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Disentangling observer error and climate change effects in long-term monitoring of alpine plant species composition and cover

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Abstract

Questions: Long-term programs monitoring the impact of climate change on alpine vegetation necessarily involve changing observers. We aim at quantifying observer errors and ask if the signal of alpine vegetation transformation due to climate change exceeds pseudo-changes caused by observer errors.

Location: Two mountain regions in the Alps, Schrankogel and Hochschwab (both Austria), and one in the High Tatra Mountains (Slovakia).

Methods: Vascular plant species presence and cover were recorded on 10–12 1-m^2 plots by 13–14 observers per site. Observer errors were calculated as species turnover, and deviations of species cover and the plot thermic vegetation indicator (which is correlated with temperature) from the mean over all observers. Observer errors in estimating species cover were split into a random and systematic part. The influence of plot and species characteristics on observer errors was investigated using (generalized) linear mixed-effect models. Changes over time from three surveys in species turnover, cover and the thermic vegetation indicator were related to the amount of observer error using a bootstrap approach.

Results: Species cover was the most influential factor affecting observer errors in recording species lists and in species cover estimation. Plot attributes and observer identity had a weak but significant influence on errors in the thermic vegetation indicator. Systematic errors in estimating species cover were ≤5%. Changes over time in estimating species cover, as well as in species turnover and the thermic vegetation indicator exceeded observer errors in all cases where the observation period was ≥10 years.

Conclusions: The thermic vegetation indicator, which combines species composition and cover with species' elevational distributions, provides a reliable estimate of warming-related vegetation changes. Our results underline the importance of long-term

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in the landscape diversity and biodiversity caused by natural and anthropogenic factors".

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monitoring and long observation periods, which enable us to account for short-term fluctuations and observer errors alike.

KEYWORDS

alpine plants, Alps, climate change effects, cover, GLORIA (Global Observation Research Initiative in Alpine Environments), High Tatras, long-term monitoring, observer error, species composition, species turnover, thermic vegetation indicator

1 | INTRODUCTION

The present era of the "Anthropocene" is characterised by direct and indirect impacts of global climate change, which will affect ecosystems irrespective of their distance from human settlements, transport routes and intensive agricultural and forestry areas (Garavito, Newton, Golicher, & Oldfield, 2015; Sala, Chapin, & Huber-Sannwald, 2001). Climate change is expected to have a continued and growing influence on the composition of species in natural and semi-natural vegetation (van Vuuren, Sala, & Pereira, 2006). Model projections in mountain regions indicate accelerating upward shifts of species distributions driven by climate warming (Dullinger et al., 2012; Engler et al., 2011). Indeed, such shifts have already been observed in the European Alps (Rumpf et al., 2018) and on more than 300 mountain summits across Europe (Steinbauer et al., 2018). This might foster competitive pressure on small and light-demanding alpine plants, associated population declines, and species disappearance from increasingly unsuitable habitats (Lamprecht, Semenchuk, Steinbauer, Winkler, & Pauli, 2018; Rumpf et al., 2018). To assess changes in alpine plant species composition, species inventories and long-term monitoring of permanent plots are essential. Given the global dimension of climate change impact, a large number of study sites is required, including sites in remote areas.

A well-established method of investigating temporal changes in species composition is the comparison of species inventories over time (Pauli et al., 2012). Changes in species composition, however, are affected not only by ecological factors but also by chance events. To avoid erroneous conclusions, it is vital to distinguish between ecological signals and noise resulting from stochastic ecological fluctuation or from observer errors (Legg & Nagy, 2006; Mason, Holdaway, Richardson, & Chao, 2018) such as overlooking or misidentifying a species.

By comparing different methods to record alpine vegetation, Vittoz and Guisan (2007) suggested that lists of species are insufficient for monitoring and recommended to incorporate cover estimates as additional information. Estimating percent species cover is an intuitive and low-cost measure of estimating species abundance that does neither require the identification of individual numbers nor a destructive measurement of biomass, but is directly related to the latter (Elzinga, Salzer, & Willoughby, 1998). Point method cover estimates such as point-line intercepts (Dickinson, Mark, & Lee, 1992) or pointing with a grid frame (Everson, Clarke, & Everson, 1990), yielded the best consensus among observers. While being fairly reliable in this sense, these methods tend to capture only a very limited number of species with a sufficiently high cover (Friedmann, Pauli, Gottfried, & Grabherr, 2011; Vittoz & Guisan, 2007). Visual cover estimation thus remains the most effective method to obtain a complete record of a plot (Friedmann et al., 2011). Yet it involves a certain degree of inaccuracy and the resulting chance variability may be larger than the actual change in the composition of a patch of vegetation. It is therefore crucial to determine the amount of uncertainty associated with the species recording process (Morrison, 2016).

Vittoz et al. (2010) showed at Swiss sites of the international GLORIA program (Global Observation Research Initiative in Alpine Environments; Pauli et al., 2015) that observer errors in species lists and coefficients of variation of cover estimates were smaller than in previously published reports. On the other hand, the authors concluded that changes in cover were only likely to exceed noise for abundant species (>10% cover) or if relative changes were larger than 50% (Vittoz et al., 2010). For long-term monitoring, where observers inevitably change with increasing duration of the monitoring activity, it is also important to know whether involved observers tend to produce a noticeable amount of systematic errors, or mostly random errors (Gottfried et al., 2012). A systematic error occurs when a particular person notoriously over- or under-estimates the actual cover of species. Such an error would be constantly present for a particular person, but would vary in direction and size between observers. Random errors, on the other hand, fluctuate among subsequent estimates of species cover, either of one and the same observer or among different observers.

Finally, monitoring the impact of climate warming on alpine vegetation requires an indicator capable of showing whether the observed changes are related to actual changes in thermal conditions. An indicator that combines both species presences and their respective cover with species' elevational distributions is the thermic vegetation indicator (Gottfried et al., 2012). This biological indicator can be used as a surrogate for the thermal conditions at a plot, because it is correlated with in situ measured soil temperatures (Lamprecht et al., 2018).

