Revision Biogeosciences

RC #1

1. Quantitative assessment
The main weakness is there is no quantitative assessment of the results, even at a very basic level. Without some assessment of whether the resulting data are fit for purpose, we have no idea whether it's worth pursuing or not. At the very least I'd expect more than the 1 or 2 images presented, compared with some 'known' alternative assessment, just to give a first pass assessment of the approach.

Answer: We agree with the point that more classifications could be included in the manuscript to illustrate that the method delineates the land cover types accurately. However, we cannot see how we could get hold of reference material to validate our plots, because the results are based on information very similar to what is experienced if being on site doing a manual land cover inventory. The validation is done by the person who takes the close-up images that represent the different classes (acting as reference data as the view of these close-up images has the same detail richness as if standing on-site in situ), and then the person that does the image processing when setting thresholds and manually cleaning up the classification. The accuracy is therefore related to the classification interpretation of the person taking the close-up images and the image processer. To make it more robust, several interpreters can be used. In this case, three of the authors (Gålfalk, Karlsson and Bastviken) visited all sites and discussed the image interpretation, so the classification is based on their joint assessment at each site. In the end, this approach is similar to in-situ visual inspection of surface cover types, which are regarded as fundamental reference data, although subjective and dependent on the knowledge of the person(s) doing the inspections. The difference is that our suggested method is much faster in the field.

Changes made:

- We have now added three classification examples in Supplementary material S2 (Figures S4, S5, and S6 on pages 20-22), which means that there are now five examples of classifications in the manuscript (one in the main text and four in S2).

2. Sensitivity assessment

How robust are results to different users collecting data, different light conditions, times of day and so on?

You might even expect more than one camera to be looked at. Sure, GoPros are common and the methods *ought* to work for other cameras, but we don't know. Mobile phone camera data might potentially be even more useful.

Also what about details of processing - various indices are mentioned but how sensitive are the results to these choices?

Answer: Any camera can be used, and we have now clarified this by adding a custom step-by-step guide of how the image distortion is done for a custom camera in Matlab using the built in Camera calibration application. The problem with mobile phones is that the field of view is often really narrow, requiring a much higher viewing altitude in the field to map 10 x 10 m which could become impractical and less useful. The method is however just as valid for any other cameras than a GoPro; we just used a GoPro for the very large field of view, and because it is a very popular cheap light-weight camera that is easily available with many possibilities for mounting as it has lots of accessories for this. Doubling the camera altitude (to about 6 meters) 10 x 10 meters could be mapped with a mobile phone, which could be controlled by a Bluetooth remote control, and 20 x 20 meters mapped with a GoPro which would be a good area for e.g. 10 x 10 meters Sentinel satellite pixels.

About the indices and sensitivity for different choices – the method provides a palette of potential discriminators (colors, indices and textures) from which the user needs to identify the most appropriate ones based on trial and error. It will depend on the lighting conditions (e.g. water reflecting clouds or a blue sky), the white balance of the camera, and the color of different vegetation.

Importantly, as the close-up images have high detail richness, they allow identification, and color and texture assignment of the different land cover classes during similar light and weather conditions as when the whole-plot image is taken.

Changes made:

- This has now been further clarified in the manuscript (page 10, lines 12-15) and makes results robust regarding different users collecting data, with respect to light conditions, times of day etc. The sensitivity is instead affected by the person defining the classes, just as with normal visual inspection.

- We have also added in the manuscript that it is important to write down notes for each close-up image, making a judgement in the field of the vegetation in each of the three close-up images per plot (page 10, line 7; page 16, line 3-4). This will aid in the calibration process as e.g. a class can contain several vegetation types, having different colors, that are classified separately and merged into the same class.

- We have added to the manuscript that we recommend a higher camera altitude (page 10, lines 2-3; page 12, lines 14-15; page 15, line 6), and that it would be possibility to use a mobile phone (page 12, lines 14-16)

- We have added a custom step-by-step guide of how the image distortion is done for any custom camera in Matlab (pages 5-6).

3. Geometric correction

The manual part needs to have clear step by step guidance to the geometric correction aspect as that is a key part of the method and may vary from camera to camera.

How long does it take to do the geometric calibration (which is one-off or only needs to be done occasionally) and the processing of an image to something useful? How automatic is the geometric correction process? The text implies some manual input is required. Clearly, again the onus is on the user and how they choose to do this, but the authors ought to give us an idea of timings for their workflow. If the aim is to do validation of LC data at anything other than trivial scales (few pixels), this is likely to require processing of 100s of images. If this requires significant manual input then the method may be limited. I note their generous offer to process data for users - but how prepared are they to process a large amount of data from many users with many different systems? Is this feasible and for how long?

Answer:

The time taken to classify the images depend on the user, and is a trial-and-error process, involving trying different color differences (such as Green – Red) and setting limits of the classes. The manual part, setting these limits and reclassifying parts of the image, could be a very small effort for some images but take more time for others, and is often the step that takes the most time – compared to correction of lens distortion and ground geometry. However, as images involving different vegetation (say about 10 plots) have been classified, the classification becomes much faster as there will be similar vegetation and thus similar color differences for separating vegetation.

Changes made:

- A clear step-by-step guide has now been added showing how to do a geometric lens distortion correction for any camera (pages 5-6). We have also added that this only has to be done once, when using a new camera or a new field of view setting (page 7, lines 4-9). This means once for a whole data collection campaign or a whole project (if the same camera model and field of view is used).

- We have now added information about the time used for different steps in our workflow in section 4: "In a test study, we were able to make classifications of about 200 field plots in northern Sweden in a three-day test campaign despite rainy and windy conditions. For each field plot, surface area (m2) and coverage (%) were calculated for each class. The geometrical correction models (lens distortion and ground projection) was made in about an hour, while the classifications for all plots took a few days." (page 11, lines 11-14)

- The same applies to the calibration of the projected geometry, it only has to be done once for a certain camera and field of view setting. (page 7, lines 4-6)

- The geometric correction process is fast and fully automatic (only the height of the camera needs to be entered). We have also added a clearer description of how the calibration images should be obtained for the geometrical projection. (page 7, lines 5-9).

4. General issues.

A more general issue that probably needs to be addressed at least in passing is cheap UAVs. The processing methods could be very similar (in the rgb sense), the geom is dealt with already by SfM (Structure from Motion?) software and you can cover much larger areas. Clearly this method is far more robust to wind, but is that the main / only benefit given the larger area UAVs can cover? My feeling is there is a place for this method *if* it is more clearly demonstrated, but it may be superseded very quickly (which is less likely if it can be applied to mobile phone data for example).

Answer: UAVs can be more advantageous if only one larger area is to be mapped in greater detail per day and if it is possible to wait for favorable weather conditions. However, if there is a need to visit many locations in a region without time to wait for good weather, UAVs (especially cheap ones below 10 000 USD) have several disadvantages. They can only fly at low to medium wind speeds and cannot fly when it is raining. Flight times are often around 20 minutes (when continuously in the air), but become much shorter when many takeoffs and landings are made, which would be the case when moving between plots (in our case about 70 plots per day) and can only take off or land on flat dry surfaces, unless hand-cached which

is a risk in itself for larger more robust UAVs. A very large amount of batteries would have to be carried as they take too long time to recharge during the measurements.
As for mobile phone cameras, yes, they can be used with our method, but field of views are often so small that this becomes very inefficient.

Mobile phones could work efficiently if a wide-angle lens was mounted to the mobile phone but then it just becomes a less robust and more expensive adventure camera (also having similar image distortion from the added lens). A dedicated adventure camera (e.g. GoPro) is cheaper than a mobile phone or a drone, which is advantageous when funding is limited or for citizen science efforts.

Changes made:

- We have now added a paragraph about using UAVs or mobile phones in the conclusions. (page 12, lines 9-16)

We would like to thank both anonymous reviewers for their valuable comments for improving the manuscript.

RC #2

1. Comparison to other (similar) methods (My first question is how this compares to the methods used currently)

How long did it take to collect the 200 reference data points versus if they were collected in the "typical" fashion? (page 3)

What is the computer processing time to create and classify the images and is that a major addition in time spent creating reference data? This system could potentially trade time in the field for time behind a computer time, not a bad option as processing time can be spread out over multiple analysts and a larger time frame.

Answer:

It is true that less time in the field is traded in for more time behind a computer classifying images semi-automatically (compared to the traditional methods). We agree that this is a nice tradeoff, and in addition that the method is very robust for different weather conditions (high wind, rain) which would not be the case for a e.g. a drone (see RC #1–4).

Traditional methods are described on page 2 (visual estimation, point frame assessment and digital photography), and are generally slow on large areas such as 10 x 10 m (or even 20 x 20 m which is possible using a camera height of 6 meters which is now suggested in the manuscript) as they require individual attention to multiple smaller sub-areas e.g. 1 x 1 m representing grid cells of the larger area. If extent of individual land cover classes are measured accurately in each such grid cell the traditional methods are very slow. Therefore, land cover fractions in each grid is often arbitrarily estimated visually to speed up assessments, likely resulting in lower accuracy and greater subjectivity among persons, than photographic methods such as proposed here. Digital photography is faster, but often downward facing cameras from small heights have been used. Our method captures 10 x 10 m in one image (seconds in the field) and then a few close-up images for reference of typical land cover under current light and weather conditions.

Changes made:

- We have now added information about the time used for different steps in our workflow in section 4: “In a test study, we were able to make classifications of about 200 field plots in northern Sweden in a three-day test campaign despite rainy and windy conditions. For each field plot, surface area (m2) and coverage (%) were calculated for each class. The geometrical correction models (lens distortion and ground projection) was made in about an hour, while the classifications for all plots took a few days.”. (page 11, lines 11-14).

2. Accuracy assessment (This methodology seems like it worked but did it?)

No discussion is made on how the results from the 200 plots performed and if they would help in classification. The level of accuracy achieved is an important metric for many and if this shows similar or a marginal decreases in accuracy with greatly reduced time or cost in data collection it would be well received. The risk of reduced accuracy may not be worth researcher changing the methods they currently use and some discussion on expected results of this new method should be included. The clarification of this topic would explain how data is integrated into classification of land cover and how this method compares to the current methods in terms of time savings and accuracy estimates?

