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




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RESEARCH



Efficient sampling for ecosystem service supply assessment at a landscape scale

Francisco Javier Ancin-Murguzur ^a, Lorena Munoz ^a, Christopher Monz ^b, Per Fauchald ^c
and Vera Hausner ^a

^aDepartment of Arctic and Marine Biology, Faculty of Biosciences Fisheries and Economics, UiT-The Arctic University of Norway, Tromsø, Norway; ^bDepartment of Environment and Society and The Ecology Center, Utah State University, Logan, UT, USA; ^cNorwegian Institute for Nature Research, Fram Center, Tromsø, Norway

ABSTRACT

Decision makers and stakeholders need high-quality data to manage ecosystem services (ES) efficiently. Landscape-level data on ES that are of sufficient quality to identify spatial trade-offs, co-occurrence and hotspots of ES are costly to collect, and it is therefore important to increase the efficiency of sampling of primary data. We demonstrate how ES could be assessed more efficiently through image-based point intercept method and determine the tradeoff between the number of sample points (pins) used per image and the robustness of the measurements. We performed a permutation study to assess the reliability implications of reducing the number of pins per image. We present a flexible approach to optimize landscape-level assessments of ES that maximizes the information obtained from 1 m² digital images. Our results show that 30 pins are sufficient to measure ecosystem service indicators with a crown cover higher than 5% for landscape scale assessments. Reducing the number of pins from 100 to 30 reduces the processing time up to a 50% allowing to increase the number of sampled plots, resulting in more management-relevant ecosystem service maps. The three criteria presented here provide a flexible approach for optimal design of landscape-level assessments of ES.

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Introduction

Landscape-level assessment of ecosystem services (ES) is highly relevant for managing the impact of land-use change and other drivers on the landscape (Naidoo et al. 2008; Nelson et al. 2009). Landscape scale assessments allow for identification of spatial tradeoffs, co-occurrence of multiple ES and locations of high value for beneficiaries. However, most current ES maps are not at the relevant scale (Malinga et al. 2015) nor do they provide fine-scale information for local decision-making (Martínez-Harms and Balvanera 2012). Primary data collection for ES supply assessments on a landscape scale poses cost and logistic challenges (Kremen 2005), and most landscape assessments therefore rely on secondary and coarse data (Martínez-Harms and Balvanera 2012; Englund et al. 2017). Although secondary data can inform on coarse patterns in the landscape (e.g. ecosystem-state shifts), they miss resolution to assess the gradual changes that may need to be managed. In order to deliver relevant information to decision makers, there is a need for time-efficient, scalable methods for detailed ES supply mapping that can provide primary data with the relevant resolution and scalability (Daily et al. 2009), and sufficient

accuracy for making decisions about land use affecting a specific site (Lavorel et al. 2011; Perrings et al. 2011).

One promising approach to multiple ES assessments is transect sampling using digital photos. Digital photo analyses have been used for measurements of plant cover (e.g. Chen et al. 2010) or for ground truthing of high-resolution remote sensing of vegetation cover (Cagney et al. 2011). Using digital photos for rapid assessment of ES has the advantage of maximizing field sampling of an area in a short period of time (Chen et al. 2010; Getzin et al. 2012), thus reducing the fieldwork costs, and at the same time, they can be reanalyzed if needed. The digital photos are analyzed off-season to detect ES, rare plant species, wildlife cues, evidence of recreation use, or other disturbances using specialized software such as Sample Point (Booth et al. 2006) or VegMeasure (Johnson et al. 2003). Digital photo sampling reduces time and costs of fieldwork, but it still requires a significant amount of office time to process and accurately estimate the abundance of ES.

Quantitative estimation of ES using point sampling of digital imagery relies on the same principles as the point intercept method (PIM) (Jonasson 1988). The PIM method (both in-field and in images) consists of

CONTACT Francisco Javier Ancin-Murguzur  francisco.j.murguzur@uit.no

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a frame with a certain amount of pins, placed on the vegetation where the experts count the number of times a plant species or functional group hits the pins as a proxy for biomass or vegetation cover. Several studies (e.g. Floyd and Anderson 1987; Meese and Tomich 1992; Godínez-Alvarez et al. 2009) have shown that PIM provides reliable and precise estimates of species richness and vegetation cover.