The current study used vegetation records of different observers from the same 1 m × 1 m plots with species lists and visually estimated percentage cover in three alpine study sites with contrasting bedrock and different elevations and, thus, of different species composition, growth form distribution and ecological complexity. Further, the amount of variation among observers was compared with changes over time. A total of 28 observers who were familiar with the local flora but had different levels of experience participated in this study. The current study thus provides a representative estimate of the precision that can be expected in long-term monitoring using precisely re-located plots.

Specifically, we ask the following questions: (a) Do species attributes (species cover and growth form) and plot attributes (species richness and total vascular plant cover) have a larger influence on observer error than observer identity? (b) What is the magnitude of systematic compared to random observer errors in species cover estimation? (c) Are changes in species composition and cover over time larger than observer errors? Furthermore, we discuss the implications of observer errors on long-term monitoring.

2 | METHODS

2.1 | Study area

Observer error in recording the presence and cover of vascular plant species was assessed on three mountains where long-term monitoring is conducted in the frame of the GLORIA programme: Schrankogel (in the following abbreviated as SCH; Tyrol, Austria, 47°02'25" N, 11°05'41″ E, elevation 3,000 m a.s.l.), Hochschwab (HSW; Styria, Austria, 47°37'16'' N, 15°08'56″ E, 2,150 m a.s.l.) and the High Tatra Mountains (CTA; Prešov Region, Slovakia, 49°11'25'' N, 20°11'53" E, 2000 m a.s.l.). SCH and CTA consist of siliceous bedrock, whereas HSW is a calcareous mountain range. The vegetation on SCH is less dense than on HSW and CTA with a mean cover of vascular plants of 21.9%, 35.2% and 75.3%, respectively. While cushions are the dominant growth form on SCH both in terms of cover and species number, most species on HSW and CTA are rosette plants, and graminoids dominate in terms of cover (Appendix S1).

On HSW and in CTA, vascular plant species have been monitored in the uppermost 10 m of four summits arranged along an elevational gradient from the treeline upwards and additionally in four permanently marked 1-m^2 plots in each cardinal direction embedded in the summit areas since 2001 (Gottfried et al., 2012; Pauli et al., 2015). To avoid excessive disturbance in the summit area — which is being monitored as well — observer error plots were clustered in an easily accessible area with similar vegetation (Appendix S2d–f) and on the same bedrock but at a distance of several km from the monitoring summits (Appendix S2b, c). On SCH, the monitoring plots are arranged in transects (Lamprecht et al., 2018) and can be accessed without disturbing other monitoring plots. Therefore the observer error plots were chosen from the pool of monitoring plots (Appendix S2a). The observer error surveys were conducted in the same year (SCH) or one year before (HSW and CTA) a regular monitoring re-survey.

2.2 | Taxon nomenclature

Taxon names follow Fischer, Adler, and Oswald (2008).

2.3 | Field methods

Vascular plant species were recorded by 28 observers in a total of 34 1 m × 1 m plots, and their cover was visually estimated following the guidelines stated in Pauli et al. (2004, 2015). On SCH, each of 14 observers recorded ten plots in the year 2014. On HSW and CTA, each of 14 and 13 observers, respectively, recorded 12 plots in the year 2007. Nine observers participated in two of the study regions and two observers in all three. Recording was "blind", i.e., without information from the records of other observers or on previous records (if available). Sampling time was not restricted. Observers were familiar with the flora of the respective regions. Additionally, to smooth out different levels of experience, observers were trained prior to recording, i.e., all species occurring in the area around the observer error plots were identified and their differential traits discussed in the team with particular regard for difficult taxa and similar species. Plots were marked at the four corners and photographed to ensure precise re-location.

2.4 | Data analysis

All statistical analyses were carried out using the software R (R Core Team, 2016).

2.4.1 | Presence of species

Species turnover is the difference in species composition between two species lists. Species turnover over time is defined as the difference between species lists compiled at two points in time, whereas pseudo-turnover is the difference in two species lists compiled by different observers which is purely caused by observer errors. Both types of turnover were calculated following Nilsson and Nilsson (1985):

$$T = (X_A + X_B) / (S_A + S_B),$$

where S is the total number of species and X is the number of species exclusively found in a given plot in survey A and B, respectively. For species turnover over time, A and B represent surveys at different times, and for pseudo-turnover surveys carried out by different observers. The turnover value can range from 0 (the two species lists are equal) to 1 (no overlap of the species lists).

2.4.2 | Species cover

The coefficient of variation (CV) was calculated as the standard deviation of cover estimates of all observers per species-quadrat combination divided by the mean.

The cover estimation error was calculated as the difference of each estimated cover value of each observer to the 'true' value. As the true cover of a species is unknown, we assumed the mean cover value of all observers (i.e., the consensus estimate) to be its best approximation. As the cover estimates range over several orders of magnitude (<0.001% – 100%), the error was calculated in percent for the entire dataset and for each region separately as follows:

$$\text{Cover estimation error} = \left[\left(x - \bar{x}\right) / \bar{x}\right] * 100$$

where x is the cover estimate obtained by each observer and $\bar{x}$ is the consensus value.

2.4.3 | Thermic vegetation indicator

The thermic vegetation indicator (TVI) was calculated for each plot as an averaged composite score of the altitudinal ranks (a species' distribution centre along the elevation gradient; 1 = subnival–nival, 2 = alpine–subnival, 3 = alpine, 4 = treeline–alpine, 5 = treeline, 6 = montane) weighted by the cover of each species following Gottfried et al. (2012):

$$\text{TVI} = \left(\sum \text{rank}(\text{species}_i) \times \text{cover}(\text{species}_i)\right) / \sum \text{cover}(\text{species}_i)$$

The difference between the TVI values obtained by each observer and the mean TVI over all observers (i.e., the consensus value) was calculated for the entire dataset and for each region separately.

