Can remote sensing estimate fine-scale quality indicators of natural habitats?

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ABSTRACT

Efficient management and conservation of natural habitats requires a thorough knowledge and sustained monitoring of their ecological quality. In recent years, several methods have been developed to assess the local conservation status in the field. These typically combine estimates of coarse-scale indicators, such as tree and grass encroachments, with very fine-scale indicators that require precise fieldwork, such as the number of key species present. We first tested whether coarse-scale field characteristics can provide information on fine-scale indicators. Then, this idea was extended to remote sensing techniques to derive estimates of fine-scale properties that cannot be derived directly by the sensors. The method was elaborated for two Natura 2000 heathland areas, combining field conservation status assessments of over 650 locations with remote sensing information derived from an airborne hyperspectral scanner image. Boosted regression trees using field estimates of coarse-scale parameters as predictors were able to explain up to 43% of the variation in the fine-scale indicators. When using remote sensing data, models performed only slightly less. Up to 35% of the variation was explained using remote sensing estimates of coarse-scale parameters as predictors, and up to 39% was explained when additional remotely sensed land cover data were included in the models. Although these rates are not high in absolute terms, model predictions for certain parameters were more precise than field estimates, especially for criteria with a high between-observer variability. These results clearly illustrate the potential of remote sensing imagery to derive information on the conservation status of habitats, even for fine-scale elements that are too small to be derived directly.

KEYWORDS: remote sensing; conservation status; habitat quality; Natura 2000; heathland; boosted regression trees

RUNNING TITLE: Remote sensing of habitat quality

1 INTRODUCTION

1.1 Conservation status assessment

Deterioration of natural areas has a strong negative impact on the local biodiversity, and may put rare and threatened species at a serious risk. Many monitoring programmes have been initiated to detect such alterations, often in response to national and international obligations (e.g. the Vital Signs Monitoring by the National Park Service in the USA; monitoring programmes of various member states of the European Union related to the Habitats and Birds Directives). In most programmes, the required information is visually extracted from aerial photographs, in combination with field visits for a detailed description of the local situation (Allard, 2003; Aplin, 2005; Vanden Borre et al., 2011). In recent years, several methods have been developed to assess the quality of habitat patches in the field (e.g. Fancy et al., 2009; Parkes et al., 2003; T'jollyn et al., 2009). Parameters that are typically evaluated comprise structural characteristics (e.g. proportion of dead wood in a forest), disturbance-related criteria (e.g. grass and tree encroachment in open habitats), characteristics related to the floristic composition (e.g. number of occurring key species) and landscape configuration (e.g. connectivity and isolation) (Bock et al., 2005; Tiner, 2004). As all these parameters relate to specific properties of the habitat (Bock et al., 2005; Parkes et al., 2003; Søgaard et al., 2007), estimates of each individual indicator are desired, rather than combining them in one joint quality indicator (T'jollyn et al., 2009).

1.2 Field assessment

National and regional field monitoring programmes provide accurate indications of the actual conservation status of natural habitats, and they are definitely helpful to detect and follow pressures and threats on natural systems. However, field methods have some major drawbacks. First, a frequent wall-to-wall coverage of large areas solely based on fieldwork is highly unrealistic due to budget constraints. Moreover, field visits to inaccessible zones such as military terrains, large wetlands or remote areas are inherently difficult. Second, field mapping is relatively slow, and the digitalization and processing of field data from large areas can take up to several years. Third, despite the existence of strict rules for field mapping, between-observer errors clearly remain an issue (Hearn et al., 2011; Sykes et al., 1983), making it extremely difficult to compare and integrate results, let aside to quantify the occurring changes.

1.3 Remote sensing assessment: opportunities and limitations

Remote sensing techniques have often been suggested as valuable tools for mapping and monitoring natural areas. Based on (semi-)automated analysis of air- and spaceborne images, the accurate detection of changes is possible in nearly real-time (Stone, 2010). Additionally, vast areas can be covered simultaneously, and a wide range of automated image processing algorithms avoids observer bias. As a result, remote sensing has been successfully used for many ecological applications, such as detecting land-use changes, monitoring deforestation, estimating carbon sequestration, detecting vegetation stress,… (reviewed by Aplin, 2005; Horning et al., 2010; Kerr & Ostrovsky, 2003; Wang et al., 2010; Xie et al., 2008). Surprisingly, the use of remote sensing for accurate, detailed and complete conservation status assessment and monitoring of natural habitats, such as required in the European Natura 2000 context, is still rarely exploited (Vanden Borre et al., 2011, but see Förster et al., 2008 and Haest et al., 2010 for two recent examples). Possibly, a historical gap between the remote sensing and the nature conservation communities has caused a delay in the development of such applications (Asner et al., 1998; Wang et al., 2010). However, the limited capacity of current sensors to discriminate individual herbs at a species level still discourages many vegetation ecologists (Bradley & Fleishman, 2008). Indeed, discerning small and similar-looking structures belongs to the major limitations of current remote sensing (Lechner et al., 2009). Despite the advances in air- and spaceborne sensors, with an ever-increasing spectral and spatial range and resolution, and despite the parallel growth in data analysis approaches, the identification of small non-dominant plants, especially herbs, remains a huge challenge. Although recent developments in the domains of spectral unmixing and fuzzy classifications (Foody & Cox, 1994), super-resolution image reconstructions (Park et al., 2003) and data fusion may provide details on a sub-pixel level, it remains unlikely that individual herbs will be recognizable from the sky in the near future.

But do we really need extremely detailed imagery for a complete conservation status assessment? Or in other words, are fine-scale indicators really unmeasurable with current remote sensing techniques? Many of these indicators are probably correlated with coarse-scale parameters, and hence, they can indirectly be derived from indicators that can be measured with remote sensing. To investigate this idea, we first determined to what extent the coarse-scale field characteristics can model the more subtle fine-scale indicators, based on an extensive dataset of conservation status assessments of heathland patches visited in the field. In a second step, we checked if these fine-scale parameters could also be predicted by remote sensing estimates of the coarse-scale characteristics. Finally, we tested if the inclusion of other land cover data from remotely sensed origin could further improve the model performances (see workflow of the study in Figure 1).

