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Sampling for landscape elements—a case study from Lower Saxony, Germany

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Abstract The estimation of coverage, i.e., the proportion of the total area in a study region covered by a given target class, is essential to many aspects of environmental monitoring. We analyze and compare the efficiency of different sample-based approaches for the estimation of coverage of different land cover classes from aerial imagery in a case study in Lower Saxony, Germany on the basis of the estimated standard errors. A complete delineation of vegetation classes in n=279 aerial photo plots of 400 × 400 m thrown onto the study region of 1,117.7 km^2 in accordance with a systematic grid is compared to different configurations of line intercept sampling and clusters of points. The observation designs under study are characterized by different complexity and total size of the observation units and therefore also to the efforts related to yield a single observation. Especially for those classes that cover a relatively large proportion of the sampling frame, our results show that difference in performance between the different designs are negligible. A cluster of four transects of 200 m each allows estimating the area of land cover classes with high coverage with nearly similar precision as a complete mapping of fixed area plots of 16 ha each. Clusters of points show unexpected high precision for the estimated coverage of land cover classes with relatively high coverage.

Keywords Land cover classes · Area estimation · Observation design · Line intercept sampling · Point cluster

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Introduction

The estimation of coverage, i.e., the area proportion of a study region covered by a certain target class, is essential to many aspects of environmental monitoring on different spatial scales, ranging from forest cover of countries to lichen cover on rocks or applications in microscopy (Kaiser 1983; Barabesi and Marcheselli 2008). Information on the area of different forest types and their changes over time is important also for Measuring, Reporting, and Verification for REDD+. In context of recent common agricultural policy within the European Community (CAP), the coverage of certain landscape elements like single trees, bushes, or hedgerows in cultivated farmland is needed (European Commission 2011). Estimates of the area of different land cover classes are relevant for nature conservation planning and the management of woody biomass resources in context of renewable energy (Bull 1997; McKendry 2002; Berndes et al. 2003). Depending on the landscape structure and the predominant land use, biomass potentials from trees outside forest are a significant source of raw material. In many regions of the world, biomass density and related carbon stocks per area outside forest are sometimes even higher than in degraded areas that still comply with a forest definition (Kleinn 2000; Bellefontaine et al. 2002; Fischer et al. 2011; Baffetta, Corona and Fattorini 2011a).

The most frequently used information sources for assessments of vegetation area and coverage are remote sensing imagery and field sampling. Frequently, both sources are used together in an integrated approach: while remote sensing imagery allows the production of wall-to-wall maps, probabilistic sampling offers the possibility to derive design-based inference on many ecologically variables. In this study, we focus on sampling techniques applied to aerial photographs. Standard sampling techniques and plot designs as applied for example in forest inventories typically fail for the assessment of woody resources outside the forest, mainly because of the different spatial distribution and relative sparseness of woody vegetation embedded in the agricultural landscape (Kleinn 2000, 2002). As a consequence, the development of new sampling protocols that are adapted towards the recent information need has become a field of research (Ramezani and Holm 2011; Baffetta, Fattorini and Corona 2011b). Depending on the goals, sample surveys cannot only be more cost efficient than complete mapping but also of higher accuracy since data collection can be implemented in a more detailed and careful manner if restricted to smaller areas (Freese 1962; Raj 1968; Corona et al. 2004).

Line intersect sampling, often abbreviated as LIS, is a well-known sampling protocol that has been applied to a wide range of target objects including hedges, roads, forest edge, coarse woody debris in forests, landscape metrics, etc. (Warren and Olsen 1964; Matérn 1964; DeVries 1986; Battles et al. 1996; Ringvall and Ståhl 1999; Corona et al 2004; Esseen et al. 2006; Woodall and Nagel 2006; Affleck 2010; Ramezani and Holm 2011; Kleinn et al. 2011). The literature on line sampling is fairly inconsistent in regard to a clear distinction between line intersect sampling and line intercept sampling, and often both are used synonymously. Even if there are notable differences in how observations are obtained from linear observation units, both alternatives can be analyzed by a unifying framework (Kaiser 1983; Valentine et al. 2001).