2.4.4 | Variables affecting observer errors

To assess the effect of species and plot attributes, and observer identity on observer errors in recording species presence, cover and the TVI, generalized linear mixed-effect models (GLMMs) or linear mixed-effect models (LMMs) were applied (details see below). Species attributes include growth form (annual, cushion, graminoid, rosette, other herbaceous, woody plants) and species cover (log-transformed, base 10). Plot attributes were total vascular plant cover (mean over all observers) and plot species richness (i.e., the number of species found by the majority of observers). Models were calculated for the entire dataset as well as for each region separately.

Predictor variables were tested for collinearity using variance inflation factors (function *corvif* available from http://highstat.com/index.php/mixed-effects-models-and-extensions-in-ecologywith-r; Zuur, Ieno, Walker, Saveliev, & Smith, 2009). The square root of the variance inflation factor of a variable states how much larger the standard error of the coefficient estimate is, compared to a model where that variable is uncorrelated with the other predictors. Variance inflation factors were <2, except for species presence and cover on SCH (where the variance inflation factor for total vascular plant cover and plot species richness ranged between 2.01 and 2.16). In the latter cases, the concerned variables were not removed, but their effect may be more difficult to disentangle from that of other covariates.

In the (G)LMMs, the above listed variables were used as fixed effects, and observer as well as plot nested in region as random intercept terms. The latter term reflects the hierarchical structure of the dataset and accounts for potential spatial dependencies. Note, however, that the variance of the random intercept region cannot be reliably estimated because region has only three levels (i.e., SCH, HSW and CTA). Parameters were estimated by the Laplace approximation using the function *glmmTMB* as implemented in the R package *glmmTMB* (Brooks et al., 2017). The relative impact of the fixed effects as well as the random effect "observer" was assessed by comparing the deviance of the full model with models where one variable was excluded at a time as follows: −2 * (log likelihood of reduced model − log likelihood of full model). The larger the deviance, the higher is the impact of the excluded variable on the explanatory power of the model. Significance of the deviance was tested with χ^2 tests using the function *anova* (R package *stats*).

To assess which variables affect observer errors in recording species presence, binomial GLMMs with a logit link were used. As it is unknown which species were actually present in a plot, we compared individual species presence records with three scenarios where a species was considered to be truly present if found by (a) the majority of observers, (b) all observers, and (c) at least one observer. Thus, the binary response variable (in the following referred to as "detection error") was set to one if (a) a species presence record deviated from the majority of observers; (b) an observer recorded a species in a plot that was not found by all other observers; and (c) an observer failed to record a species that was found by at least one observer in a given plot. Correct records were set to zero.

To assess which variables affect observer errors in estimating species cover as well as in the TVI, LMMs (family Gaussian, identity link) were applied. The response variable was transformed as follows:

$$abs[\log(x/\bar{x})]^{0.14}$$

where x is the cover estimate or TVI obtained by each observer and $\bar{x}$ is the consensus value (i.e., the mean over all observers). Values were power-transformed ($\text{value}^{0.14}$) to obtain homogeneous variances (Appendix S3). For cover, only those species recorded by at least two observers were included. As TVI is a plot-based indicator, only total vascular plant cover and species richness were included as fixed effects in these models.

2.4.5 | Systematic versus random observer errors in species cover estimation

Two types of errors in cover estimation can be distinguished: random errors, i.e. imprecisions one observer makes from one estimate to the next, and systematic observer errors, i.e. systematic over- or underestimation of the true cover value (Gottfried et al., 2012). As a measure of the relative magnitude of the systematic observer errors vs. random errors, the variance of the random effect "observer" in the LMMs was divided by the residual variance. In order to investigate whether some observers' estimates were systematically too large or too small, observer-specific systematic errors were measured both in terms of the difference to the average (mean) and the median of all observers (i.e., the consensus).

2.4.6 | Comparison of observer errors with changes over time

For comparisons between observer errors and changes over time, data from historical surveys were used. On SCH, surveys from the year 1994 (Pauli, Gottfried, & Grabherr, 1999), 2004 (Pauli, Gottfried, Reiter, Klettner, & Grabherr, 2007) and 2014 (Lamprecht et al., 2018) were available for 355 plots. On HSW and CTA surveys from the years 2001, 2008 (Gottfried et al., 2012) and 2015 (M. Winkler et al. unpublished data) were available from 64 long-term monitoring plots on four summits in each region. Using non-metric multidimensional scaling (NMDS; function *metaMDS* in R package *vegan*; R Core Team, R Foundation for Statistical Computing, Vienna, Austria), the similarity between the vegetation in the observer error plots and the vegetation present in the monitoring plots was assessed (Appendix S2d–f). The ellipse enclosing the observer error plots (function *ordiellipse* with kind="ehull") did not overlap with the easternmost monitoring plots on SCH (21 plots, block D; Appendix S2d), the lowest summit on HSW (16 plots, Appendix S2e) and the highest summit on CTA (16 plots, Appendix S2f), which were therefore not used for comparisons between observer errors and changes over time. This resulted in 334 monitoring plots on SCH, and 48 on both HSW and CTA. Furthermore, the vegetation of four observer error plots on HSW deviated from all other plots and these were consequently excluded from this analysis as well (Appendix S2e). Since the historical surveys on HSW and CTA were conducted on plots different to those used for the observer error surveys and represented only a small subset of monitoring plots on SCH, we assume for all comparisons of observer errors with changes over time that (a) the historical and observer error surveys had the same level of precision; (b) the precision in the observer error plots is representative for the whole region; and (c) observed changes over time are representative for the region.

