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PAPER

# Measurement error in remotely sensed fractional snow cover datasets: implications for ecological research

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## Abstract

Snow cover and snow melt patterns are important features of the Arctic environment, with wide-ranging repercussions for ecology. Datasets based on satellite imaging—often freely available—provide a powerful means for estimating snow cover. However, researchers should be aware of the possible error and bias in such datasets. Here, we quantify measurement error in commonly used data on snow cover, and demonstrate how biases have the potential to alter conclusions of ecological studies. We established 38 quadrats (80 m $\times$ 50 m) across a study site of Arctic tundra near Utqiaġvik, Alaska. At each quadrat, we estimated fractional snow cover (FSC) and the timing of snow melt using data from moderate resolution imaging spectroradiometer (MODIS), visible infrared imaging radiometer suite (VIIRS), and Sentinel-2 satellites. We compared satellite-based estimates with data from drone imagery to quantify measurement error and bias. We then evaluated whether the measurement error and bias alter conclusions about the relationship between the timing of snow melt and the breeding phenology of a population of pectoral sandpipers *Calidris melanotos*. We found that satellite datasets tended to overestimate FSC, leading to late estimates for snow melt dates. The Sentinel-2 dataset gave the most accurate results, followed by VIIRS, with MODIS giving the least accurate results. The degree of error varied substantially with the level of FSC, with biases reaching up to 60% for MODIS and VIIRS datasets at intermediate FSC values. Consequently, these datasets resulted in substantially different conclusions about how snow melt patterns were related to settlement and nesting dates of pectoral sandpipers. Our study indicates that measurement error in FSC can be large with substantial variation in the degree of error among satellite products. We show that these biases can impact conclusions of ecological studies. Therefore, ecologists should be conscious of the limitations of satellite-derived estimates of snow melt, and where possible should consult studies validating snow measurements in environments comparable to that of their study system.

## 1. Introduction

Snow cover and the timing of snow melt are important characteristics of Arctic habitats with a wide array of ecological consequences. The proportion of the area covered by snow may impact plant community composition (Niittynen *et al* 2020), trophic interactions (Byrkjedal 1980, Boelman *et al* 2019), migration timing (Boelman *et al* 2017), nest site selection (Niffenegger *et al* 2023), and foraging ecology (Fancy and White 1985, Anderson *et al* 2012), while the timing of snow melt drives the spring phenology in these ecosystems (Liebezeit *et al* 2014, Bjorkman *et al* 2015, Sherwood *et al* 2017, Kwon *et al* 2019, Rixen *et al* 2022). As climate change disproportionately affects Arctic ecosystems (Box *et al* 2019, IPCC 2023), it is important to understand the ecosystem responses to changes in snow conditions. A prerequisite for studying the effects of changes in the timing of snow melt is an unbiased measure of the environmental variable, i.e. the patterns of snow cover. Given the remoteness of most of the Arctic habitats, remote sensing approaches are essential.

Remote sensing is a powerful tool for continuous monitoring of ecological processes across the globe (Pettorelli *et al* 2014, Rose *et al* 2015). Several methods have been developed for measuring the fractional snow cover (hereafter, FSC) and the timing of snowmelt (Dietz *et al* 2012, Masson *et al* 2018). A widely adopted index of snow cover derived from satellite imagery is the normalized difference snow index (NDSI; Dozier 1989, Hall and Riggs 2011). NDSI is based on the distinctive property of snow that it reflects visible light but absorbs infra-red light (unlike cloud cover). Three satellite datasets are commonly used to obtain the NDSI: (1) the moderate resolution imaging spectroradiometer (**MODIS;** Riggs *et al* 2019), (2) the visible infrared imaging radiometer suite (**VIIRS**; Justice *et al* 2013), and (3) the multi-spectral instrument (**MSI**) aboard the **Sentinel-2** satellites (Drusch *et al* 2012). The standard products derived from the MODIS instrument have a 500 m resolution, and a daily revisit rate worldwide. Data are available from the year 2000 onwards. The VIIRS instrument is intended to provide operational continuity from the soon-to-be-retired MODIS instrument, but with an improved spatial resolution of 375 m (Key *et al* 2013, Riggs and Hall 2020). Finally, the MSI instrument aboard the Sentinel-2 satellites has the advantage that it has a much higher spatial resolution (10–60 m) compared to MODIS and VIIRS, but the disadvantage that it has a lower revisit rate (5 d at the equator (Drusch *et al* 2012). Once NDSI data are available, FSC can be calculated using either a linear (Salomonson and Appel 2006, Aalstad *et al* 2020) or a nonlinear function (Gascoin *et al* 2020).