2 MATERIAL & METHODS

2.1 Heathland ecosystems

In this article, we focus on the conservation status assessment of four typical habitat types of West-European lowland heathland: dry sand heaths with *Calluna* and *Genista*, inland dunes with open *Corynephorus* and *Agrostis* grasslands, European dry heaths with *Calluna*, and Northern Atlantic wet heaths with *Erica tetralix* (Table 1). As a result of drastic changes in agricultural practice (Webb, 1998), these semi-natural habitats have shown a dramatic decline since the early 19th century. Heathlands are now largely restricted to nature reserves, military zones and remote areas. Despite their legal protection under the European Habitats Directive (92/43/EEC), atmospheric nitrogen deposition, desiccation, tree and grass encroachment, and invasive species continue to impose severe pressures on the remaining heathland ecosystems. Consequently, their ecological value is further decreasing, potentially resulting in a rapid change of the conservation status (De Blust, 2005). The impact of these pressures can be measured in the field by evaluating several “quality indicators” (e.g. Ellmauer, 2005; Søgaard et al., 2007; T’jollyn et al., 2009; Verbücheln et al., 2002 and Table 1). For example, a dry heathland in good condition is characterized by a rich structural variation with young and old heather plants (*Calluna vulgaris)*, which can be evaluated by verifying the presence of the different age classes of the shrub (T’jollyn et al., 2009; Verbücheln et al., 2002).

2.2 Fieldwork

In the summer of 2009, we evaluated the local conservation status of habitat patches in two Natura 2000 heathland sites in northern Belgium (“Kalmthoutse Heide” and “Klein en Groot schietveld”; 51°22’N, 4°27’E). First, a set of 559 sample points were selected following a stratified random design, taking in-between distance and vegetation type into account. Around these points, one or more vegetation patches were delineated based on the guidelines for European habitat surveillance (“BioHab”, Bunce et al., 2005, 2008), which resulted in a total of 671 plots of 0.37 hectares on average (range 0.04 to 1.0 ha). For all these patches, the Natura 2000 habitat type was defined and the quality indicators relevant for that habitat type were estimated (Table 1). Vegetation cover was determined visually, either on a continuous scale (but showing a typical bias towards multiples of ten), or on a Tansley scale (see T'jollyn et al. 2009 for details). T'jollyn et al. (2009) provides relevant indicators and corresponding threshold values to evaluate the conservation status of all Natura 2000 habitats, including heathland habitat types. It was approved by policy makers, conservation scientists and land-using stakeholder representatives (farmers, industry), and has become the standard for conservation status assessment in Flanders (northern Belgium).

2.3 Remote sensing data

An Airborne Hyperspectral Scanner (AHS 160) image with 2.4m spatial resolution was acquired in June 2007. The image was classified with a linear discriminant analysis using an independent training dataset of 1325 carefully selected, homogeneous plots (details in Haest et al., 2010). We used the four-level hierarchical classification scheme for heathlands that was developed in the HABISTAT project, with six broad land cover classes at level 1, reaching 24 detailed classes at level 4 (Table 2). The classification scheme not only includes classes needed to distinguish the Natura 2000 habitat types, but also contains some classes related to the conservation status of natural habitats. The approach resulted in a series of four hierarchical maps with an increasing number of land cover classes, but also with a decreasing accuracy: the overall accuracy of the land cover maps estimated by a leave-one-out cross-validation was 93%, 88%, 84% and 74% for level 1 to 4 respectively (Haest et al., 2010). Based on these four maps, we derived remote sensing estimates of the coarse-scale indicators, as well as the proportion of each land cover class in each vegetation patch that was delineated and assessed in the field, for all four levels of the classification scheme.

2.4 Estimating fine-scale indicators

Some of the quality indicators used for assessing the local conservation status typically occur on a coarse scale and are detectable in a straightforward manner (e.g. using supervised classification) with remote sensing techniques (such as grass encroachment, e.g. Clinton et al., 2010; Peterson, 2005; shrub and tree encroachment, e.g. Bai et al., 2005; Waser et al., 2008; and cover of sand, e.g. Ivits et al., 2009; Shanmugam et al., 2003). In contrast, other indicators such as the number of key species or the age classes of *Calluna* are of much finer nature, and hence pose much bigger challenges to be detected from a distance (Lechner et al., 2009). The cut-off between what is considered small-scale and coarse-scale will clearly depend on the spatial resolution of the imagery used. Here, we define fine-scale as occurring in patches (or requiring details) much smaller than 1 m². These characteristics are therefore too fine for a reliable detection from space, even with very high resolution satellites. Difficulties to directly derive very detailed indicators may, however, be circumvented if fine-scale indicators can be estimated indirectly from remote sensing data. To find out to what extent "measurable" characteristics can predict the "unmeasurable" fine-scale indicators, we used stochastic gradient boosting (Friedman, 1999), better known as boosted regression trees (BRT). BRT combine regression models with a stochastic boosting algorithm (Friedman, 1999), resulting in a flexible and powerful technique that has recently gained popularity in ecological applications (De'ath, 2007; Elith et al., 2008; Leathwick et al., 2006). In the first set of BRT, fine-scale characteristics that were *a priori* expected to be difficult to detect with remote sensing techniques were modelled using the field estimates of the coarse-scale indicators as predictors (i.e. tree encroachment, grass encroachment, occurrence of dwarf shrubs and cover of sand). In a second step, we used remote sensing estimates of the same coarse-scale quality indicators as explaining variables. Lastly, we modelled the fine-scale parameters based on the proportion of all land cover classes in the sample plots, for each level of the classification scheme (see workflow in Figure 1). BRT analyses were performed using the R-package "gbm" (Ridgeway, 2007) and the R-script supplied by Elith et al. (2008). Models were built with a learning rate of 0.001 and a bag fraction of 0.5 for the habitattypes 2310, 4010 and 4030, and 0.0001 and 0.75 respectively for habitat type 2330 to account for the smaller sample size. Tree complexity was set at 4. We performed a 10-fold cross-validation by dividing the dataset randomly following a 9:1 training:validation ratio. Models were evaluated based on the proportion of the deviance explained, the Pearson correlation coefficient between fitted and observed values, and the root mean square error (RMSE), all of which were averaged over the 10 repeats. Due to the small number of Natura 2000 habitats, classification levels and indicators considered in this study, non-parametric statistics were used for all model comparisons; details on these tests can be found in Lehman (1998).

2.5 Validation: comparison with variability of field estimates

To place our results in a proper context, the same evaluation criteria were calculated for a small field exercise to document between-observer variability of conservation status assessments. For this test, seven experienced observers were asked to independently estimate habitat quality indicators of dry sand heath 2310 in 13 habitat patches in the "Kalmthoutse heide". Habitat patches averaged 0.4 ha (ranging from 0.1 to 0.9 ha). In order to avoid error due to variation in patch boundaries, the delineation was done in advance by a single person, based on Bunce et al. (2005, 2008). Estimates of each quality indicator of each observer were then compared with the mean value of the six other observers. The latter was considered to be a proxy of the true value.