A bootstrap approach was used to compare the magnitudes of changes over time in species lists, cover estimates and TVI with the amount of difference expected purely by observer errors: two observers were randomly drawn without replacement, independently for each observer error plot. Then the difference between their species lists (pseudo-turnover), their cover estimates and TVIs were calculated, and the respective means over all plots computed. For cover, this difference was calculated from the power-transformed cover estimates to ensure a closer fit to a normal distribution. The differences were subsequently squared because it is biologically meaningless whether the difference in cover estimates between two observers is positive or negative. To assess the divergence between observers across a whole region, the average of the squared differences was taken across all plots of a region. Since the above explained sample of the two paired observers was random, this process was repeated 1,000 times with independently drawn observer pairs. The 1,000 resulting average differences were plotted as histograms

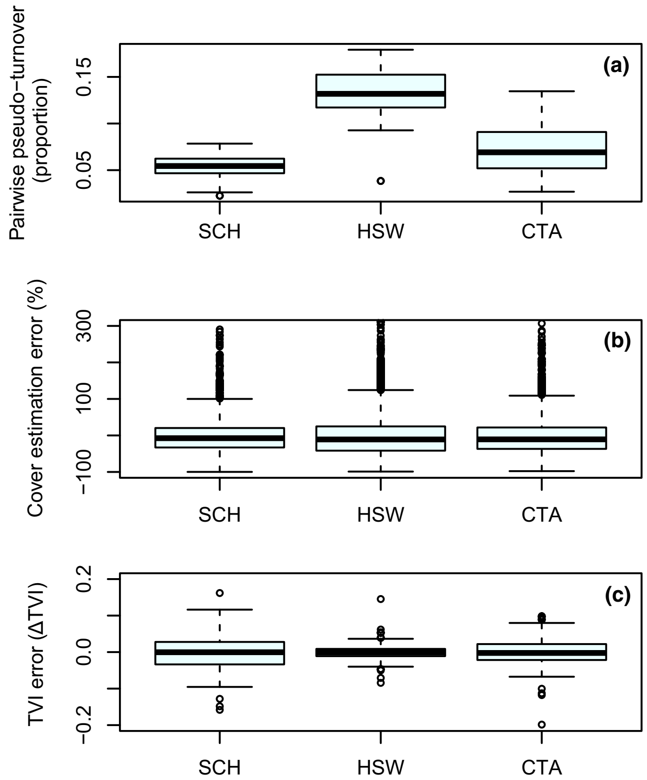

FIGURE 1 Boxplots of pairwise pseudo-turnover (a) and observer errors in estimating species cover (b) and the plot thermic vegetation indicator TVI (c) in the three mountain regions Schrankogel (SCH), Hochschwab (HSW) and High Tatras (CTA). Observer errors in (b) and (c) are defined as differences with the values obtained by the majority of observers. Outliers beyond 300% in (b) are not shown

and graphically compared with the corresponding changes over time in species turnover, cover and TVI. Changes over time were calculated for 48 long-term monitoring plots on three summits each on HSW and CTA for the period 2001–2008 (for TVI cf. Gottfried et al., 2012), 2008–2015 and 2001–2015, and 334 plots on SCH for the periods 1994–2004, 2004–2014 and 1994–2014 (for TVI cf. Lamprecht et al., 2018), respectively. More formally, we computed also p-values for testing whether changes over time were larger than observer errors. As the outcomes generated by bootstrap were normally distributed, we computed our p-value as $p = 1 \times \Phi((t \times \mu)/SD)$, with Φ denoting the cumulative distribution function of the standard normal distribution, t the mean change over time, and μ and SD the mean and standard deviation of the bootstrapped observer error values, respectively.

3 | RESULTS

3.1 | Presence of species

The total number of species found by at least one observer was 36 on SCH, 95 on HSW, and 41 in CTA, respectively. Overall, 17% of the species on HSW and CTA, and 3% on SCH were recorded only once (i.e., by only one observer in a single plot). The proportion of species records (presence of a given species in a given plot) registered by the majority of observers ranged from 60.4% on HSW to 82.5% on SCH. On the other hand, 8.7%, 21.5% and 11.8% of the species records were recorded by only one observer on SCH, HSW and CTA, respectively (Appendix S4).

Mean pseudo-turnover among pairs of observers was 0.053 (*SD* = 0.007) for SCH, 0.134 (*SD* = 0.015) for HSW, and 0.071 (*SD* = 0.017) for CTA. Variation in performance among observers was highest on HSW, and lowest at SCH (Figure 1a, Appendix S5).

3.2 | Species cover

CV of the overall data set was 60.6 ± 35.6% (mean ± *SD*); calculated for each region separately CV was 58.6 ± 27.5% on SCH, 65.3 ± 39.3% on HSW, and 54.5 ± 34.7% in CTA.

Figure 1b shows the boxplot of the cover estimation errors as differences (in %) of the cover estimates from the consensus estimate separately for each region. Observer errors in cover estimation were similar among the three regions, with the 25%–75% quantile ranging from −33.0% to + 20.4% in SCH, −41.7% to + 24.7% on HSW, and −36.8% to 21.8% in CTA, respectively. The 25%–75% quantile (i.e., the box) of observer-specific errors in cover estimation (Appendix S6a) ranged between −59.1% and + 90.5%, and the 2.5%–97.5% quantile between −95.0% and + 241.7%. The average relative deviations from the consensus ranged between −25.8% and 58.0% for the different observers (Appendix S5). Statistically significant systematic errors (i.e., deviations of the median from zero) were obtained for twelve of the 28 observers, seven of whom produced estimates that were significantly too low. However, the amount of systematic error was moderate in general (±16.0% on average). Species-specific boxplots show idiosyncratic patterns of observer errors in cover estimation with the 25%–75% quantile of most species remaining within ± 50%. Notable exceptions are *Arenaria ciliata*, *Campanula pulla*, *Gentiana brachyphylla* and *Sedum atratum*, all usually small individuals with a scattered distribution (Appendix S6b). Cover estimation error patterns are remarkably similar among growth forms with the median close to zero and the 25%–75% quantile in the range of *c.* -40% and +25% with the exception of *annuals* and *other herbaceous*, both of which have a broader interquartile range and a median of −25.7% and −16.3%, respectively (Appendix S6c).