Line intersect sampling (LIS) is a field protocol that is often applied such that lines or transects are used to decide about the inclusion of elements into a probabilistic sample. The variable of interest is measured on those elements that are intersected by a transect line, while their design-based inclusion probability depends on the element's width and orientation (Affleck et al. 2005). If the population parameter of interest is the total length of linear features, like, for example, the length of the forest boundary or roads, no measurement other than simple count of intersections is needed (Matérn 1964; Kleinn et al. 2011). The individual probability of intersection (viz. the respective inclusion probability) is a function of the transect length. A probabilistic estimate of the total length per unit area can then be obtained with the Horvitz–Thompson estimator. For a comprehensive overview of line intersect sampling, see for example Gregoire and Valentine (2008), Kaiser (1983), or Barabesi and Marcheselli (2008).

With line intercept sampling, the intercept length of a line falling into a certain target class (e.g., forest crown cover in a landscape) is the basis to obtain an unbiased estimate of the fraction of this class on the total area of the sampling frame. The estimated fraction of the target class multiplied with the area size of the sampling frame gives an unbiased estimate of its total coverage. It is obvious that sampling does not refer to a discrete population of disjoint elements but to a continuous population in this case (Cochran 1977). Obviously, both approaches of line sampling can be integrated and applied simultaneously, e.g., in order to produce estimates on forest cover and the length of the forest boundary, like frequently done in large area forest inventories.

The purpose of this study is a performance comparison of different sampling schemes based on plots, lines, and clusters of points for estimating coverage of target land-use classes in the study region from aerial photographs. Special focus is laid on the estimation of coverage of different classes of woody vegetation outside forest (WOF).

Methods

Sampling scheme

The population under study is the infinite population of points constituting the study area of the administrative district of Göttingen in Southern Lower Saxony, Germany, with a total size of 1,117.7 km^2. Sampling locations are selected from this continuum in accordance with a systematic square sampling grid of 2 × 2 km. Starting point and orientation (North–South) of the grid are aligned to the sampling design of the national forest inventory (BWI) of Germany (BMELV 2007) that has a base grid of 4 × 4 km. While the German NFI selects forest plots only, we extended the observations also to non-forest areas. The resulting sample size (number of sample locations) for the study area is n=279 (Fig. 1).

A complete cover of digital aerial imagery with a ground resolution of 20 cm was acquired from the land survey administration for the district of Göttingen for the year 2010.

Land cover was classified according to the biotope survey guide of the German Federal Agency of Nature Conservation (BfN 2002). At the highest level of detail, this hierarchical classification scheme distinguishes more than 600 different biotope and land cover classes (LCC). As a clear distinction of all biotopes is not always possible from aerial photographs, many classes were assigned a coarser level of aggregation that was adapted to the target of our study. We used a higher level of detail in the classification of trees outside forest, hedgerows, or groves than for urban areas, water bodies, or agricultural areas (Table 1).

The FAO forest definition is widely adopted in many national forest inventories, and it is the definition to which the international forest reporting of FAO refers to. According to this definition, forest land is characterized by a tree crown cover (or equivalent stocking level) of more than 10 % and area of more than 0.5 ha. The trees should be able to reach a minimum height of 5 m at maturity in situ. Further, forest formations must have a minimum width of 20 m.

Plot sampling

At each of the 279 selected sampling points, a quadratic aerial photo plot of 400 × 400 m (16 ha) was established, so that in total an area of 4,464 ha was observed, which is equivalent to a sampling intensity of 3.9 %. All land cover types inside these sample quadrates were delineated in a GIS environment, and the resulting polygons were subsequently classified according to the LCC.

Line intercept sampling

Based on the completely mapped land cover classes inside the sample of aerial photo plots, we performed five different variations of LIS at all sampling locations. The different linear observation units were superimposed onto the fully delineated land cover polygons and the respective land cover classes were assigned to the resulting line intercepts by standard GIS procedures.

As basic approach, a single line of 200 m (L1) and 400 m (L2) length was centered at each sampling location in random orientation (Fig. 2).

Further, we adopted clusters of four line segments, each of 100 m (CL1) and 200 m (LC2) length and random orientation (Fig. 3). As the single line segments within such a cluster are not selected independently, they are treated as one single observation for estimation. As a further design alternative, the circumference line of a circle with radius 100 m was used.