Remote sensing is subject to various sources of error, including geometric distortion, the perspective of the sensor optics, and the motion of the scanning system or the platform (Lunetta *et al* 1991, Sulla-Menashe *et al* 2016). Furthermore, the NDSI estimates can be influenced by landscape features such as vegetation (Hall *et al* 1998), surface water (Dixit *et al* 2019), and topography (Zhang *et al* 2021). Thus, NDSI-based snow cover algorithms require validation across different environments. MODIS snow cover products have been extensively evaluated and refined since their inception (Salomonson and Appel 2004, Hall and Riggs 2007, Hall *et al* 2019, Heim *et al* 2022). MODIS datasets that estimate FSC using the NDSI tend to have a reasonable level of overall accuracy, with a root-mean-square error (RMSE) of 10%–15%, and are positively biased, overestimating FSC by 5%–10% on average (Salomonson and Appel 2004, 2006, Aalstad *et al* 2020, Stillinger *et al* 2023). Fewer validation studies have been conducted on FSC estimates based on the newer VIIRS snow cover data or on Sentinel-2 data. Early validations of VIIRS snow cover data showed that in landscape-scale snow mapping (i.e. classification of pixels as snow-covered or snow-free) VIIRS has upwards of 90% agreement with MODIS snow datasets (Key *et al* 2013, Riggs and Hall 2020). A more recent study specifically examined error in VIIRS FSC estimates, and found that the FSC tended to be underestimated by 0%–5% (Stillinger *et al* 2023). Similarly, two validation studies measuring FSC using Sentinel-2 datasets have shown low levels of bias (<1%), but different RMSE ranging from <10% (Aalstad *et al* 2020) to 25% (Gascoin *et al* 2020).

Previous validation studies typically report the overall extent of error averaged across all images, but they rarely directly quantify how error varies at different levels of snow cover. Recently Stillinger *et al* (2023) demonstrated that error in NDSI-based snow cover estimates from MODIS and VIIRS were typically lowest near 0% cover, and peaked near 50% cover. This result is notable for ecologists, because estimates of the date of 50% snow cover is frequently considered as an indicator of spring phenology in arctic or alpine ecosystems and used as the environmental covariate in studies of ecological events and processes (e.g. Smith *et al* 2010, Grabowski *et al* 2013, Kankaanpää *et al* 2018, Assmann *et al* 2019).

The aforementioned ecological studies often test for a relationship between a long-term shift in the phenology of free-living populations and a long-term shift in the timing of snow melt. However, in such analyses, the amount of error in assigning a pixel on remote-sensed imagery as '50% snow free' is usually not considered. Given that the observed shifts in the timing of snowmelt and in the ecological responses of flora and fauna are typically at a level of a few days per decade (Root *et al* 2003, Schmidt *et al* 2023), a relatively small measurement error can potentially change conclusions about whether the phenological response of a population to climate change is adequate or not.

The aims of this study are (1) to quantify measurement error in snow cover datasets, and (2) to show how biases in snow cover data have the potential to alter conclusions of ecological studies. First, we quantified the error in satellite-derived estimates of FSC and snowmelt timing on a study plot of arctic tundra near Utqiaġvik, Alaska. We used MODIS, VIIRS, and Sentinel-2 datasets to calculate FSC from NDSI, and we validated these satellite-based estimates using photographs made with a drone as the 'ground truth'. Second, we demonstrate how the source-dependent biases can alter the conclusions of ecological studies. Specifically, we examined whether FSC and the date of snow melt are related to two key phenological traits of an arctic-breeding shorebird, the pectoral sandpiper: the date of male territorial settlement and nest initiation date (Martin *et al* 2018). Several studies have shown strong correlations between the seasonal timing of snow melt, the timing of invertebrate emergence and the timing of shorebird breeding (Høye and Forchhammer 2008, Saalfeld *et al* 2019, Chagnon-Lafortune *et al* 2024). In particular, the average nest initiation date of pectoral sandpipers strongly correlated with the local timing of snow melt (Saalfeld and Lanctot 2017). Based on our results, we provide recommendations to researchers who seek to use snow cover datasets in ecological studies.

## 2. Materials and methods

### 2.1. Study area

This study was conducted on a 2 km$^2$ plot of Arctic tundra near Utqiaġvik, Alaska (figure 1). The plot consists of a mosaic of tundra polygons, with high-arctic vegetation (sedges, mosses, and lichens). Elevation is low (1–8 m ASL) across the plot. Data were collected between late May and late July 2022. During this period, there is 24 h daylight and the daily mean temperature in June was 2.2 °C with minimal fluctuations (1991–2020, NOAA 2024).

### 2.2. Drone photography dataset & processing

#### *2.2.1. Data acquisition*

We conducted 22 drone surveys between 29 May–24 June 2022 using a DJI Mavic 2 Pro drone equipped with a Hasselblad L1D-20c RGB camera with 20-megapixel resolution (5464 × 3640 pixels). We aimed to conduct daily drone surveys during this period, but on four days no survey was possible due to adverse weather conditions with too low visibility. Each drone survey captured photographs at 38 locations distributed across the plot in a randomly generated hexagonal grid (figure 1). All photographs were taken from an altitude of 60 m with the front of the drone facing due west, and the camera angled directly downwards towards the ground. The ground area captured by each photograph was a rectangle of approximately 79 m × 53 m, further referred to as a quadrat. The 38 quadrats constituted approximately 8% of the total plot area.

#### *2.2.2. Snow cover estimation*

For each drone photograph, the FSC was estimated as the proportion of pixels with a blue-channel value higher than a critical threshold (Salvatori *et al* 2011; figure S1). To determine the threshold for classifying snow, a histogram of blue pixel intensity values (range 0–255) was created with a bin width of 5, and the histogram was smoothed by averaging across the five nearest points. The threshold was set as the first local minimum above a blue pixel intensity of 90 in the smoothed histogram. If no local minimum was found, then 90 was used as the threshold. Previous studies measuring snow cover from web cam images used a threshold of 127 (e.g. Salvatori *et al* 2011, Portenier *et al* 2020, Caparó Bellido and Rundquist 2021). However, this threshold resulted in under-detection of snow in our system. We determined the threshold value of 90 by visualizing the pixels classified as ‘snow covered’ for each photograph at decreasing thresholds, until there was satisfactory alignment with what we observed in the photo. Based on field observations, we assumed that the actual FSC was 100% prior to the first drone survey date, and 0% after the final drone survey date.