TABLE 1 Importance of variables affecting observer errors based on model deviance

	Overall	SCH	HSW	CTA
(a) Detection error				
Growth form	74.9***	12.6*	50.9***	32.7***
Species cover	**401.3*****	**137.6*****	**162.3*****	**124.5*****
Plot species richness	11.5***	0.3 n.s.	14.9***	0.1 n.s.
Vascular plant cover	1.9 n.s.	0.4 n.s.	1.7 n.s.	4.3*
Observer	25.1***	−8.8 n.s.	13.2***	17.5***
(b) Cover estimation error				
Growth form	18.4**	8.2 n.s.	7.9 n.s.	10.5**
Species cover	**834.5*****	**210.2*****	**435.2*****	**190.0*****
Plot species richness	19.0***	<0.1 n.s.	24.9***	<0.1 n.s
Vascular plant cover	10.5**	1.8 n.s.	1.9 n.s.	8.7**
Observer	137.1***	14.1***	56.1***	74.7***
(c) Thermic vegetation indicator error				
Plot species richness	1.0 n.s.	0.2 n.s.	**5.6***	0.7 n.s.
Vascular plant cover	**9.8****	1.1 n.s.	0.5 n.s.	1.1 n.s.
Observer	8.3**	0.3 n.s.	0.6 n.s.	**5.2***

Notes: Models are binomial generalized mixed-effect models (a) and linear mixed-effect models (b–c) of factors affecting errors of 28 observers recording the presence and cover of vascular plant species and the plot thermic vegetation indicator (TVI) on 34 plots in in the three mountain regions Schrankogel (SCH), Hochschwab (HSW), and High Tatras (CTA). (a) Detection errors in recording species presence; (b) observer errors in cover estimation, and (c) observer errors in TVI. Observer errors are defined as deviations from the majority of the observers. The deviance of models with one explanatory factor removed is calculated in relation to the full model as −2 * (log likelihood reduced model − log likelihood full model). The most important factor is given in bold. Asterisks indicate significance of deviance (Chi-square test). Observer is a random effect in the models. Fixed effects of models are shown in Appendix S7.

*$p < 0.05$;

**$p < 0.01$;

***$p < 0.001$.

3.3 | Thermic vegetation indicator

Observer errors in TVI ranged from −0.292 to 0.359. Errors were smallest on HSW with the 25%–75% quantile between −0.011 and 0.008, followed by CTA with ± 0.022, and SCH with 0.033 and 0.028, respectively (Figure 1c). The difference between each observer's TVI ranged from −0.039 to +0.024 on SCH, −0.008 to 0.015 on HSW and −0.036 to +0.045 in CTA, respectively (Appendix S5).

3.4 | Variables affecting observer errors

Detailed results of binomial GLMMs and LMMs for the overall data-set and each region separately are shown in Appendix S7.

TABLE 2 Effect of plant growth form on observer error when recording the presence of vascular plant species on 34 plots in three mountain regions

	Detection error (%)			
Growth form	Overall	SCH	HSW	CTA
Annual	**14.3**	1.4	**21.4**	–
Graminoid	9.8	4.6	14.5	**9.4**
Cushion	7.7	5.2	9.4	-
Rosette	8.8	**6.6**	10.9	5.9
Other herbaceous	5.5	4.0	6.2	–
Woody plant	4.8	–	5.8	3.0

Percent false records per growth form type overall, Mt Schrankogel (SCH), Hochschwab (HSW), and High Tatra Mountains (CTA). False records are defined as those deviating from the majority of observers. The growth form with the highest detection error is given in bold.

3.4.1 | Species presence

As the scenarios of what constitutes the "true" value (majority, all observers, at least one observer) delivered qualitatively almost identical results regarding the ranks of importance of the variables (Appendix S8), only the results for the majority scenario are shown in the main text. Model comparisons based on deviance showed that species cover had by far the greatest influence on detection error, followed by growth form in the overall dataset and each region (Table 1a). Observer ranked third in the overall dataset as well as on SCH and CTA, and fourth on HSW. Plot species richness was only significant in the overall dataset (rank 4) and on HSW (rank 3), whereas total vascular plant cover was only significant in CTA (Table 1a).

The plant growth form *annuals* had the highest detection error, followed by *graminoids*. With regard to single study regions, the same pattern was found on HSW, whereas in CTA (where no *annuals* occurred), *graminoids* followed by *rosettes* had the highest error probabilities. On SCH *rosettes* followed by *cushions* led to the most frequent errors (Table 2). The detection error decreased with increasing plant species cover in all regions (Figure 2a). Only on HSW, the detection error increased slightly with increasing species richness (Figure 2b), whereas in the other two regions there was no clear relationship. The effect of total vascular plant cover was region-specific with no obvious overall trend (Figure 2c).

3.4.2 | Species cover

Model comparisons based on deviance showed that species cover had by far the greatest influence on differences in cover estimates from the consensus, followed by the random effect "observer" both overall and in each separate region (Table 1b). Plot species richness was the