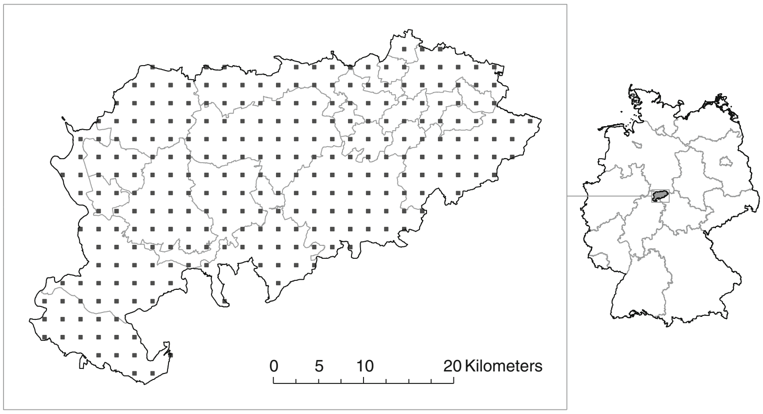

Fig. 1 Administrative district of Göttingen in Southern Lower Saxony, Germany overlaid with a systematic sampling grid of 2 × 2 km. At each of the 297 sampling locations, a quadratic sample plot of 400 × 400 m was established

Table 1 Overview of biotopes and land cover classes (LCC) adopted from the BfN-Survey guide (BfN 2002)

LCC level I	LCC level II	LCC level III
Water	Water body	River
		Lake
Agriculture	Crop field	
	Grassland	
	Field margin	
Woody vegetation outside forest (WOF)	Hedge	Hedge (bushes dominant)
		Hedge (bushes and trees)
		Hedge (trees dominant)
	Grove	Grove (with bushes)
		Grove (mainly trees)
	Bush/shrub	Single bush
		Group of bushes
	Single tree	
	Woody vegetation along roads	
Forest	Forest (FAO definition)	
Infrastructure	Settlement area	
	Road	Road (usually public)
		Way (forest roads, field tracks)
	Railway	

Some classes of special interest were modified

Clusters of points

In addition to square plots and the different linear observation units, we also tested the efficiency of estimating land cover classes by using clusters of points. Therefore, we classified only the start- and endpoints of the four line segments in design LC1 (Fig. 2) which makes a cluster of eight points on each grid point. Contrary to the continuous scale of observations that result from the line intercepts, this design allows observing a discrete number of nine area proportions only (0/8, 1/8, …, 8/8).

Table 2 gives an overview about the size and shape of applied observation units.

Estimation

We estimate the coverage of land cover classes (LCC) within a bounded two-dimensional region of known area by means of the sample proportion of these classes observed either as (1) their coverage observed in fixed area sample plots, (2) their proportion intercepted by randomly oriented lines of fixed length, and (3) the proportion of points within a cluster falling into the respective classes. Each selected observation unit produces one observation of coverage for each LCC, taking on values between 0 and 1. Clusters composed of multiple unconnected line segments or points are treated as one observation unit for estimation. It should

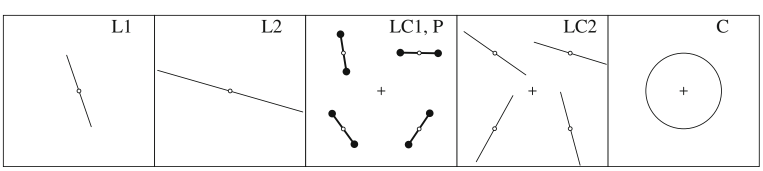

Fig. 2 Different configuration of observation designs. *L1* a single line of 200 m; *L2* a single line of 400 m; *LC1* a cluster of four lines, each of 100 m; *LC2* a cluster of four lines, each of 200 m; *C* the circumference of a circle with 100 m radius. *P* is a cluster of the eight start- and endpoints of the line segments in design LC1

Fig. 3 One aerial photo plot of 400 × 400 m (F) showing different landscape elements (*left*) and delineated land cover classes (LCC coded following BfN 2002) overlain with a cluster of four sampling lines implemented as design LC2 (*right*)

be noted that our interest is in estimating the total coverage of LCCs only and not in any mean characteristics, e.g., the mean density or size of distinct land cover patches in the area under study.