Depending on the purpose, PIM could be performed with low pin densities (Ravolainen et al. 2011) or high pin densities (Bråthen and Oksanen 2001; Sitters et al. 2017), making PIM a flexible method for capturing vegetation at different resolutions. Performing in-field PIM is still time demanding and logistically challenging to implement at a landscape scale: there may be a time lag between different PIM-measurements (i.e. early season and late season), resulting in vegetation changes due to time in the season, rather than in relation to the land-use or climate change. Imagery-based PIM, on the other hand, only requires a few days of training of field workers who will be able to move rapidly in the terrain to take pictures over a large area. A disadvantage of using imagery-based PIM is the underestimation of ES where there are multiple vegetation layers, such as high shrubs and woodland, covering the ground vegetation layer. Image-based PIM is therefore best suited for ecosystems with a limited vertical structure such as grasslands, tundra, deserts, coastal habitats, croplands or forest understory.

The amount of pins used in PIM (either in field, or image-based) varies largely among studies. It is common practice to use 25, 50 or 100 (and up to 500) pins as a rule of thumb (Fisser and Dyne 1966), but other authors have used different amount of pins (e.g. Speed et al. 2014). However, the decision on the number of pins applied is often based on financial and logistic constraints, with limited empirical assessment of how reducing number of pins affects the quality of the data. Bråthen and Hagberg (2004) assessed to what extent it is possible to reduce the number of pins per plot in field assessments with minimal loss in precision. They concluded, agreeing with Meese and Tomich (1992), that it is preferable to maximize the number of plots taken at a larger scale to obtain management relevant, time-efficient biomass measurements by reducing the effort per plot. However, field assessments of ES indicators, expressed as plant functional groups or species to record biomass, species richness, rare plants, vegetation cover or phenology (e.g. flowers and berries), will need different number of pins to produce data at the appropriate resolution and scale. For some ES indicators, it may suffice to record presence/absence in plots (e.g. mushrooms, wildlife cues, recreational use and/or impacts). Furthermore, number of pins or pictures/plots needed to quantify ES on landscape scale depends on the ecosystems, as high variation within and

among plots may require higher sampling efforts. In order to more efficiently measure ES on images, there is a need for an empirical examination of the tradeoff between the number of pins, the reliability and the time required for each image. Such knowledge will help managers to establish guidelines on the amount of pins needed to measure ES within a target accuracy.

In this study, we performed a permutation study to find the tradeoffs between the reliability and the time needed to achieve it. Our research objective was to examine how three criteria could be used to optimize the number of pins needed to detect the ES indicators in the digital photos. The first criterion assessed is the 95% confidence interval (CI) of the measurements to ensure sufficient reliability of the detection within certain confidence margins. The second criterion is the coefficient of variation that measures the variability within each measurement and the third is an optimized learning rate based on how much the CV is reduced when adding pins. The combination of these three criteria will help identify the optimal number of pins necessary to detect ES indicators relevant for landscape assessments. The three criteria allow researchers to determine the amount of effort needed to gain sufficient accuracy for a specific ecosystem prior to designing a full-scale landscape assessment.

Material and methods

Study area

The study area is located on the Varanger peninsula in northern Norway (Figure 1). The dominating vegetation is tundra, but with rich meadows along the river catchments and birch forests along the south and southwest coastline (see Henden et al. 2010). Varanger is sparsely populated and about 2090 km² of the peninsula consists of protected areas. Due to the remoteness, the low population density and the protected areas, there is minimal human impact and ES indicators can be measured at a landscape scale with a minimal effect of human disturbances such as garbage, trails or infrastructure. The tundra areas host important ES supply for the residents such as wild food, wood and peat for fuel, and fodder and pastures for sheep and semidomesticated reindeer. The supply of such ES may change in the coming decades as the arctic tundra is warming rapidly and tourism is increasing in the area. Landscape-level assessment could inform decision makers about the change in ES expected from climate change, and the potential tradeoffs between conservation, local needs and qualities enjoyed by tourists. Landscape-level assessments could capture the variation in both human



Figure 1. Location of the Varanger Peninsula seen from satellite pictures. Black dots represent the landscape-level sampling, and white dots represent the images used in this study.

activities and environmental variation by using the coastland–inland gradient, which range from 0 m a.s.l. to approximately 600 m a.s.l., to capture the variation in ES present in the peninsula.