3 RESULTS

3.1 Analysis of field data

Habitat quality strongly differed between plots. All coarse-scale parameters (i.e. tree, dwarf shrub, grass and open sand cover, Table 1) showed substantial variation, especially in the amount of grass encroachment and the occurrence of dwarf shrubs (see Figure 2). Some fine-scale parameters also differed between the plots (e.g. the cover of native mosses and the invasive *Campylopus*), while other parameters showed almost no variation in our study site (e.g. the number of key species in dry heathland ‘4030’, see Figure 3).

Field estimates of some - but not all - fine-scale indicators could be adequately approximated by BRT using the four coarse-scale field parameters as predictors (evaluation statistics are given in Table 3a). This was especially true for the cover of native mosses in sand heath and the number of key species in wet heathland and in sand heath, for which over 30% of the deviance was explained by the model. BRT performed less for other parameters and were worst for fine-scale characteristics showing almost no variation in the field (e.g. cover of lichens on inland dunes 2330, number of *Sphagnum* species in wet heathland 4010, number of key species in dry heathland 4030, Figure 3), although this trend was not significant (Spearman rank test, $p = 0.92$). Despite the moderate performances, the models were still able to predict values that are correlated with the field estimates of the fine-scale parameters (Table 3a; all correlations $p < 0.05$). No differences were found in BRT performances between the four Natura 2000 habitat types (Kruskal-Wallis rank sum test, $p = 0.16$). The few indicators that are identical for two habitat types (i.e. cover of *Campylopus* in 2310 and 2330 and the age structure of *Calluna* in 2310 and 4030) showed rather similar results in both habitat types. Given the positive results for at least some fine-scale indicators, we further explored the possibilities of BRT to obtain information on the fine-scale parameters from a remote sensing product.

3.2 Analysis of remote sensing data

Remote sensing estimates of the coarse-scale parameters correlated well with our field estimates, although differences between field and remote sensing estimates were often substantial (Figure 2). Many of these errors corresponded with “avoidable confusions”: overestimation of tree cover by remote sensing (Figure 2a) mostly related to misclassification of cloud and tree shadows, mixed pixels and ecotone vegetations resulted in the underestimation of grass cover (Figure 2c), and confusion between bare agricultural fields and freshly sod-cut sandy soils hampered the estimation of open sand (Figure 2d). As a result of these confusions, remote sensing estimates of the four coarse-scale parameters were slightly less suitable to predict the fine-scale parameters compared to field estimates (Wilcoxon signed rank paired test $p = 0.049$ and $p = 0.19$ for the correlation coefficients and the proportions of the deviance explained respectively). Still, for three fine-scale parameters, over 30% of the deviance was explained, and correlations between predicted and observed values were (mostly) significant (Table 3b; individual p-values not shown).

When predictor variables were not restricted to the coarse-scale parameters, i.e. when all remotely sensed land cover classes of Table 2 were included, model performances varied depending on the classification level (aligned ranks test, $Q = 21.42$, $df = 3$, $p < 0.0001$, Figure 4). Models based on level 1 land cover classes (only six broad categories) were slightly worse than models based on the four coarse-scale indicators, while models based on level 2, 3 and 4 performed significantly better (Table 4, Figure 4). Evaluation statistics for the model based on level 4 are given in Table 3c.

3.3 Comparison with field estimates

BRT models did not explain all variation observed in the fine-scale parameters, and might therefore seem unsuitable. Based on a small-scale field exercise, however, we found that there is also substantial variation between observers in estimating the exact value of some of the fine-scale characteristics (Table 3d, Figure 5d). In general, field estimates of the fine-scale parameters are better compared to estimates derived from hyperspectral image classification (Table 3), but there is strong overlap. For example, we found that predictions from the best BRT models using remote sensing data are better than field estimates of the parameters with the highest between-observer variability, as illustrated for the cover of the invasive moss *Campylopus introflexus* in Figure 5. Although the small sample size does not permit to draw solid conclusions from this exercise alone, it seems that model predictions using level 2 to 4 classes as predictors are well suited to predict some fine-scale indicators.

4 DISCUSSION

4.1 Predictability of fine-scale indicators

In this study, we tested if coarse-scale quality indicators could model the fine-scale quality indicators of heathland habitats, and used this approach to indirectly derive estimates of fine-scale indicators from remotely sensed data. On the one hand, our results showed that some fine-scale indicators , such as the cover of native and invasive mosses on inland dunes and the cover of *Sphagnum* mosses, can indeed adequately be predicted based on coarse-scale parameters that are mappable with remote sensing techniques. We found only minor differences in model performances between models based on field and remotely sensed estimates of coarse-scale parameters, or between models based on other measures derived from the remote sensing map as predicting variables. Only when a limited number of very broad land-cover categories were used as predictors (i.e. our level 1, with only six classes), the model performance dropped significantly, as hardly any relevant quality information is included in these land cover units. On the other hand, models for some other fine-scale indicators performed very badly, especially for indicators that varied very little among field plots (e.g. cover of lichens on inland dunes 2330, number of *Sphagnum* species in wet heathland 4010, number of key species in dry heathland 4030). Not surprisingly, such data could not be properly approached by statistical models.

When focussing on the characteristics with higher variability, boosted regression tree models were able to yield predictions that were strongly correlated with independent field estimates (correlation coefficients ranging from 0.5 to 0.7). But with only 25 – 40 % of the deviance explained, there were still substantial differences between field estimates and model predictions. However, it should be noted that different observers show an equal amount of variation in their estimates, especially for features that are difficult to assess in the field. In this study, this was the case for the invasive moss *Campylopus introflexus* and for the number of age classes of *Calluna*; but other studies documented high variability between observers for a whole range of plant species and vegetation types, especially when estimates are made in larger areas (e.g. Bergstedt et al., 2009; Cherrill & McClean, 1999; Kennedy & Addison, 1987; Sykes et al., 1983). In the framework of this study, such high variation between field observers is relevant in two ways. First, the modelling approach of this study is yielding estimates that are as valid as field estimates. This is one of the important prerequisites for potential users to accept remote sensing as a tool for habitat monitoring (Vanden Borre et al., 2011). Second, since the models are trained and validated with field data, errors in these data will propagate in the model evaluation, hereby underestimating the actual potential of BRT modelling for predicting fine-scale parameters. Under ideal conditions, very accurate data should be used for training and validation of the models, but knowing the true plant cover and quality values in real-life field situations will, of course, always remain problematic.

