Norsk Geografisk Tidsskrift–Norwegian Journal of Geography
https://doi.org/10.1080/00291951.2020.1717595

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Bridging theory and implementation – Testing an abstract classification system for practical mapping by field survey and 3D aerial photographic interpretation

Heidrun A. Ullerud, Anders Bryn & Helle Skånes

Heidrun A. Ullerud, Geo-Ecology Research Group, Natural History Museum, University of Oslo, P.O. Box 1172, Blindern NO-0318 Oslo, Norway; Anders Bryn, Geo-Ecology Research Group, Natural History Museum, University of Oslo, P.O. Box 1172, Blindern NO-0318 Oslo, Norway, and Mapping and Statistics Division, Norwegian Institute of Bioeconomy Research, P.O. Box 115, NO-1431 Ås, Norway; Helle Skånes, Biogeography and Geomatics research unit, Department of Physical Geography, Stockholm University, SE-106 91 Stockholm, Sweden

ABSTRACT
The abstract classification system Nature in Norway (NiN) has detailed ecological definitions of a high number of ecosystem units, but its applicability in practical vegetation mapping is unknown because it was not designed with a specific mapping method in mind. To investigate this further, two methods for mapping – 3D aerial photographic interpretation of colour infrared photos and field survey – were used to map comparable neighbouring sites of 1 km^2 in Hvaler Municipality, south-eastern Norway. The classification accuracy of each method was evaluated using a consensus classification of 160 randomly distributed plots within the study sites. The results showed an overall classification accuracy of 62.5% for 3D aerial photographic interpretation and 82.5% for field survey. However, the accuracy varied for the ecosystem units mapped. The classification accuracy of ecosystem units in acidic, dry and open terrain was similar for both methods, whereas classification accuracy of calcareous units was highest using field survey. The mapping progress using 3D aerial photographic interpretation was more than two times faster than that of field survey. Based on the results, the authors recommend a method combining 3D aerial photographic interpretation and field survey to achieve effectively accurate mapping in practical applications of the NiN system.

ARTICLE HISTORY
Received 17 February 2019
Accepted 14 January 2020

EDITORS
Ivar Svare Holand, Catriona Turner

KEYWORDS
classification, colour infrared photos, mapping accuracy, Nature in Norway (NiN), vegetation mapping

Ullerud, H.A., Bryn, A. & Skånes, H. 2019. Bridging theory and implementation – Testing an abstract classification system for practical mapping by field survey and 3D aerial photographic interpretation. *Norsk Geografisk Tidsskrift–Norwegian Journal of Geography* Vol. 73, 00–00. ISSN 0029-1951.

Introduction

Land cover maps provide spatially explicit information about the physical cover of the Earth. As the human population grows and the climate is changing, pressure on nature is increasing (Vitousek et al. 1997; Erb et al. 2017), leading to degradation and loss of habitats and ecosystem services (Foley et al. 2005). Land cover maps provide information on relative frequencies of different land cover classes and their spatial location, along with properties related to the state of the land cover, thereby forming the basis for knowledge-based nature management and monitoring (Bunce et al. 2008).

A wide range of land cover classification systems for nature management exists (Ichter et al. 2014). For example, the EcoVeg approach has several hierarchical classification levels, from local to global scales (Faber-Langendoen et al. 2014). The European Union has developed several classification systems with different levels of detail that are used for different purposes, including the LUCAS survey and EUNIS habitat classification (European Commission 1992; 2015). Also, most countries have several national classification systems that have been developed and improved according to their societies' need for spatial information (Bryn et al. 2010). Some classification systems have been developed directly for practical mapping (e.g. Rekdal & Larsson 2005), while others are theoretical constructions generated without adapting the classes according to practical mapping considerations such as available material and

CONTACT Heidrun A. Ullerud hullerud@gmail.com
Supplemental data for this article can be accessed at https://doi.org/10.1080/00291951.2020.1717595.

methods but rather to describe a common framework (Påhlsson 1998). The latter are often made with the intention of describing land cover in as much detail as possible based on phytosociology or ecological gradient theory (Whittaker 1967). An example is the recently developed classification system Nature in Norway, NiN 2.0 (Halvorsen et al. 2015). The target of NiN is ecosystem units, which comprise species composition as well as environmental factors such as humidity and nutrient composition. The system is rooted in gradient theory (Whittaker 1967), and the number of ecosystem units is calculated from species turnover along complex gradients compiled in accordance with available Norwegian research (Halvorsen et al. 2015).

However, the use of a theoretically sound classification system does not per se ensure a smooth and effective production of maps that are reliable and consistent (Ullerud et al. 2018). A prerequisite for consistent mapping is a detailed description and documentation of the mapping system. Furthermore, the quality of the resulting map depends on the mapping method and material by which the land cover is mapped. If the classification system is predefined, the mapping method should be chosen based on how the properties and qualities of the classification system can be mapped (Käyhkö & Skånes 2006; Takács & Molnár 2009).

Land cover mapping methods vary greatly, from field surveys to remote sensing methods such as automatic classifications of satellite or aerial imagery, as well as aerial photographic interpretation. All mapping methods depend on available material, as well as hardware, software, knowledge, and experience (Takács & Molnár 2009). Coarse-scale mapping of large areas is often based on automated image processing, frequently employing satellite images (Wyatt 2000; Walker et al. 2005; Xie et al. 2008; Hussain et al. 2013; Fassnacht et al. 2016). For detailed mapping of smaller areas, especially for classes defined by specific species or species groups, manual mapping methods such as visual 3D aerial photographic interpretation (API) and field survey (hereafter abbreviated as FS) are common (Nämnden för skoglig fjärranalys 1993; Dramstad et al. 2002; Rekdal & Larsson 2005; Ihse 2007; Andersson 2010; Guðjónsson 2010; Morgan et al. 2010; Ståhl et al. 2011; Janssen et al. 2017). According to the review by Fassnacht et al. (2016), challenges with remote sensing of land cover classes defined by different tree species still exist and therefore most inventories are still field-based.

API, in its most evolved form, is mapping performed using 3D photogrammetric computer systems, with trained interpreters. Classification and delineation of polygons is carried out, typically in a GIS environment linked to a photogrammetric system where a database is superimposed in the 3D window, allowing for a seamless data capture (Skånes et al. 2007). Colour, texture, topographic position, vegetation density, altitude, and object form are amongst the criteria used to recognize ecosystem units in API (Ihse 2007). Colour infrared (CIR) photographs are most commonly used due to their enhanced information content on vegetation qualities (Ihse & Wastenson 1975; Ihse 1978; 1995; 2007; Solheim 1978; Ihse & Lindahl 2000).

FS are based on in situ observations of physiognomic structures, characteristic species and topographic variation during fieldwork. Orthophotos and GPS are commonly used to aid classification, location, and delineation during FS (Rodwell 2006). Although both

Table 1. Aerial photographic interpretation and field survey by parameters most often used to define an applicable method for a given project

Defining parameter	API (aerial photographic interpretation)	FS (field survey)
Purpose of mapping (end users' needs)	Overview of land cover content or detailed knowledge of local area, monitoring of land cover distribution and changes	Detailed knowledge of species distribution and land cover state of local area
Available classification systems (ecological resolution and information complexity)	Typically coarser systems that focus on spectral properties, vertical structure and texture indirectly assessing species composition	Detailed systems with focus on indicator species and species composition
Spatial resolution (the intended map scale and minimum mapping area, mma)	Coarser mapping (scales 1:5000–1:50,000, mma from 0.01–4 ha)	Detailed mapping (scales 1:500–1:25,000, mma from 0.0001–2 ha)
Available economic resources for mapping (budget)	Small budget (given available photographs and equipment) or large area	Large budget or small area
The time schedule versus size of the area intended for mapping	Fast mapping progress	Slow mapping progress
Human resources and competence	Experience of API and geographic information system (GIS) methods, good computer skills, and basic photogrammetry skills Knowledge of land cover, land use, and vegetation in region Knowledge of species ecology improves interpretation	Experience of field survey methods Knowledge of species, ecology, edaphic conditions, and land use in the study area
Limiting factors of the study area (context-dependent variation)	Shadow effects in steep areas Tree-coverage, mosaic features	Accessibility, infrastructure
Available technical solutions and material (equipment, software and material)	Aerial photographs 3D photogrammetric computer station, digitizing software	Orthophotos in GIS on a field computer *or* printed orthophotos and digitizing software
Scientific point of departure	Geosciences, resource management, and planning	Biosciences, nature management and conservation

API and FS can be used for detailed mapping, the methods are often applied for different purposes (Table 1).

In 2015 the Norwegian parliament, Storting, passed an Act specifying that the classification system NiN should be used in all publicly financed, detailed, land cover mapping (Meld. St. 14 (2015–2016). The NiN system defines ecosystem units based on species turnover along ecological complex gradients (Halvorsen et al. 2015). The system therefore implies a high focus on field-layer and bottom-layer indicator species and composition of vascular plants, lichens and bryophytes. As a consequence, it has been taken for granted that the best mapping method is FS. However, to our knowledge, no research has focused on the applicability of API for different aspects of NiN mapping.

The aim of the study on which this article is based was to compare the success of two common mapping methods in implementing Nature in Norway, NiN 2.0, a theoretically constructed classification system. The two methods were field survey (FS) and 3D aerial photographic interpretation (API). Both methods have been implemented at a mapping scale and generalization scale of 1:5,000. Success was measured by the accuracy of the classification (producer's accuracy), defined as the degree to which the land cover of a map agreed or corresponded with a reference land cover classification.