### 2.3. Satellite-based datasets

We used four satellite-based datasets, described in table 1. We acquired all available satellite images collected between 12 May and 15 July 2022 ($N_{\text{total}} = 1376$ images). Only a fraction of the images was cloud-free and passed all data quality screens ($N_{\text{used}} = 175$).

#### *2.3.1. MODIS*

We obtained MODIS collection 6.1 snow data from the National Snow and Ice Data Center (NSIDC). We pooled the level 2 datasets collected via the terra (MOD10_L2) and aqua (MYD10_L2) satellites into one dataset (hereafter referred to as MODIS_L2). Similarly, the level 3 daily products (M*D10A1) were pooled (dataset hereafter named MODIS_L3). The level 2 images were acquired in the UTM 4 N projection, and the level 3 images in the sinusoidal projection with a fixed grid. Each pixel in the grid is populated with the ‘best’ observation available from the level 2 images collected during that day, based on nearness to nadir and solar noon. Consequently, the level 2 and level 3 datasets are similar, but the L3 product has a different projection, and less frequent data acquisitions available. We compared both products as these differences might lead to different estimates of snowmelt patterns. Note that there were typically between 9–10 images available per day for the level 2 dataset at the latitude of our study site due to the overlap of photos from adjacent swaths. All MODIS images were acquired and reformatted to GeoTIFF via the NSIDC’s data access API. FSC is no longer provided as a data layer in collection 6 MODIS products, but can still be calculated using a regression

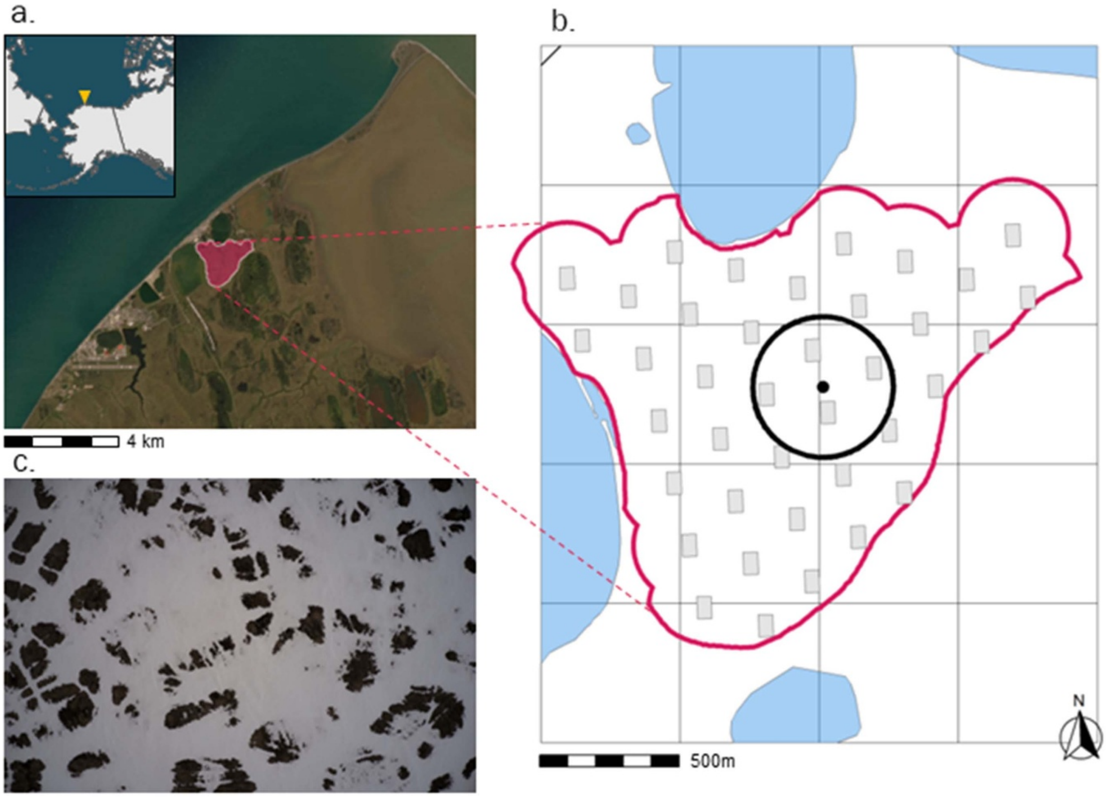


**Figure 1.** (a). Maps showing the location of the study plot (in red) near Utqiaġvik, Alaska (71°19′N, 156°39′W). (b). Map of the study plot (outlined in red) showing the quadrats sampled using drone photography (grey rectangles), grid cells from a sample MODIS_L2 satellite raster (black grid lines), and a sample nest (black dot) with a 500 m diameter buffer (black circle). (c). Sample drone photograph. To compare ground-truth (drone) data with satellite-based data, we estimated fractional snow cover (FSC) as a weighted mean from the four grid cells that intersect the buffer area (black circle), whereby the contribution of each grid cell to the average is weighted by the amount of overlap between the circle and the grid cell. In our example, the average would be approximately the average of the lower left and lower right grid cells, because the upper two grid cells overlap minimally and hence will only contribute minimally to the weighted mean.