4.2 Using indicators for monitoring the conservation status?

Despite the equal performance of some BRT models and field-driven estimates, differences between observers and between field and remote sensing estimates can still be large in absolute terms, even for the indicators that are easy to estimate. This questions the usability of estimating some of the habitat quality indicators for conservation status assessment and long term monitoring, not only when using remote sensing data, but also when using field-driven estimates. While our method can easily calculate an overall figure for each quality indicator or provide rough maps of both coarse- and fine-scale quality indicators, it is much more challenging to detect statistically reliable changes in the conservation status with such noisy data. Several options are available to solve the problem. First, the most pragmatic solution is to ignore all parameters that are too difficult to estimate – either in the field or by remote sensing. However, as indicators are typically chosen because they respond to a specific process of interest, some important threats to the ecosystem would be overlooked. This option is therefore undesirable. A second way is to increase the sample size. When remote sensing products are available, this can easily be done at (almost) no extra costs. In contrast, fieldwork costs are directly related to the sample size. Similarly, it may be easier to obtain detailed (yearly) time series from remote sensing imagery than from fieldwork. Third, reducing the error of the estimates can further help to detect relevant changes. For fieldwork, there are few possibilities to improve the visual estimations: e.g. focussing on small permanent fieldplots, averaging estimates of several observers, or computer-aided training (Gallegos Torell & Glimskär, 2009). However, for our method, more possibilities for improvement are at hand, both in terms of modelling and image processing. Some examples: i) focussing on the “avoidable confusions” (e.g. by including ancillary data in the classification) may further improve classification results; ii) alternative ways of classification (e.g. fuzzy classification, spectral unmixing) may be better suited for areas with many gradients between classes; iii) alternative modelling approaches may perform even better than the BRT used in this study, a.o. because regression trees are known to have difficulties with modelling linear relations (Elith et al. 2008); iv) model performances may further increase when they are trained using selected sites covering the whole quality range, rather than the random samples we used here. Of course, some of these improvements will be more successful than others, and this will depend on each specific situation. As a fourth option, the issue of noisy estimates of quality indicators can also be avoided. Remote sensing methods may be better suited to detect the underlying processes influencing the habitat quality, rather than the quality indicators that were essentially designed for fieldwork. For example, shifting inland dunes can be documented directly using time series (Vermeesch & Drake, 2008), and several indices can be used to estimate biophysical or stress parameters (Delalieux et al., 2009; Ustin et al., 2005), all of which are potentially relevant for conservation status assessment (Vanden Borre et al 2011). So even if remote sensing cannot exactly measure the quality indicator of interest, it may often be of help in other ways (see also Bradley & Fleishman, 2008). Unfortunately, alternative methods for conservation status assessments of habitats are still little developed, as current approaches have mainly focussed on field methods. The long tradition of field-based conservation status assessments may even impede the acceptance of novel, alternative approaches by ecologists.

4.3 Mapping the conservation status: practical and operational considerations

Although care is required when aiming at very detailed monitoring, remote sensing seems nevertheless very suitable for an indicative mapping of the conservation status, not only for coarse-scale characteristics such as grass and tree encroachment, but also for less evident characteristics such as the number of key species in wet heathland or the encroachment by the invasive moss *Campylopus introflexus*. By applying this method, it becomes possible to produce wall-to-wall maps of the quality of natural habitat, even for large and inaccessible terrains. Based on such maps, terrain managers can assess where and how much effort is needed to bring or keep an area in a favourable conservation status. The method also seems very flexible, as illustrated by the comparable performance with different remote sensing classifications as input, as long as the classes are specific and numerous enough. Furthermore, both manually and automatically delineated habitat patches can be used as objects of interest, in which the composition of coarse-scale indicators or other landcover classes can easily be calculated. Finally, modelling the fine-scale characteristics can easily be done with boosted regression trees, which are currently available in many statistical software packages, including in the free, open-source software environment R.

When considering an operational system, an extensive cost-benefit analysis remains essential. Although the advantages of a detailed, wall-to-wall conservation status map are obvious, two major limitations of the newly proposed method should be closely considered. First, a very high resolution airborne hyperspectral scanner image was used in this study, and ample training points were available for the classification of the imagery. Obtaining such imagery and associated field dataset is costly, and therefore it may be unrealistic to have such imagery available at regular intervals for large areas. However, our results indicates that the most detailed classes are not essential for predicting the small-scale indicators (we found only minor differences between levels 2, 3 and 4), and that lower resolution imagery might hence suite the purpose as well. Second, the flexible, non-parametric modelling techniques we applied here are also data-hungry. For training and testing the BRT models, we used conservation status assessments of more than a tenth of the core heathland area of the study site. The use of less data-hungry modelling techniques might be an option, and more efficient field sampling (e.g. Foody et al. 2006) may further reduce the required sample size.

To summarize, this study clearly illustrated the current and discussed the future potentials of combining remote sensing methods with advanced statistical modelling techniques. This way, information on habitat quality can be derived, even for characteristics that were *a priori* unexpected to be detectable from the sky. By doing so, a fast and regular wall-to-wall evaluation of the quality of natural areas at a local or regional scale becomes more realistic.

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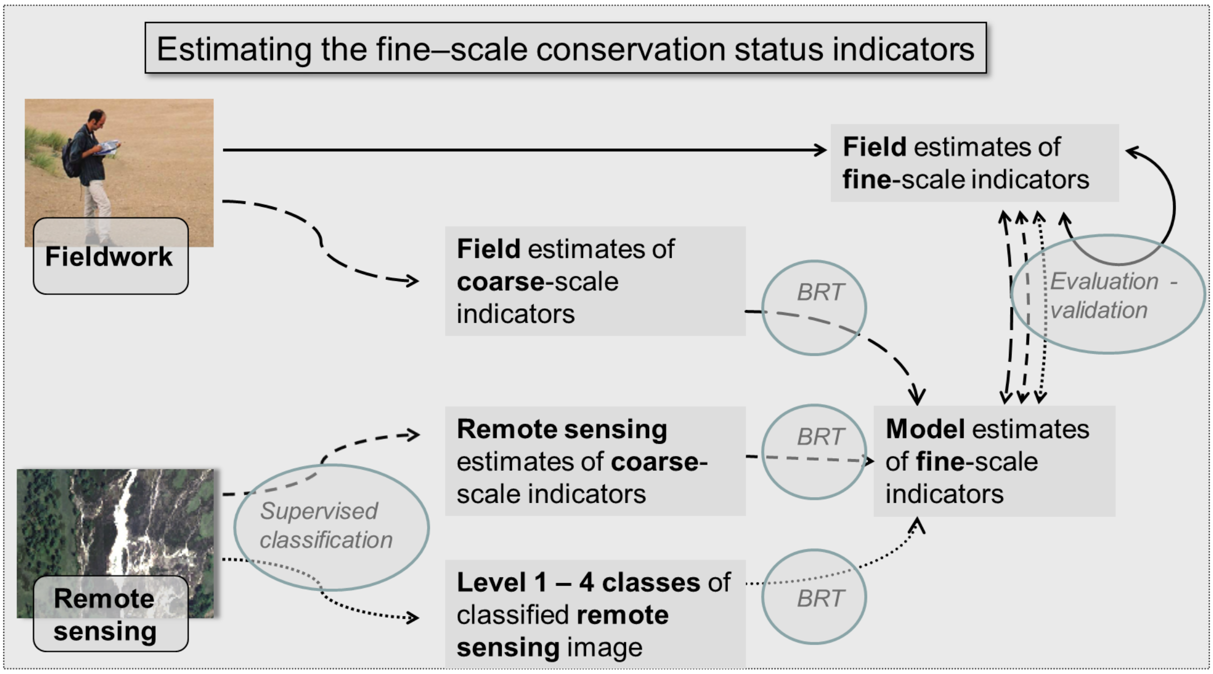