The study was designed to answer the following questions:

- Which ecosystem units are classified accurately by using FS and by using API?
- What characterizes the ecosystem units that either are or are not classified accurately by either method?
- What is the optimal method for land cover mapping of ecosystem units based on the NiN system when relating classification accuracy to resources spent on mapping?

Materials and methods

Study area

The study area was situated in south-eastern Norway, on two islands in Hvaler Municipality, Østfold County (Fig. 1). The area was within the boreonemoral zone and in a slightly oceanic vegetation section (Moen 1999; Bakkestuen et al. 2008), with an elevation in the range 0–72 m a.s.l. The bedrock consists of acidic granite. The landscape is dominated by rounded hills with thin soil coverage, broken up by abrupt fissure valleys formed in weaker lines of the bedrock (Eriksen et al. 2019). The valleys are covered with fine-grained marine sediments containing remains of calcareous shells (NGU n.d.). This gives a characteristic landscape with large areas of bare rock and sparse trees, interrupted by narrow valleys with productive forests.

The vegetation in the study area is structured partly by natural processes and partly by cultural influence (Eriksen et al. 2019). Scattered and shallow soils, exposure to seawater and strong winds have generated large open areas. Bare rock is often found in a mosaic with a thin soil layer dominated by heather (*Calluna vulgaris*). In convex land forms with slightly deeper soils, though still exposed to drought, Scots pine (*Pinus sylvestris*) dominates the sparse tree layer (Eriksen et al. 2019). Due to poor drainage, small patches of wetland dominated by bog myrtle (*Myrica gale*) occur in local depressions in the otherwise convex bedrock. Most of fertile land was utilized for agriculture during the 1850–1930 population peak but most agricultural areas were later abandoned, allowing spontaneous regrowth of forest (Eriksen et al. 2019).

Currently, Norway spruce (*Picea abies*) dominates the valley forests, with patches of ash (*Fraxinus excelsior*), pedunculate oak (*Quercus robur*), hazel (*Corylus avellana*), and aspen (*Populus tremula*). Grey alder (*Alnus incana*) dominates recently abandoned land, while alder (*Alnus glutinosa)* occurs in wet depressions. The flora varies with level of basicity, from bilberry (*Vaccinium myrtillus*) and red-stemmed feather moss (*Pleurozium schreberi*) in acidic areas to basophilic herbs such as dropwort (*Filipendula vulgaris*) and yellow bedstraw (*Galium verum*) in calcareous areas.

Within the study area, four rectangular study sites were selected, each measuring 1 × 0.5 km and matching the standard Norwegian 0.5 km statistical grid (Strand & Bloch 2009). Sites API1 and API2 (centre coordinates 6557250 and 265000/263500 WGS 1984 UTM Zone 32N, respectively) were mapped by aerial photographic interpretation. Sites FS1 and FS2 (centre coordinates 6556250 and 263000/266000 WGS 1984 UTM Zone 32N, respectively) were mapped by field survey (Fig. 1). A topographic map (AR5) (Tenge 2016) on a scale of 1:5000, depicting land cover in 11 classes, was used to select study sites with similar land cover composition. The sites were located within a 4 × 1.5 km rectangle to minimize natural variation between the sites. In order to avoid large parts of the study area consisting of houses and roads, densely populated areas were avoided.

Classification system

The land cover classification implemented in the study followed NiN version 2.0 (Halvorsen et al. 2015; Ullerud et al. 2018; Eriksen et al. 2019). The NiN system divides terrestrial Norway into 59 major ecosystem types and 444 basic ecosystem types. The system has

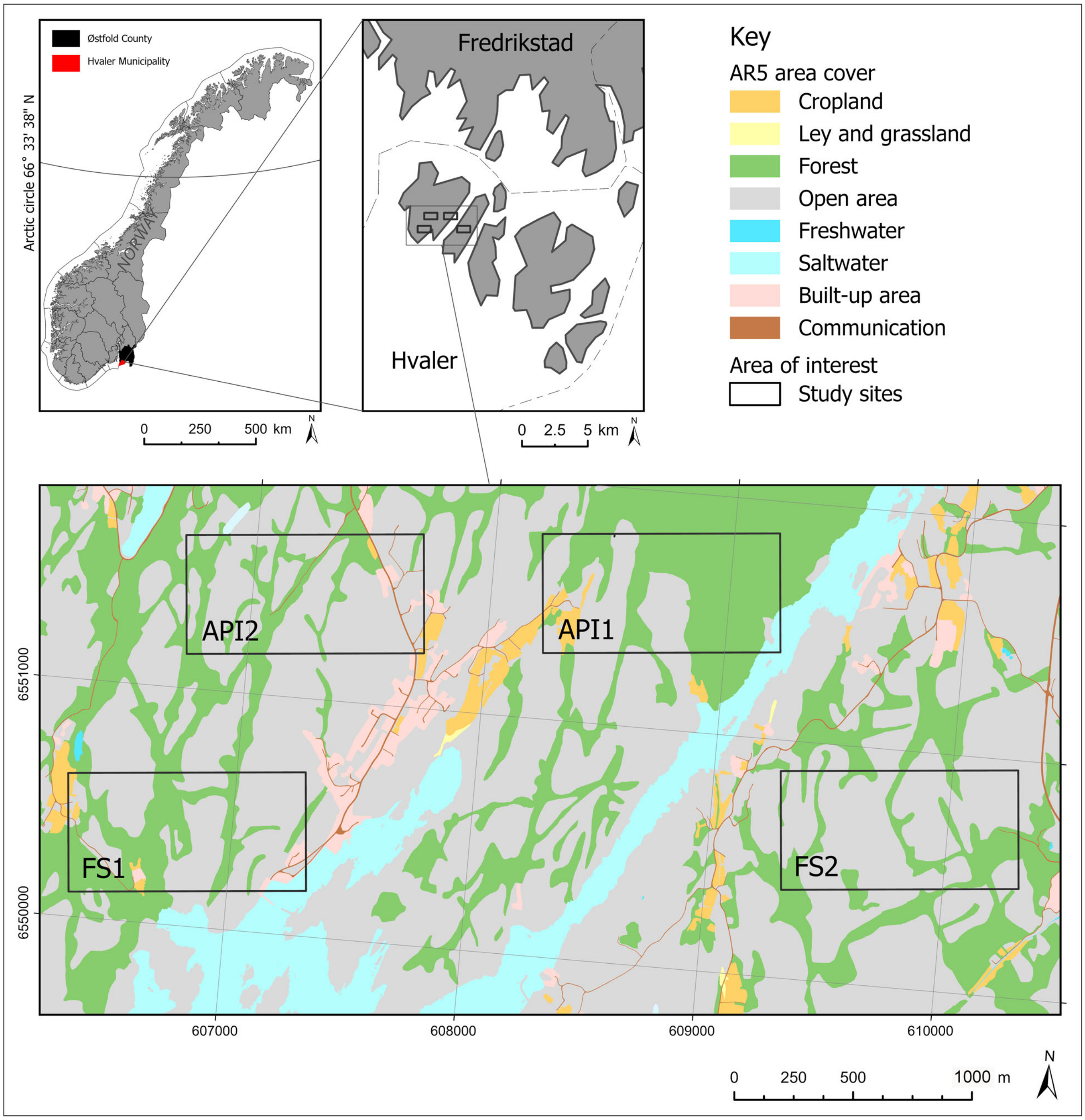

Fig. 1. Study area with four rectangular study sites on Hvaler Municipality, south-east Norway (Maps from Geonorge (N2000 maps and AR5 area cover), WGS 1984 UTM Zone 32N, rotation -5.1 degrees)

been adapted for mapping at different geographical scales by aggregating basic types into ecosystem units and by providing mapping rules for each scale in a hierarchical system (Bryn & Halvorsen 2015). At the lowest hierarchical level, the basic ecosystem types are applied for mapping at a scale of 1:500, whereas for mapping at a scale of 1:5000 the basic types are aggregated into 277 ecosystem units. Of these, 41 NiN ecosystem units are defined by other characteristics than species composition, such as land use or properties of applied surface materials. The ecosystem unit defines the polygons but a number of supplementary registrations can be added. Examples of supplementary registrations include tree coverage, occurrence of invasive species and a variety of management regimes (Halvorsen et al. 2015).

Mapping methods

The four study sites (Fig. 1) were all mapped following the rules and units for mapping at 1:5000 scale (Bryn & Halvorsen 2015). Two sites were mapped by 3D aerial photographic interpretation (API), while the other two sites were mapped by field survey (FS).

All mapping was carried out by the first author. The most important NiN standard guidelines for mapping were followed for both methods. The minimum mapping area (mma) was 250 m^2 for all ecosystem units. When two ecosystem units occurred intermixed, with patch sizes below 250 m^2, both ecosystem units were registered as parts of a mosaic polygon.

For aerial photographic interpretation, both classification and delineation were done in June 2015. Digital CIR aerial photographs with 0.2 m resolution acquired on 5 August 2011 (Appendix 1) were used with 3D-vision technology and photogrammetric software Summit Evolution TM version 7.5 (DAT/EM Systems International® connected) to ArcMap 10.2.2 (Esri, 2014).

Before API was done, calibration of classification and delineation was done in a neighbouring area (Svarteberget in Hvaler Municipality) mapped with FS by others in 2010 (Halvorsen et al. 2011). To optimize systematic API of details not directly visible in the photographs, specific aerial photo characteristics, such as colour composition, vertical structure, texture, and terrain position were denoted and described for all ecosystem units present on the maps. The characteristics were used to describe proxies enabling API assessment of all ecosystem units, including units defined by species composition. Terrain form was used as a proxy to determine risk of severe drought stress, while terrain position was used to indicate level of soil nutrients. As the bedrock of the area is mainly acidic and weathers slowly, forests with low crown coverage and situated at higher terrain with shallow soils were interpreted as low-productive and acidic. Due to the presence of marine sediments, grasslands and forests with high crown coverage on valley floors were interpreted as productive and calcareous from their position in the terrain.

