279

280 *Virtual sampling, digital archiving and addressing problems of scale in ecology*

281 With sampling now achievable at sub-centimetre resolutions, ecosystems can be digitally captured to
282 a degree that in some instances exceeds the resolution possible using *in situ* human observation. There
283 are, however, still limitations of completely removing the human observer element. Macroalgal
284 canopy cover estimates on rocky shores are indistinguishable between “virtual quadrats” from drone-
285 derived image mosaics and *in situ* human observers using field quadrats, but understory turfing algal
286 species are under-sampled in virtual quadrats [65]. Sampling of cryptic species and multi-layered
287 features will remain challenging to sample using remote sensing. Despite some limitations, the
288 potential advantages of sub-centimetre digital mapping of ecosystems are hugely exciting, including
289 automated species detection and identification using machine learning [66], entire extent sampling
290 that removes interpolation issues when scaling up from replicate samples [3], and simultaneous
291 biological and environmental sampling [65] (figure 4). Capturing and archiving detailed digital
292 snapshots of ecosystems in a rapidly changing world is likely to prove invaluable for future, currently
293 unknowable analytical approaches.

294 Organisms interact with their environment at a range of scales, but understanding scale-dependent
295 patterns and processes is a long-standing challenge in ecology [67,68]. Observation of organisms and
296 their environment is often conducted at spatial, temporal and thematic scales that are human-centric
297 and chosen arbitrarily or logistically, rather than guided by the ecological processes being studied
298 [1,67,68]. Due to the versatility of high-resolution remote sensing methods like terrestrial laser
299 scanning and structure-from-motion, studies can now be conducted at scales that have previously been
300 underexplored in ecology (figure 1) [3]. One of the difficulties in multiscale analysis is the time and
301 resource constraints of sampling the same extent at different resolutions [1]. With the ability to
302 rapidly sample large extents at high-resolution, multiscale data can be digitally generated by
303 resampling. We have increasing flexibility to move away from arbitrarily chosen sampling scales and
304 observe ecosystems at ecologically relevant and mechanistic scales.

305

306 *Value to managers, policy makers and the public*

307 In a rapidly changing world, tools to efficiently record accurate, detailed snapshots of the environment
308 and monitor ecosystem health are extremely valuable to environmental managers and policy makers.
309 Policy makers require high quality environmental information to make evidence-based decisions
310 aimed at limiting environmental impact, conserving ecosystems and maintaining ecosystem services,
311 to the benefit of the public. Often availability of technology to environmental managers is not
312 limiting, but without practical information on how to efficiently utilise tools, and analyse and interpret
313 new data types with confidence, there may be a lag in adoption of emerging technologies in favour of
314 more familiar methods, despite their known limitations [69,70]. A benefit of high-resolution 3D
315 mapping technologies for public facing research groups and environmental bodies is the easily
316 interpreted visual data products generated. Photo-realistic 3D models of ecosystems aid explanation of
317 ecological processes and issues, improving public communication and education through digitally
318 annotated still images, animations or virtual reality systems.

319

320 **Barriers to wider uptake in ecology**

321 While some sub-disciplines of ecology are making headway in using high-resolution remote sensing
322 methods to answer questions and test ecological paradigms across scales, in general the methods
323 remain underutilised across the discipline. A Web of Science search conducted in December 2019
324 found that just 1.4% (59 out of 4348) of articles about terrestrial laser scanning or structure-from-
325 motion were categorised as “ecology” compared to 23.7% (1031) categorised as “geosciences
326 multidisciplinary”. Further, 67.8% of these articles were published in the last three years
327 (2017–2019), highlighting the emerging adoption of these techniques. Here we identify four
328 perceived barriers to wider uptake in ecology.