We consider a continuous population of points p constituting the whole study region A with known horizontal area A. For each land cover class j, we introduce the survey variable $y_{j(p)}$ which is equal to 1 if p belongs to the class j and 0 otherwise. Then the coverage of the class j can be rigorously defined as A_j/A.

The line intercept design involves selecting a linear transect of fixed length l with random orientation, centered at a selected sampling location i. The proportion P_j covered by the area of class j is estimated from the sample proportion p_j by

$$\widehat{p}_{ij} = \frac{l_{ij}}{l_i},$$

where l_{ij} represents the intercept length of the transect falling in A_j. The length l_{ij} may result from multiple partial intercepts whenever a sample line intersects a set A_j more than one time. As $\widehat{p}_{ij}$ is an unbiased estimator of the population proportion A_j/A, the total area of class j at sample location i is estimated as $\widehat{A}_{ij} = \widehat{p}_{ij}A$. Alternatively, if the interest is in the relative

Table 2 Configuration of different observation designs

Design	Description	Unit	Total size
F	400 × 400 m aerial photo plot	Area	16 ha
L1	Single line of 200 m	Length	200 m
L2	Single line of 400 m	Length	400 m
LC1	Cluster of 4 lines at 100 m	Length	400 m
LC2	Cluster of 4 lines at 200 m	Length	800 m
C	Circle of 100 m radius	Length	628 m
P	Start- and endpoints of lines in LC1	Count	8 points

All designs are implemented at the same sampling n=279 locations within the aerial photo plots of 400 × 400 m. For illustration of design F and LC2, see Fig. 3

coverage of A_j only, the constant area of A can be ignored. For the clusters of points implemented as design P, the relative share of a land cover is estimated from the proportion of points per cluster falling in the respective class as $\widehat{p}_{ij} = n_{ij}/8$.

We adopt a systematic distribution of the sampling locations in our study (Fig. 1). An unbiased estimator for the area of coverage class j from n samples is given by

$$\widehat{A}_j = \frac{1}{n}\sum_{i=1}^{n}\widehat{A}_{ij},$$

and the variance is estimated—though not unbiasedly—by:

$$\widehat{\mathrm{V}}\left(\widehat{A}_j\right) = \frac{1}{n-1}\sum_{i=1}^{n}\left(\widehat{A}_j - \widehat{A}_{ij}\right)^2.$$

We apply this simple random sampling estimator to systematic sampling, expecting that it is usually upwards biased and produces a conservative estimate of variance (Gregoire and Valentine 2008). In order to compare the statistical precision resulting from the different observation designs, we estimate the standard error of estimates as $\mathrm{SE} = \left(\widehat{\mathrm{V}}\left(\widehat{A}_j\right)/n\right)^{-1/2}$ and the relative standard error as $\mathrm{RSE} = \mathrm{SE}/\widehat{A}_j \times 100\%$.

If sampling locations are selected unrestrictedly in the study area, there is concern about edge effects as plots, lines, or point clusters might overlap the boundary of the sampling frame (Gregoire 1982; Gregoire and Monkevich 1994; Gregoire and Valentine 2008). While edge correction techniques are relatively straightforward for single lines, corrections for clusters of lines are more complex. However, at the scale of our study, possible edge effects are of less concern and were not considered. Only six aerial photo plots partially overlap the boundary that is a political boundary and not related to any changes of the configuration of landscape elements.

Results

Table 3 summarizes the results of our sampling study for the sample size of n=279 and all observation designs. As the implemented observation designs are design-unbiased, the differences in estimated coverage are a result of sampling errors. As to be expected, the complete delineation of land cover classes inside the aerial photo plots of 16 ha each (approach F as of Table 2) results in the highest precision of estimated area for all land cover classes. However, the differences in precision of estimates in terms of the estimated relative standard errors (RSE) are minor between the different observation designs. They are minor especially for those classes that cover a relatively large portion of the total landscape. For correct interpretation, it should be noted that the estimated RSE given in Table 3 is a relative error for a proportion.