After sites API1 and API2 were mapped, one day was spent in field at the adjacent test sites. Some classifications were corrected based on field observations. The time spent actively interpreting the aerial photographs and producing the maps was recorded and no post-production work was needed. The time needed to organize the interpretation environment and combine characteristics into ecosystem units was not recorded, as this was considered methodological development and the time spent would not have been representative of routine work.

The field survey included mapping in the field followed by digitization of the maps. Classification and delineation on orthophotos identical to those acquired for API, printed at a scale of 1:2500 with a 15.8 m grid, were conducted in situ in July and August 2015. Knowledge of the ecosystem units in the study area was based on the same test day as for the API method. Ecosystem units were classified based mainly on field-layer and bottom-layer plant species composition. Delineation was based on a combination of characteristics in orthophotos and field observations of the patch borders. A handheld GPS (Garmin eTrex30) was used to confirm geographical position. The progress in field depended on terrain and vegetation. Subsequently, the orthophotos, with delineated polygons, were scanned and manually digitized using Q-GIS (Version 2.12). The time spent actively mapping in the field was recorded and the transport between the study sites was included in the registered time. Time spent digitizing the maps after fieldwork was not included as currently most field surveys are carried out using digital platforms.

Evaluation dataset

An evaluation dataset of ecosystem units for 40 plots for each study site (160 plots in total) was gathered in situ in June 2016 by a team of surveyors. For each site, 20 plots were mapped individually by six surveyors. For these plots, the ecosystem unit that was registered by the highest number of surveyors was included in the evaluation dataset. In cases when several ecosystem units had the same number of registrations, the unit registered by the most experienced surveyor was included. A further 20 plots for each site were mapped by consensus among 11 surveyors and the consensus ecosystem unit was registered. Plot registration followed NiN, with the same minimum mapping area (250 m^2). The plots were identified by points, which were expanded by the surveyors to plots of uniform nature and larger than the minimum mapping area. The minimum size ensured that ecosystem units appearing in small patches would not dominate the evaluation dataset. To ensure representability, the evaluation plots were distributed randomly within five different types of terrain as defined by topography. For each plot, the surveyors also noted the ecosystem unit at a given point, without enforcing a minimum mapping area. The applicability of plot data was compared with the applicability of the point data for evaluation.

Analysis of results

All spatial analyses were performed using ArcMap 10.3.1 (Esri, 2015). The ecosystem units present in each map were counted and land cover statistics for each mapping method were calculated. Landscape-level metrics were calculated using FragStats Version 4.2.1.603 to explore and understand the differences between the maps made by different methods (Table 2).

The plot data were used to evaluate the classification accuracy within and between ecosystem units, as well as within and between maps and mapping methods.

Table 2. FragStats metrics used to describe differences between the vegetation maps, and the meaning of each metric

Metric (FragStats code)	Explanation
Number of polygons (NP)	Count of number of polygons
Edge density (ED)	Metres of edge per hectare (m/ha)
Mean polygon area (A_MN)	Mean polygon size (ha)
Median polygon area (A_MD)	Median polygon size (ha)
Standard deviation of area (A_SD)	Standard deviation of polygon area (ha)
Area of largest polygon (LPI)	Percentage of map area covered by the largest polygon in each map
Connectance index, threshold distance set to 10 m (CONNECT)	Functional connection on a scale from 0 to 100, where 100 means that all patches are connected
Shannon's diversity index (SHDI)	Diversity of ecosystem units quantified by the probability of encountering new units in the map, recorded on a scale from 0 to infinite. The probability of encountering new ecosystem units increases with larger numbers.

As the plots were randomly distributed, several evaluation plots could be located within one polygon, while other polygons did not contain any plots. The position of the plots and information about the ecosystem type in each plot was used to determine the number of map polygons and type of ecosystem units that could be evaluated. The ecosystem unit registered for the plot was compared with the ecosystem unit on the map at the same spatial location. After comparison, the plots were partitioned into three categories: 'match', 'match with small delineation variation' and 'different classification' (Table 3). The percentage of plots in the different categories was calculated. Classification accuracy was quantified as the sum of the two match categories. Producer's accuracy above 80% was considered as 'high', in line with The Nature Conservancy & Environmental Systems Research Institute (1994), Skånes et al. (2007) and Robertson & Grieve (2010).

For plots classified as different, the ecological distance between the map and plot unit was estimated. The ecological distance quantifies the theoretical magnitude of deviation between the recorded ecosystem units (Eriksen et al. 2019). Since ecosystem units within the NiN system are separated based on species turnover along defined complex gradients, the ecological distance between units can be estimated as steps along the same gradients. Hence, a comparison of positions along the gradients indicates the ecological distance between the unit in the plot and the unit on the map (Fig. 2). The ecosystem units for forest in NiN 2.0 (i.e. those not influenced by spring water) are defined by the gradients 'Risk of severe drought' and 'Basicity'. There are many different gradients in the NiN system applicable for different main types, but the aforementioned two are among the most common gradients.

Figure 2 shows two examples of 'different classification' for forest. Plot 1 was classified as Sparse low-herb forest, while the map at the same geographical location had a polygon classified as Heather-bilberry forest. These types on forest are one step apart on each gradient and therefore the ecological distance between the plot and the map is two steps. Plot 2 was classified as Lichen forest, while the map at the same geographical location had a polygon classified as Calcareous low-herb heather-bilberry forest. These types are three steps apart on the gradient Basicity and two steps apart on the gradient Risk of severe drought, thus the ecological distance between the plot and the map is five steps.

To detect what characterizes ecosystem units mapped accurately by the two methods, the units were grouped according to basicity and agricultural management. Both groups were binary and the classification accuracy was calculated for each group (Table 4).

The total number of hours spent making each map was recorded and the total number of hours for each mapping method was summarized. The number of accurate classifications was divided by the number of hours used for making the maps to quantify accuracy relative to the resources invested in the mapping.

Table 3. Criteria used for partitioning plot and map relations into three categories

Category	Criteria
Match	Plots where the • map and the plot had corresponding ecosystem units • primary ecosystem unit in a mosaic polygon matched • mosaics matched but the order of ecosystem units was switched
Match with small delineation variation	• plots closer than 5m to delineation and that matched the ecosystem unit on the other side of the polygon border • plots that matched with a secondary ecosystem unit in a mosaic
Different classification	Plots with different classification (DC) than given by the polygon

Results

Map statistics

In the two sites mapped by API, 27 ecosystem units were registered. In the two sites mapped by FS, 34 units were registered (Fig. 3) (Supplementary Appendix 2; for unit names, see Supplementary Appendix 3). We selected areas that resembled each other in composition of area cover, to enable comparison of different methods. The total unit count for all four sites was 40. Of these, 25 were recorded in both API sites and FS sites.

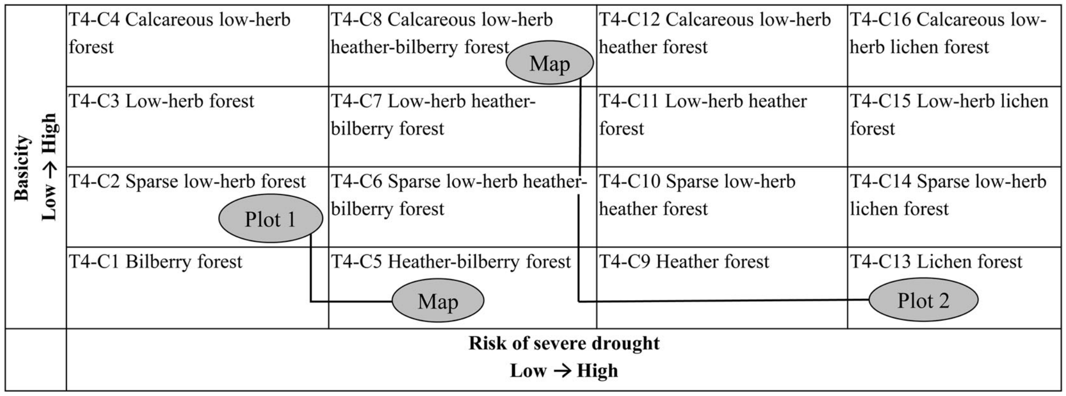

Fig. 2. The ecosystem units for forest in NiN 2.0 as defined by the gradients 'Risk of severe drought' and 'Basicity'; two examples of 'different classification' with ecological distances of two and five

Table 4. Grouping of ecosystem units present in study areas, with ecosystem unit codes and names

Binary group	Unit codes	Unit names
Basicity	T32-C3–5	Intermediate and moderately calcareous grasslands with low and moderate management intensity
	T4-C2	Sparse low-herb forest
	T4-C6	Sparse low-herb heather-bilberry forest
	V2-C2	Intermediate wetland forest
Acidity	All other units	
Agriculture	T32-C3–5	Intermediate and moderately calcareous grasslands with low and moderate management intensity
	T44-C1	Ploughed field
No agriculture	All other units	

The FragStats results show that the largest polygons were found in the API sites (Table 5). The maps for these sites had fewer polygons compared with the maps for the FS sites and hence fewer metres of edge and larger mean polygon size. The median polygon size was 0.11 ha for API and 0.09 ha for FS, while the standard deviation of polygon size was 0.96 for API maps and 0.52 for FS maps. The Shannon diversity index value was 1.86 in the FS sites and 1.73 in the API sites.