Research design for the landscape-level assessments

Our research was designed for landscape-level assessment of ES covering the whole Varanger peninsula. A random location was selected for the first transect that would follow a coast-to-inland gradient and then the next transects were regularly spaced 10 km from the next one. Since rivers were impossible to cross in some places, we also located additional transects in the innermost part of the peninsula that could be accessed from the National Park (Figure 1). We used a subset of the pictures (see Figure 1) in our study to assess the needed number of pins for reliable ES assessments using image-based PIM.

Image acquisition and processing

For each transect, a 20-megapixel photo was taken perpendicular to the ground every 100 m with a Sony alpha 5100 by placing a 1 × 1 m quadrat on the ground. We assessed the surrounding vegetation class in a 5-m

circular buffer around the photographed point (Table 1) to analyze whether the dominating vegetation affects the number of pins required. Cropping of images, lens distortion and highlight/shadow adjustments were

Table 1. Description of the habitat types registered at a 5-m radius around each photograph.

HABITAT TYPE	Description
Deciduous forest	Forest dominated by deciduous species, mainly <i>Betula pubescens</i>
Deciduous shrubs	Open landscape dominated by deciduous shrubs (<i>Salix</i> spp., <i>vaccinium</i> spp.)
Juniper shrubs	Open landscape dominated by juniper shrubs (<i>Juniperus communis</i>)
Dwarf birch	Open landscape dominated by dwarf birch (<i>Betula nana</i>)
Heath	Heath, dominated by crowberry (<i>Empetrum nigrum</i>), heather (<i>Calluna vulgaris</i>) or blueberries (<i>Vaccinium</i> spp.)
High herbs	Ground cover dominated by high herbs (over 30 cm height)
Low herbs	Ground cover dominated by low herbs (under 30 cm height)
Ferns	Open landscape dominated by ferns
Grass	Open landscape dominated by grasses or sedges
Mire	Area of saturated soil/lakeshores, dominated by sedges such as <i>Carex rostrata</i> L.
Moss	Ground cover dominated by mosses
Lichen	Areas dominated by fruticose lichens
Bog	Poorly drained soil with scattered dry soil mounds
Rock	Ground cover dominated by naked bedrock or stones
Snowbed	Areas with late snowmelt, dominated by mosses

performed in Adobe® Lightroom® 5.6. We avoided vegetation higher than 50 cm (measured as knee height) due to the lack of depth in images, which would overestimate the cover of high vegetation in detriment of the understory.

Tradeoffs between effort and reliability

For the PIM measurements, we categorized the plant species into ES indicator categories following the ES they provide according to the CICES classification (Haines-Young and Potschin 2018) and performed PIM in the images using the Sample Point software (www.samplepoint.org). We used 100 evenly distributed pins (10 × 10 grid) for each image to measure the true pin proportion of each ES indicator (Table 2) and use as reference measurement for the permutation study.

Permutation study

We estimated the optimal number of pins by means of a permutation study (Figure 2) using the 100-pin dataset as a reference measurement: only ES indicators that had a cover higher than 5% were considered in this study. We selected n pins (ranging from 1 to 99) from the 100-pin dataset at random to measure the ES indicator frequencies. These measurements were repeated 1000 times for each pin number, e.g. for 3 pins we estimated the ES frequencies 1000