329 Firstly, potential users may be unaware that such techniques exist, so a major aim of this article is to
330 introduce ecologists and environmental managers to two of the most common and powerful
331 techniques in an accessible manner. Second, potential users may be somewhat aware of the techniques

332 discussed, but perceive them to be specialised tools and inaccessible due to high expertise, cost or
333 time requirements. Technological advances in hardware and user-friendly software mean non-
334 specialists can now be using these techniques in a basic form within a day with a small amount of
335 training or self-learning. Equipment, software and training costs can still be significant, especially for
336 terrestrial laser scanning, with further costs incurred for maintenance and insurance. However, the
337 multidisciplinary applications of the techniques mean many institutions will already have access to
338 suitable equipment and software, or can gain access to shared resources. Structure-from-motion costs
339 can be comparable to many other field techniques, especially if using a handheld camera and open
340 source software. Practical field time requirements are context dependent. In coastal habitats we found
341 that terrestrial laser scanning took 15 – 20 min between stations for a typical medium resolution (10
342 cm point spacing at 100 m range) survey. Structure-from-motion time requirements ranged from
343 approximately 20 minutes for a 25 m² area surveyed using a pole mounted camera, to 2 hr for a 10 ha
344 area surveyed at 2-cm resolution using a multi-rotor drone (45 m altitude). As a photographic
345 technique, structure-from-motion is slowed or halted in low-light, while terrestrial laser scanning can
346 be conducted in darkness. Processing of terrestrial laser scanning data is rapid (1 – 2 hr) and can even
347 be conducted on a laptop in the field directly after surveying. Processing a basic structure-from-
348 motion model can be achieved in a similar amount of time, but an accurate, detailed model typically
349 takes a day or more to process depending on processing power and number of images. For a
350 comparison of practical considerations for terrestrial laser scanning and structure-from-motion for
351 geoscience see [71].

352 A third possible barrier to uptake in ecology is that potential users are aware of 3D mapping tools and
353 understand how they are conducted but do not see value in their use, or are resistant to exploring
354 technology-based alternatives to traditional field methods. Technology is unlikely to ever completely
355 replace a human ecologist in the field for direct observation and interpretation, but can augment data
356 collection and improve efficiency and quantification of specific variables if used appropriately [72].
357 By separating tasks that require human engagement from those that are more efficiently performed
358 using technology, field time can be optimised [65]. These technologies allow us to test existing

359 ecological concepts at novel scales and inspire new questions that could result in novel paradigms and
360 understanding.

361 Finally, potential users may be aware of the techniques and understand how they are conducted but
362 are sceptical about the accuracy of the outputs at their spatial scales of interest; this is especially
363 relevant for structure-from-motion photogrammetry. To address this, in this paper we have presented
364 results from an assessment specifically to test the realistic accuracy and characteristics of structure-
365 from-motion models in contexts and at spatial scales relevant to ecologists and environmental
366 managers (figure 3). Our results demonstrate that millimetre to centimetre scale variation in
367 topography can be measured in space and time using high-resolution 3D mapping techniques in the
368 field, making them valuable for numerous ecological applications (figure 4).

369 The perceived barriers to adoption of 3D mapping techniques for ecological data collection are now
370 low. However, system-specific challenges remain in survey design, data processing and interpretation.
371 With terrestrial laser scanning in complex environments, line-of-sight obstructions and moving
372 vegetation combined with the spatial characteristics of the point cloud data generates challenges for
373 interpretation and analysis [49,73,74]. While the moving vantage aspect of structure-from-motion data
374 capture means more homogenous data coverage, repeatability of coral reef rugosity measurements
375 were impacted by high habitat complexity, environmental conditions and variation in methods [75].
376 The use of drone-mounted sensors for field ecology comes with an additional suite of considerations
377 for training, permissions and constantly evolving regulations that govern their safe and legal usage
378 [76]. Data processing still requires manual input at various stages, and automated workflows can be
379 computationally demanding, especially for structure-from-motion. Various algorithms and software
380 packages are being developed for 3D point cloud processing, including open source projects like
381 CloudCompare [48]. After the initial processing stages required to generate a 3D model, further
382 processing and analysis currently requires non-trivial technical skill or novel approaches specific to
383 the task. As 3D methods become more common in ecology, an increase in demand and funding for
384 user-friendly and powerful processing techniques, including packages for open-source platforms like
385 Python and R, can be expected.