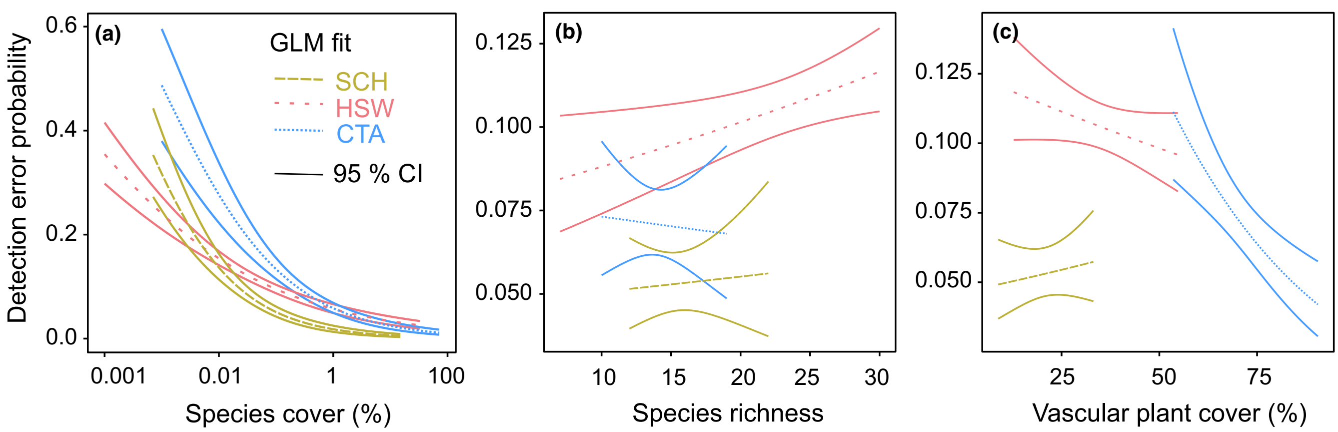

FIGURE 2 Observer error probabilities in recording species presence depending on species and plot characteristics. Probability of detection error, in relation to (a) species cover, (b) plot species richness, and (c) total vascular plant cover in three mountain regions (SCH: Schrankogel; HSW: Hochschwab; CTA: High Tatras). Lines represent generalized linear model fit (function geom_smooth with method glm, family = binomial from R-library ggplot2; Wickham, 2016) and 95% confidence bands for the true regression curve. In (a), the *x*-axis is logarithmic. Due to the small number of points and large residual variance, the confidence bands are often wide. The effects of species and plot characteristics on observer errors were tested with generalized linear mixed-effect models (Appendix S7) [Colour figure can be viewed at wileyonlinelibrary.com]

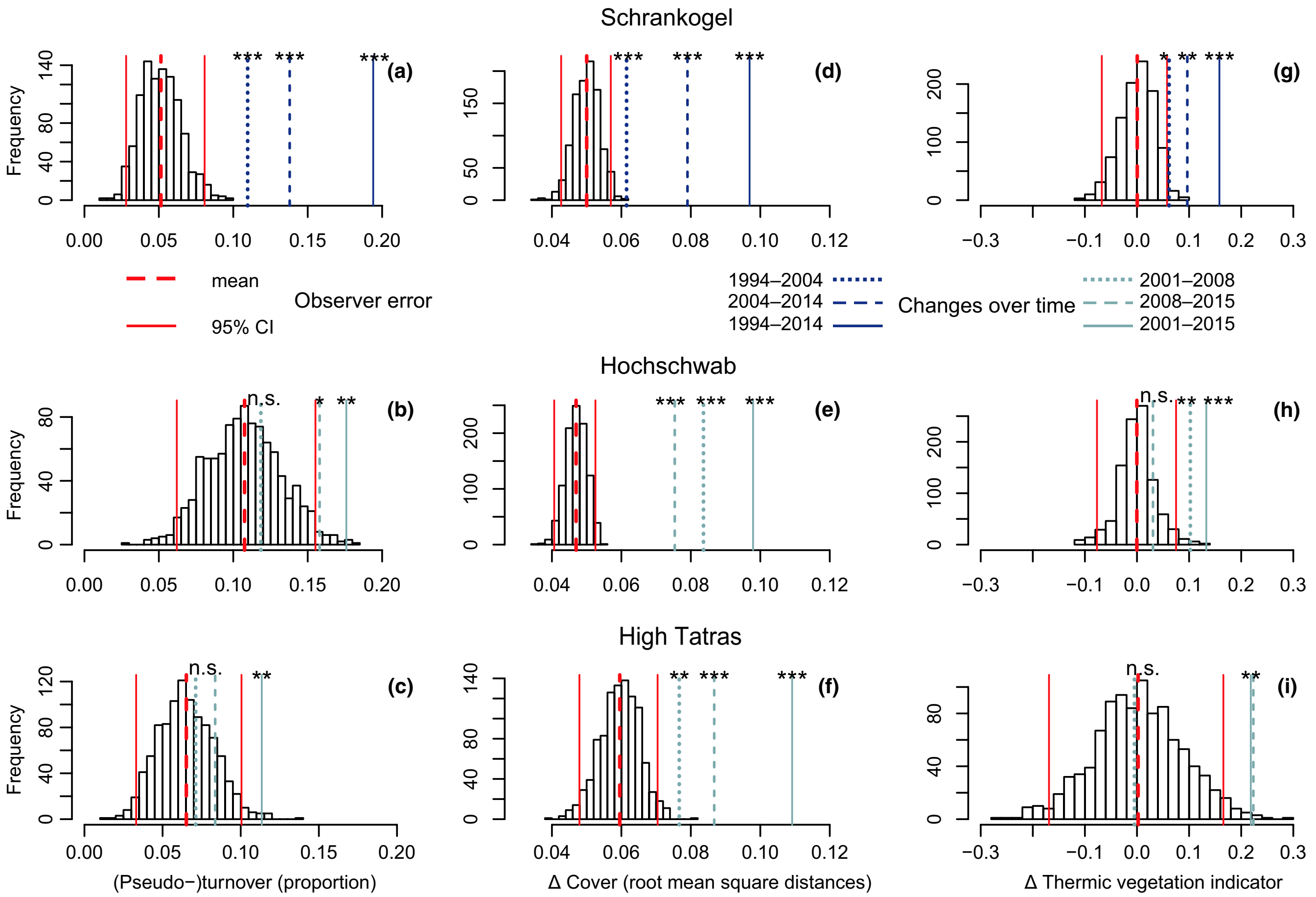

FIGURE 3 Comparison of changes over time with observer errors in recording the presence and cover of vascular plant species and the thermic vegetation indicator in three mountain regions. Histograms of bootstrapped inter-observer errors (a, d, g) on Schrankogel (SCH), (b, e, h) on Hochschwab (HSW), and (c, f, i) in High Tatras Mountains (CTA) of (a–c) pseudo-turnover, (d–f) root mean squared errors in transformed cover estimates, and (g–i) absolute differences in thermic vegetation indicator between observer pairs. Asterisks indicate whether changes over time are statistically significantly larger than observer errors (p-value: *, <0.05; **, <0.01; ***, <0.001; n.s., ≥0.05). For further details, see section 2 Methods, in the main text [Colour figure can be viewed at wileyonlinelibrary.com]

third most important factor overall and on HSW, and growth form on SCH and CTA. Systematic observer errors in cover estimation accounted for 2.4% of the residual variance in LMMs in the overall dataset, and 1.5% on SCH, 2.5% on HSW, and 5.0% in CTA, respectively.