times, by combining 3 random pins from the 100 pins contained in the database. Afterward, the optimal number of pins for landscape assessments was determined based on three parameters: first, a 95% CI ($CI = 1.96 * sd$, where CI = confidence interval and sd = standard deviation) to assess the reliability related to each ES indicator/pin combination. Second, we measured the coefficient of variation ($CV = sd/\mu$, where CV = coefficient of variation, sd = standard deviation and μ = mean ES indicator cover) to assess the variability associated to each pin frequency. Finally, we calculated the slope of the CV for each adjacent pin frequency to measure how much information was retrieved when adding more pins (i.e. learning rate based on slope). We smoothed the slope with a moving average (window size $w = 3$) to mitigate the effect of local peaks. Finally, we established a landscape-scale threshold for the three criteria as follows: we estimated number of pins for each ES indicator within a 95% confidence ensuring that the lower end of the CI always remained positive; we set CV at 0.5 (or 50%) as an acceptable variability threshold, and a learning rate (slope) of 1% to assess the number of pins after which adding a new pin does not add new information.

The combination of the CI, CV and slope aims to set guidelines to find the tradeoff between intensive sampling (i.e. 100 pins per image) in fewer images and a more extensive sampling with fewer pins. We assessed these parameters given by the number of pins needed in

Table 2. Description of ES indicators mapped in this study according to the CICES framework.

Category	Category description	CICES division	CICES codes	ES description
Woody	Shrubs (e.g. <i>Salix</i> spp., <i>Betula nana</i>)	Provisioning, regulation, cultural	1.1.5.1/1.1.5.2/2.2.1.1/2.2.1.2/2.2.2.X/2.2.4.X/3.1.1.1/3.1.2.4	Habitat for wildlife, preservation of ecosystem functioning, carbon capture, erosion control
Crowberry	Vegetative and flowering structures of crowberry (<i>Empetrum nigrum</i>)	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/2.2.4.X/3.1.2.3/3.1.2.4	Long-term berries supply, erosion control, traditional use, local culture
Blueberry	Vegetative and flowering structures of blueberry (<i>Vaccinium myrtillus</i>)	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/2.2.4.X/3.1.2.3/3.1.2.4	Long-term berries supply, local culture, aesthetics
Lingonberry	Vegetative and flowering structures of lingonberry (<i>Vaccinium vitis-idaea</i>)	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/2.2.4.X/3.1.2.3/3.1.2.4	Long-term berries supply, local culture, aesthetics
Cloudberry	Vegetative and flowering structures of cloudberry (<i>Rubus chamaemorus</i>)	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/2.2.4.X/3.1.2.3/3.1.2.4	Long-term berries supply, local culture, aesthetics
Bilberry	Vegetative and flowering structures of bilberry (<i>Vaccinium uliginosum</i>)	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/2.2.4.X/3.1.2.3/3.1.2.4	Long-term berries supply, local culture, aesthetics
Grass	Graminoids, sedges and rushes	Provisioning, regulation	1.1.5.1/2.2.1.1	Summer pastures for reindeer or sheep, erosion control
Herbs	Herbaceous dicotyledons	Provisioning, regulation, cultural	1.1.5.1/2.2.1.1/3.2.1.1	Summer pastures for reindeer or sheep, erosion control, symbolic meaning
Lichen	Lichens	Provisioning	1.1.5.1	Winter pastures for grazers (reindeer)
Moss	Mosses	Provisioning	1.1.5.1	Winter pastures for grazers (reindeer)
Flowers	Reproductive structures of plants (with exception of crowberry, blueberry, lingonberry, cloudberry and bilberry)	Provisioning, regulation, cultural	1.1.5.1/2.2.2.1/3.1.2.4	High productive conditions (nutrients and climate), pollination, aesthetics
Others	Non-vegetation categories (stones, litter, bare soil)			

We selected the specific ES Indicator groups based on interviews with local communities, literature reviews and the features that are possible to detect using image-based PIM.