**Table 1.** Characteristics of the satellite-based datasets used in this study.

| Name | Code (s) | Spatial resolution | Revisit frequency | *N* images available | *N* images suitable for analysis |
|---|---|---|---|---|---|
| MODIS_L2 | MOD10_L2 | 500 m | 1 d | 560 | 55 |
| MODIS_L2 | MYD10_L2 | 500 m | 1 d | 555 | 37 |
| MODIS_L3 | MOD10A1 | 500 m | 1 d | 67 | 19 |
| MODIS_L3 | MYD10A1 | 500 m | 1 d | 67 | 16 |
| VIIRS_L3 | VNP10 | 375 m | 1 d | 67 | 26 |
| Sentinel-2 | Sentinel-2 L2A | 20 m | <5 d | 50 | 22 |

on NDSI (Hall *et al* 2019). We conducted this calculation using the 'universal' equation in Salomonson and Appel (2006):

$$\begin{aligned} &\mathrm{FSC} = 1.45 * \mathrm{NDSI} \; - 0.01 \\ &\mathrm{FSC} \in [0, 1] \end{aligned} . \tag{1}$$

We used the data quality screens built-in to the MODIS snow products to filter out problematic pixels (e.g. cloud detection). We also excluded any pixels flagged as water by the 'inland water' screen and pixels flagged with the optional data quality screens 'probable cloud cover', or 'low solar zenith' (>70°), because they sometimes had erratic NDSI values.

Snow cover values were extracted from satellite rasters at quadrats using the R-package 'exactextractr' (Baston 2023). If a quadrat intersected multiple pixels, FSC was averaged across those pixels, weighted by the degree of overlap between the quadrat and the pixel. A snow cover value was only calculated for a quadrat if at least 50% of the quadrat area had usable satellite data available.

#### 2.3.2. VIIRS

We also obtained VIIRS collection 2 data from the NSIDC. We used the level 3 daily product (VNP10A1), which uses the same algorithm as the level 3 MODIS daily snow product, but is produced at 375 m resolution. Due to a lack of a widely adopted correction formula for calculating FSC from NDSI using VIIRS data, we followed Stillinger *et al* (2023) and used the 'universal' equation developed for MODIS images to convert NDSI to FSC (Salomonson and Appel 2006). All other data processing for the VIIRS_L3 dataset is the same as described above for the MODIS_L3 dataset.

#### 2.3.3. Sentinel-2

We analysed the Sentinel-2 level 2 A product (L2A) in Google Earth Engine (Gorelick *et al* 2017) using the R-package RGEE (Aybar *et al* 2020, Versluijs 2023). A full description of the analysis is given in the supplementary materials (see A. Supplementary Methods). We excluded images with more than 75% cloud cover and masked all cloudy pixels in the remaining images. Cloud masking was conducted using the S2 cloud probability dataset (i.e. python package s2cloudless; Zupanc 2017). We calculated the average NDSI for all pixels within each area of interest using the equation provided by Dozier (1989):

$$\mathrm{NDSI} = \frac{(\mathrm{Green}_{B03} - \mathrm{SWIR}_{B11})}{(\mathrm{Green}_{B03} + \mathrm{SWIR}_{B11})} \tag{2}$$

where $B_i$ refers to the raw value for band *i.* The Green band has a 10 m spatial resolution, while the short-wave infrared (SWIR) band has a 20 m spatial resolution. We therefore first used bicubic interpolation to resample the resolution of the Green band to match that of the SWIR band (Gascoin *et al* 2019). As water surfaces (e.g. rivers and lakes) can have high NDSI values (Hall *et al* 1995, Dixit *et al* 2019, Gascoin *et al* 2019), we also masked pixels corresponding to water bodies based on the ESA WorldCover V100 dataset with a 10 m resolution (Zanaga *et al* 2021).

Because there is no widely adopted method for measuring FSC using Sentinel-2 imagery, we used three approaches: (1) Salomonson and Appel's (2006) 'universal' FSC equation developed for MODIS data (equation (1)), (2) Gascoin *et al*'s (2020) correction formula:

$$\mathrm{FSC} = 0.5 * \tanh(2.65 * \mathrm{NDSI} - 1.42) + 0.5 \tag{3}$$

and (3) a binarization (i.e. NDSI threshold) approach, calculating the proportion of pixels in a region of interest with an NDSI value greater than a snow classification threshold (Dietz *et al* 2012). We found that Salomonson and Appel's (2006) FSC equation yielded the smallest error, so we present only this approach in the main text (for a comparison among the three approaches, see figure S2 and table S1).

### 2.4. Data on pectoral sandpipers

#### 2.4.1. Male settlement date

We surveyed the study plot for male pectoral sandpipers daily between 1 and 20 June 2022. We attempted to immediately capture each male that demonstrated signs of competing for a territory (i.e. made a territorial display flight or flew while producing hooting calls) using a mist net held by two people. Upon capture, each individual was banded with a U.S. Geological Survey metal band and a unique combination of four colour bands, which allowed individuals to be identified in the field after release. We used the date of first capture as a proxy for the date of territorial settlement (hereafter referred to as 'settlement date') and the capture site as the 'settlement site'. Our catching method may have created a sampling bias because it was easier to pursue and capture individuals in snow-free areas. However, we use this measure only for the purpose of demonstrating how biases in snow cover estimates may influence the interpretation of timing of settlement.