Taking coverage of forest (resp. forest crown cover) as example, it is estimated to be 35.87±6.8 % (viz. a 95 % confidence interval between 33.4 and 38.3 %) of the total study area based on the complete delineation of aerial photo plots and 35.88±6.8 % using the line cluster LC2. In both cases, the estimated RSE is lower than 7%. For rare classes, e.g., the coverage of single tree crowns in the landscape, the precision of estimates is much lower, as expected. Their total crown coverage in the study area is estimated to be 0.14 % with a RSE of 20.7 % from completely mapped plots and 0.12 % with a RSE of 27.9 % from design LC2. The different performance of observation designs is in general more obvious for those classes that are relatively rare, like single trees or bushes and shrubs (Fig. 4).

All designs estimate the total coverage of crop fields, and in a forest with RSE lower than 10 %, the differences in precision are very small. Furthermore, all designs estimate the coverage of aggregated woody vegetation outside forest (WOF) with RSE between 10 and 20 %. The line cluster LC2, which has the longest total line length (800 m) of the LIS designs, has the second best overall performance for all relevant classes. In general, the order of RSE follows the observed line length in most cases. If we calculate a mean RSE over all land cover classes, the descending order of overall performance is F, LC2, C, P, LC1, L2, and L1.

Comparing designs L2 and LC1 that are of same total line length (400 m), the difference between a single long line and a cluster of shorter spread out line segments becomes obvious. The line cluster performs better for most classes. Exception is the coverage of single tree crowns, where a single line of same total length (L2) and even a shorter line (L1) results in a higher precision.

The performance of the point cluster (P) is even better than for some of the LIS designs for those classes that have a relatively high coverage. For the estimation of forest cover, the RSE is estimated to be 6.9 %, for that of cropland 5.6 %, and for that of grassland

10.3 %, respectively. The precision of estimates is therefore only marginally lower than with the full delineation F or design LC2 for these classes. However, the point clusters fail in case of rare elements. The coverage of single tree crowns is estimated to be 0 % with design P, as no single tree crown was hit by a point.

Discussion

In our study, we compare a plot design and different configurations of line intercept and point cluster designs applied in high-resolution aerial imagery with constant sample size of n=279. As the applied estimators yield estimates of variance that are expected to be upwards biased to an unknown extent for systematic sampling, small differences in the performance between the alternative observation designs should not be overinterpreted. The efforts to obtain a single observation $\widehat{p}_{ij}$ are quite different and dependent on the total size of the observation units shown in Table 2. As sampling was performed in aerial photographs only, considerations about possible field implementation of the different observation units were not taken into account. A complete delineation and classification of all land cover polygons in aerial photographs in all quadrates (4,464 ha in total) is a huge effort and very costly. Cutting line segments at their intersections with the different land-use classes in a GIS environment is, depending on the total length of these lines, much faster and straightforward to implement (Ramezani and Holm 2011). The point cluster design P is by far the most basic, fastest, and cheapest approach among the alternatives. Kleinn (1991, 1994) compared line intercept sampling and point clusters of the start- and endpoints of the line segments alone in a simulation study on area estimation. There appear to be few studies comparing the performance of these two alternatives in statistical and practical terms. None of the approaches is free of interpretation errors. Even the full delineation of landscape elements in the 400 m × 400 m is prone to errors. However, an argument for sampling is that such errors occur on a lower scale and that the selective interpretation on smaller areas can be implemented in a more detailed and careful manner (Eysn et al. 2012).

An interesting advantage of the point clusters is that it can be, contrary to the other observation designs, implemented without any GIS expertise. If the points are visualized and overlain on any available imagery with sufficient resolution, the observations can be obtained by simply counting the points per cluster and LCC. In case of our study area, it would be possible to derive the same estimates also based on freely

Table 3 Estimated coverage of land cover classes (LCC) in the study area (in %) for each observation design and constant sample size of n=279