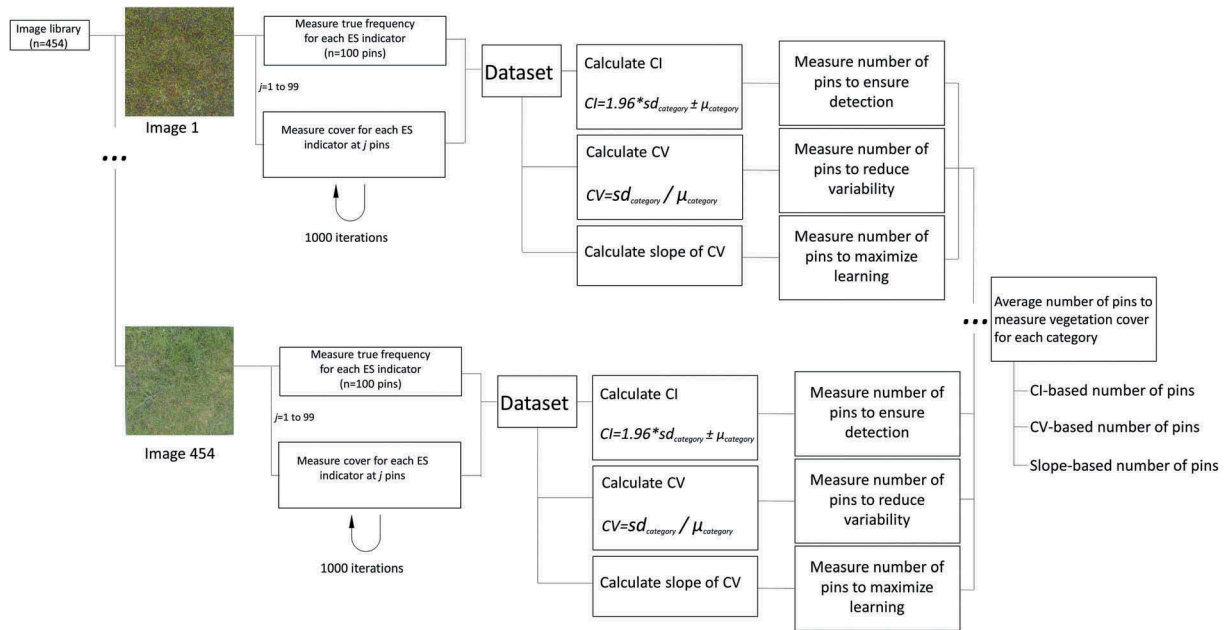


Figure 2. Conceptual map of the permutation process applied to the 453 images in the database. sd: Standard deviation, μ : mean; CI: confidence interval; CV: coefficient of variation.

relation to (a) the *surrounding habitat type* to each plot to unravel potential confounding habitat-specific trends. For instance, herb-rich vegetation that has higher diversity surrounding the plot may influence the number of pins needed; (b) the likelihood of detecting *different ES indicators*. For example, flowering plants could require more pins to detect because they have rare occurrences; (c) *vegetation cover* as higher % cover makes ES easier to detect.

Results

A total of 454 images were analyzed in a total of 15 habitat types. A total of 1925 ES indicators with frequencies higher than 5% were registered in the photos, with an average of 4.25 ES indicators present at each image.

Tradeoffs between effort and reliability

There is a clear tradeoff between the number of pins and the reliability (Figure 3(a)), where higher number of pins results in higher reliability with longer time needed to analyze each image. A similar trend can be seen with the coefficient of variation (Figure 3(b)) and the slope (Figure 3(c)): both parameters reach a plateau where the improvement given by the addition of pins is marginal. ES indicator detection based on the CI resulted in an optimal number of 18 pins and shows a semi-linear increase in reliability where the addition of a pin decreases the uncertainty between 1% and 2% (Figure 3(a)). The CV analyses show that there is an exponential decrease in need of pins to reduce the CV: there is a threshold between 10 and 20

pins, indicating that the addition of pins has a strong effect on the CV up to 20 pins and is less influential afterward (Figure 3(b)). The slope analyses indicate that the addition of pins after 13 pins does not result in an improvement of the learning rate, meaning that the information added with subsequent pins is below 1% (Figure 3(c)). When comparing the landscape-level assessment criteria (i.e. ensuring detection of ES indicators based on the 95% CI, stability of the measurements based on the CV and maximizing the learning rate based on the slope) to the vegetation cover (Figure 3(d)), a threshold around 20 pins can be found. After 20 pins, the 3 parameters stagnate: detecting ES indicators with a cover higher than 80% require 1–2 pins, and ES with a cover of 5% require up to 38 pins, with a shoulder between 10 and 15 pins (Figure 3(d)).