Three ecosystem units made up 81.2% versus 75.3% of the area of the API and FS sites respectively: Drought-prone acidic rock (45.0% versus 29.5%), Heather forest (23.5% versus 31.5%) and Heather-bilberry forest (12.7% versus 14.3%). No other ecosystem units covered more than 2% of the mapped area in both sites mapped by API and FS (Table 6).

Table 5. Landscape metrics given as average results for the two aerial photographic interpretation (API) sites and the two field study (FS) sites

Metric and FragStats code	API	Field study
Number of polygons (NP)	148	209
Edge density (ED)	609	831
Mean polygon area (A_MN)	0.34	0.24
Median polygon area (A_MD)	0.11	0.09
Standard deviation of area (A_SD)	0.96	0.52
Area of largest polygon (LPI)	18.1	7.8
Connectance index (CONNECT)	2.09	2.37
Shannon diversity index (SHDI) value	1.73	1.86

Evaluation of maps

The 160 evaluation plots covered a total of 18 ecosystem units, of which 14 units were found in the API sites and 12 in the FS sites (Table 6). Eight ecosystem units were represented by at least one plot in both the API sites and the FS sites. In the API sites, three ecosystem units were registered in plots without being present on the map, and one further unit was only present as the secondary unit in mosaic polygons. In the FS sites, all ecosystem units registered in plots were present as primary units on the maps. The three most frequent ecosystem units in the evaluation plots were also the most frequent on the maps: Heather forest (17.5%), Drought-prone acidic rock (12.5%) and Heather-bilberry forest (10%). In addition, Open acidic shallow-soil heath, Bilberry forest and Acidic wetland forest were represented by at least three plots in either API sites or FS sites.

The overall classification accuracy was 62.5% for API and 82.5% for FS (Fig. 4). However, the accuracy varied from 0% to 100% for the six ecosystem units that were evaluated by three or more plots for both methods. Both methods included comparisons of plots and maps (producer's accuracy) of 100% for the most common ecosystem unit, Drought-prone acidic rock. The second most common type, Heather forest, had an accuracy of 81% for API and 100% for FS (Table 6). There was greater variation in less common units, indicating lower mapping robustness with increasing rarity. The average ecological distance for different classifications was 1.37 for API and 1.07 for FS. The map and plot

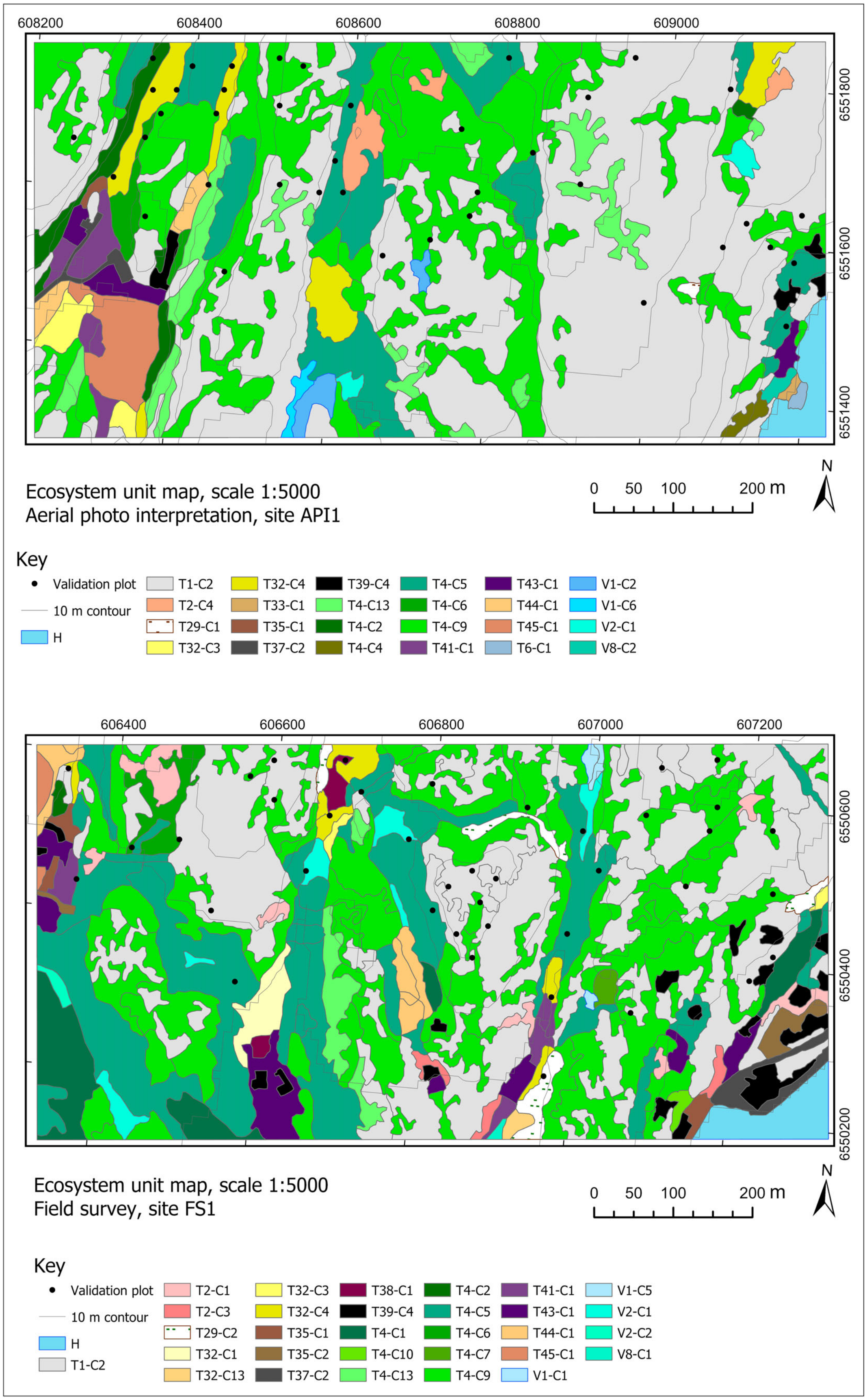

Fig. 3. Ecosystem unit maps for sites API1 and FS1N; with different sites (coordinates WGS 1984 UTM Zone 32N, rotation -5.1 degrees)

Table 6. Area covered by the primary ecosystem units, given for units evaluated by a minimum of one plot, including the number of plots for each ecosystem unit, the percentage accuracy in plot and map comparisons (producer's accuracy), and the percentage accuracy of map and plot comparison (user's accuracy)

Ecosystem unit		API (aerial photographic interpretation)					FS (field survey)				
Name	Code	Land cover (%)	Number of plots	Plot & map accuracy	Number of plots on map	Map & plot accuracy	Land cover (%)	Number of plots	Plot & map accuracy	Number of plots on map	Map & plot accuracy
Drought-prone acidic rock	T1-C2	45	17	100.0	30	90.0	29.5	24	100.0	27	100.0
Heather-bilberry forest	T4-C5	12.7	13	61.5	18	38.9	14.3	13	53.8	9	77.8
Heather forest	T4-C9	23.5	21	81.0	19	68.4	31.5	22	100.0	23	73.9
Open acidic shallow-soil heath	T2-C1	-	5	80.0	-	-	6.2	4	75.0	5	80.0
Bilberry forest	T4-C1	0.1	9	11.1	-	-	1.7	3	0.0	-	-
Acidic wetland forest	V2-C1	0.5	4	25.0	1	100.0	2.4	5	80.0	4	50.0
Intermediate grasslands with low management intensity	T32-C3	0.8	1	0.0	-	-	0.1	1	0.0	-	-
Arable field	T44-C1	0.3	2	50.0	1	100.0	0.6	1	0.0	-	-
Sparse low-herb forest	T4-C2	1.3	2	0.0	2	50.0	0.1	-	-	-	-
Sparse low-herb heather-bilberry forest	T4-C6	0.4	1	0.0	1	0.0	0.5	-	-	2	100.0
Lichen forest	T4-C13	2.9	-	-	1	0.0	0.8	-	-	-	-
Upper rock/gravel beaches with pioneer vegetation	T29-C1	0.1	-	-	-	-	0.3	1	0.0	-	-
Upper rock/gravel beaches with established vegetation	T29-C2	-	-	-	-	-	0.6	-	-	1	0.0
Intermediate grasslands, moderate management intensity	T32-C4	1.8	-	-	5	0.0	0.6	1	100.0	2	0.0
Moderately calcareous grasslands, low management intensity	T32-C5	-	1	0.0	-	-	-	-	-	-	-
Plantation forest	T38-C1	-	-	-	-	-	0.2	1	100.0	1	100.0
Stone heap	T39-C1	-	-	-	-	-	4.2	4	100.0	5	100.0
Meadow-like ploughed field	T41-C1	1.0	-	-	-	-	0.4	-	-	1	100.0
Lawns, parks, etc.	T43-C1	1.2	1	100.0	1	0.0	1.3	-	-	-	-
Very acidic mire	V1-C1	-	1	0.0	-	-	0.2	-	-	-	-
Fairly acidic mire	V1-C2	0.7	-	-	1	0.0	-	-	-	-	-
Intermediate wetland forest	V2-C2	-	2	0.0	-	-	0.1	-	-	-	-
Total		87.7	80	62.5	80	62.5	93.8	80	82.5	80	82.5
Count selection		15	14		11		20	15		11	
Count total	41	27	14				34	12			

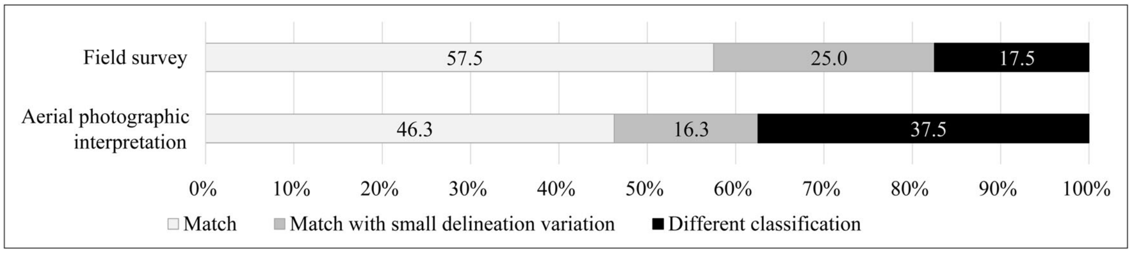

Fig. 4. Evaluation results in three categories, with the sum of 'Match' and 'Match with small delineation variation' used as a measure for classification accuracy

classification accuracy portrayed the same trends as the plot and map classification accuracy for the three most common units. Plot data were more suitable than point data for evaluation of polygon classification (Appendix 4).