Answer: See RC #1–1 and RC #2–1

3. Geometric correction (The section on distortion models is important for the research and could throw off all results for anyone using it. (page 4)).

What model was used and why was it used, enough explanation should be included for researchers to understand the difference distortion models would make on results and the sensitivity of different models. This is important especially if comparisons between research groups or sharing of data is going to occur.

Answer: See RC #1–3

4. Use of terms (ground truth data)
Calling validation “ground truth” should not be done, even if it’s explained. The fact that it was explained means that there is an understanding that it’s a bad term, call it reference data and remove any reference to "ground truth." The next sentence goes on to state 100% accurate reference data is not possible, reference data should be 100% accurate within the margin of possible error, it is not however 100% guaranteed that it represents the population or a large study area, nor is it 100% guaranteed due to geolocation error that it is correctly located in your image compared to the true ground location. Clarification on this topic by the author would be helpful.

Answer:

Changes made:

We have now changed the term “ground truth” to “reference data” throughout the text.

5. Limitations for high vegetation (Higher vegetation causing problems is made (page 7))

What is high vegetation and when does it start to deteriorate the data? Was high vegetation seen in the 200 plots created here and at what rate did tall vegetation cause problems? Knowing this would allow a decision on the applicability of this method to different research.

Answer: High vegetation is for example high grass type vegetation that is also dense enough to obscure the ground behind it. Increasing the camera height will decrease this potential problem, and it will be worse for large distances (near the edge of the field of view) as the viewing angles increases from nadir. For short grass, rocks etc. we did not have any problems from this, neither did we have problems from Birch trees as they do not grow on the mires and the shrub/brushwood was only a couple of decimeters high.

For plots with high vegetation we used a larger camera height for this reason. Another solution for such plots could be to direct the camera towards nadir, making angles smaller and the obscuration less – this is mentioned in the supplementary information S1 (manual), step 2, "Alternative 2 is to stand in the center of the plot and… as tall vegetation will not obscure the view towards lower vegetation as much".

Changes made:

- We have now added a paragraph on vegetation height, our experiences, and solutions, at the end of section 3 (page 9 line 16 – page 10 line 3):

"There is however a small difference, as the geometry (due to line of sight) does not provide information about the ground behind high vegetation in the same way as an image taken from overhead. In cases with high vegetation (which is some of our 200 field plots), mostly high grass, we used a higher camera altitude to decrease obscured areas. Another possibility is to direct the camera towards nadir (see the manual in Supplementary material S1) to image areas -5 to +5 meters from the center of a plot, further decreasing the viewing angles from nadir. We did not have any problems with shrub or brushwood as it was only a couple of decimeters high, and Birch trees did not grow on the mires. We also recommend using a camera height of about 6 meters to decrease obscuration and to increase the mapped area."

6. Writing

The sentences and paragraphs are well written, however in a few cases they start weak with; however, for example, to resolve this, etc. An effort should be made to start sentences with the primary subject of the sentence and tighten up some of the language and remove extra words seen throughout the paper. The acknowledgement heading is floating on page 10 line 15 as well.

Answer:

Changes made:

The acknowledgement heading has now been moved closer to the acknowledgement text. The start of sentences have also been improved throughout the paper.

We would like to thank both anonymous reviewers for their valuable comments for improving the manuscript.

Technical note: A simple approach for efficient collection of field reference data for calibrating remote sensing mapping of northern wetlands

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Abstract. The calibration and validation of remote sensing land cover products is highly dependent on accurate field reference data, which are costly and practically challenging to collect. We describe an optical method for collection of field reference data that is a fast, cost-efficient, and robust alternative to field surveys and UAV imaging. A light weight, water proof, remote controlled RGB-camera (GoPro) was used to take wide-angle images from 3.1 - 4.5 m altitude using an extendable monopod, as well as representative near-ground (< 1 m) images to identify spectral and structural features that correspond to various land covers at present lighting conditions. A semi-automatic classification was made based on six surface types (graminoids, water, shrubs, dry moss, wet moss, and rock). The method enables collection of detailed field reference data which is critical in many remote sensing applications, such as satellite-based wetland mapping. The method uses common non-expensive equipment, does not require special skills or education, and is facilitated by a step-by-step manual that is included in the supplementary material~~information~~. Over time a global ground cover database can be built that ~~is relevant for ground truthing~~can be used as reference data for~~of~~ wetland studies from satellites such as Sentinel 1 and 2 (10 m pixel size).

1 Introduction

Accurate and timely land cover data are important for e.g. economic, political, and environmental assessments, and for societal and landscape planning and management. The capacity for generating land cover data products from remote sensing is developing rapidly. There has been an exponential increase in launches of new satellites with improved sensor capabilities, including shorter revisit time, larger area coverage, and increased spatial resolution (Belward & Skøien 2015). Similarly, the development of land cover products is increasingly supported by the progress in computing capacities and machine learning approaches.

~~However,~~ A~~a~~t the same time it is clear that the knowledge of the Earth´s land cover is still poorly constrained. ~~For example,~~ A~~a~~ comparison between multiple state-of-the-art land cover products for West Siberia revealed disturbing uncertainties (Frey and Smith 2007)~~.~~ as e~~E~~stimated wetland areas ranged from 2 - 26% of the total area, and the correspondence with *in situ* observations for wetlands was only 2 - 56%. For lakes, all products revealed similar area cover (2-3%), but the agreement with field observations was as low as 0-5%. Hence, in spite of the progress in technical capabilities and data analysis progress, there are apparently fundamental factors that still need consideration to obtain accurate land cover information.

The West Siberia example is not unique. Current estimates of the global wetland area range from 8.6 to 26.9 x 10^6 km^2 with great inconsistencies between different data products (Melton et al. 2013). The uncertainty in wetland distribution has multiple consequences, including being a major bottleneck for constraining the assessments of global methane (CH_4) emissions, which was the motivation for this area comparison. Wetlands and lakes are the largest natural CH_4 sources (Saunois et al. 2016) and available evidence suggest that these emissions can be highly climate sensitive, particularly at northern latitudes predicted to experience the highest temperature increases and melting permafrost – both contributing to higher CH_4 fluxes (Yvon-Durocher et al. 2014; Schuur et al. 2009).

CH_4 fluxes from areas with different plant communities~~plant functional groups~~ in northern wetlands can differ by orders of magnitude. Small wet areas dominated by emergent graminoid plants account for by far the highest fluxes per m^2, while the more widespread areas covered by e.g. Sphagnum mosses have much lower CH_4 emissions per m^2 (e.g. Bäckstrand et al. 2010). The fluxes associated with the heterogeneous and patchy (i.e. mixed) land cover in northern wetlands is well understood on the local plot scale, whereas the large-scale extrapolations are very uncertain. The two main reasons for this uncertainty is that the total wetland extent is unknown and that present map products do not distinguish between different wetland habitats which control fluxes and flux regulation. As a consequence the whole source attribution in the global CH_4 budget remains highly uncertain (Kirschke et al. 2013; Saunois et al. 2016).

~~To resolve this, I~~improved land cover products being relevant for CH_4 fluxes and their regulation are therefore needed to resolve this. The detailed characterization of wetland features or habitats requires the use of high resolution satellite data and sub-pixel classification that quantify percent, or fractional, land cover. A fundamental bottleneck for the development of fractional land cover products is the quantity and quality of the ~~the ground truth, or~~ reference~~,~~ data used for calibration and validation (Foody 2013; Foody et al. 2016). ~~While the concept "ground truth" leads the thoughts to a perfectly represented reality, 100% accurate reference data do not exist.~~ In fact, reference data can often be any data available at higher resolution than the data product, including other satellite imagery, airborne surveys, in addition to field observations. In turn, the field observations can range from rapid landscape assessments to detailed vegetation mapping in inventory plots, where the latter yields high resolution and high-quality data but is very expensive to generate in terms of time and manpower (Olofsson et al. 2014; Frey & Smith 2007). Ground-based reference data for fractional land cover mapping can be acquired using traditional methods, such as visual estimation, point frame assessment or digital photography (Chen et al. 2010). These methods can be applied using a transect approach to increase the area coverage in order to match the spatial resolutions of different satellite sensors (Mougin et al. 2014).

The application of digital photography and image analysis software has shown promise for enabling rapid and objective measurements of fractional land cover that can be repeated over time for comparative analysis (Booth et al. 2006a). While several geometrical corrections and photometric setups are used, nadir (downward facing) and hemispherical view photography are most common, and the selected setup depends on the height structure of the vegetation (Chen et al. 2010). ~~However,~~ M~~m~~ost previous research has however focused on distinguishing between major general categories, such as vegetation and non-vegetation (Laliberte et al. 2007; Zhou & Liu 2015), and are typically not used to characterize more subtle patterns within major land cover classes. Many applications in literature have been in rangeland, while there is a lack of wetland classification. Furthermore, images have mainly been close-up images taken from a nadir view perspective (Booth et al. 2006a; Chen et al. 2010; Zhou & Liu 2015), thereby limiting the spatial extent to well below the pixel size of satellite systems suitable for regional scale mapping.

From a methano-centric viewpoint, accurate reference data at high enough resolution, being able to separate wetland (and upland) habitats with differing flux levels and regulation, is needed to facilitate progress with available satellite sensors. The resolution should preferable be better than 1 m^2 given how the high emitting graminoid areas are scattered on the wettest spots where emergent plants can grow. Given this need, we propose a quick and simple type of field assessment adapted for the 10 x 10 m pixels of the Sentinel 1 and 2 satellites.