Landscape-level assessments

Analyses of the habitat type surrounding the plot at a 5-m radius show that the number of pins required for landscape-level assessments is similar for all classes (Figure 4), within 15–20 pins per image. Therefore, we assessed amount of pins needed for landscape-level assessments independently of the habitat types surrounding the images.

The average number of pins split by ES type shows that the pin number necessary for landscape-level assessments of the studied ES lies within 20–30 pins: this indicates that robust detection of multiple ES indicators requires approximately 30 pins per image (Figure 5).

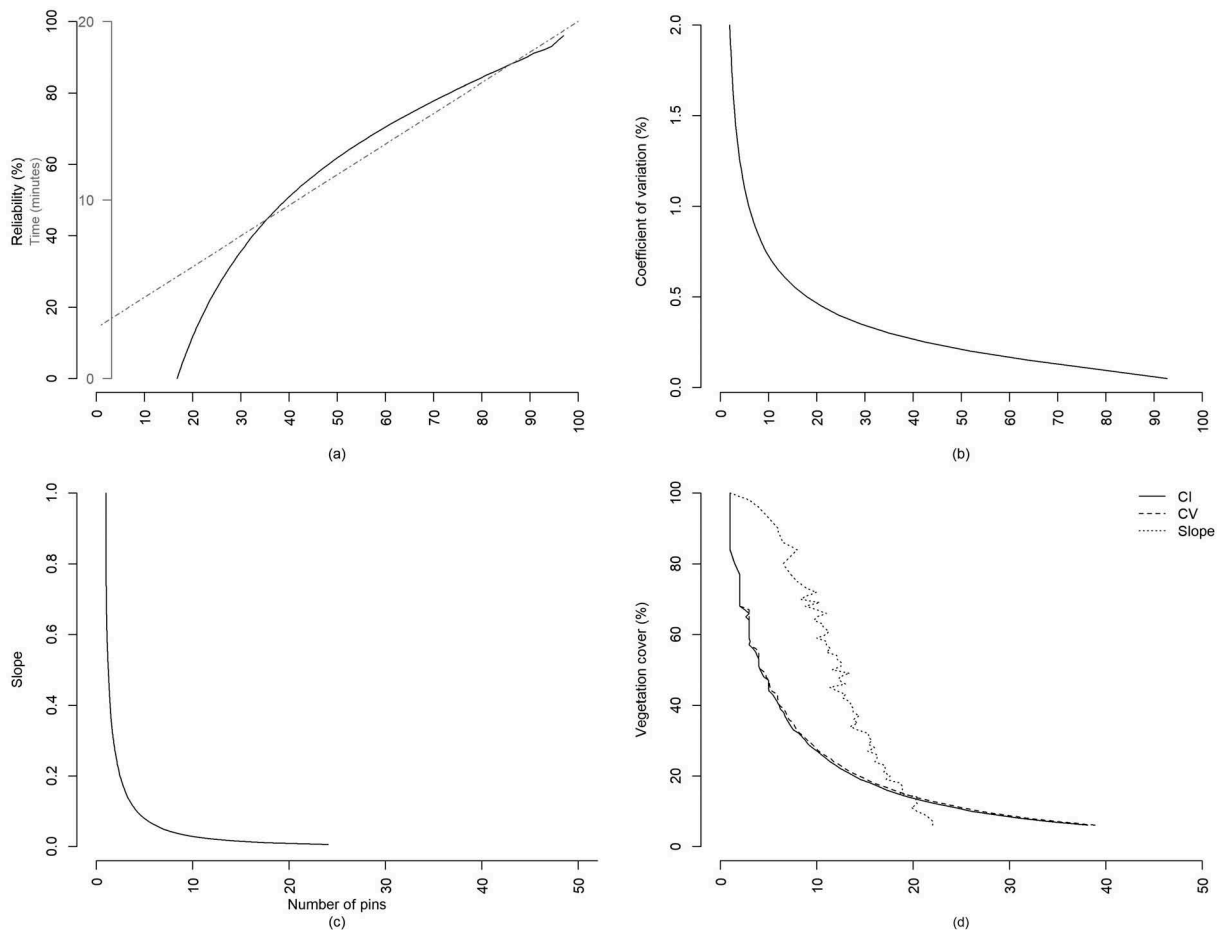


Figure 3. (a) Number of pins required to achieve a given reliability with a 95% confidence (reliability 0 indicates detection), and the time required to achieve the reliability; (b) number of pins required to achieve a given coefficient of variation; (c) number of pins required to achieve a given learning rate (slope); and (d) number of pins required to fulfill the reliability (based on the CI), variability (based on the CV) and the learning rate (based on the slope) requirements for landscape-scale assessment of ES indicators at different habitat types.

Discussion

Our study shows that image-based PIM is a method that is not constrained by the habitat type surrounding the plot, rather the cover (in percentage) and the desired measurement reliability when assessing ES indicators or other habitat types. Studies focusing on rare plants, phenology or plant community dynamics on a fine scale may require a high number of pins per plot. However, estimations of the abundance of multiple ES indicators at landscape scale will benefit from increasing the number of plots and decreasing the number of pins per plot, rather than having fewer plots with very high resolution (Meese and Tomich 1992; Southwood and Henderson 2000). Once an accuracy threshold has been met, adding more pins only helps increase fine-detail accuracy and not landscape-level information (Fisser and Dyne 1966; Bråthen and Hagberg 2004).