When all calcareous units were combined, the producer's accuracy was 0% in the API maps and 50% in the FS maps. Acidic units had an accuracy of 68% in the API maps and 83% in the FS maps. Calcareous units were used in the API maps, but five of the eight plots placed in polygons labelled calcareous were classified as acidic in the validation plots (Table 6) (Appendix 4). For agricultural units, which included semi-natural grasslands, the classification accuracy was 25% in the API maps and 33% in the FS maps. Units not affected by agriculture had an accuracy of 64% in the API maps and 84% in the FS maps.

The total time spent making the maps was 21.2 hours for the API sites and 48.7 hours for the FS sites. The number of accurate classifications for the API sites was 50, while the same number for the FS sites was 66. The number of accurate classifications per hour spent making the maps was 2.4 for API and 1.4 for FS.

Discussion

Pros and cons of API and FS as separate methods

The practical part of a land cover mapping process, the delineation of polygons and the assignment of associated land cover units can be performed using different methods. We tested two methods, namely field survey (FS) and aerial photo interpretation (API), and the results showed that the two methods had different advantages and challenges. API is considerably faster than FS (Vesterbukt et al. 2013); we found it was more than two times faster. However, the classification accuracy of the NiN classification system was lower when using API compared with when using FS. Previous studies have found that the classification accuracy for land cover mapping by API varied between 60% and 77% (Barr et al. 1993; Prosser & Wallace 1999; Strand et al. 2002; Engan 2012). The overall API classification accuracy found in our study was at the lower end of that range (62.5%) and probably indicates compatibility issues with the tested classification system, which is based on several definitions that are not directly detectable in aerial imagery.

Classification systems specifically tailored for successful API must be adapted to the mapping method and all mapping units need to be recognizable from 3D interpretation of CIR aerial photography. This has been implemented in, for example, the National Inventory of Landscapes in Sweden (NILS) (Ståhl et al. 2011) and the Natura 2000 base inventory (Skånes et al. 2007), both of which use 3D CIR aerial photography, as well as the 3Q programme in Norway (Engan 2004; 2012), which uses 3D colour aerial photography. Since the tested classification system (NiN) (Halvorsen et al. 2015) has not been adapted for mapping by API, we could not have expected any better results than those supported by previous studies (Barr et al. 1993; Prosser & Wallace 1999; Strand et al. 2002; Engan 2012).

The overall classification accuracy documented by FS in our study was 82.5%. Therefore, FS is currently a more reliable mapping method than API when implementing the NiN classification system for land cover mapping. Although more reliable classifications exist, errors are still frequent with FS (Eriksen et al. 2019). Further, since the mapping progress is slow, the related costs of FS mapping are considerably higher than mapping done using API. This implies that the FS method is not optimal for NiN classification. With ongoing climate changes and increasing loss of biodiversity (Bellard et al. 2012), the need for an improved and faster mapping process is pressing.

Implications of mapping according to the NiN system

The NiN land cover classification system was established without any pre-adaptations regarding mapping method, with many classes purely separated by field-layer and bottom-layer species turnover along defining ecological complex gradients (Bryn & Halvorsen 2015;

Eriksen et al. 2019). Therefore, it is probably a lack of representation of several key object characteristics within the aerial photography that causes the low classification accuracy obtained by API (Käyhkö & Skånes 2006).

The overarching aim of NiN is to characterize ecological gradients in nature, but the system still confines variation into discrete classes. The approach intended to solve this challenge is to incorporate many classes that each include a narrow part of the ecological space. The result is a classification system with many classes, even along short ecological gradients. This proves to be particularly difficult to handle by API. Details such as the abundance of specific indicator species or detailed state condition variables cannot be directly identified with API. The method is therefore dependent on a systematic use of spectral characteristics, topography, tree species composition, crown cover, or other proxies (Käyhkö & Skånes 2006; Ihse 2007; Skånes et al. 2007) to separate the predefined NiN classes.

Three major gradients, which in many cases are interwoven, stand out as particularly challenging when using API for mapping of NiN land cover classes. The three gradients are described in the following three subsections.

Challenge 1: the gradient in the soil from acidic to calcareous

Land cover classification of areas by varying levels of soil basicity or acidity is common (Ichter et al. 2014 and references therein). Classes separated by such characteristics, which lead to multiple within-class spectral responses, are genuinely challenging to capture with any optical remote sensing (Xie et al. 2008). Furthermore, recent studies have shown that these characteristics are difficult to assess, even by FS (Eriksen et al. 2019). Since almost all classes in NiN reflect soil basicity and acidity differences (Bryn & Halvorsen 2015), this also poses a major problem for the implementation of API.

In our study, calcareous conditions were mapped with low accuracy by both API and FS. The low result for API was expected because nutrient level is mapped based on presence of certain basophilic species that are not visible from aerial photographs and thus cannot be mapped by API (Ihse 2007). Accuracy can only be improved if the interpreter has access to additional material, such as high-resolution maps of bedrock, soil or geochemistry, showing lime content in detail (Engan 2013). As such maps are either not currently available or are not at a sufficiently detailed scale, most edaphic properties of potential interest to users cannot be registered without extensive field survey (Rapp et al. 2005; Pancer-Koteja et al. 2009).

The heavy dependency on soil basicity and acidity differences in the NiN system is probably a major reason behind the low classification accuracy for both the API method and the FS method with regard to agricultural land, including semi-natural grasslands. As major carriers of biodiversity, these have many classes to choose from (Bryn & Halvorsen 2015), including a number of classes with different levels of basicity that are difficult to separate from aerial photographs (Aune et al. 2018). Another factor influencing classification success of agricultural classes is disproportionately high number of units related to different agricultural practices of a varying intensity (a total of 48 units in NiN). Information on land use, as required for certain semi-natural units, needs a good definition and an experienced interpreter (Ihse 2007; Norderhaug et al. 2012). Furthermore, Engan (2012) found that agricultural areas under encroachment, which thus included different state conditions, were mapped with low accuracy.

Challenge 2: the gradient in light availability for the different layers of vegetation, or indirectly the coverage of trees and bushes

Land cover classification systems based on vegetation, are often dependent on species characteristics in the field layers and bottom layers or moisture conditions (Ichter et al. 2014 and references therein). Clearly, this poses a problem for mapping by API in all areas where a dense tree canopy obscures the visibility of key characteristics below trees or bushes. This is a common challenge with API (Ihse 2007; Skånes et al. 2007), but is also a general challenge for most remote sensing methods.

In our study, high classification accuracy for both the API method and the FS method was mainly related to dry and open areas such as Drought-prone acidic rock, Heather forest (sparse tree crown cover) and Open acidic shallow-soil heath. This indicates that some areas can be classified equally well with API and FS. The good API results for acidic environments were not due to the interpreter being able to sense the lack of basicity, but rather to the fact that acidic bedrock is more typical for the area.

By contrast, Bilberry forest (dense tree crown cover) was mapped with low accuracy and Heather-bilberry forest (intermediate tree crown cover) was mapped with medium accuracy for both the API method and the FS method. The accuracy for forest types thus decreases with increasing crown coverage for both methods. For API, this is logical because dense canopy prevented the interpreter from identifying pivotal characteristics of the forest floor. The poor FS results for forest were less intuitive, but have been documented in other studies (e.g. Mõisja et al. 2018). Since our study was based on work by one mapper only, and between-mapper inconsistency is high, even in FS (Cherrill & McClean 1999), the results might have been due to misconceptions and errors made by that mapper. Eriksen et al. (2019) came to a similar result after using the same ecosystem units as in our study. Their results, like ours, indicated lower accuracy for Bilberry forest. Low accuracy might therefore be an effect of unclear definitions of the specific ecosystem units or the deviant nature in the study area, where the bilberry cover is lower than a more typical inland forest and not a property related to mapping method or mapper.

Challenge 3: the soil moisture gradient

The soil moisture gradient is often visible from aerial photos in areas without dense cover of trees and bushes, but as the tree canopy cover increases, this important factor is partly obscured from the AP interpreter. In our study, all plots of wetland forests except one were by API registered as non-wetland forests, Heather-bilberry forest or Heather forest. Moreover, we observed that wetland forests in the studied region constituted small patches that dried up during summertime. In the field, these patches are often identified by bog myrtle (*Myrica gale*), a fragrant bush that dominates the bush layer of wetland forest, but which for API is hidden below a dense tree layer.