Our method uses true color images of the ground, followed by image analysis to distinguish fractional cover of key land cover types relevant for CH_4 fluxes from northern wetlands, where we focus on few classes, that differ in their CH_4 emissions. We provide a simple manual allowing anyone to take the photos needed in a few minutes per field plot. Land cover classification can then be made using the Red-Green-Blue (RGB) field images (sometimes also converting them to the Intensity-Hue-Saturation (IHS) color space) by software such as e.g. CAN-EYE (Weiss & Baret 2010), VegMeasure (Johnson et al. 2003), SamplePoint (Booth et al. 2006b), or eCognition (Trimble commercial software). With this simple approach it would be quick and easy for the community to share such images online and to generate a global reference database that can be used for land cover classification relevant to wetland CH_4 fluxes, of other purposes depending of the land cover classes used. We use our own routines written in Matlab due to the large field of view used in the method, in order to correct for the geometrical perspective when calculating areas (to speed up the development of a global land cover reference database, we can do the classification on request if all necessary parameters and images are available as given in our manual).

2 Field work

The camera setup is illustrated in Fig.1, with lines showing the spatial extent of a field plot. Our equipment included a lightweight RGB-camera (GoPro 4 Hero Silver; other types of cameras with remote control and suitable wide field of view would also work) mounted on an extendable monopod that allows imaging from a height of 3.1 - 4.5 meters. The camera had a resolution of 4000 x 3000 pixels with a wide field of view (FOV) of 122.6 x 94.4 deg. and was remotely controlled over Bluetooth using a mobile phone application that allows a live preview, making it possible to always include the horizon close to the upper edge in each image (needed for image processing later – see below). The camera had a waterproof casing and could therefore be used in rainy conditions, making the method robust to variable weather conditions. Measurements were made for about 200 field plots in northern Sweden in the period 6-8 September 2016.

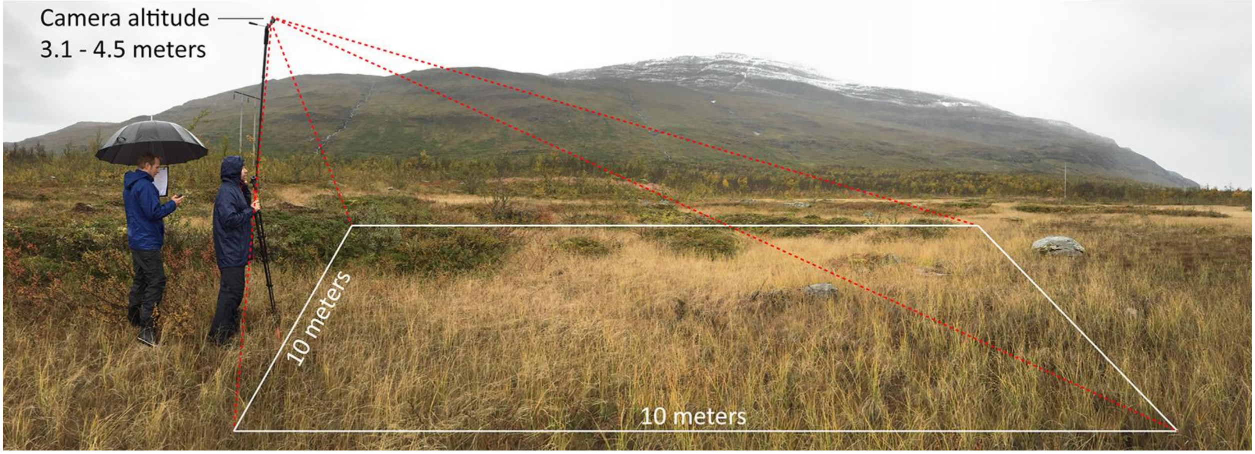

Figure 1: A remotely controlled wide-field camera mounted on a long monopod captures the scene in one shot, from above the horizon down to nadir. After using the horizon image position to correct for the camera angle, a 10 x 10 m area close to the camera is used for classification.

For each field plot, the following was recorded:

- One image taken at > 3.1 m height (see illustration in Fig. 1) which includes the horizon coordinate close to the top of the image.
- 3-4 close-up images of common surface cover in the plot (e.g. typical vegetation) and a very short note for each image indication what is shown, e.g. if a close-up image shows dry or wet moss (two of our classes) as there can be different colors within a class.
- GPS position of the camera location (reference point)
- Notes of the image direction relative to the reference point.

The long monopod was made from two ordinary extendable monopods taped together, with a GoPro camera mount at the end. The geographic coordinate of the camera position was registered using a handheld Garmin Oregon 550 GPS with a horizontal accuracy of approximately 3 m. The positional accuracy of the images can be improved by using a differential GPS and by registering the cardinal direction of the FOV. The camera battery typically lasts for a few hours after a full charge, but was charged at intervals when not used, e.g. when moving between different field sites.

3 Image processing and models

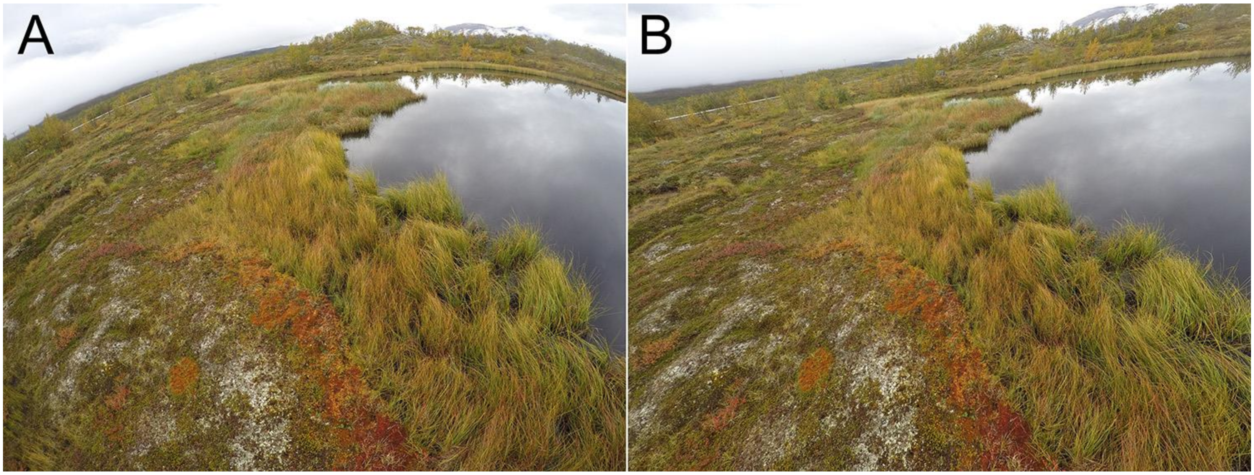

Figure 2: Correction of lens distortion. (A) Raw wide-field camera image. (B) After correction.

As the camera had a very wide FOV, the raw images do have a strong lens distortion (Fig. 2). This can be corrected for many camera models (e.g., the GoPro series) using ready-made models in Adobe Lightroom or Photoshop, or by modelling the distortion for any camera using the camera calibrator application in Matlab's computer vision system toolbox as described below. A checkboard pattern is needed for the modelling (Fig. 3), which should consist of black and white squares with an even number of squares in one direction and an odd number of squares in the other direction, preferably having a white boarder around the pattern. The next step is to take images of this pattern from 10-20 unique camera positions, providing many perspectives of the pattern with different angles for the distortion modelling (Fig. 3). In order to make accurate models it is important both to have sharp images with no motion blur (e.g. due to movement or poor lighting) and to include several images where the pattern is close to the edges of the image as this is where the distortion is greatest. An alternative but equivalent method, preferably used for small calibration patterns printed on a standard sheet of paper (e.g. letter or A4), is to mount the camera and instead move the paper to 10-20 unique positions having different angles to the camera. A quick way to do this with only one person present is by recording a video while moving the paper slowly and then selecting calibration images from the video afterwards. The illustration of camera positions used (Fig. 4) can also be displayed in the application as a mounted camera with different positions of the calibration pattern. The next step is to enter the size of a checkerboard square (mm, cm, or in) which is followed by an automatic identification of the corners of squares in the pattern (Fig. 3). Images with bad corner detection can now be removed (optional) to improve the modelling. As a last step, camera parameters can now be calculated by the press of a button and be saved as a variable in Matlab (cameraParams). This whole procedure only has to be done once for each camera and field-of-view setting used, meaning once for a data collection campaign or a project if the same camera model and field of view is used. Applying the correction to images is done using a single command in Matlab: img_corr = undistortImage(img, cameraParams). Here img and img_corr are variables for the uncorrected and corrected versions, respectively.

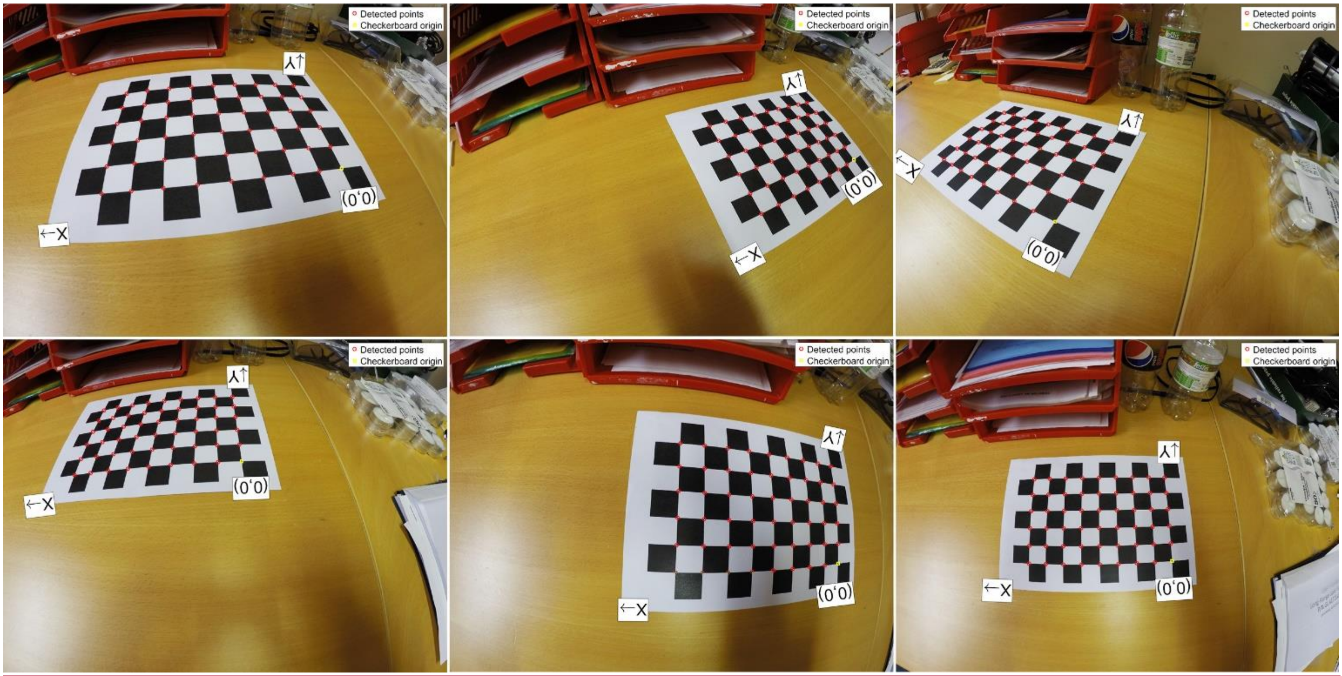

Figure 3: Modelling of lens distortion. Checkboard pattern used for calibrations. Red circles are used to mark automatically detected square corners while the yellow square marks the origin of the coordinate system. Images of the pattern are taken from 10-20 different camera angles.