#### 2.4.2. Nesting data

We searched for nests on a daily basis from 19 June onwards with a team of 1–10 people. We used two methods to find nests: (1) we surveyed the plot to search for females on incubation breaks, and followed them until they returned to their nest, and (2) we exhaustively searched the entire study plot for nests twice using a rope dragging method between 29 June–4 July.

For each nest, we estimated the date of clutch initiation (laying date) in one of three ways, as described in Lesku *et al* (2012). (1) If nests were found during laying, we calculated the date of laying the first egg by assuming that females laid one egg each day. (2) If nests were found with a completed clutch (usually four, sometimes three eggs), laying date was estimated by subtracting 22 d from the hatching date. (3) If the exact hatching date was not known (e.g. due to predation of eggs), then hatch date was estimated using the egg flotation method (Liebezeit *et al* 2007), and the laying date was assumed to be 22 d earlier than the estimated hatch date.

### 2.5. Ground-truthing analyses

#### 2.5.1. Snow cover point estimates

To quantify error in point estimates of FSC, we compared satellite- and drone-based measurements at each of the 38 quadrats. Estimates of FSC from the satellite were paired to measurements from the drone dataset collected at the same quadrat within 12 h (see figure 1(b)). 8.7% of satellite-based data had to be excluded from this part of the analysis because a time-matched drone image was not available. We assessed the error in satellite-derived snow cover by calculating the mean absolute error in FSC (i.e. bias), the RMSE, and the Pearson's correlation coefficient for the satellite- and drone-based estimates.

#### 2.5.2. Snow melt timing estimates

We estimated the date at which a specific snow cover threshold was reached for each quadrat, using both drone- and satellite-based datasets. The snow cover threshold of interest depends on the ecological process in question, so we present results for three thresholds: 75%, 50%, and 25% snow cover. We estimated threshold crossing dates by fitting models of snow cover over time for each quadrat. For satellite-based data we modelled snow melt over time using generalized linear models with a logistic link function and Gaussian errors, representing a sigmoid curve. The response variable was the time series of snow cover point estimates for that quadrat, and datetime was the sole predictor. For the drone-based data, snow cover thresholds were estimated by linearly interpolating FSC estimates from the relevant two consecutive photographs for a given quadrat. We then extracted the datetime at which the models predicted that snow cover reached each threshold. Some quadrats had limited satellite-based data available and models failed to converge. Therefore, for this analysis, we only retained quadrats that had a snow model available from every satellite dataset ($n = 29$ quadrats), so that the same quadrats can be compared for each type of data. Results were similar if the analyses were conducted using all available quadrats (table S2).

### 2.6. The relationship between snow cover and pectoral sandpiper phenology

We investigated how the date of male territory settlement and female laying date related to snow cover. To extract relevant snow cover measures, we considered a circular buffer zone around each capture site or nest with a 250 m radius (figure 1(b)). This buffer zone size was chosen because it corresponds roughly to the home range of a resident individual as we observed in the field (our unpublished data), and is similar to the spatial scales of the MODIS and VIIRS datasets. Furthermore, this area is similar to the spatial scale at which snow melt date had the strongest effect on habitat patch occupancy in pectoral sandpipers (Anderson *et al* 2023). We extracted estimates of the average FSC within every buffer zone from every satellite raster using the R-package 'exactextractr' (Baston 2023). As 'ground truth' we also extracted a drone-based FSC estimate for each survey, calculated as the average FSC over any quadrats within the buffer zone. Buffer zones contained an average of 5.2 quadrats (range: 2–7). For each buffer zone, we extracted the date on which the 50% snow cover threshold had been reached, and the estimate of the percent snow cover at the time of male settlement or of laying. All statistical analyses were conducted using R 4.3.3 (R Core Team 2023). All bootstrapped confidence intervals represent 95% quantile confidence intervals based on non-parametric (case) bootstrapping with 10 000 bootstrap samples.

### 2.7. Full-plot snow cover

We estimated the snow cover on the entire study plot for descriptive purposes and for use in some analyses. For satellite-based data, we used a polygon representing the outline of the study area (see figure 1), and estimated the weighted average cover from pixels within this polygon. Values were only calculated when 50% of the polygon area had data available in the respective satellite dataset.

We also calculated a full-plot snow cover value based on the drone data, by taking the average FSC measured during a given drone survey (i.e. the average over 38 quadrats). We modelled snow cover over time using sigmoid curves for satellite-based data, and using piecewise linear interpolation for drone-based data, as described above.

## 3. Results

### 3.1. Snow cover estimates

#### 3.1.1. Error in FSC point estimates

FSC trajectories estimated by satellite- and drone-based data showed sigmoid curves (figure 2, see figure S3 for trajectories for each individual quadrat). Many quadrats had missing MODIS_L3 data for the critical period when most of the snow melted, but the other datasets had better coverage.