3.4.3 | Thermic vegetation indicator

Observer errors in TVI were significantly influenced by vascular plant cover and observer in the overall dataset and by plot species richness on HSW and observer in CTA, whereas none of the factors was significant on SCH. However, deviance was <10 in all cases (Table 1c).

3.5 | Comparison of observer errors with changes over time

Species turnover over time was significantly larger than pseudo-turnover in all periods (1994–2004, 2004–2014, 1994–2014) on SCH, in the periods 2008–2015 and 2001–2015 on HSW and only in 2001–2015 on CTA (Figure 3a–c). Cover changes over time were clearly beyond estimation noise and statistically significant in all three regions regardless of the period (Figure 3d–f). Observer errors in the TVI were normally distributed around zero and, except for the period 2008–2015 on HSW and 2001–2008 in CTA, all changes in the thermic vegetation indicator values over time were significantly larger than expected under a scenario involving observer errors only (Figure 3g–i).

4 | DISCUSSION

In the present inter-observer error study, we evaluated the relative effect of observer, plot and species characteristics on several types of common errors in long-term monitoring of vascular plant species composition: pseudo-turnover, errors in species cover estimation (Mason et al., 2018; Morrison, 2016) and in a community-weighted trait measure, the plot-based TVI.

Pseudo-turnover among pairs of observers was between 0.053 and 0.134 and thus in the lower range of values found in grassland plots (0.09–0.2; reviewed in Morrison, 2016) and forest plots (0–0.21; Allegrini, Canullo, & Campetella, 2009) of comparable size. A proportion between approximately one third to two thirds of the species per plot were recorded by all observers (Appendix S4), which is in the same range (39%–77%) obtained by Vittoz and Guisan (2007) and Vittoz et al. (2010) for 0.4-m^2–4-m^2 plots in similar vegetation types.

The observed ca. 60% overall CV of visual cover estimates was in the same range as reported in studies with similar vegetation, plot size and estimation method (Vittoz et al., 2010; Vittoz & Guisan, 2007). CVs were considerably smaller in two studies of low-elevation grasslands (7%–15%; Klimeš, 2003; West, 1938 in Morrison, 2016). However, the reason for lower CVs is probably methodological differences: the study by West (1938) was based on estimation of total vegetation cover rather than individual species, and in the study by Klimeš (2003) all cover values below 1% were set to the arbitrary value 0.5%. Thus, species with low cover which may have very large CVs (Morrison, 2016) were effectively not included in the calculation of the CV. On the other hand, CV was almost three times higher in forests (~170%; Helm & Mead, 2004), where plots usually are much larger than in the present study and thus cover estimation may be less reliable.

Species attributes were the most influential factors affecting observer errors in the compilation of species lists, with species cover being by far the most important factor (Table 1). This finding was robust regardless of the definition of the "true" species list (i.e., species found by the majority of observers, by all observers or at least one observer; Appendix S8). As observed in previous studies (Burg, Rixen, Stöckli, & Wipf, 2015; Milberg, Bergstedt, Fridman, Odell, & Westerberg, 2008; Vittoz et al., 2010; Vittoz & Guisan, 2007), error probabilities decreased clearly with increasing cover (Figure 2). The effect of growth forms was mainly attributable to annuals, with the main cause being disagreement on species identity in one species pair on HSW (*Euphrasia minima* vs. *E. salisburgensis*); followed by graminoids which may be challenging to identify when not flowering. The majority of species, however, has flowers or fruits in the midst of the short alpine growing season of temperate biomes, when vegetation recording is conducted. Annual species, contributing only marginally to the alpine species diversity, may show large inter-annual fluctuations in cover (cf. Lamprecht et al., 2018) and, therefore, are of limited relevance for the detection of multi-year effects of climate change. Other factors such as the clusteredness of species' fine-scale distribution patterns, the absence of features critical for species identification (such as flowers or fruits) in some individuals or small sizes of individuals are also expected to play a role for observer errors, but could not be recorded in the present study.

Observer identity had a larger influence than plot attributes, such as species richness and total plant cover. Noteworthy, only about half of the observers participating in two or three regions showed similar deviations from the consensus in all regions (i.e. had a systematic error). Moreover, the overall level of precision was region-specific which could be explained only partly by plot attributes. Regional species diversity and species composition may have played a role, since HSW, the region with both the highest species richness and the highest absolute number of graminoid species also had the lowest level of precision across the observers. Length of ascent as suggested by Burg et al. (2015) appears to be an unlikely explanation for higher observer errors, since errors were smallest in the region with by far the longest ascent (SCH). Furthermore, weather conditions on SCH are by far the harshest among the three regions due to its high elevation.

As with species lists, species cover had by far the largest effect on cover estimation errors, followed by observer identity. Again, errors increased with increasing species cover. In contrast to species lists, effects of growth form and plot attributes were of minor importance (Table 1). Other studies showed that observer variation in cover estimates increased with increasing plot richness (Kercher, Frieswyk, & Zedler, 2003), increasing total plant cover in a plot (Klimeš, 2003), increasing cover (Johns, Brownstein, Blick, Erskine, & Fletcher, 2015), and variation in species morphology (Klimeš, 2003), but found no relationship with growth form (Johns et al., 2015).