Figure 1. Pathways to derive fine-scale indicators from fieldwork and remote sensing imagery. Fine-scale indicators were estimated directly in the field (solid line), or were modelled with boosted regression trees (BRT) using either field estimates of coarse-scale indicators (long dashed line), remote sensing estimates of coarse-scale indicators (short dashed line), or all landcover classes from a classified hyperspectral image (dotted line).
For validation, model estimates were compared to field estimates, while the between-observer variation was documented to validate the field estimates themselves.

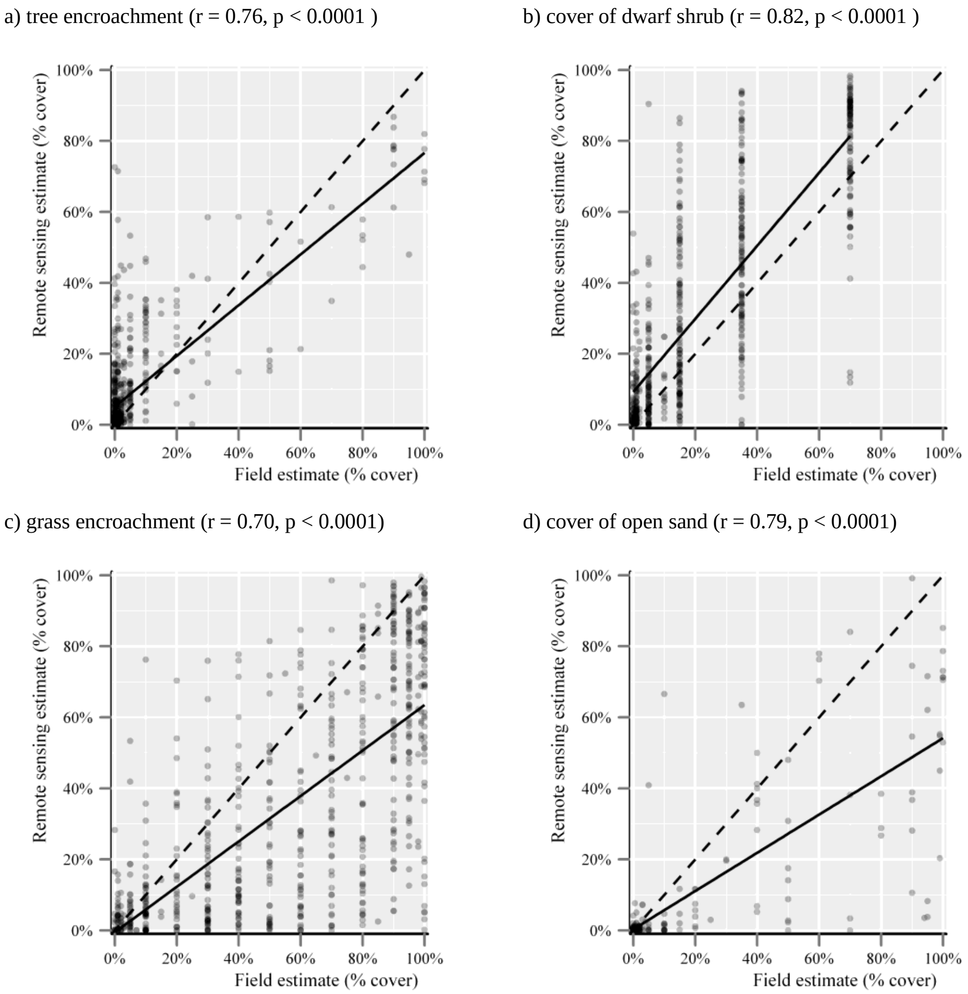

Figure 2. Relationship between field estimates and estimates derived from a remote sensing land cover map for four coarse-scale quality indicators. Indicators were estimated visually in the field, either on a continuous scale (plots a,c and d, showing the typical bias towards multiples of ten) or as classes of dominance (plot b). Darker dots indicate overlaying data points. The solid black trend line summarizes the observed relationship, the dashed diagonal represents a hypothetical situation with perfect agreement between field and remote sensing estimates.

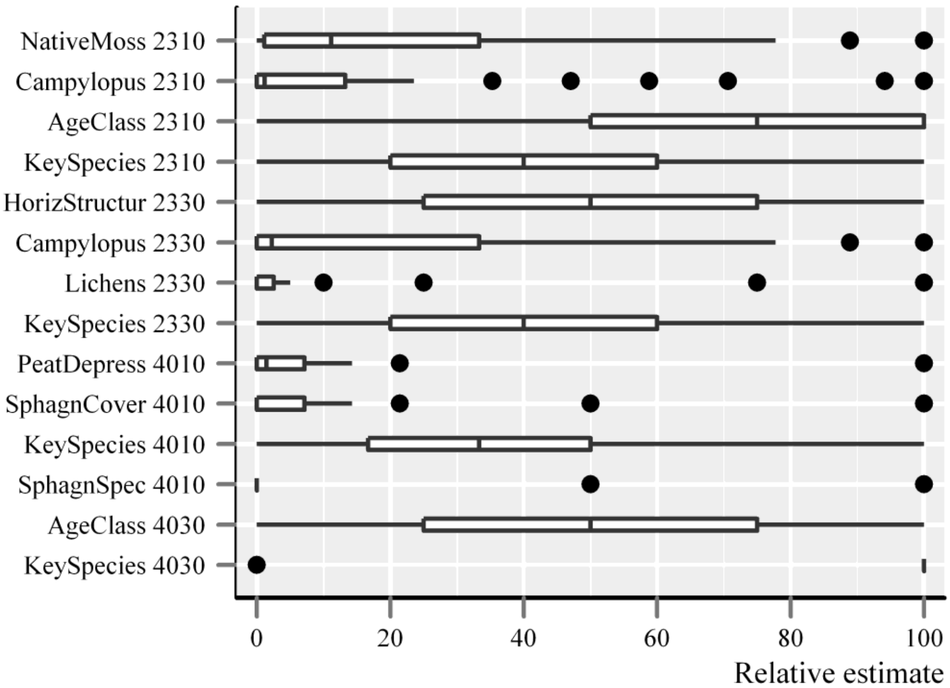

Figure 3. Comparison of the variability in the 14 fine-scale quality indicators amongst the study plots. Boxes represent the interquartile range (IQR), whiskers cover 1.5 time the IQR. All variables are rescaled to 0 – 100; the width of the rescaled IQR was used as measure of variability for further analysis.