The quadrat-scale analysis showed that satellite-derived FSC point estimates had a positive bias, indicating that they tended to estimate higher levels of FSC than the actual values obtained from the

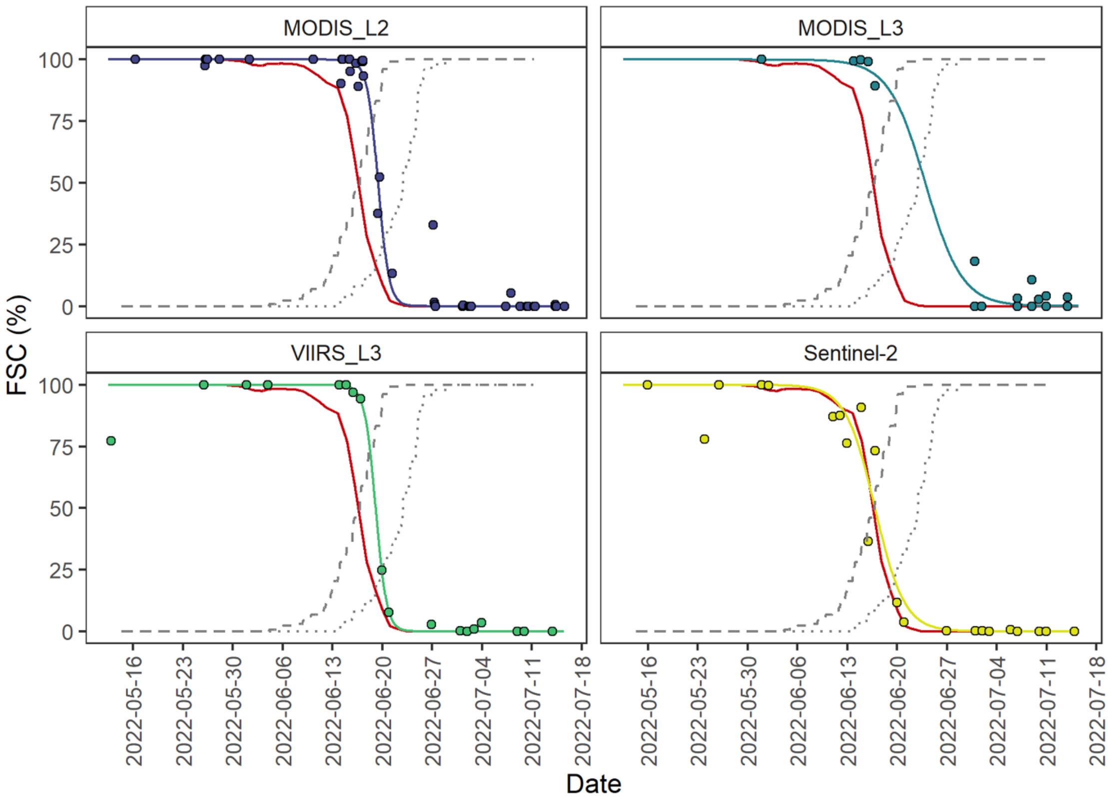


**Figure 2.** Mean plot-wide fractional snow cover (FSC) estimates from each available satellite image (points), and the sigmoid curves that best fit the data (coloured lines). The actual snow cover ('ground truthed', based on drone photography) is shown with a red line calculated using linear interpolation. The cumulative number of captured male pectoral sandpipers (i.e. territory settlement) and the cumulative number of initiated clutches is shown with a grey dashed line and a grey dotted line, respectively. The plot-wide mean was only calculated if >50% of the study area had NDSI data available for a given date.

**Table 2.** Overall summary statistics for error in FSC point estimates and snow melt timing estimates from satellite datasets compared with the drone-based photography data as 'ground truth'). The degree of error is shown as the mean absolute error (bias), the root-mean-squared error (RMSE) and the Pearson's correlation coefficient ($r$).

| | FSC estimates | | | Time estimates |
|---|---|---|---|---|
| Dataset | Bias (%) | RMSE | $r$ | Bias (d) |
| MODIS_L2 | 7.36 | 19.54 | 0.93 | 3.47 |
| MODIS_L3 | 5.87 | 17.91 | 0.94 | 3.01 |
| VIIRS_L3 | 4.74 | 16.08 | 0.95 | 2.75 |
| Sentinel-2 | 1.33 | 7.65 | 0.99 | 1.24 |

drone-based photos, particularly for MODIS and VIIRS datasets (table 2, figures 3 and S4). The pattern of bias was similar for raw satellite-based data and for the predictions from sigmoid snow cover models, and the mean absolute error in FSC models was <3% for all datasets, suggesting that the snow models did not introduce significant bias (see Discussion).

The degree of bias and overall accuracy (RMSE) varied with the extent of true snow cover for all satellite-based data, and were more pronounced at intermediate levels of snow cover, and minimal when the plot was fully snow covered (100%) or completely snow-free (0%, figure 3). For MODIS and VIIRS datasets, the bias in FSC exceeded 50% at intermediate levels of cover (figure 3). Thus, MODIS and VIIRS data tended to show FSC values close to 100% until the true snow cover dropped below 50%.

### *3.1.2. Snow melt timing bias*

MODIS and VIIRS datasets tended to estimate the date of reaching the 75%, 50%, and 25% snow cover thresholds ~1–4 d later than the ground-truthed date (based on drone photography), and with higher variance, whereas the Sentinel-2 based estimates had the lowest mean bias (~0–2 d) and the least variance (figure 4). For all satellite-based data, the median bias increased with higher snow cover thresholds, but remained smaller than 3 d for all thresholds (figure 4).