386 Conclusion

387 Technology is available and accessible to non-specialist ecologists that enables the detailed mapping
388 of habitats and organisms accurately in 3D. These techniques unlock a wealth of new spatial and
389 temporal ecological questions that were logistically impossible to ask only a few years ago. As with
390 any sampling method the limitations should be understood as uncertainty may not be readily detected,
391 and there is a need for standardisation of protocols. The power of these techniques mean they are
392 rapidly becoming standard and essential tools in various disciplines. By embracing emerging
393 technologies, modern ecologists can overcome longstanding challenges in studying scale-dependent
394 organism-environment relationships. Digital ecosystem analysis and multiscale 3D spatial ecology is
395 continuing to evolve, and high-resolution remote sensing techniques are becoming instrumental as
396 part of the modern spatial ecologist's tool kit.

397

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404

405 Data accessibility

406 Data and R code supporting this manuscript are available in a figshare repository:

407 <https://figshare.com/s/a623925eb42f4fc32e9a>

408

409

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414

415 **Ethics**

416 Land owner permission was granted for all fieldwork.

417

418 **Competing interests**

419 We declare we have no competing interests.

420

421 **Author contributions**

422 TDJ, AJD and GJW conceived and drafted the review. TDJ and AJD designed the primary data
423 component and TDJ and GWS conducted the fieldwork. TDJ processed and analysed the data. All
424 authors helped revise the manuscript and gave final approval for publication.

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432 **Figure captions**

433 Figure 1.

434 An overview of high-resolution three-dimensional ecosystem mapping tools, data formats and scales.
435 Tools include terrestrial laser scanning and structure-from-motion photogrammetry. Point cloud data
436 can be processed into mesh formats by interpolating between points, and raster formats to produce
437 digital elevation models (DEMs) by averaging point elevations in a regular 2D grid. 3D information
438 can be analysed at multiple spatial scales from organism to ecosystem. These tools enable
439 investigation at spatial scales (resolution and extent) that are understudied in ecology. Plot shading
440 (adapted from [3]) indicates number of ecological studies at specific scales, dashed areas represent the
441 approximate sampling scales for terrestrial laser scanning and structure-from-motion (using drone-
442 mounted and handheld cameras).

443

444 Figure 2.

445 Major steps for capturing data with terrestrial laser scanning and structure-from-motion using
446 handheld and drone-mounted cameras. A) Identify features of interest and estimate scanning positions
447 or camera angles. B) Set out reference targets for terrestrial laser scanning, or ground control points,
448 check points and scaling objects for structure-from-motion. For laser scanning, targets are used to
449 align data from different stations, although scene geometry can sometimes be used for alignment
450 instead of, or in addition to targets. For structure-from-motion, reference points are used for aligning
451 images and constraining the modelling process, and for accuracy assessment and scaling. C)
452 Terrestrial laser scanning collects data from a number of discrete stations, to be combined during
453 processing. For structure-from-motion, many overlapping photographs are taken, from which a 3D
454 model is generated during processing. D) Georeferencing, typically using a commercial grade Global
455 Navigation Satellite System, is required to position the resulting 3D models in real-world space, and
456 for scaling in large structure-from-motion models.

457

458 Figure 3.

459 Accuracy of a structure-from-motion point cloud quantified as the point-by-point distance to a
460 reference terrestrial laser scanning point cloud in three habitats (rocky shore, biogenic reef and
461 saltmarsh) and at three scales (fine: 25 m² with < 1 cm resolution, medium: 2500 m² with < 2 cm
462 resolution and broad: 2500 m² with 5 cm resolution). Distances were measured at 100,000 points and
463 plotted as density curves, with the area under each curve being equal. Curve tails beyond 0 ± 0.1 m
464 are not shown. Mean absolute error (MAE) \pm 1 standard deviation (m) distance is reported.