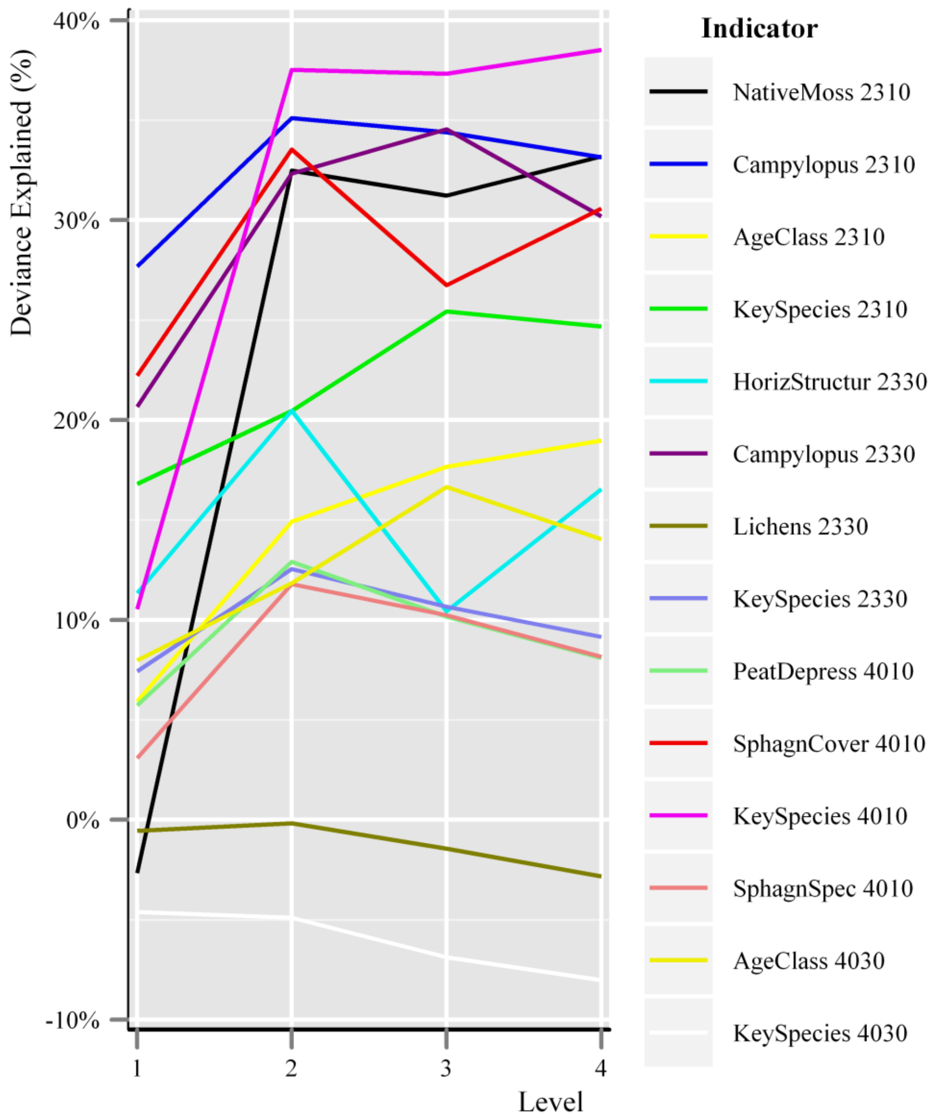

Figure 4. Performance of boosted regression trees predicting the 14 fine-scale quality indicators listed in Table 1, based on the percentages of land cover classes for the four levels of the classification scheme. The proportion of the deviance explained is used as a measure for model performance. Numbers following the indicator correspond with the Natura 2000 Habitat code (see Table 1). For a colour version of this figure, we refer to the electronic version of the article.