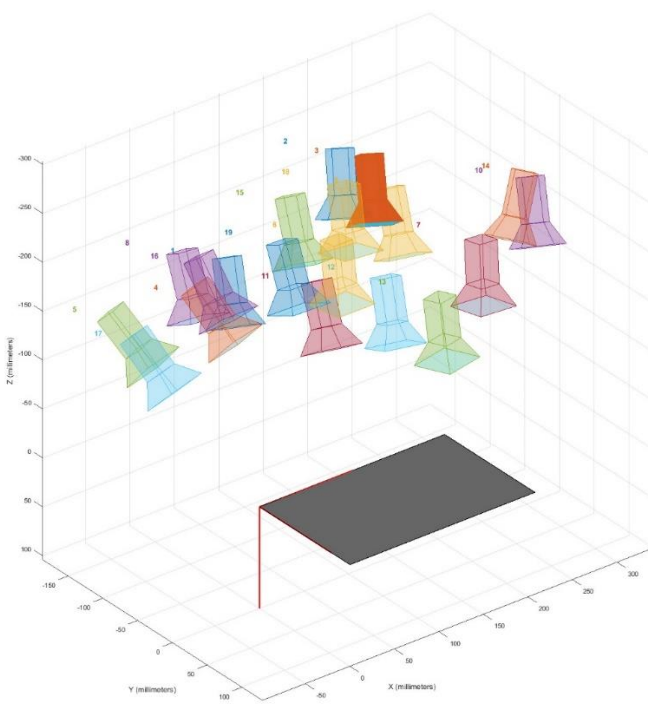

Figure 4. Illustration using Matlab's Camera calibration application of the camera positions used when taking the calibration images.

Using a distortion corrected calibration image, we then developed a model of the ground geometry by projecting and fitting a 10 x 10 m grid on a parking lot with measured distances marked using chalk (Fig. 5). Such calibration of projected ground geometry only needs to be done when changing the camera model or field of view setting, and is valid for any camera height as long as the heights used in field and in the calibration imaging are known. It is done fast by drawing short lines every meter for distances up to 10 meters, and some selected perpendicular lines at strategic positions to obtain the perspective. At least one, preferably two, perpendicular distances should be marked at a minimum of two different distances along the central line (in Fig. 5 at 2 and 4 meters left of the central line at distances along the central line of 0 and 2.8 meters). The geometric model uses the camera FOV, camera height, and the vertical coordinate of the horizon (to obtain the camera angle). We find an excellent agreement between the modeled and measured grids (fits are within a few centimeters) for both camera heights of 3.1 and 4.5 m.

The vertical angle α from nadir to a certain point in the grid with ground distance Y along the center line is given by $\alpha = \arctan(Y/h)$, where h is the camera height. For distance points in our calibration image (Fig. 5), using 0.2 m steps in the range 0 – 1 m and 1 m steps from 1 to 10 m, we calculate the nadir angles $\alpha(Y)$ and measure the corresponding vertical image coordinates $y_{calib}(Y)$.

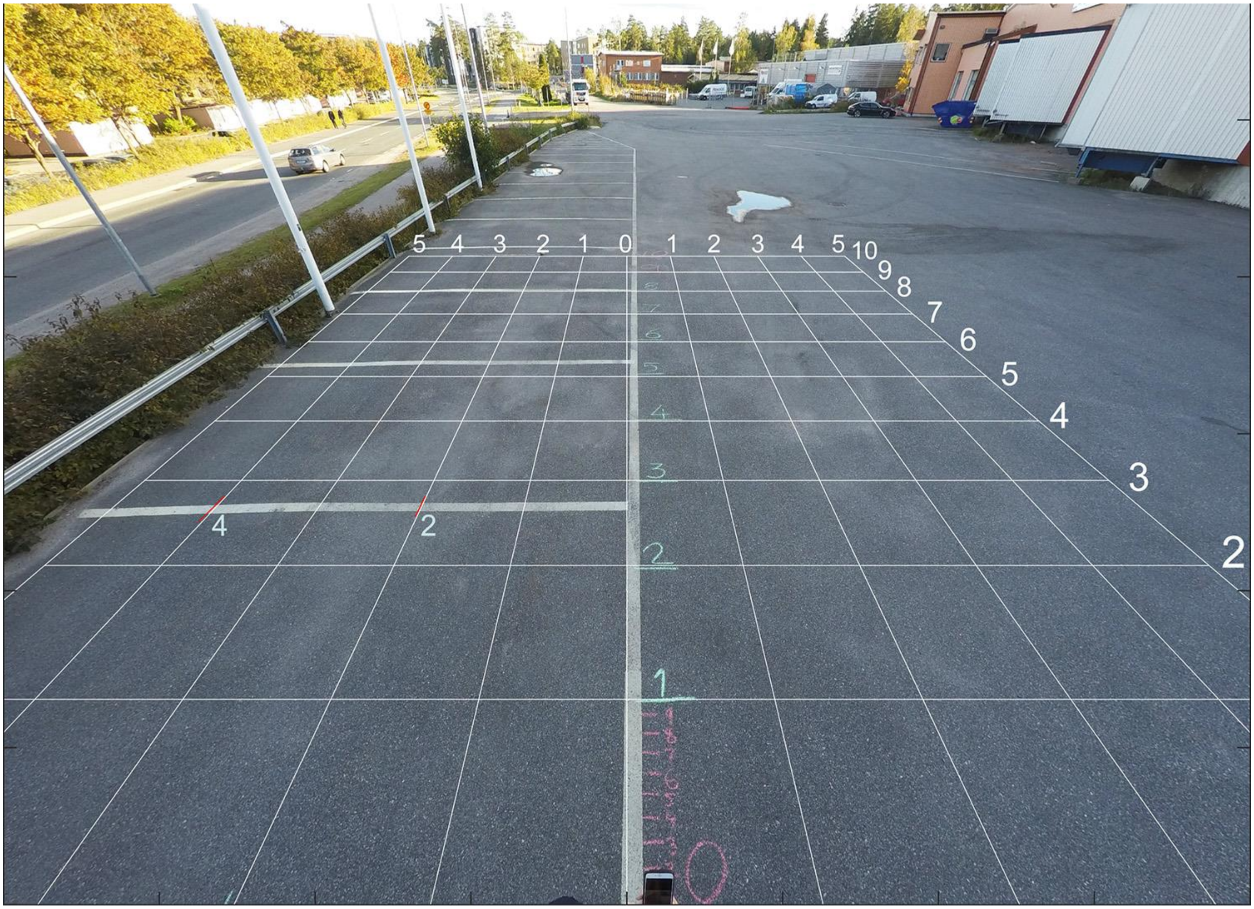

Figure 5: Calibration of projected geometry using an image corrected for lens distortion. Model geometry are shown as white numbers and a white grid, while green and red numbers are written on the ground using chalk (red lines at 2 and 4 m left of the center line were strengthened for clarity). The camera height in this calibration measurement is 3.1 m.

In principle, for any distortion corrected image there is a simple relationship $y_{img}(\alpha) = (\alpha(Y) - \alpha_0)/PFOV$, where y_{img} is the image vertical pixel coordinate for a certain distance Y, $PFOV$ the pixel field of view (deg pixel^{-1}), and α_0 the nadir angle of the bottom image edge. In practice, however, correction for lens distortion is not perfect so we have fitted a polynomial in the calibration image to obtain $y_{calib}(\alpha)$ from the known α and measured y_{calib}. Using this function we can then obtain the y_{img} coordinate in any subsequent field image using

$$y_{img} = y_{calib}\left(\alpha + PFOV_{hor} \cdot \left(y_{img}^{hor} - y_{calib}^{hor}\right)\right) \quad (1)$$

where y_{img}^{hor} and y_{calib}^{hor} are the vertical image coordinates of the horizon in the field and calibration image, respectively. As the $PFOV$ varies by a small amount across the image due to small deviations in the lens distortion correction, we have used $PFOV_{hor}$ which is the pixel field of view at the horizon coordinate. In short, the shift in horizon position between the field and calibration images is used to compensate for the camera having different tilts in different images. In order to obtain correct ground geometry it is therefore important to always include the horizon in all images.

The horizontal ground scale dx (pixels m^{-1}) varies linearly with y_{img}, making it possible to calculate the horizontal image coordinate x_{img} using

$$x_{img} = x_c + X \cdot dx = x_c + X \cdot \left(y_{img}^{hor} - y_{img}\right) \cdot \frac{dx_0}{y_{calib}^{hor}} \cdot \frac{h_{calib}}{h_{img}} \tag{2}$$

where dx_0 is the horizontal ground scale at the bottom edge of the calibration image, x_c the center line coordinate (half the horizontal image size), X the horizontal ground distance, and h_{calib} and h_{img} the camera heights in the calibration and field image, respectively.