465

466 Figure 4.

467 Examples in ecology and environmental management with existing or potential applications for 3D
468 ecosystem mapping. 1) Multiscale experimental design with high-resolution 3D mapping across large
469 extents. 2) Mapping fine-scale variation in topography across tidal flats and wetlands. 3) Automated
470 species identification and biometric measurement in forests. 4) Comparing topographic variation in
471 natural and artificial hard coastal substrates. 5) Digital archiving of 3D habitat structure in
472 inaccessible ecosystems. 6) Monitoring variation in reef topography in space and time. 7) Modelling
473 growth in complex 3D organisms like mangrove trees. 8) Mapping 3D structure in habitats with
474 canopy cover and overhangs.

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482 **References**

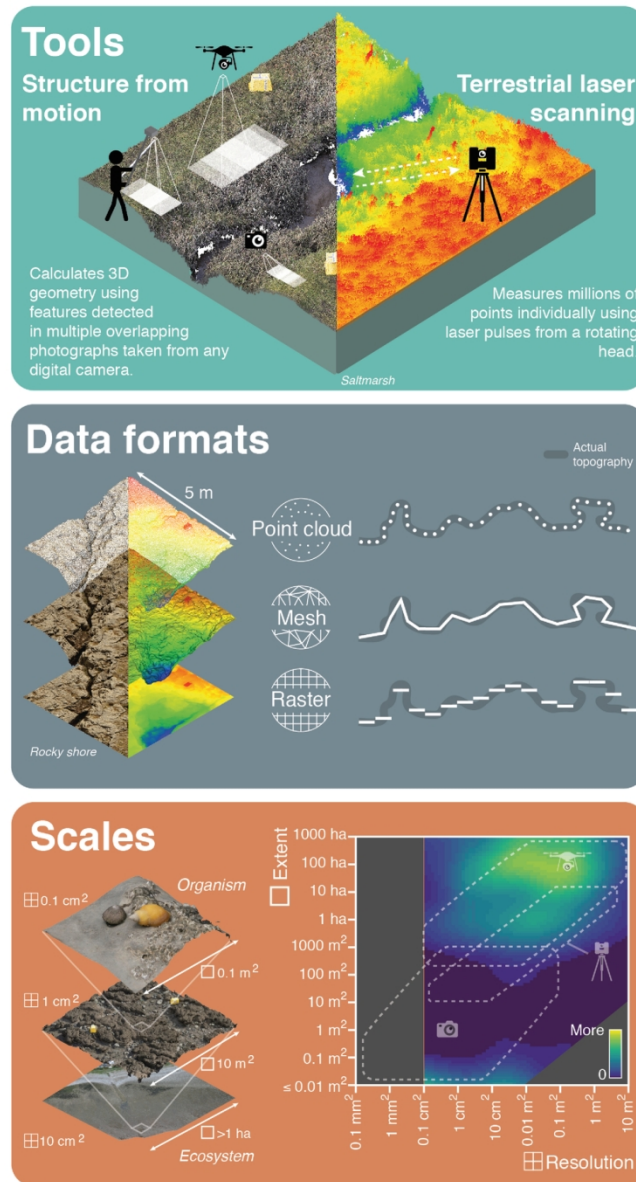
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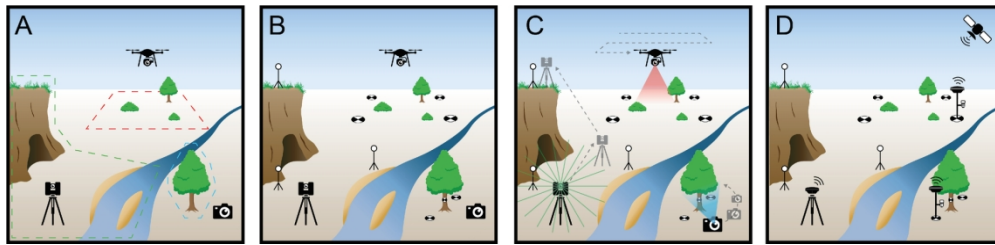