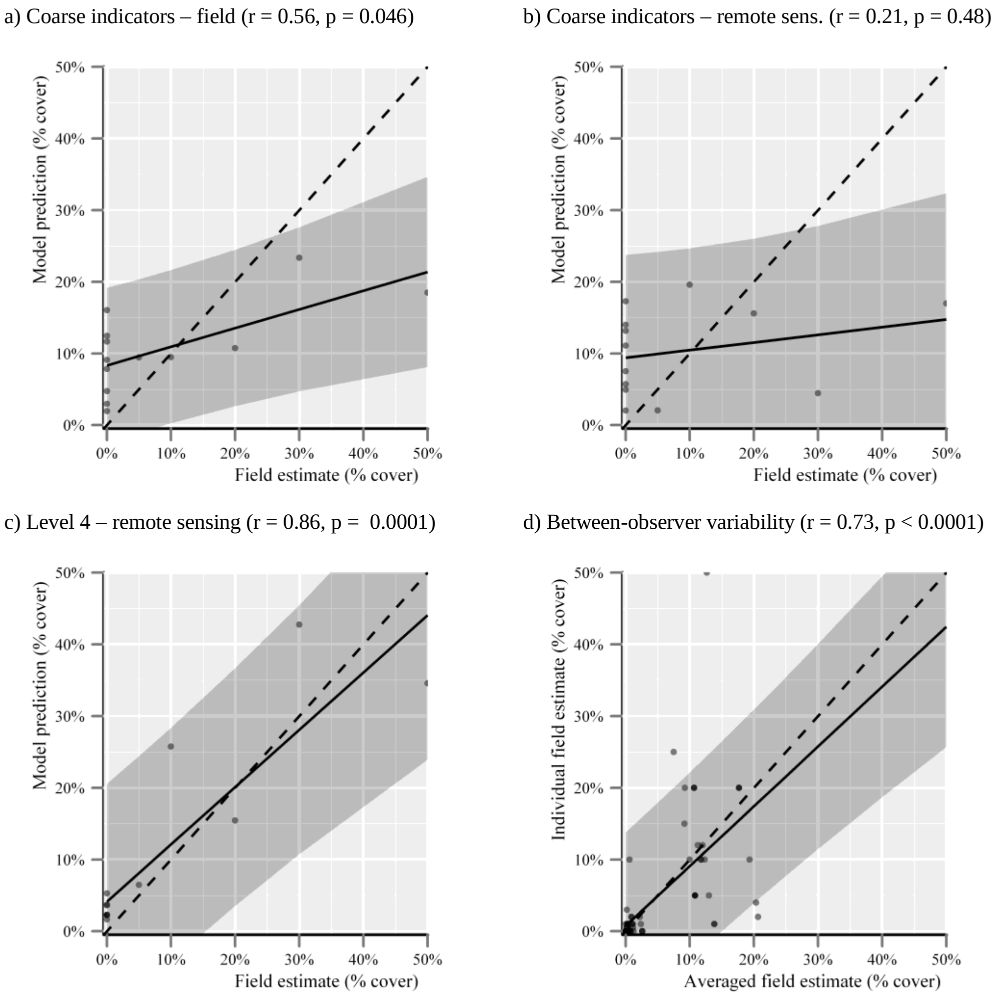

Figure 5. Example of relationship between field estimates and model predictions, here for the small-scale indicator "cover of invasive *Campylopus*" using three sets of predictor variables (a-c). The results of a small exercise to document between-observer variability are given in d), where individual field estimates are compared with the averaged field estimates (details in methodology). In all four graphs, data are shown only for plots where the observer variability was documented (N = 13). The trend line ± 95% prediction interval summarizes the observed relationship; the dashed diagonal represents a hypothetical situation with perfect agreement between field estimates and model predictions.

Table 1. Four most common Natura 2000 habitat types in the heathland study area, with indication of sample size in the dataset, and quality indicators for each habitat type. Characteristics are indicative for a positive$^{(+)}$ or a negative$^{(-)}$ status of the habitat patch. For a full description of the indicators, we refer to T'jollyn et al. (2009).

Natura 2000 habitat code and name	Number of samples (area sampled)	Quality assessment characteristics (C = coarse-scale, F = fine-scale)
2310 - Dry sand heaths with *Calluna* and *Genista*	180 samples (61ha)	C: Tree-encroachment$^{(-)}$ C: Occurrence of dwarf shrubs $^{(+)}$ C: Grass-encroachment$^{(-)}$ C: Cover of open soil$^{(+)}$ F: Cover of native mosses$^{(+)}$ F: Cover of invasive *Campylopus*$^{(-)}$ F: Age structure of *Calluna*$^{(+)}$ F: Number of key species$^{(+)}$
2330 - Inland dunes with open *Corynephorus* and *Agrostis* grasslands	81 samples (20ha)	C: Tree-encroachment$^{(-)}$ C: Grass-encroachment$^{(-)}$ C: Cover of open soil$^{(+)}$ F: Variation in horizontal structure$^{(+)}$ F: Cover of invasive *Campylopus*$^{(-)}$ F: Cover of lichens$^{(+)}$ F: Number of key species$^{(+)}$
4010 - Northern Atlantic wet heaths with *Erica tetralix*	265 samples (93ha)	C: Tree-encroachment$^{(-)}$ C: Occurrence of dwarf shrubs$^{(+)}$ C: Grass-encroachment$^{(-)}$ F: Occurrence of peat depressions$^{(+)}$ F: Occurrence of *Sphagnum*$^{(+)}$ F: Number of key species$^{(+)}$ F: Number of *Sphagnum* species$^{(+)}$
4030 - European dry heaths	145 samples (48ha)	C: Tree-encroachment$^{(-)}$ C: Occurrence of dwarf shrubs$^{(+)}$ C: Grass-encroachment$^{(-)}$ F: Age structure of *Calluna*$^{(+)}$ F: Number of key species$^{(+)}$

Table 2. Hierarchical classification scheme of the land-cover classes in the heathland study area. (adapted from the HABISTAT classification scheme, http://habistat.vgt.vito.be/modules/Results/FWDL.php).

Level 1		Level 2		Level 3		Level 4	
H	Heathland	Hd	Dry heathland	Hdc	*Calluna*-dominated heathland	Hdcy	*Calluna*-stand of predominantly young age
						Hdca	*Calluna*-stand of predominantly adult age
						Hdco	*Calluna*-stand of predominantly old age (open)
						Hdcm	*Calluna*-stand of (2 or 3) mixed age classes
		Hw	Wet heathland	Hwe	*Erica*-dominated heathland	Hwe-	*Erica*-dominated heathland
		Hg	Grass-encroached heathland	Hgm	*Molinia*-dominated heathland	Hgmd	*Molinia*-stand on dry soil (presumed to have developed from former Hdc)
						Hgmw	*Molinia*-stand on moist (wet) soil (presumed to have developed from former Hwe)
G	Grassland	Gt	Temporary grassland	Gt-	Temporary grassland	Gt--	Temporary grassland
		Gp	Permanent grassland	Gpa	Permanent grassland in intensive agricultural use	Gpap	Species-poor permanent agricultural grassland
						Gpar	Species-rich permanent agricultural grassland
				Gpn	Permanent grassland with semi-natural vegetation	Gpnd	Dry semi-natural permanent grassland
				Gpj	*Juncus effusus*-dominated grassland	Gpj-	*Juncus effusus*-dominated grassland
F	Forest	Fc	Coniferous forest	Fcp	Pine (*Pinus* sp.) forest	Fcpc	Corsican pine (*Pinus nigra laricio*)
						Fcps	Scots pine (*Pinus sylvestris*)
		Fd	Deciduous forest	Fdb	Birch (*Betula* sp.) forest	Fdb-	Birch (*Betula* sp.) forest
				Fdq	Oak (*Quercus* sp.) forest	Fdqz	Pedunculate oak (*Quercus robur*)
S	Sand dune	Sb	Bare sand	Sb-	Bare sand	Sb--	Bare sand
		Sf	Fixated sand dune	Sfg	Sand dune with grasses as important fixators	Sfgm	Sand dune fixated by grasses and mosses
				Sfm	Sand dune with mosses as dominating fixators	Sfmc	Fixated sand dune with predominantly *Campylopus introflexus*
						Sfmp	Fixated sand dune with predominantly *Polytrichum piliferum*
W	Water body	Wo	Oligotrophic water body	Wov	Shallow, vegetated oligotrophic water body (banks of 'moorland pools')	Wov-	Shallow, vegetated oligotrophic water body (banks of 'moorland pools')
				Wou	Unvegetated (deep) oligotrophic water (centre of 'moorland pools')	Wou-	Unvegetated (deep) oligotrophic water (centre of 'moorland pools')
A	Arable fields	Ac	Arable field with crop	Acm	Arable field – maize	Acm-	Arable field – maize
				Aco	Arable field - other crops	Aco-	Arable field - other crops