Our flexible approach of using three criteria to measure optimal number of pins provides guidelines for research designs to achieve high-quality primary data that can reveal landscape patterns. We suggest our results to be applicable to any ES indicator or

vegetation type with a cover higher than 5% inside the quadrat area for any ecosystem with short vegetation (i.e. under 50 cm height), when the interest is the crown cover (i.e. the horizontal structure of the vegetation).

Reliable landscape assessment of multiple ES indicators required approximately 30 pins, while categories that do not reflect ES such as stones or bare soil (Figure 5, grey area) required a number close to 20 pins, as opposed to the widely used 100-pin density (Kaarlejärvi et al. 2017). Applying 30 pins ensures robust measurements for all ES indicators considered in this study and provides high-quality primary data for landscape-level ES indicator assessment, while reducing data processing time up to a 50% compared to a 100-pin analyses. The saved time can be allocated toward analyzing more plots to assess landscape-scale distribution of ES indicators (Nelson et al. 2009). For example, Speed et al. (2014) used 16 pins in 50×50 cm quadrats, which could be translated into 64 pins/m^2 (to be comparable to our study), a sampling effort that measures ES indicators with a very

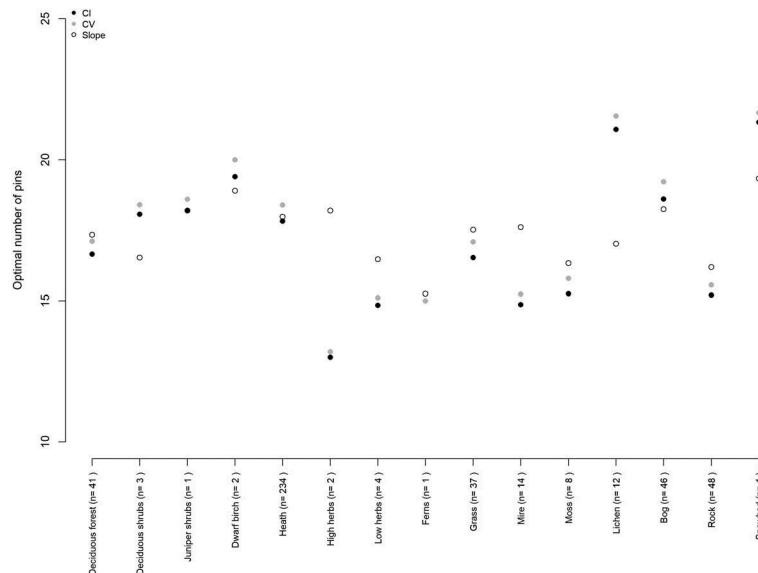


Figure 4. Optimal number of pins needed for landscape scale ES indicator assessment in the different habitat types surrounding the images based on three criteria: 95% confidence interval – CI – (black dots), coefficient of variation – CV – (gray dots) and slope (hollow dots). The value in brackets corresponds to the amount of pictures analyzed for each habitat type. The number of pins was decided to fulfill landscape-level requirements (consistent detection based on the 95% CI, variability (CV) of 0.5 and a slope lower than 1%).