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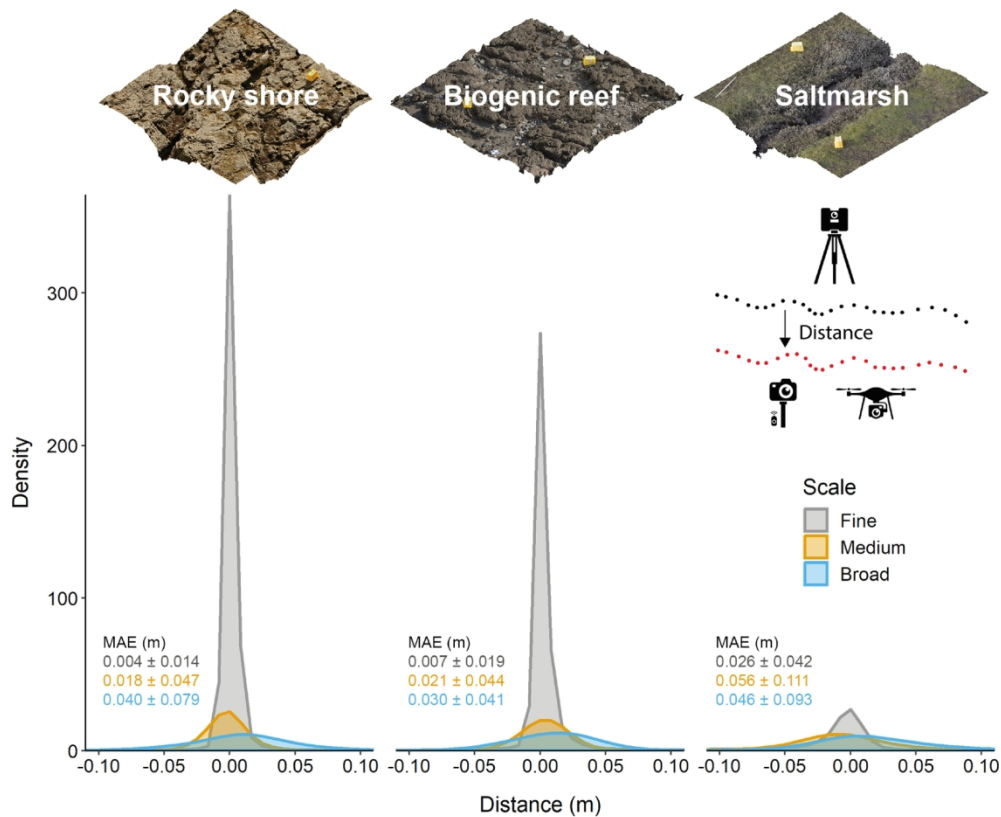
An overview of high-resolution three-dimensional ecosystem mapping tools, data formats and scales. Tools include terrestrial laser scanning and structure-from-motion photogrammetry. Point cloud data can be processed into mesh formats by interpolating between points, and raster formats to produce digital elevation models (DEMs) by averaging point elevations in a regular 2D grid. 3D information can be analysed at multiple spatial scales from organism to ecosystem. These tools enable investigation at spatial scales (resolution and extent) that are understudied in ecology. Plot shading (adapted from [3]) indicates number of ecological studies at specific scales, dashed areas represent the approximate sampling scales for terrestrial laser scanning and structure-from-motion (using drone-mounted and handheld cameras).