Implications of mapping according to the NIN system – summary

As illustrated by the three challenges discussed above, the NiN classification system per se restricts full implementation of API as a methodological framework for increasing the rate of progress when mapping at a regional or national level. Several solutions are possible, but the most appropriate would probably be to generalize the classification system in accordance with the findings of this study and previous studies (e.g. Skånes et al. 2007; Ullerud et al. 2018; Eriksen et al. 2019). Ecologically and physiognomically neighbouring land cover classes that are challenging to separate with high accuracy using API could be merged into more robust classes that are more easily separated by interpretation of aerial photography. However, this would increase the ecological space embraced within each class and decrease the ecological precision of the map, leading to a loss of potentially important information compared with the information potentially present in a NiN map made by FS. To guide such decisions, the mapping purpose, the expected progress, available funding, and equipment, as well as access to trained interpreters and field workers should be taken into consideration.

Advantages of combined mapping methods including both API and FS

Tools available for land cover mapping have improved greatly in recent years, and combination methods can benefit from new technology (Allard 2007; Skånes et al. 2007; Gallegos Torell & Glimskär 2009; Takács & Molnár 2009; Nilsen et al. 2013; Santangelo et al. 2015). The resolution and availability of both aerial photographs and orthophotos have improved greatly. A standardized aerial photographic campaign started in Norway in 2006 aims at covering 15% of the country every year (Kartverket n.d.). Digital photogrammetric 3D vision and GIS software is continuously developing (e.g. DAT/EM 2019), while adapted applications and portable field computers enable digitized FS (Nilsen et al. 2013).

From our point of view, traditions within a country are strong drivers for the choice of mapping method. For example, Norway has a long tradition of land cover mapping based on FS (Bryn et al. 2018). However, the results of our study show that a workflow that integrates API and FS could become a more optimal mapping methodology for the NiN classification system. Both API and FS require specialized hardware and software, as well as trained and experienced personnel (Takács & Molnár 2009). Experience of FS is an asset also for API, but most mappers are either field mappers or interpreters (Morgan et al. 2010). The initial cost of implementing a combination method is therefore high. Currently in Norway, where land cover mapping is traditionally carried out by FS, including API in the mapping process would require investments in equipment and extensive training of interpreters. Any new workflow should be standardized and described in detail to ensure that it is understandable and accessible for all mappers.

Practical mapping of land cover in Norway, following the NiN classification system, is currently solely based on FS (Bryn & Halvorsen 2015). The mapping is expensive and the progress is slow, even compared with traditional vegetation mapping based on FS (Bryn et al. 2018; Ullerud et al. 2018). Provided the fact that mapping tailored for API enables a much higher rate of progress than FS (Vesterbukt et al. 2013), and that Norway is a country with large remote or inaccessible areas for which API has an advantage (Ståhl et al. 2011; Johansen 2013), it should be a general goal to phase in more API in the mapping process based on NiN in Norway.

A high rate of progress combined with high classification accuracy is likely to be achieved if the methods combining API and FS are optimally organized (Skånes 1997; Sickel et al. 2004; Bunce et al. 2006; Groom et al. 2006; Wehn et al. 2015). Combined methods starting with API and followed by FS reduce the amount of work to be done in field, thus reducing the cost of land cover mapping (Lewis et al. 2013). According to Fox et al. (2000), API gives a better overview of the study area and enables more precise delineations than FS. Wehn et al. (2015) found that the probability of detecting abandoned semi-natural land cover classes is higher with API than with FS. However, in our study, not all ecosystem units present in the mapped sites were detected using API. Furthermore, the larger polygons and the lower connectivity in the API maps, highlighted in the FragStats metrics, showed that some polygons were missed by the API method. The same result for API mapping was found by Rapp et al. (2005). By contrast, the evaluation plots for the FS sites only identified ecosystem units that were already present on the maps. This shows that API can be applied for mapping of some NiN ecosystem units, while FS is needed for others.

Another solution would be to combine API and FS in such a way that API would only be used for classes with high classification accuracy, such as API for first stage mapping of classes at a higher hierarchical level of the NiN classification system. This indicates potential for the increased use of API in practical applications of the NiN classification system. Some modification in certain parts of the NiN system would enable further use of API.

However, mapping exclusively by FS cannot be recommended, as the mapping progress with API was found to be more than two times higher than the mapping progress with FS, a difference expected to increase as the area to be mapped is increased. Similar results were found in previous studies (Fox et al. 2000; Benz et al. 2004; Ihse 2007; Wehn et al. 2015). A high rate of progress combined with high classification accuracy is likely to be achieved by methods that combine API and FS (Skånes 1997; Sickel et al. 2004; Bunce et al. 2006; Groom et al. 2006; Wehn et al. 2015).

For optimal API, interpreters should be subjected to training and calibration that enables comparison of the visual signature of land covers in aerial photographs with the actual land cover in the field (Takács & Molnár 2009; Morgan et al. 2010; Wehn et al. 2015). In our study, a field trip was taken to the test sites adjacent to the API sites after the main part of the API. Efficient calibration of polygon delineations and classifications was ensured by taking the field trip after initial API. Based on these experiences, a possible workflow for a combination method should include two rounds of API and FS (Fig. 5). The workflow in Fig. 5 is very similar to the procedure recommended by Nämnden för skoglig fjärranalys (1993) and Ihse (2007). A simplified FS-API-FS procedure is recommended by Rapp et al. (2005) for mapping in USA and by both Sickel et al. (2004) and Wehn et al. (2015) for mapping semi-natural nature in Norway.

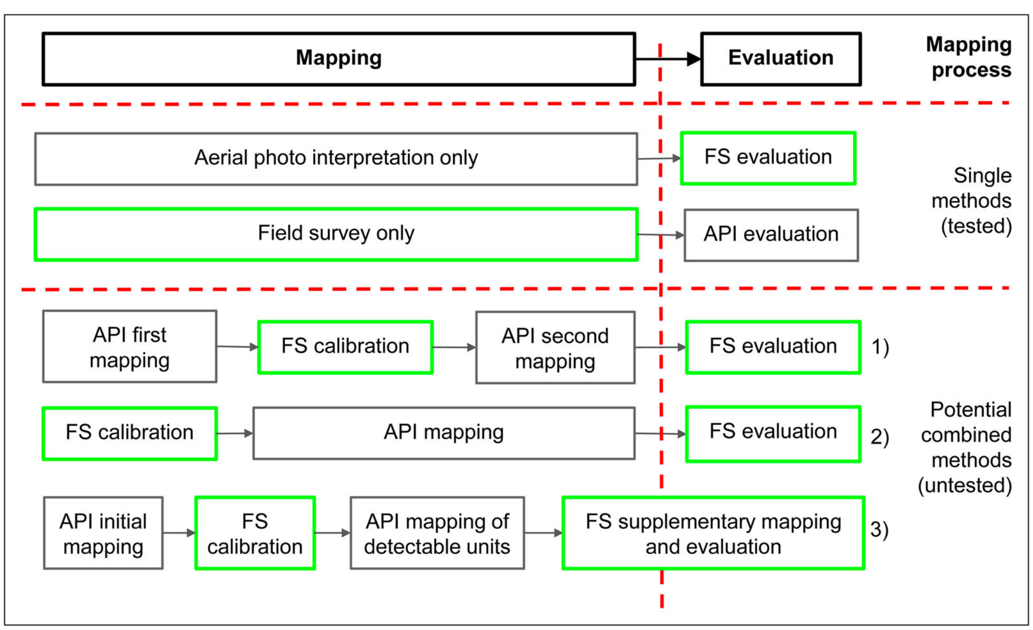

Fig. 5. The mapping process and use of aerial photographic interpretation (API) (grey boxes) and field survey (FS) (green boxes) both as single methods tested in the study and as combinations suggested by the study

Improving classification accuracy

The field trip carried out before the API maps was finalized and before the start of the FS mapping did not target specific ecosystem units. At the point of departure, no studies had yet revealed any need to focus on particular NiN ecosystem units. In the future, ecosystem units conditioned by agriculture, separated by the basicity–acidity gradient, or that for other reasons have low classification accuracy, should be targeted specifically when improving the documentation of the classification system or, as proposed by Mõisja et al. (2018), during additional training of fieldworkers and interpreters. Other efforts to improve the classification accuracy could be to redefine the troublesome classes or to use a higher level of classification, as suggested by Rapp et al. (2005) and Xie et al. (2008). The lowest loss of map information would probably result from merging the most troublesome units (i.e. to generalize the classification system). This would also lower the number of available units and system complexity, which several studies have documented as being more accurate and robust to misclassifications than diverse systems (Cherrill & McClean 1999; Halvorsen et al. 2011; Hearn et al. 2011; Ullerud et al. 2018). It should come as no surprise that it is easier to hit a larger target than to hit small ones.

All mapping, regardless of method, should be subjected to evaluation as a means to report and eventually take action to improve the accuracy (Strand et al. 2002; Bunce et al. 2008; Stehman 2009). Evaluation plots or other methods for evaluating classification should be included for all ecosystem units. In addition, polygon delineation uncertainty should be evaluated, including an evaluation of omission and commission (Mõisja et al. 2018). This could, for example, be implemented in mapping programmes by introducing a small but consistent overlap in mapping areas between different mappers, companies or methods, and would enable a structured consistency.

Conclusions

The ecosystem units Drought-prone acidic rock, Heather forest and Open acidic shallow-soil heath are classified with high accuracy by both 3D aerial photographic interpretation (API) and field survey (FS). These ecosystem units are acidic and found in dry, open terrain. Calcareous ecosystem units, wetlands and areas with dense tree coverage are mapped with higher accuracy by FS than by API. The rate of mapping progress by API is higher than by FS and can therefore be applied for ecosystem units that can be delineated and classified correctly by API. A standardized workflow for mapping following the NiN system would preferably include both API and FS. As accurate API mapping results are enhanced by field calibration, a two-round API-FS procedure is recommended.