Thus, using Eqs. (1) and (2) we can calculate the image coordinates (x_{img}, y_{img}) in a field image from any ground coordinates (X, Y). A model grid is shown in Fig. 5 together with the calibration image, illustrating their agreement.

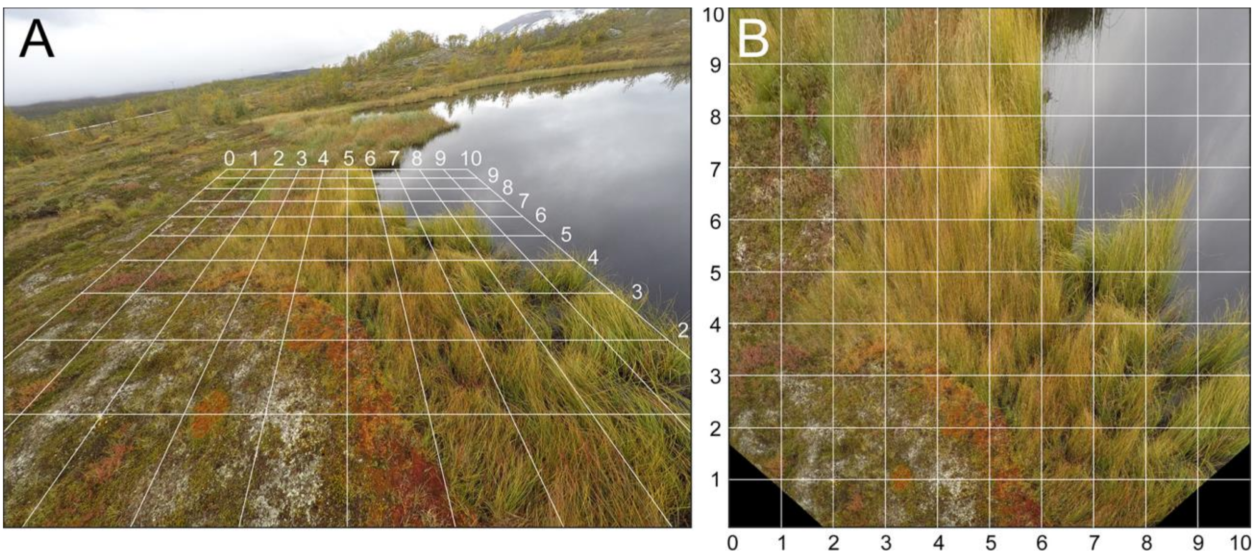

Figure 6: One of our field plots. (A) Image corrected for lens distortion, with a projected 10 x 10 m grid overlaid. (B) Image after recalculation to overhead projection (10 x 10 m).

For each field image, after correction for image distortion, our Matlab script asks for the y -coordinate of the horizon (which is selected using a mouse). This is used to calculate the camera tilt and to over-plot a distance grid projected on the ground (Fig. 6A). Using Eqs. (1) and (2) we then recalculate the image to an overhead projection of the nearest 10 x 10 m area (Fig. 6B). This is done using interpolation, where a (x_{img}, y_{img}) coordinate is obtained from each (X, Y) coordinate, and the brightness in each color channel (R, G, B) calculated using sub-pixel interpolation. The resulting image is reminiscent of an overhead image, with equal scales in both axes. There is however a small difference, as the geometry (due to line of sight) does not provide information about the ground behind high vegetation ~~(such as high grass)~~ in the same way as an image taken from overhead. In cases with high vegetation (which is some of our 200 field plots), mostly high grass, we used a higher camera altitude to decrease obscured areas. Another possibility is to direct the camera towards nadir (see the manual in Supplementary material S1) to image areas -5 to +5 meters from the center of a plot, further decreasing the viewing angles from nadir. We did not have any problems with shrub or brushwood as it was only a couple of decimeters high, and Birch trees did not grow on the mires. We also recommend using a camera height of about 6 meters to decrease obscuration and to increase the mapped area.

4 Image classification

After a field plot has been geometrically rectified, so that the spatial resolution is the same over the surface area used for classification, the script distinguishes land cover types by color, brightness and spatial variability. Aided by the close-up images of typical surface types also taken at each field plot (Fig. 7) and short field notes about the vegetation, providing further verification, a script is applied to each overhead-projected calibration field (Fig. 6B) that classifies the field plot into land cover types. This is a semi-automatic method that can account for illumination differences between images. In addition, it facilitates identification as there can for instance be different vegetation with similar color, and rock surfaces that have similar appearance as water or vegetation. After an initial automatic classification, the script has an interface that allows manual reclassification~~movement~~ of areas between classes. The close-up images have high detail richness, allowing identification, and color and texture assignment of the different land cover classes during similar light and weather conditions as when the whole-plot image is taken. This makes results robust regarding different users collecting data, with respect to light conditions, times of day etc. The sensitivity is instead affected by the person defining the classes, just as with normal visual inspection.

For calculations of surface-color we filter the overhead projected field-images using a running 3 x 3 pixel mean filter, providing more reliable statistics. Spatial variation in brightness, used as a measurement of surface roughness, is calculated using a running 3 x 3 pixel standard deviation filter. Denoting the brightness in each (red, green, and blue) color channel R, G and B, respectively, we could for instance find areas with green grass using the green filter index $2G/(R+B)$, where a value above 1 indicates green vegetation. In the same way, areas with water (if the close-up images show blue water due to clear sky) can be found using a blue filter index $2B/(R+G)$. If the close-up images show dark or gray water (cloudy weather) it can be distinguished from rock and white vegetation using either a total brightness index $(R+G+B)/3$ or an index that is sensitive to surface roughness, involving $\sigma(R)$, $\sigma(G)$, or $\sigma(B)$, where σ denotes the 3 x 3 pixels standard deviation centered on each pixel, for a certain color channel.

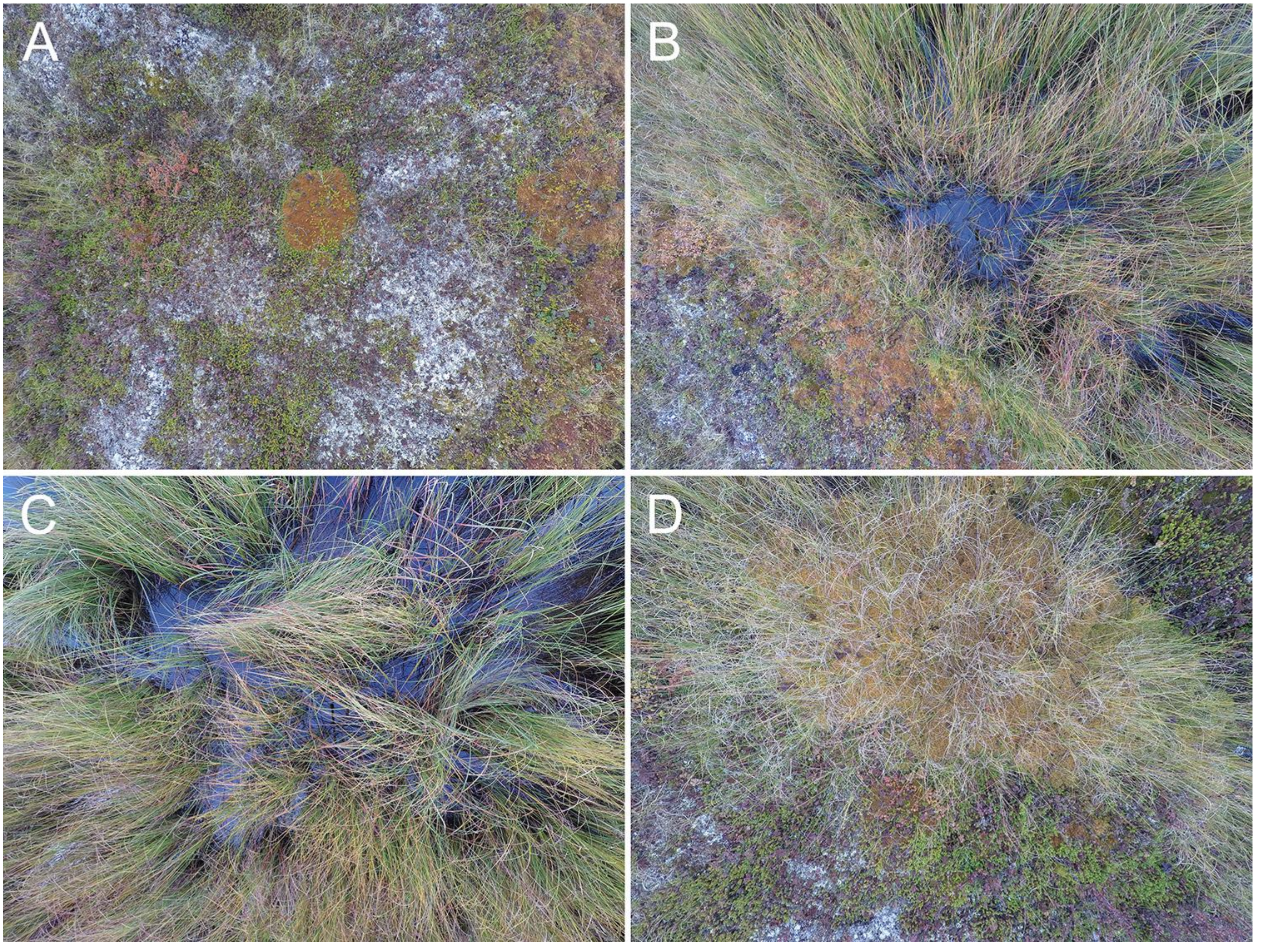

Figure 7: Close-up images in one of our 10 x 10 m field plots (Fig. 6).