4.1 | Implications for long-term monitoring

Long-term vegetation monitoring is inevitably linked with the employment of multiple changing observers and, therefore, with the associated inter-observer errors (Legg & Nagy, 2006). Ideally, observer error should be estimated at each monitoring cycle and at each observation site separately, considering the substantial regional variation in some types of observer errors we found here. However, this is resource- and time-consuming and especially at sites with a short vegetation period, such as in high-mountain environments, it may be too difficult to accommodate both the monitoring fieldwork and the observer error assessment. Furthermore, repeated plot observations by many observers may cause trampling damage (Vittoz et al., 2010). Therefore, we conducted the observer error survey directly in the monitoring plots only if this could be done without disturbing the surrounding monitoring plots. On HSW and in CTA this was not possible because the 1-m^2 plots are embedded in larger summit area sections which are also monitored in the framework of the GLORIA programme (Pauli et al., 2015). Strategies to deal with observer error in long-term monitoring programmes include the minimization of errors, identification of systematic bias, the use of robust indicators of change, and finally, observation periods of sufficient length for the signal to exceed observer error noise.

4.1.1 | Error minimization

Species identification skills are the most crucial and central issue in long-term vegetation monitoring (Legg & Nagy, 2006), underlining the importance of training with a special focus on small, critical and difficult species and previous agreement on a regional species list (Klimeš, Dančák, Hájek, Jongepierová, & Kučera, 2001; Vittoz & Guisan, 2007). Graminoid species require particular attention, because identification errors may occur even at larger species cover values if an observer is not sufficiently familiar with the identification features of species within and even among genera. A couple of days, therefore, should be set aside in the field, prior to the actual vegetation recording, for knowledge transfer among all team members. This also concerns the visual estimation of species cover, requiring training and calibration which can be aided by the use of transparent templates showing different cover sizes (Pauli et al., 2015). A detailed quality-assurance procedure was suggested by Allegrini et al. (2009). Less experienced observers may profit from experts when working in pairs, although a joint recording with two observers did not improve cover estimations in a study by Vittoz and Guisan (2007).

4.1.2 | Systematic bias

Over all regions, 97.6% of the errors in cover estimation could be attributed to random errors, and the remaining 2.4% to systematic observer bias. In studies distinguishing between systematic and random error, the systematic portion ranged between 0% and 33% (Archaux, Berges, & Chevalier, 2007; Gottfried et al., 2012; Milberg et al., 2008; reviewed in Morrison, 2016). Milberg et al. (2008) considered a systematic error contribution of <10% as acceptable, which is of particular relevance in long-term monitoring, where observers unavoidably change. Theoretically, it is possible to apply a correction factor to account for systematic over- or underestimation of cover. However, this appears to be impractical as for each observer–species combination a separate correction factor would have to be applied (Sykes, Horrill, & Mountford, 1983). Random errors will partially cancel out when species are observed several times in different plots by the same observer. However, they lead to lower statistical power (i.e., the probability of rejecting the null hypothesis when it is false) which should be accounted for in data analysis and the design of long-term monitoring projects (Legg & Nagy, 2006; Milberg et al., 2008).

4.1.3 | Robust indicators of change

Neither species turnover nor overall cover changes permit directly inferring climate change effects on vegetation. To detect these, an indicator combining both species composition and cover, the TVI, has been applied to pan-European monitoring data (Gottfried et al., 2012). Thermophilisation observed over time (Gottfried et al., 2012; Lamprecht et al., 2018) exceeded pseudo-changes in the TVI in all but two cases (2001–2008 in CTA, and 2008–2015 on HSW) where actual thermophilisation was close to zero. Another advantage for long-term monitoring efforts is that the effects of plot characteristics and observer identity on TVI estimation errors were generally rather weak (Table 1). Furthermore, pseudo-thermophilisation was centred around zero, whereas thermophilisation over time was always positive (Figure 3g–i). Thus, the TVI provides a reliable estimate of real vegetation changes, which proved to be correlated with changes in temperature (Gottfried et al., 2012). While this indicator might not be feasible in all regions of the world, another community-weighted plant functional trait, plant height, was found to respond to warming in the tundra biome (Bjorkman et al.,2018). Plant height increased rapidly over 27 years of monitoring in nearly all of 117 observed tundra sites. However, although there was a detailed assessment of errors regarding trait values assigned to species, observer errors in species list compilation and abundance estimation were not considered in this study.

4.1.4 | Long observation periods

Long-term vegetation monitoring is set up to detect changes over time, for example due to climate change (Guisan & Theurillat, 2005). This requires assessing if observed changes exceed noise due to observer errors (Mason et al., 2018; Scott & Hallam, 2003). Changes over time in all measures (species turnover, species cover, and TVI) were significantly larger than pseudo-changes for longer observation periods (≥10 years), whereas the signal of changes over seven-year periods often did not exceed observer error noise (Figure 3). This underlines the importance of long-term monitoring and long observation periods, which enable us to account for short-term fluctuations and observer errors alike.

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AUTHOR CONTRIBUTIONS

MG, AF, HP and MW conceived and designed the study, AL, HP, KS, PB and AP collected data in the field. AF, MW and SBR analysed the data. AF, MW and HP wrote the text with contributions from all authors. All authors (except MG) read and approved the final version of the manuscript.

DATA AVAILABILITY STATEMENT

Raw data of species presence and cover on observer error plots are available as online supplementary material in csv and pdf format (Appendix S9).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

Appendix S1. Growth form distribution of vascular plants

Appendix S2. Location of observer error and monitoring plots and NMDS of vegetation

Appendix S3. Power transformation

Appendix S4. Percentage of vascular plant species records registered by a given number of observers

Appendix S5. Observer error in recording presence and cover of species and the plot thermic vegetation indicator on (a) Schrankogel; (b) Hochschwab; and (c) High Tatra Mountains

Appendix S6. Errors in species cover estimation per (a) observer; (b) vascular plant species; and (c) growth form

Appendix S7. Effects of species and plot characteristics on observer errors in recording species presence and cover and the plot thermic vegetation indicator

Appendix S8. Comparison of importance of variables affecting observer errors in recording the presence of vascular plant species based on model deviance with different scenarios for the 'true' value

Appendix S9. Raw data of species presence and cover on observer error plots

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