86x158mm (300 x 300 DPI)



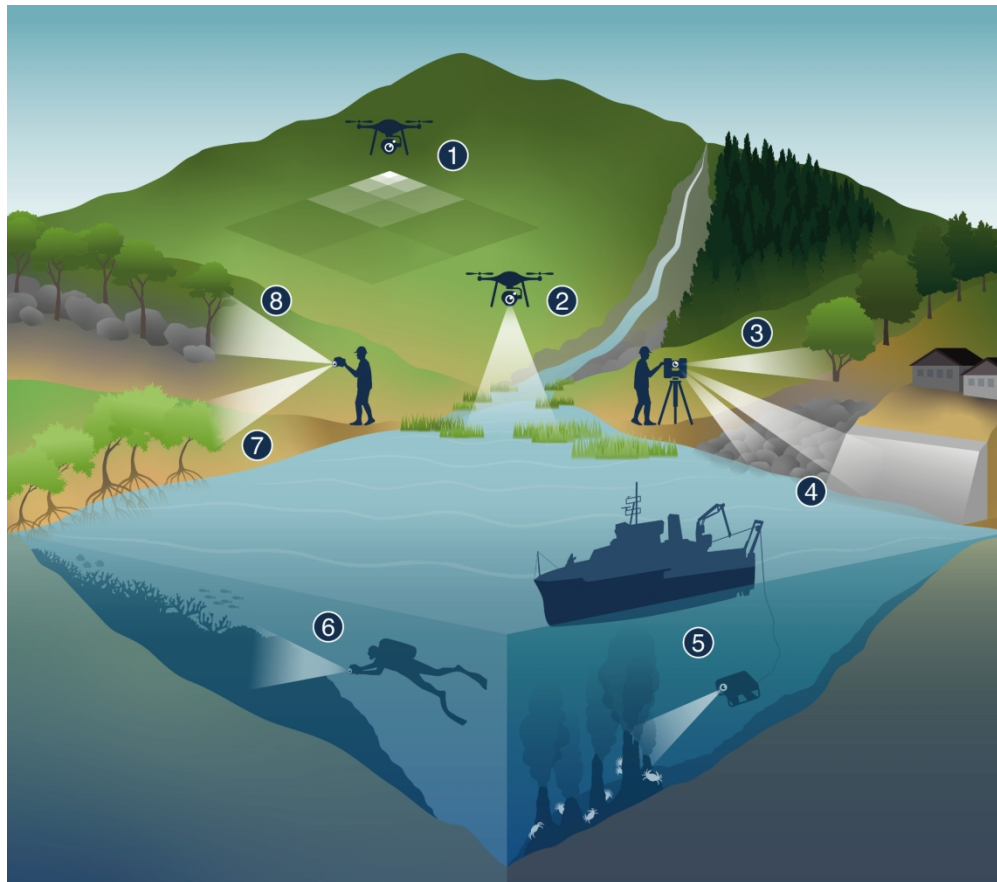
Major steps for capturing data with terrestrial laser scanning and structure-from-motion using handheld and drone-mounted cameras. A) Identify features of interest and estimate scanning positions or camera angles. B) Set out reference targets for terrestrial laser scanning, or ground control points, check points and scaling objects for structure-from-motion. For laser scanning, targets are used to align data from different stations, although scene geometry can sometimes be used for alignment instead of, or in addition to targets. For structure-from-motion, reference points are used for aligning images and constraining the modelling process, and for accuracy assessment and scaling. C) Terrestrial laser scanning collects data from a number of discrete stations, to be combined during processing. For structure-from-motion, many overlapping photographs are taken, from which a 3D model is generated during processing. D) Georeferencing, typically using a commercial grade Global Navigation Satellite System, is required to position the resulting 3D models in real-world space, and for scaling in large structure-from-motion models.

159x38mm (300 x 300 DPI)



Accuracy of a structure-from-motion point cloud quantified as the point-by-point distance to a reference terrestrial laser scanning point cloud in three habitats (rocky shore, biogenic reef and saltmarsh) and at three scales (fine: 25 m² with < 1 cm resolution, medium: 2500 m² with < 2 cm resolution and broad: 2500 m² with 5 cm resolution). Distances were measured at 100,000 points and plotted as density curves, with the area under each curve being equal. Curve tails beyond 0 ± 0.1 m are not shown. Mean absolute error (MAE) ± 1 standard deviation (m) distance is reported.

150x126mm (300 x 300 DPI)



Examples in ecology and environmental management with existing or potential applications for 3D ecosystem mapping. 1) Multiscale experimental design with high-resolution 3D mapping across large extents. 2) Mapping fine-scale variation in topography across tidal flats and wetlands. 3) Automated species identification and biometric measurement in forests. 4) Comparing topographic variation in natural and artificial hard coastal substrates. 5) Digital archiving of 3D habitat structure in inaccessible ecosystems. 6) Monitoring variation in reef topography in space and time. 7) Modelling growth in complex 3D organisms like mangrove trees. 8) Mapping 3D structure in habitats with canopy cover and overhangs.

171x150mm (300 x 300 DPI)