We recommend that API should be included in the mapping process when it would be the most efficient method. To facilitate this, the NiN system should be updated with decision trees, whereby several mappers could contribute to different parts of the mapping process. Also, API should be primarily used to delineate the 59 main classes and not primarily aim for the more detailed mapping units. By using the strengths of each method in combination, theory and implementation might be bridged.

Acknowledgements

Thanks are due to Hanne Gro Wallin at NIBIO for technical assistance and use of a 3D computer station. Eva Lieungh Eriksen is thanked for organizing the evaluation data fieldwork in 2016, and Sigrun Aune, Harald Bratli, Eva Lieungh Eriksen, Rune Halvorsen, Johnny Hofsten, Inger K. Volden, Espen A. Værland and Anders K. Wollan for participating in that fieldwork.

ORCID

Heidrun A. Ullerud http://orcid.org/0000-0003-0467-7089
Anders Bryn http://orcid.org/0000-0003-4712-8266
Helle Skånes http://orcid.org/0000-0003-4845-977X

References

Allard, A. 2007. *Instruktion för flygbildsinventeringen vid nationell inventering av landskapet i Sverige (NILS)*. Umeå: Sveriges Lantbruksuniversitet.

Andersson, L. 2010. Geographical vegetation data of Lantmäteriet in Sweden. Bryn, A., Dramstad, W. & Fjellstad, W. (eds.) *Mapping and Monitoring of Nordic Vegetation and Landscapes*, 9–12. Viten fra Skog og Landskap 1(10). https://pdfs.semanticscholar.org/f208/eb991a90b6190f2e7a05c0911c04023b4b42.pdf (accessed January 2020).

Aune, S., Bryn, A. & Hovstad, K.A. 2018. Loss of semi-natural grassland in a boreal landscape: Impacts of agricultural intensification and abandonment. *Journal of Land Use Science* 13(4), 375–390.

Bakkestuen, V., Erikstad, L. & Halvorsen, R. 2008. Step-less models for regional environmental variation in Norway. *Journal of Biogeography* 35(10), 1906–1922.

Barr, C.J., Bunce, R.G.H., Clarke, R.T., Fuller, R.M., Fume, M.T., Gillespie, M.K., Groom, G.B., Hallam, C.J., Hornung, M., Howard, D.C. & Ness, M.J. 1993. *Countryside Survey 1990: Main Report*. London: Department of the Environment.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. 2012. Impacts of climate change on the future of biodiversity. *Ecology Letters* 15, 365–377.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. & Heynen, M. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing* 58 (3), 239–258.

Bryn, A. & Halvorsen, R. 2015. *Veileder for kartlegging av terrestrisk naturvariasjon etter NiN (versjon 2.0.2)*. Trondheim: Artsdatabanken.

Bryn, A., Dramstad, W. & Fjellstad, W.J. (eds.) 2010. *Mapping and Monitoring of Nordic Vegetation and Landscapes*. Viten fra Skog og Landskap 1(10). https://pdfs.semanticscholar.org/f208/eb991a90b6190f2e7a05c0911c04023b4b42.pdf (accessed January 2020).

Bryn, A., Strand, G.-H., Angeloff, M. & Rekdal, Y. 2018. Land cover in Norway based on an area frame survey of vegetation types. *Norsk Geografisk Tidsskrift–Norwegian Journal of Geography* 72(3), 131–145.

Bunce, R.G.H., Pérez-Soba, M., Gómez-Sanz, V., García del Barrio, J.M. & Elena-Rosselló, R. 2006. European framework for surveillance and monitoring of habitats: A methodological approach for Spain. *Forest Systems* 15(3), 249–261.

Bunce, R.G.H., Metzger, M.J., Jongman, R.H.G., Brandt, J., de Blust, G., Elena-Rossello, R., Groom, G.B., Halada, L., Hofer, G., Howard, D.C., Kovář, P., Mücher, C.A., Padoa-Schioppa, E., Paelinx, D., Palo, A., Perez-Soba, M., Ramos, I.L., Roche, P., Skånes, H. & Wrbka, T. 2008. A standardized procedure for surveillance and monitoring European habitats and provision of spatial data. *Landscape Ecology* 23(1), 11–25.

Cherrill, A. & McClean, C. 1999. Between-observer variation in the application of a standard method of habitat mapping by environmental consultants in the UK. *Journal of Applied Ecology* 36(6), 989–1008.

DAT/EM. 2019. *Summit Evolution: World-class Photogrammetric Workstation*. http://www.datem.com/summit-evolution/ (accessed December 2019).

Dramstad, W., Fjellstad, W.J., Strand, G.-H., Mathiesen, H.F., Engan, G. & Stokland, J. 2002. Development and implementation of the Norwegian monitoring programme for agricultural landscapes. *Journal of Environmental Management* 64, 49–63.

Engan, G. 2004. *3Q Instruks for flybildetolkning*. Ås: Norsk institutt for jord- og skogkartlegging.

Engan, G. 2012. *3Q Feltkontroll av flybildetolkning, 2. omdrev, 2004–2008*. Ås: Norsk institutt for skog og landskap.

Engan, G. 2013. *3Q test av flybildetolkning fra IR-bilder*. Ås: Norsk institutt for skog og landskap.

Erb, K.-H., Kastner, T., Plutzar, C., Bais, A.L.S., Carvalhais, N., Fetzel, T., Gingrich, S., Haberl, H., Lauk, C., Niedertscheider, M., Pongratz, J., Thurner, M. & Luyssaert, S. 2017. Unexpectedly large impact of forest management and grazing on global vegetation biomass. *Nature* 553, 73–76.

Eriksen, E.L., Ullerud, H.A., Halvorsen, R., Aune, S., Bratli, H., Horvath, P., Volden, I.K., Wollan A.K. & Bryn, A. 2019. Point of view: Error estimation in field assignment of land-cover types. *Phytocoenologia* 49, 135–148. doi:10.1127/phyto/2018/0293

European Commission. 1992. *Council Directive 92/43/EEC of 21 May 1992 on the Conservation of Natural Habitats and of Wild Fauna and Flora*. http://data.europa.eu/eli/dir/1992/43/2013-07-01 (accessed January 2018).

European Commission. 2015. *The State of Nature in the EU*. Natura2000 No. 38. https://ec.europa.eu/environment/nature/info/pubs/docs/nat2000newsl/nat38_en.pdf (accessed December 2019).

Faber-Langendoen, D., Keeler-Wolf, T., Meidinger, D., Tart, D., Hoagland, B., Josse, C., Navarro, G., Ponomarenko, S., Saucier, J.-P., Weakley, A. & Comer, P. 2014. EcoVeg: A new approach to vegetation description and classification. *Ecological Monographs* 84(4), 533–561.

Fassnacht, F.E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C. & Ghosh, A. 2016. Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment* 186 (1), 64–87.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N. & Snyder, P.K. 2005. Global consequences of land use. *Science* 309(5734), 570–574.

Fox, T.J., Knutson, M.G. & Hines, R.K. 2000. Mapping forest canopy gaps using air-photo interpretation and ground surveys. *Wildlife Society Bulletin* 28(4), 882–889.

Gallegos Torell, Å. & Glimskär, A. 2009. Computer-aided calibration for visual estimation of vegetation cover. *Journal of Vegetation Science* 20(6), 973–983.

Groom, G., Mücher, C.A., Ihse, M. & Wrbka, T. 2006. Remote sensing in landscape ecology: Experiences and perspectives in a European context. *Landscape Ecology* 21(3), 391–408.

Guðjónsson, G. 2010. Large-scale vegetation mapping in Iceland. *Viten* 1, 51–54.

Halvorsen, R., Mazzoni, S., Bratli, H., Engan, G., Fjeldstad, H., Gaarder, G., Larsen, B.H. & Nordbakken, J.-F. 2011. Utprøving av NiN versjon 1.0 som naturtypekartleggingssystem. Halvorsen, R. (ed.) *NHM rapport 11*, 11–60. Oslo: Naturhistorisk museum.

Halvorsen, R., Bryn, A. & Erikstad, L. 2015. *NiNs systemkjerne – teori, prinsipper og inndelingskriterier – Natur i Norge, Artikkel 1 (versjon 2.0.3)*. Trondheim: Artsdatabanken.

Hearn, S.M., Healey, J.R., McDonald, M.A., Turner, A.J., Wong, J.L.G. & Stewart, G.B. 2011. The repeatability of vegetation classification and mapping. *Journal of Environmental Management* 92(4), 1174–1184.

Hussain, M., Chen, D.M., Cheng, A., Wei, H. & Stanley, D. 2013. Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing* 80, 91–106.

Ichter, J., Evans, D. & Richards, D. 2014. *Terrestrial Habitat Mapping in Europe: An Overview*. Copenhagen: European Environment Agency.

Ihse, M. 1978. *Flygbildstolkning av vegetation i syd- och mellansvensk terräng: en metodstudie för översiktlig kartering*. SNV PM 1083. Solna: Naturvårdsverket.

Ihse, M. 1995. Swedish agricultural landscapes – patterns and changes during the last 50 years, studied by aerial photos. *Landscape and Urban Planning* 31(1–3), 21–37.

Ihse, M. 2007. Colour infrared aerial photography as a tool for vegetation mapping and change detection in environmental studies of Nordic ecosystems: A review. *Norsk Geografisk Tidsskrift–Norwegian Journal of Geography* 61 (4), 170–191.