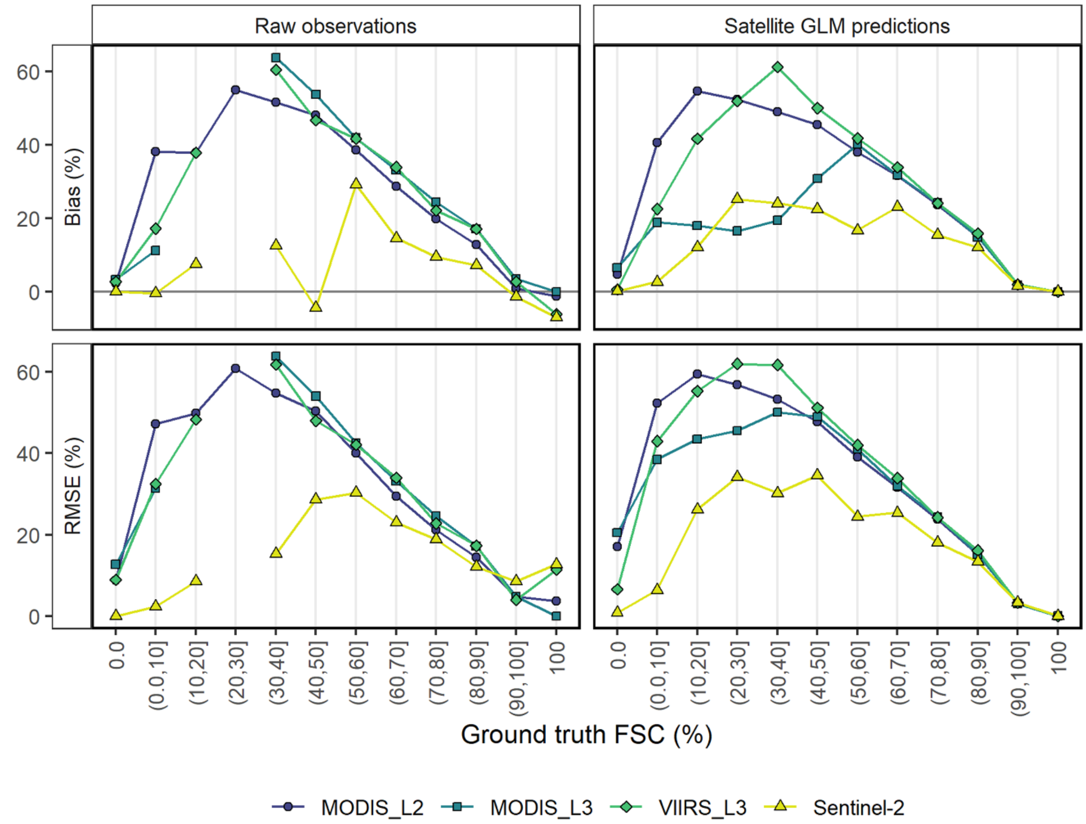


**Figure 3.** Mean bias (top row) and root-mean-square-error (bottom row) of satellite-based estimates of % snow cover in relation to variation in true snow cover based on drone photography (binned). Estimates of % snow cover at quadrats from individual satellite images are shown on the left, and estimates from a sigmoid model fit on satellite-based data are on the right. The horizontal grey line in the top panels shows perfect correspondence between drone- and satellite-based estimates (i.e. bias = 0). Binned values are not calculated whenever $n < 3$.