LCC	Observation design						
	F	L1	L2	LC1	LC2	C	P
Crop field	39.31 (5.5)	38.00 (6.5)	39.58 (6.0)	40.37 (5.6)	39.99 (5.6)	39.60 (5.9)	39.56 (5.6)
Forest	35.87 (6.8)	35.89 (7.4)	35.88 (7.1)	35.51 (7.0)	35.88 (6.8)	35.86 (7.1)	35.57 (6.9)
Infrastructure	11.91 (10.9)	12.59 (12.6)	12.07 (11.9)	11.61 (11.4)	11.66 (11.3)	11.87 (11.9)	11.78 (11.5)
Grassland	8.05 (9.1)	8.61 (13.7)	7.66 (12.2)	8.13 (10.5)	7.83 (10.0)	7.84 (11.8)	8.38 (10.3)
Field margin	2.48 (6.4)	2.59 (13.4)	2.60 (10.0)	2.04 (9.5)	2.31 (8.2)	2.49 (9.2)	2.37 (15.5)
Grove*	0.79 (12.0)	0.74 (26.6)	0.58 (22.0)	0.72 (21.8)	0.72 (14.1)	0.70 (18.0)	0.76 (27.6)
WOF al. road*	0.70 (28.7)	0.81 (33.5)	0.73 (41.8)	0.70 (34.3)	0.76 (31.6)	0.71 (31.4)	0.49 (37.1)
Hedge*	0.47 (11.0)	0.60 (27.3)	0.55 (25.2)	0.61 (21.3)	0.49 (16.1)	0.52 (17.7)	0.72 (25.9)
Single tree*	0.14 (20.7)	0.10 (50.3)	0.03 (43.3)	0.08 (57.8)	0.12 (27.9)	0.14 (41.0)	0.00 (n.d.)
Bush/shrub*	0.08 (28.3)	0.05 (64.0)	0.09 (55.0)	0.07 (52.7)	0.08 (43.8)	0.09 (44.2)	0.13 (57.5)
WOF	2.18 (11.6)	2.30 (17.7)	1.98 (19.0)	2.18 (15.7)	2.16 (14.0)	2.15 (14.6)	2.11 (16.1)

The estimated relative standard error (RSE) is given in parentheses. Classes marked with * are aggregated into woody vegetation outside forest (WOF)

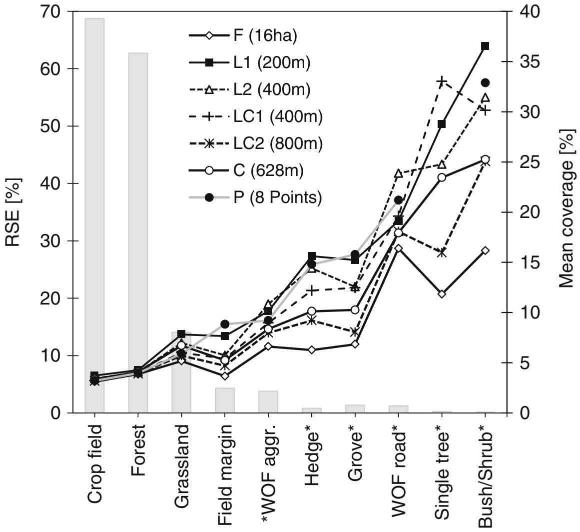

Fig. 4 Estimated relative standard errors (RSE) of coverage per land cover class (in ascending order) for the different observation designs. The total size of each observation unit is given in the legend. *Bars* show the estimated coverage of LCCs based on design F

available imagery in virtual globes like, e.g., Google Earth, as high-resolution imagery is available for our study area and the visual discrimination of land cover classes is possible.

One of the most important guiding principles of planning any kind of natural resources inventory is the conformity with the objectives of the study. Constraints lead the planner to a design that offers the best anticipated precision yet satisfying the constraints on time, costs, and logistics. This efficiency is given as the relation between invested resources and resulting precision of estimates. Despite the differences in complexity of observation designs under study, the resulting estimated standard errors (RSE) of the coverage of different land cover classes are minor in many cases. Especially for those classes that cover relatively large proportions of the sampling frame, they seem even negligible. Our results show that an estimate of agricultural crop land for example can be obtained with nearly similar precision from either a time-consuming fully mapped plot design on a total area of 279×16 ha (4,464 ha) or a very simple classification of eight points per plot (2,232 points). The same holds for the estimation of forest crown cover and the area of grassland.

Kleinn (1991) compared the precision of estimates for forest area by using either lines as observation units or the start- and endpoints of these lines only. He concluded that the start- and endpoints deliver comparable or even higher precision as observations from the total lines, while the difference in performance was related to the fragmentation of the land cover classes and the length of the line samples relative to this fragmentation. The results of our empirical study lead to similar conclusions for the main land cover classes. However, we must not generalize this observation as it might be dependent on how well the observation units are adapted and optimized towards the special target variables of an observational study and the landscape structure. Our results show that clusters of points (P) might have a huge potential to increase the overall efficiency of a sampling study if they are well adapted to the spatial structure and patch size of the target classes. It is interesting to note that their better performance for some classes is due to assessing less redundant information at each sampling location. Therefore, applying well-adapted clusters of points might be a win-win situation, as uncertainty and costs might be reduced at the same time.