Ihse, M. & Lindahl, C. 2000. A holistic model for landscape ecology in practice: The Swedish survey and management of ancient meadows and pastures. *Landscape and Urban Planning* 50(1–3), 59–84.

Ihse, M. & Wastenson, L. 1975. *Flygbildstolkning av fjällvegetation – en metodstudie för översiktlig kartering/ Swedish Mountain Vegetation – a Methodological Study of Medium Scale Mapping*. SNV PM 596. Solna: Statens Naturvårdsverket.

Janssen, J.A.M., Haveman, R. & Schaminee, J. 2017. Vegetation mapping in the Netherlands. *Prodrome et cartographie des végétations de France* 6, 116–132.

Johansen, L. 2013. *Basiskartlegging etter NiN i utvalgte deler av Lomsdal-Visten nasjonalpark: Erfaringer og drøftinger i bruk av NiN og kartleggingsinstruks*. Kvithamar: Bioforsk Midt-Norge.

Kartverket. n.d. *Nasjonalt program for omløpsfotografering*. https://www.kartverket.no/geodataarbeid/Flyfoto/Nasjonalt-program-for-omlopsfotografering/ (accessed 5 May 2017).

Käyhkö, N. & Skånes, H. 2006. Change trajectories and key biotopes—Assessing landscape dynamics and sustainability. *Landscape and Urban Planning* 75(3), 300–321.

Lewis, D., Phinn, S. & Arroyo, L. 2013. Cost-effectiveness of seven approaches to map vegetation communities – A case study from Northern Australia's tropical savannas. *Remote Sensing* 5(1), 377–414.

Meld. St. 14 (2015–2016). *Natur for livet, norsk handlingsplan for naturmangfold*. Oslo: Klima- og miljødepartementet.

Moen, A. 1999. *National Atlas of Norway: Vegetation*. Hønefoss: Norwegian Mapping Authority.

Mõisja, K., Uuemaa, E. & Oja, T. 2018. The implications of field worker characteristics and landscape heterogeneity for classification correctness and the completeness of topographical mapping. *International Journal of Geo-Information* 7(6). doi:10.3390/ijgi7060205

Morgan, J., Gergel, S. & Coops, N.C. 2010. Aerial photography: A rapidly evolving tool for ecological management. *Bioscience* 60(1), 47–59.

Nämnden för skoglig fjärranalys. 1993. *Flygbildsteknik och fjärranalys*. Jönköping: Skogsstyrelsen.

NGU. n.d. *Norges geologiske undersøkelse: Marin grense og mulighet for marin leire*. http://geotest.ngu.no/kart/losmasse/ (accessed 17 November 2011).

Nilsen, A.-B., Stensgaard, K. & Wallin, H.G. 2013. Nettbrett til seterregistrering. *Kart og Plan* 73, 179–185.

Norderhaug, A., Halvorsen, R., Johansen, L., Mazzoni, S., Bratli, H., Svalheim, E., Jordal, J.B. & Pedersen, O. 2012. *Kulturmarkseng i Naturindeks – utvikling av kunnskapsgrunnlaget for overvåking og forvaltning*. Kvithamar: Bioforsk Midt-Norge.

Påhlsson, L. 1998. *Vegetationstyper i Norden*. 3rd ed. Copenhagen: Nordiska ministerrådet.

Pancer-Koteja, E., Szwagrzyk, J. & Guzik, M. 2009. Quantitative estimation of vegetation changes by comparing two vegetation maps. *Plant Ecology* 205(1), 139–154.

Prosser, M.V. & Wallace, H.L. 1999. *Countryside Survey 2000 Quality Assurance Exercise: Second Draft*. http://nora.nerc.ac.uk/id/eprint/17490/1/N017490CR.pdf (accessed January 2020).

Rapp, J., Wang, D., Capen, D., Thompson, E. & Lautzenheiser, T. 2005. Evaluating error in using the National Vegetation Classification System for ecological community mapping in northern New England, USA. *Natural Areas Journal* 25 (1), 46–54.

Rekdal, Y. & Larsson, J.Y. 2005. *Veiledning i vegetasjonskartlegging M 1:20 000–50 000*. Ås: Norsk institutt for jord- og skogkartlegging.

Robertson, P.J.H. & Grieve, Y. 2010. NWSS field survey and QA procedure – Quality assuring a national native woodland survey. *Scottish Forestry* 64(4), 10–14.

Rodwell, J.S. 2006. *National Vegetation Classification: Users' Handbook*. Peterborough: Joint Nature Conservation Committee.

Santangelo, M., Marchesini, I., Bucci, F., Cardinali, M., Fiorucci, F. & Guzzetti, F. 2015. An approach to reduce mapping errors in the production of landslide inventory maps. *Natural Hazards and Earth System Sciences* 15(9), 2111–2126.

Sickel, H., Ihse, M., Norderhaug, A. & Sickel, M.A.K. 2004. How to monitor semi-natural key habitats in relation to grazing preferences of cattle in mountain summer farming areas – An aerial photo and GPS method study. *Landscape and Urban Planning* 67(1–4), 67–77.

Skånes, H. 1997. Towards an integrated ecological–geographical landscape perspective: A review of principal concepts and methods. *Norsk Geografisk Tidsskrift* 51(3), 145–171.

Skånes, H., Mäki, A.-H. & Andersson, A. 2007. *Flygbildstolkningsmanual för Basinventeringen Natura* 2000. Stockholm: Naturvårdsverket.

Solheim, E. 1978. Vegetation mapping using colour infrared air photos. *Kart og Plan* 4, 246–256.

Ståhl, G., Allard, A., Esseen, P.-A., Glimskär, A., Ringvall, A., Svensson, J., Sundquist, S., Christensen, P., Torell, Å., Högström, M., Lagerqvist, K., Marklund, L., Nilsson, B. & Inghe, O. 2011. National Inventory of Landscapes in Sweden (NILS)—scope, design, and experiences from establishing a multiscale biodiversity monitoring system. *Environmental Monitoring and Assessment* 173(1), 579–595.

Stehman, S.V. 2009. Sampling design for accuracy assessment of land cover. *International Journal of Remote Sensing* 30 (20), 5243–5272.

Strand, G.-H. & Bloch, V.V.H. 2009. *Statistical Grids for Norway: Documentation of National Grids for Analysis and Visualisation of Spatial Data in Norway*. 2009/9. Kongsvinger: Statistics Norway, Department of Economic Statistics. https://www.ssb.no/a/english/publikasjoner/pdf/doc_200909_en/doc_200909_en.pdf (accessed December 2019).

Strand, G.-H., Dramstad, W. & Engan, G. 2002. The effect of field experience on the accuracy of identifying land cover types in aerial photographs. *International Journal of Applied Earth Observations and Geoinformation* 4(2), 137–146.

Takács, G. & Molnár, Z. (eds.) 2009. *National Biodiversity Monitoring System XI. Habitat Mapping*. 2nd ed. Budapest: MTA Ökológiai és Botanikai Kutatóintézete, Vácrátót and Környezetvédelmi és Vízügyi Minisztérium.

Tenge, I.M. 2016. *Arealressurskart AR5*. Ås: Norsk institutt for bioøkonomi.

The Nature Conservancy & Environmental Systems Research Institute. 1994. *Field Methods for Vegetation Mapping: Final Draft*. https://www1.usgs.gov/vip/standards/fieldmethodsrpt.pdf (accessed January 2020).

Ullerud, H.A., Bryn, A., Halvorsen, R. & Hemsing, L.Ø. 2018. Consistency in land cover mapping: Influence of fieldworkers, spatial scale and classification system. *Applied Vegetation Science* 21, 278–288.

Vesterbukt, P., Aune, S. & Johansen, L. 2013. *Basiskartlegging etter NiN i 10 utvalgte verneområder i Østfold: Erfaringer og drøftinger i bruk av NiN og kartleggingsinstruks*. Kvithamar: Bioforsk Midt-Norge.

Vitousek, P.M., Mooney, H.A., Lubchenco, J. & Melillo, J.M. 1997. Human domination of Earth's ecosystems. *Science* 277(5325), 494–499.

Walker, D.A., Raynolds, M.K., Daniels, F.J.A., Einarsson, E., Elvebakk, A., Gould, W.A., Katenin, A.E., Kholod, S.S., Markon, C.J., Melnikov, E.S., Moskalenko, N.G., Talbot, S.S., Yurtsev, B.A. 2005. The Circumpolar Arctic vegetation map. *Journal of Vegetation Science* 16(3), 267–282.

Wehn, S., Johansen, L., Lundemo, S. & Hovstad, K.A. 2015. *Naturindeks Norge – Videreutvikling av kunnskapsgrunnlaget for åpent lavland: fase 3. Evaluering av metodikk for kartlegging og registrering av biologisk mangfold og miljøvariabler i semi-naturlig eng. «Underveisrapport»*. NIBIO Commissioned Report Vol. 1, Nr. 6, 2015. https://nibio.brage.unit.no/nibio-xmlui/bitstream/handle/11250/2379395/NIBIO_RAPPORT_2015_1_6.pdf?sequence=3&isAllowed=y (accessed January 2020).

Whittaker, R.H. 1967. Gradient analysis of vegetation. *Biological Reviews of the Cambridge Philosophical Society* 42, 207–264.

Wyatt, B.K. 2000. Vegetation mapping from ground, air and space – Competitive or complementary techniques? Alexander, R. & Millington, A.C. (eds.) *Vegetation Mapping*, 3–15. Chichester: John Wiley & Sons.

Xie, Y.C., Sha, Z.Y. & Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology* 1, 9–23.