In this study we used six different land cover types of relevance for CH_4 regulation: graminoids, water, shrubs, dry moss, wet moss, and rock. Examples of classified images are shown in Fig. 8. A~~An a~~dditional field plots and classification examples can be found in supplementary material S2. Compared to the corrections for lens distortion and geometrical projection, the classification part often takes the longest time as it is semi-automatic and requires trial and error testing of which indices and class limits to use for each image as vegetation and lighting conditions might vary. After a number of images with similar vegetation and conditions have been classified the process goes much faster as the indices and limits will be roughly the same. It may also be needed to reclassify parts manually by moving a square region from one class to another based on visual inspection. The main advantage with this method of obtaining reference data is however that it is very fast in the field and works in all weather conditions. In a test study, we were able to make classifications of about 200 field plots in northern Sweden in a three-day test campaign despite rainy and windy conditions. For each field plot, surface area (m^2) and coverage (%) were calculated for each class. The geometrical correction models (lens distortion and ground projection) was made in about an hour, while the classifications for all plots took a few days.

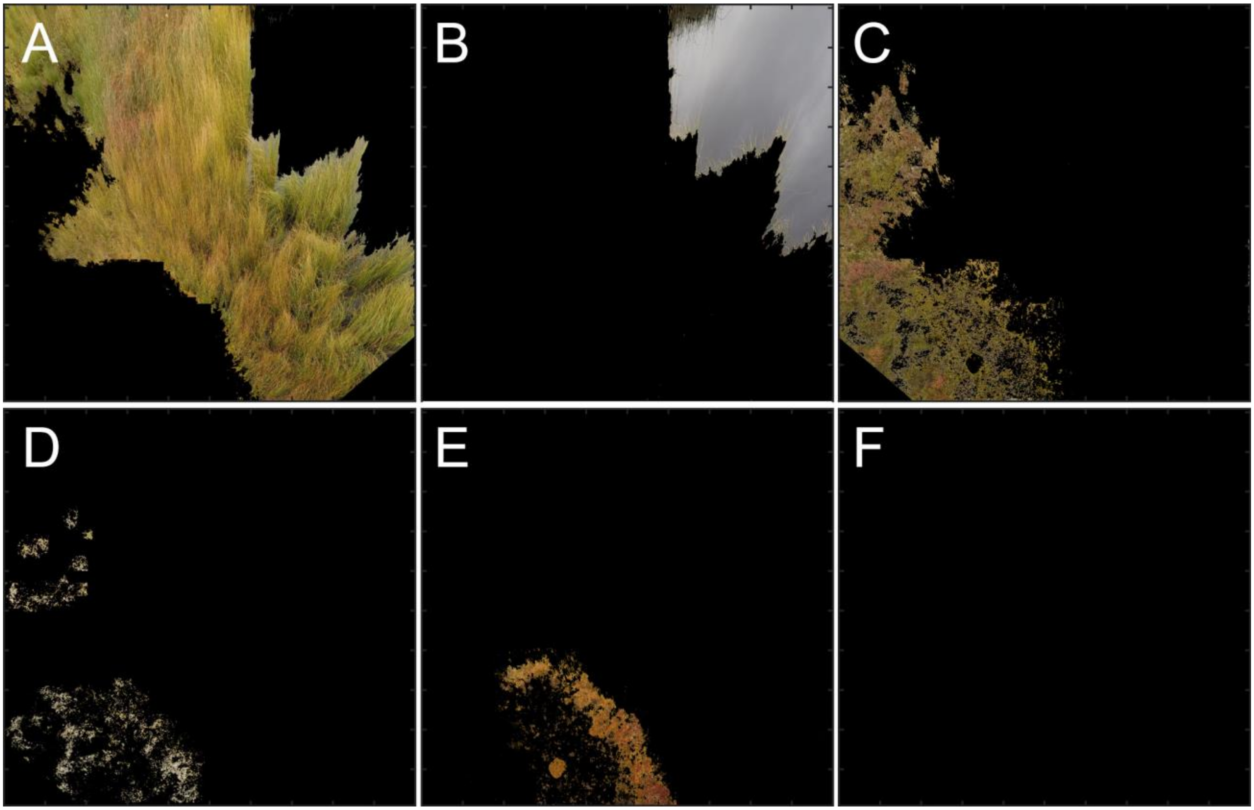

Figure 8: Classification of a field plot image (Fig. 6B) into the six main surface components. All panels have an area of 10 x 10 m. (A) Graminoids. (B) Water. (C) Shrubs. (D) Dry moss. (E) Wet moss. (F) Rock.

5 Conclusions

This study describes a quick method to document ground surface cover and process the data to make it suitable as ~~ground truth~~reference data for remote sensing. The method requires a minimum of equipment that is frequently used by researchers and persons with general interest in outdoor activities, and image recording can be made easily and in a few minutes per plot without requirements of specific skills or education. In addition to covering large areas in a short time, it is a robust method that works in any weather using a waterproof camera. This provides an alternative to e.g. using small unmanned aerial vehicles (UAVs) which are efficient at covering large areas, but have the drawbacks of being sensitive to both wind and rain and typically having flight times of about 20 minutes, considerably lower than this when many takeoffs and landings are needed when moving between plots. The presented photographic approach is also possible using a mobile phone camera, although such cameras usually have a very small field of view compared to many adventure cameras (such as the GoPro, which is also cheaper than a mobile phone). We recommend using a higher camera altitude; a height of 6 meters would make mobile phone imaging of 10 x 10 meters possible (using a remote Bluetooth controller) and 20 x 20 meters mapping using a camera with a large field of view such as the GoPro. Hence, if the method gets widespread and a fraction of those who visits northern wetlands (or other environments without dense tall vegetation where the method is suitable) contributes images and related information, there is a potential for rapid development of a global database of images and processed results with detailed land cover for individual satellite pixels. In turn, this could become a valuable resource supplying~~for~~ reference data for remote sensing~~ ground truthing~~. To facilitate this development, supplementary material~~information~~ S1 includes a complete manual and authors will assist with early stage image processing and initiate database development.

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Supplementary material~~Information~~ S1 - Manual

Preparations – what is needed?

- A remote controlled camera with a wide field of view is required, e.g. a GoPro with a waterproof casing
- Remote control for the camera (e.g. an app on a mobile phone or tablet).
- A tripod and/or monopods giving an extendable total length of at least 3 meters (e.g. a tripod and a monopod put together). > 4 m height is preferred.
- Note the camera model (if known also the horizontal and vertical field of view in degrees). This~~ese~~ is important to be able to obtain the projected geometry.~~correct for image distortion (camera model dependent).~~
- A GPS for recording GPS position of the plots
- A log to write camera altitudes, plot descriptions etc.
- Make a calibration photo of the ground, with several distances marked on the ground in both directions (see Fig. 5 which is our calibration image after correction for lens distortion). Note the camera altitude used. Other altitudes can be used in the field although only one calibration photo is needed.

For each field plot:

1. One person holds the extended tripod supported by the ground (Fig. 1) or lifts it up for higher camera altitudes (e.g. when tall vegetation such as bushes are present).

2. Imaging should be done from an altitude of at least 3 meters (for a 90 degree field of a view and 10 x 10 m area)
Alternative 1 (which we have used) is to stand at the edge of a plot and tilt the camera so that the horizon appears close to the top of the image (Fig. 2A). This horizon coordinate can then be used in post-processing to find angles in the image. With a vertical field of view of at least 90 degrees, nadir angles will also be present in the same image.
Alternative 2 is to stand in the center of the plot and tilt the camera straight down (nadir direction). This will make all the angles in the image closer to nadir which makes the classifications easier (as tall vegetation will not obscure~~struct~~ the view towards lower vegetation as much). The person and tripod will be included in the image using this method but will only take up a small part of the image which can be avoided in post processing classification.

3. Another person notes the camera height, GPS position, the direction of the field of view relative to the GPS position, and uses a remote control (such as an app on a water proof mobile phone) to take an image of the plot. The time should be noted in the log for each plot so that images can be matched to the correct GPS positions.

4. Take 3-4 close-up images (Fig. 7) of main classes of land cover (e.g. the most dominating plant types in the area). By tilting the tripod/monopod, the same wide-angle camera is used for quick close-up imaging of different parts of the plot right after taking the higher altitude image. Make a visual judgement of the close-up images and note the ground cover characteristics for each image in the log to aid in the classification later.

5. Post processing can be done in two ways:

a) Using generally available ~~or commercial~~ software for distortion correction (e.g. Adobe Photoshop~~,~~ or Adobe Lightroom which has ready-made models for most standard cameras, or the Camera calibration application in Matlab to make a custom model~~scripts in programming languages~~) and land cover classification (e.g. CAN-EYE, VegMeasure, SamplePoint, or eCognition). Recalculation of images to overhead projection can be programmed in Matlab using the formulas given in this article (Eqs. 1-2) and using two for-loops to transform each pixel in a lens distortion corrected image to ground coordinates in meters (see Fig. 6).

b) Send images and related information to the lead author who can assist. For this option, we ask image senders to agree on making images and post processed results publicly available via a database hosted by the authors. The aim of this is to over time build a public database that can be used as a source for reference data ~~ground truth archive~~ for remote sensing products.

The post processing software can be requested from the lead author (magnus.galfalk@liu.se). Users should h~~H~~owever~~, please~~ be aware that the software is not user friendly at its present stage as it is not commercial and that there is limited time for support.