Both line cluster configurations are superior compared to single lines for most classes. The rationale for selecting multiple spread out line segments rather than one single longer line is that they are expected to capture more of the given variability inside each sampling unit, reducing the variability between sample units. However, for single trees, our results show that single longer lines perform better, where the reason might be that the mean distance between these rare objects is quite large.

The circular line C that is a very compact form shows no advantages over straight lines for the estimation of classes that cover a large proportion of the landscape, even if the total length of the perimeter is relatively long. However, as shown in Fig. 4, it is superior to the line clusters for relatively small and dispersed landscape elements.

Conclusions

In general, we can conclude that manual wall-to-wall mapping of landscape elements is neither necessary nor efficient if the goal is to estimate land cover classes that have a relatively high coverage. Probabilistic sampling and design-based inference can be an attractive alternative to derive estimates with relatively high precision if sampling and observation design are well adapted to the target variables. Contrary to model-based remote sensing analysis that needs a lot of expertise, training, and capacity, sampling is easy to implement once a suitable sampling protocol is available. However, in ecological monitoring the less common land cover classes are often of main interest. Therefore, a combination of different approaches, e.g., mapping rare landscape elements like single trees or bushes while using point clusters for larger classes, might increase the overall efficiency. For the special case of rare cover types, adaptive plot designs might be an interesting alternative (Yang et al. 2011).

We further conclude that the good performance of point clusters for classes with relatively high coverage in our and other studies (Kleinn 1991; 1994) should be motivation for further research on this approach. Observations on points can be derived from or combined with any LIS approach and might help to increase the overall efficiency of line sampling in general.

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References

Affleck, D. (2010). On the efficiency of line intersect distance sampling. *Canadian Journal of Forest Research, 40*(6), 1086–1094.

Affleck, D., Gregoire, T., & Valentine, H. (2005). Design unbiased estimation in line intersect sampling using segmented transects. *Environmental and Ecological Statistics, 12*(2), 139–154.

Baffetta, F., Corona, P., & Fattorini, L. (2011a). Assessing the attributes of scattered trees outside the forest by a multiphase sampling strategy. *Forestry, 84*(3), 315–325.

Baffetta, F., Fattorini, L., & Corona, P. (2011b). Estimation of small woodlot and tree row attributes in large-scale forest inventories. *Environmental and Ecological Statistics, 18*, 147–167.

Barabesi, L., & Marcheselli, M. (2008). Improved strategies for coverage estimation by using replicated line-intercept sampling. *Environmental and Ecological Statistics, 15*, 215–239.

Battles, J. J., Dushoff, J. G., & Fahey, T. J. (1996). Line intersect sampling of forest canopy gaps. *Forest Science, 42*, 131–138.

Bellefontaine, R., Petit, S., Pain-Orcet, M., Deleporte, P., & Bertault, J.G. (2002). Trees outside forests. Towards better awareness. *FAO Conservation Guide 35,* Roma, Italy, 216p.

Berndes, G., Hoogwijk, M., & Van den Broek, R. (2003). The contribution of biomass in the future global energy supply: a review of 17 studies. *Biomass and Bioenergy, 25*, 1–28.

BfN (2002). Systematik der Biotoptypen- und Nutzungstypenkartierung. A system for the survey of biotope and land-use types (Survey guide). Standard biotope and land-use types for FCIR aerial photograph supported biotope and land-use survey for the Federal Republic of Germany. *Schriftenreihe für Landschaftspflege und Naturschutz,73.* Bonn-Bad Godesberg, 2002.

BMELV (2007). Survey instructions for the second National Forest Inventory (2001–2002). Reprint 2007. *Federal Ministry of Food, Agriculture and Consumer Protection (BMELV),* 106p.

Bull, G. (1997). The FAO Global Fibre Supply Study—Assumptions, Methods, Models and Definitions. *FAO Working paper GFSS/WP/01, FAO Rome,* 77p.