Table 3. Evaluation statistics of boosted regression trees (BRT) predicting fine-scale quality indicators. Predictors were (a) four broad-scale variables (tree encroachment, shrub cover, grass encroachment and cover of sand) estimated in the field, (b) the same broad-scale variables derived from a remotely sensed land-cover map and (c) detailed landcover classes (level 4 of the classification scheme). Evaluation statistics of field measurements are provided for comparison (d). For BRT results, mean values ± standard deviation of a 10 fold cross-validation are given.

		a) field estimates 4 coarse variables			b) remote sensing estimates 4 coarse variables		
Habitattype and indicator		Expl. Dev. (±SD)	Correlation (±SD)	RMSE (±SD)	Expl. Dev. (±SD)	Correlation (±SD)	RMSE (±SD)
2310	Cover of native mosses	0.38 (±0.06)	0.64 (±0.05)	18.24 (±0.95)	0.33 (±0.04)	0.59 (±0.03)	18.61 (±1.27)
	Cover of invasive *Campylopus*	0.18 (±0.03)	0.44 (±0.05)	15.92 (±1.63)	0.33 (±0.07)	0.62 (±0.06)	15.01 (±1.57)
	Age structure of *Calluna*	0.26 (±0.03)	0.58 (±0.05)	0.85 (±0.05)	0.16 (±0.13)	0.49 (±0.09)	0.90 (±0.06)
	Number of key species	0.31 (±0.07)	0.59 (±0.05)	0.87 (±0.05)	0.20 (±0.06)	0.50 (±0.05)	0.96 (±0.06)
2330	Variation in horizontal structure	0.07 (±0.06)	0.36 (±0.07)	1.06 (±0.07)	0.03 (±0.06)	0.29 (±0.05)	1.09 (±0.06)
	Cover of invasive *Campylopus*	0.25 (±0.09)	0.58 (±0.08)	22.37 (±2.14)	0.28 (±0.07)	0.64 (±0.06)	23.15 (±2.87)
	Cover of lichens	-0.27 (±0.68)	0.40 (±0.05)	2.54 (±1.01)	-0.05 (±0.16)	0.35 (±0.06)	3.13 (±0.91)
	Number of key species	0.08 (±0.05)	0.46 (±0.08)	1.26 (±0.12)	0.01 (±0.05)	0.23 (±0.07)	1.36 (±0.08)
4010	Occurrence of peat depressions	0.09 (±0.13)	0.42 (±0.07)	5.84 (±1.34)	0.08 (±0.08)	0.38 (±0.07)	6.03 (±1.27)
	Occurrence of *Sphagnum*	0.19 (±0.17)	0.51 (±0.05)	6.96 (±0.77)	0.23 (±0.12)	0.55 (±0.06)	7.22 (±1.21)
	Number of key species	0.43 (±0.06)	0.66 (±0.05)	1.07 (±0.05)	0.35 (±0.08)	0.62 (±0.05)	1.13 (±0.06)
	Number of *Sphagnum* species	0.16 (±0.1)	0.43 (±0.09)	0.44 (±0.03)	0.11 (±0.06)	0.44 (±0.06)	0.45 (±0.03)
4030	Age structure of *Calluna*	0.25 (±0.05)	0.55 (±0.05)	0.92 (±0.04)	0.07 (±0.06)	0.33 (±0.04)	1.04 (±0.04)
	Number of key species	0.03 (±0.04)	0.32 (±0.06)	0.23 (±0.02)	-0.05 (±0.06)	0.02 (±0.05)	0.23 (±0.04)
		c) Level 4 land cover classes			d) intra-observer variability		
Habitattype and indicator		Expl. Dev. (±SD)	Correlation (±SD)	RMSE (±SD)	Expl. Dev.	Correlation	RMSE
2310	Cover of native mosses	0.33 (±0.07)	0.60 (±0.05)	18.63 (±1.34)	0.70	0.84	15.10
	Cover of invasive *Campylopus*	0.33 (±0.07)	0.61 (±0.05)	15.03 (±1.75)	0.37	0.62	6.50
	Age structure of *Calluna*	0.19 (±0.08)	0.52 (±0.07)	0.89 (±0.05)	0.17	0.45	0.75
	Number of key species	0.25 (±0.05)	0.55 (±0.04)	0.92 (±0.05)	0.56	0.75	0.74
2330	Variation in horizontal structure	0.17 (±0.08)	0.53 (±0.10)	1.00 (±0.05)	not tested	not tested	not tested
	Cover of invasive *Campylopus*	0.30 (±0.09)	0.68 (±0.08)	22.75 (±2.90)	not tested	not tested	not tested
	Cover of lichens	-0.03 (±0.07)	0.31 (±0.11)	3.20 (±0.91)	not tested	not tested	not tested
	Number of key species	0.09 (±0.05)	0.39 (±0.07)	1.30 (±0.09)	not tested	not tested	not tested
4010	Occurrence of peat depressions	0.08 (±0.09)	0.39 (±0.07)	6.02 (±1.23)	not tested	not tested	not tested
	Occurrence of *Sphagnum*	0.31 (±0.15)	0.62 (±0.05)	6.82 (±1.15)	not tested	not tested	not tested
	Number of key species	0.39 (±0.06)	0.66 (±0.05)	1.09 (±0.04)	not tested	not tested	not tested
	Number of *Sphagnum* species	0.08 (±0.08)	0.40 (±0.06)	0.45 (±0.04)	not tested	not tested	not tested
4030	Age structure of *Calluna*	0.14 (±0.04)	0.46 (±0.07)	0.99 (±0.05)	not tested	not tested	not tested
	Number of key species	-0.08 (±0.14)	0.10 (±0.07)	0.23 (±0.03)	not tested	not tested	not tested

Table 4. Pairwise comparison of model performances using field and remote sensing (RS) estimates of the four coarse-scale quality indicators and the level 1 to 4 land cover classes as predictor variables. Results of Wilcoxon signed rank paired tests on the proportion of the deviance explained are given. The difference ("diff") corresponds with the median of the column level minus the row level; significant differences are indicated in bold.

	Level1	Level2	Level3	Level4	Coarse field indicators
- Coarse RS indicators	diff = -0.033 p = 0.15	**diff = 0.037 p = 0.0023**	**diff = 0.031 p = 0.0040**	**diff = 0.031 p=0.020**	diff = 0.040 p = 0.19
- Level1		**diff = 0.081 p < 0.001**	**diff = 0.069 p = 0.0017**	**diff = 0.067 p = 0.0017**	diff = 0.071 p = 0.11
- Level2			diff = -0.010 p = 0.50	diff = -0.013 p = 0.24	diff = -0.018 p = 0.58
- Level3				diff = -0.004 p = 0.54	diff = -0.001 p = 1.00
- Level4					diff = -0.005 p = 0.90