Supplementary material~~Information~~ S2 – Four~~An~~ additional ~~field plot~~ examples of classification

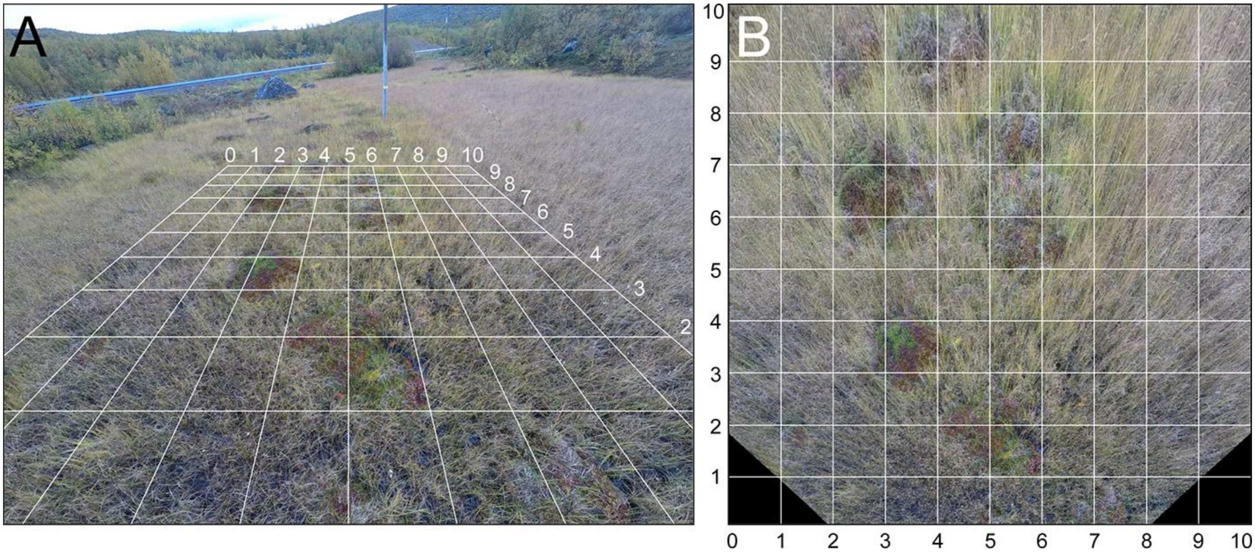

Figure S1: One of our field plots. (A) Image corrected for lens distortion, with a projected 10 x 10 m grid overlaid. (B) Image after recalculation to overhead projection (10 x 10 m).

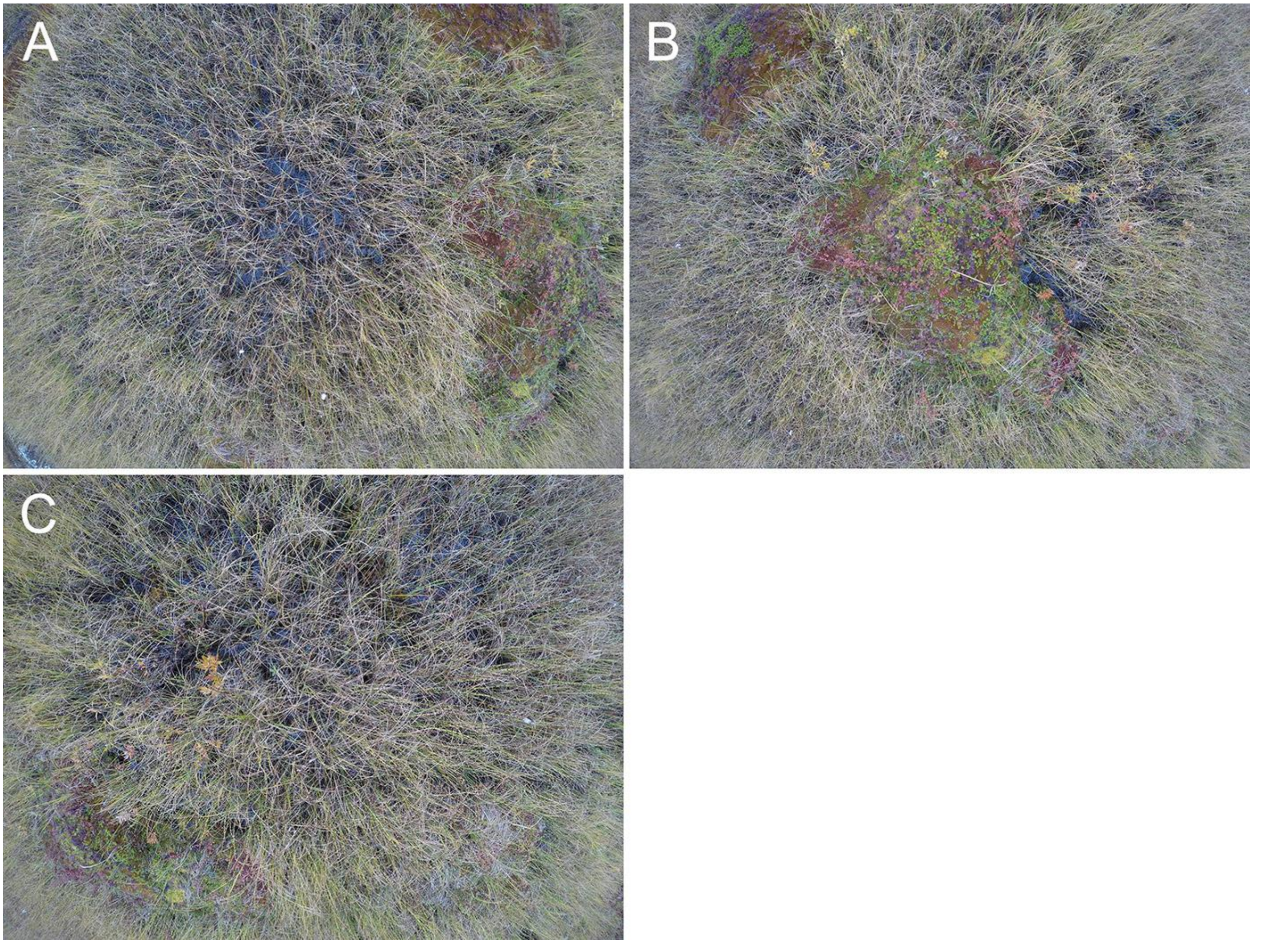

Figure S2: Close-up images in one of our 10 x 10 m field plots (Fig. S1).

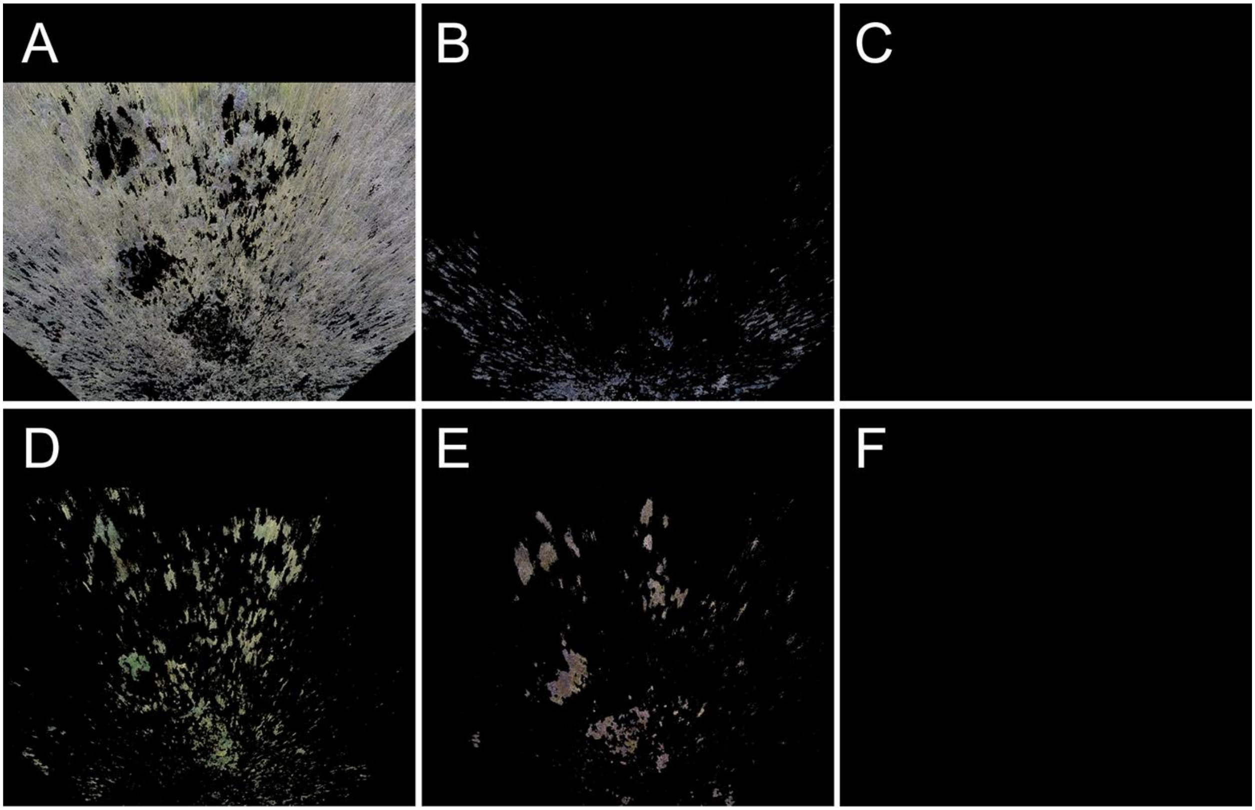

Figure S3: Additional ~~E~~example of a field plot image with classification into the six main surface components (the plot shown in Fig. S1). All panels have an area of 10 x 10 m. (A) Graminoids. (B) Water. (C) Shrubs. (D) Dry moss. (E) Wet moss. (F) Rock.