Cochran, W. G. (1977). *Sampling Techniques* (3rd ed.). New York: Wiley.

Corona, P., Chirici, G., & Travaglini, D. (2004). Forest ecotone survey by line intersect sampling. *Canadian Journal of Forest Research, 34*, 1776–1783.

DeVries, P. G. (1986). *Sampling theory for forest inventory: a teach-yourself course*. Berlin: Springer.

Esseen, P. A., Jansson, K. U., & Nilsson, M. (2006). Forest edge quantification by line intersect sampling in aerial photographs. *Forest Ecology and Management, 230*, 32–42.

European Comission (2011). Establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy. *European Commission, Brussels,* 105p.

Eysn, L., Hollaus, M., Schadauer, K., & Pfeifer, N. (2012). Forest delineation based on airborne LiDAR data. *Remote Sensing, 4*, 762–783.

Fischer, F., Kleinn, C., Fehrmann, L., Fuchs, H., & Panverov, O. (2011). A national level forest resource assessment for Burkina Faso—a field based forest inventory in a semiarid environment combining small sample size with large observation plots. *Forest Ecology and Management, 262*(8), 1532–1540.

Freese, F. (1962). *Elementary forest sampling*. Washington DC: USDA Forest Service.

Gregoire, T. G. (1982). The unbiasedness of the mirage correction procedure for boundary overlap. *Forest Science, 28*(3), 504–508.

Gregoire, T. G., & Monkevich, N. S. (1994). The reflection method of line intercept sampling to eliminate boundary bias. *Environmental and Ecological Statistics, 1*, 219–226.

Gregoire, T.G., & Valentine, H.T. (2008). *Sampling strategies for natural resources and the environment*. Applied environmental statistics. Chapman-Hall/CRC, 492p.

Kaiser, L. (1983). Unbiased estimation in line-intercept sampling. *Biometrics, 39*, 965–976.

Kleinn, C. (1994). Comparison of the performance of line sampling to other forms of cluster sampling. *Forest Ecology and Management, 68*(2–3), 365–373.

Kleinn, C. (1991). Der Fehler von Flächenschätzungen mit Punkterastern und linienförmigen Stichprobenelementen.

Dissertation. Mitteilungen der Abteilung für Forstliche Biometrie 91-1, Universität Freiburg, 128p.

Kleinn, C. (2000). On large area inventory and assessment of trees outside forests. *Unasylva, 51*, 3–10.

Kleinn, C. (2002). New technologies and methodologies for national forest inventories. *Unasylva, 53*, 10–15.

Kleinn, C., Kändler, G., & Schnell, S. (2011). Estimating forest edge length from forest inventory sample data. *Canadian Journal of Forest Research, 41*(1), 1–10.

Matérn, B. (1964). A method of estimating the total length of roads by means of a line survey. *Studia Forestalia Fennica Suecica, 18*, 68–70.

McKendry, P. (2002). Energy production from biomass (part 1): overview of biomass. *Bioresource Technology, 83*, 37–46.

Raj, D. (1968). *Sampling theory*. New York: McGraw-Hill. 302p.

Ramezani, H., & Holm, S. (2011). Sample based estimation of landscape metrics; accuracy of line intersect sampling for estimating edge density and Shannon's diversity index. *Environmental and Ecological Statistics, 18*, 109–130.

Ringvall, A., & Ståhl, G. (1999). Field aspects of line intersect sampling for assessing coarse woody debris. *Forest Ecology and Management, 119*(1–3), 163–170.

Valentine, H. T., Gove, J. H., & Gregoire, T. G. (2001). Monte Carlo approaches to sampling forested tracts with lines or points. *Canadian Journal of Forest Research, 31*, 1410–1424.

Warren, W. G., & Olsen, P. F. (1964). A line intersect technique for assessing logging waste. *Forest Science, 14*, 20–26.

Woodall, C. W., & Nagel, L. M. (2006). Coarse woody type: a new method for analyzing coarse woody debris and forest change. *Forest Ecology and Management, 227*(1–2), 115–121.

Yang, H., Kleinn, C., Fehrmann, L., Tang, S., & Magnussen, S. (2011). A new design for sampling with adaptive sample plots. *Environmental and Ecological Statistics, 18*, 223–237.