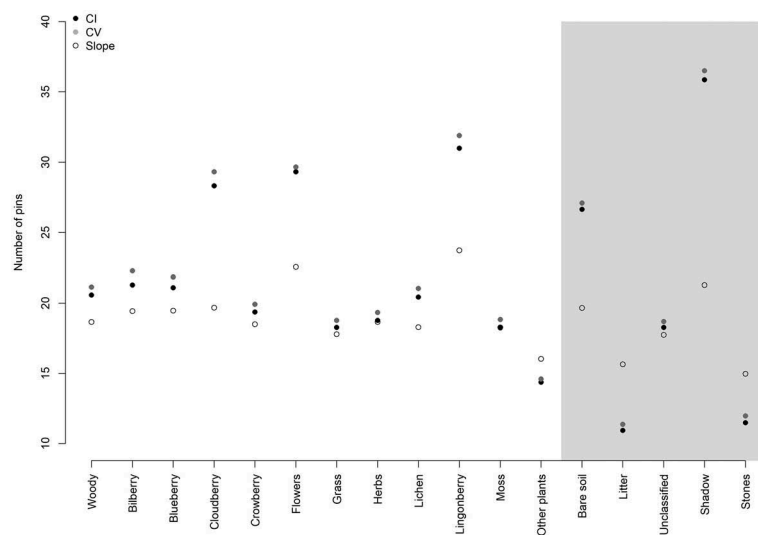


Figure 5. Optimal number of pins needed for landscape-scale ES indicator assessment in images based on three criteria: 95% confidence interval – CI – (black dots), coefficient of variation – CV – (gray dots) and slope (hollow dots). Points with gray background represent categories that do not reflect ES.

high reliability. This and other studies using 100 pins (or higher densities) are likely to benefit from reducing the amount of pins and increasing the number of plots analyzed, achieving higher spatial resolution while maintaining high quality on their data.

However, this method is constrained to low vegetation (lower than 50 cm). Since digital images detect only the crown cover of the vegetation, multiple layered vegetation types will result in an overrepresentation of the highest plants detrimental to the lower, more conspicuous plants. Complex vegetation types and high plants may benefit from other

approaches, such as in-field PIM (complex vegetation types such as bushes) or aerial imagery (forests, tall shrubs). Also, if the focus is on rare plant species (with crown cover less than 5%), the approach to analyze the pictures might need to be different. In addition, the images need to be of sufficient quality: detection of some plant species further than functional groupings (e.g. grasses) in digital images can be challenging, or even impossible, due to the limited resolution of the images.

In conclusion, landscape-scale assessment of ES supply can be effectively performed by applying 30

pins per 1 m² image over a larger amount of images. The resulting ES indicator cover measurements will be robust in reliability (consistently detecting ES indicators present in the image), variability (CV is lower than 0.5) and learning rate (slope is lower than 1%), reducing sampling costs and enhancing access to primary data to managers. Our study contributes to landscape-scale ES indicator assessment by use of imagery-based PIM, which reduces field cost and time compared to field-PIM, and by proposing the lowest optimal number of pins compared to the ones used traditionally, which reduces time in image analysis. We present our results (see [Figure 3](#)) as a tool to optimize the design of landscape-level PIM assessment of ES.


Disclosure statement

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ORCID

Francisco Javier Ancin-Murguzur  <http://orcid.org/0000-0002-1435-5190>

Lorena Munoz  <http://orcid.org/0000-0002-7514-6384>

Per Fauchald  <http://orcid.org/0000-0003-3046-0967>

Vera Hausner  <http://orcid.org/0000-0001-9825-0419>

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