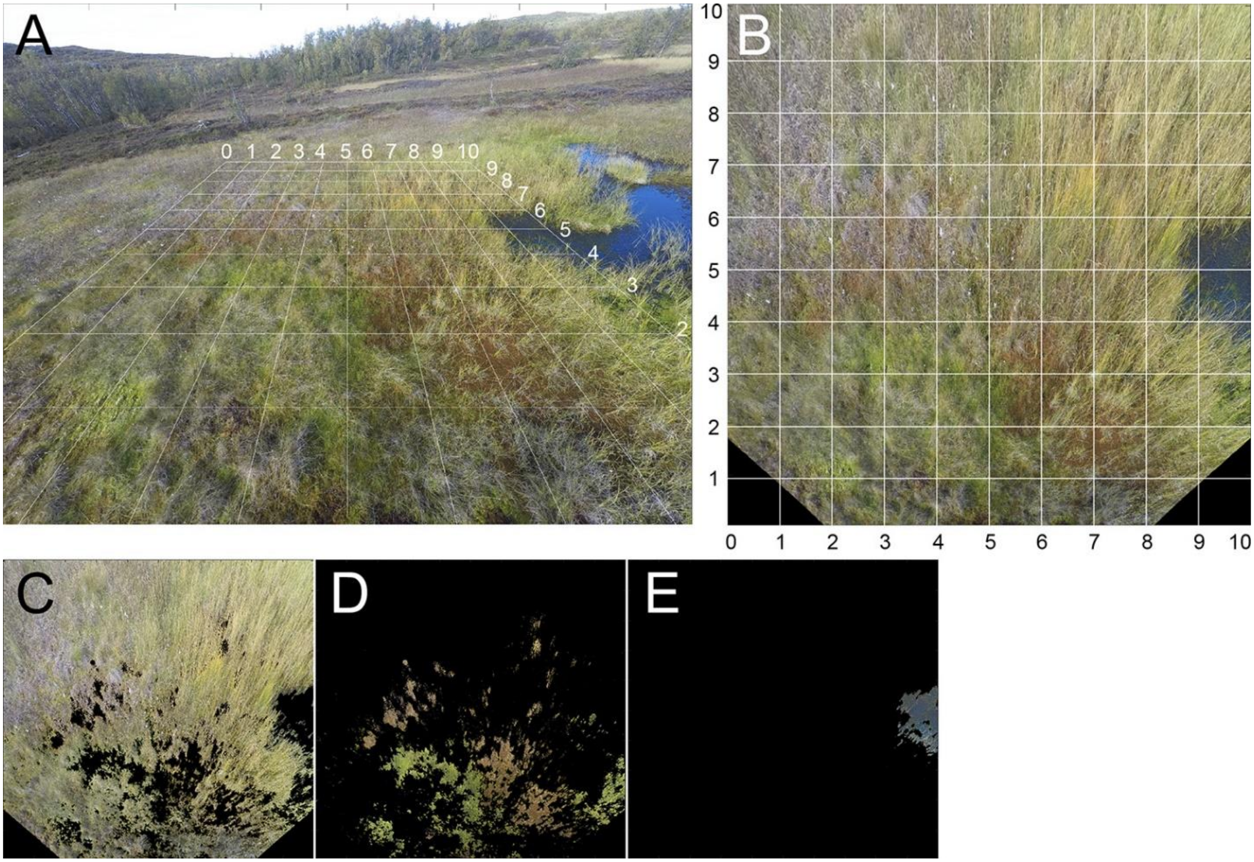

Figure S4: Additional example of plot classification. (A) Image corrected for lens distortion, with a projected 10 x 10 m grid overlaid. (B) Image after recalculation to overhead projection (10 x 10 m). (C) Graminoids. (D) Wet moss. (E) Water. Images C-E have areas of 10 x 10 m. This plot is clear example of vegetation of different color belonging to the same class as the wet moss included both green-yellow and red vegetation (field notes about the close-up images showed this to be the case).

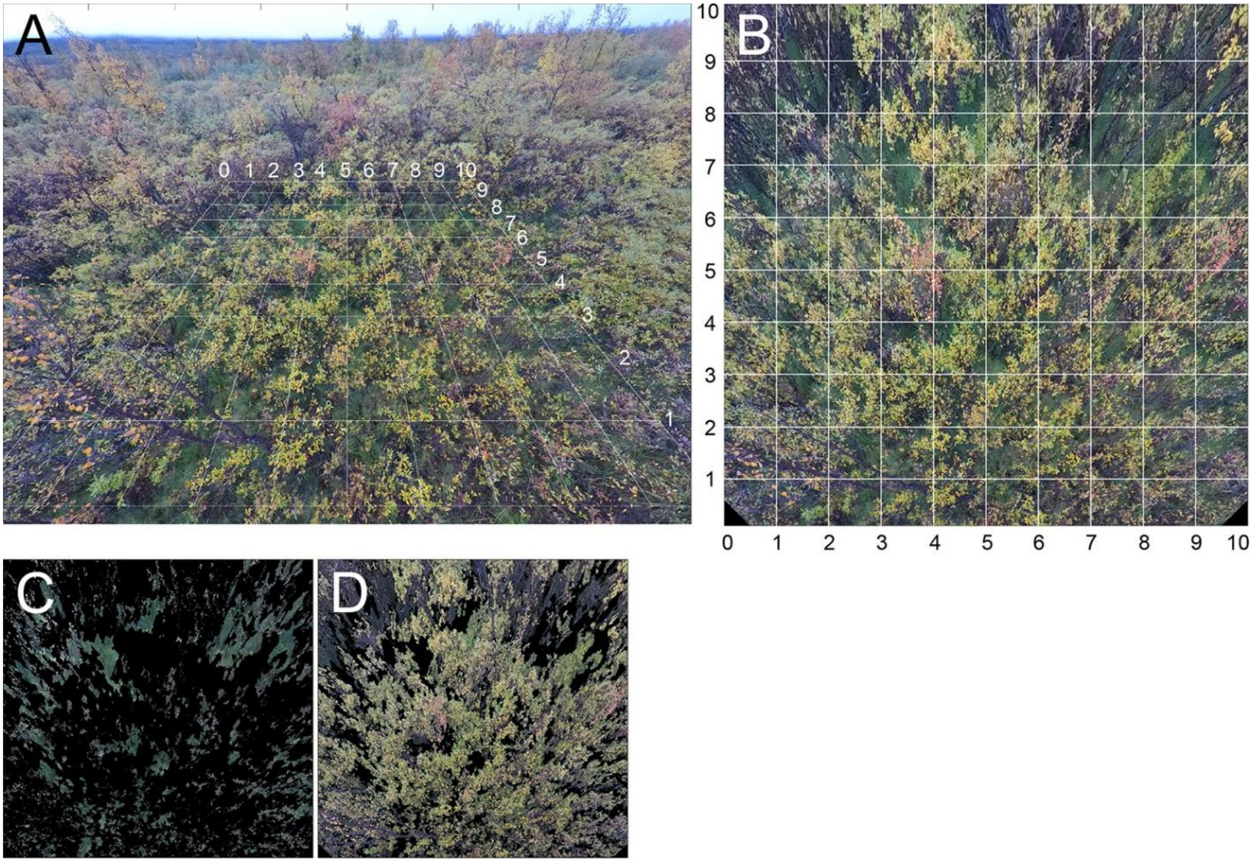

Figure S5: Additional example of plot classification. (A) Image corrected for lens distortion, with a projected 10 x 10 m grid overlaid. (B) Image after recalculation to overhead projection (10 x 10 m). (C) Graminoids. (D) Shrubs. Images C and D have areas of 10 x 10 m.

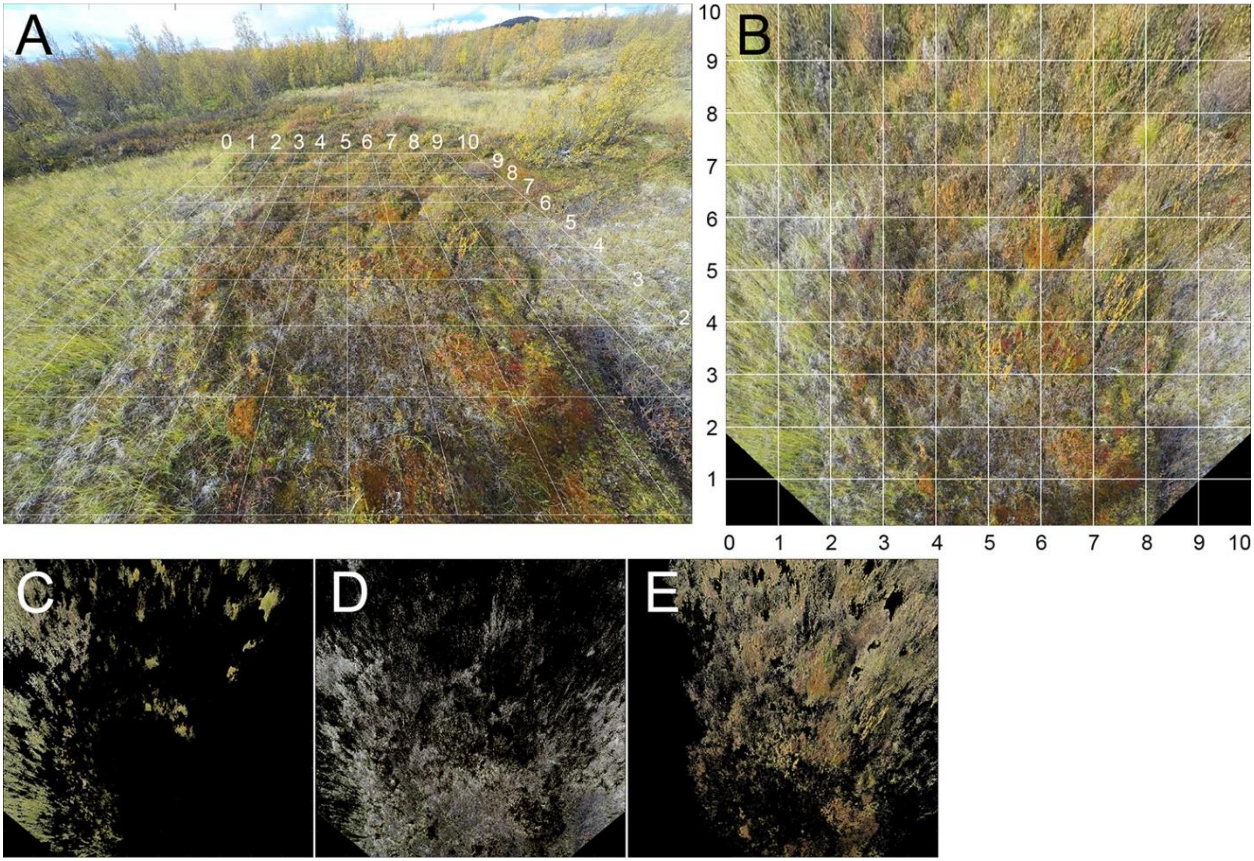

Figure S6: Additional example of plot classification. (A) Image corrected for lens distortion, with a projected 10 x 10 m grid overlaid. (B) Image after recalculation to overhead projection (10 x 10 m). (C) Graminoids. (D) Dry moss. (E) Shrubs. Images C-E have areas of 10 x 10 m.