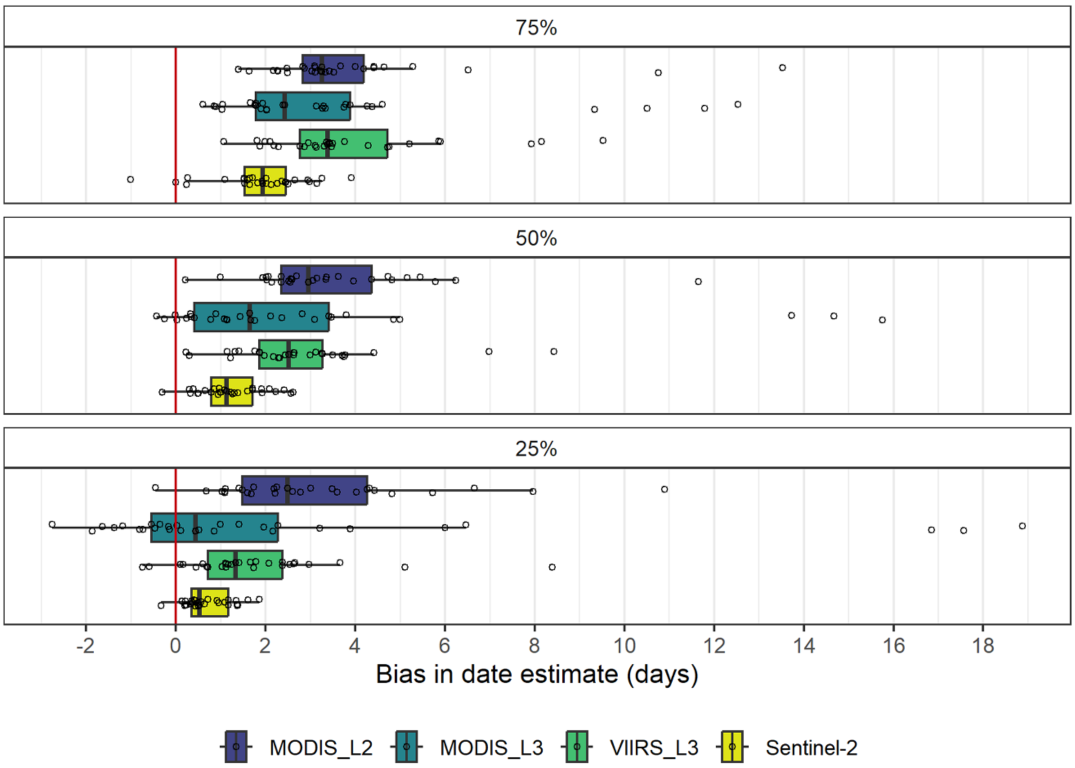


**Figure 4.** Error in the estimates of the date of reaching 25%, 50%, or 75% snow cover at 29 quadrats for different satellite-based data. A positive bias indicates that the satellite-based estimate was later than the actual value (estimated based on drone photography). The red vertical lines show where satellite- and drone-based estimates are the same (bias = 0) .

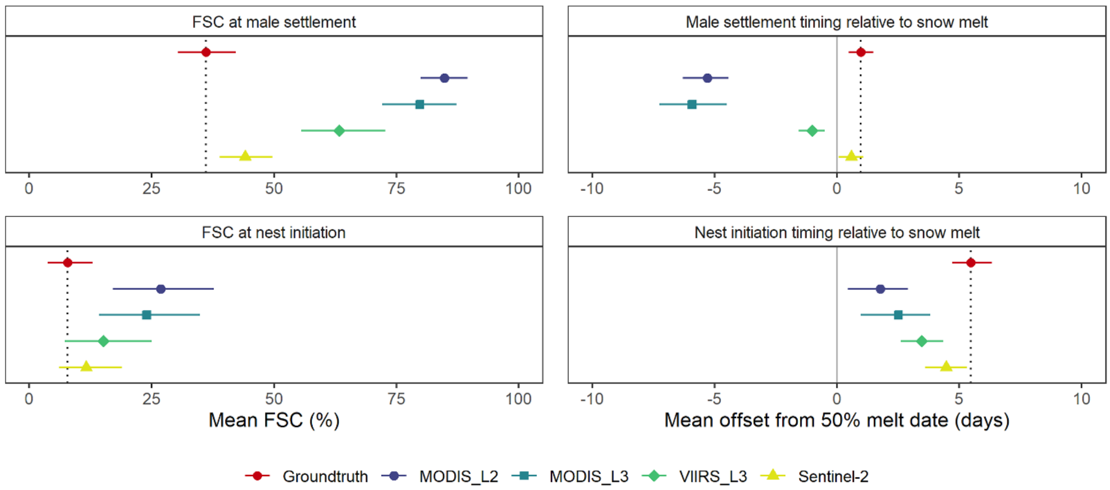


**Figure 5.** Association between snow cover patterns (per cent snow cover or date at which a threshold value of snow cover has been reached) and phenological traits of interest (date of male territory settlement and laying date in pectoral sandpipers). Shown are estimates (dots) and their bootstrapped 95% confidence intervals (horizontal lines) from drone-based photograph ('ground truth'; indicated in red and by a vertical dotted line) and satellite-based data (coloured dots). The vertical grey lines in the panels on the right indicate that the phenological trait would occur exactly on the date when the 50% snow cover threshold is reached (estimate = 0). The left panels show the percentage snow cover (FSC) and the right panels the time difference (in days) between snow melt (50% of snow cover reached) and the relevant phenological trait. Snow melt data correspond to an area with a 250 m radius around the male capture site (settlement area) at the time of capture (top panels) or around the female's nest at the time of clutch initiation (bottom panels) .

### 3.2. Relationship between snow melt patterns and pectoral sandpiper phenology

We captured 132 male pectoral sandpipers that showed territorial behaviour and obtained data on laying date for 48 nests, as 8 out of 56 nests were predated before the initiation date could be estimated. The cumulative number of males caught and nests initiated on the plot is shown in figure 2, and the spatial distribution of capture sites and nests is shown in figure S5.

Based on the ground truth data, male settlement areas were on average 36.1% snow covered at the time of capture (figure 5). All satellite-based estimates of snow cover at the time of settlement were significantly higher than the snow cover estimates based on the ground truth data (paired $t$-tests; MODIS_L2: 84.8%, $t_{81} = 17.32$, $p < 0.001$; MODIS_L3: 79.8%, $t_{81} = 10.84$, $p < 0.001$; VIIRS_L3: 63.3%, $t_{81} = 8.70$, $p < 0.001$; Sentinel-2: 44.1%, $t_{81} = 7.80$, $p < 0.001$). Similarly, the level of snow cover around the nest at the time of clutch initiation was significantly lower according to the ground truth data (7.9%) relative to MODIS_L2 (27.0%, $t_{46} = 5.15$, $p < 0.001$), MODIS_L3 (24.0%, $t_{46} = 3.50$, $p = 0.001$), VIIRS_L3 (15.5%, $t_{46} = 3.16$, $p = 0.003$), and Sentinel-2 estimates (11.8%, $t_{46} = 3.40$, $p = 0.001$).

Male settlement occurred, on average, 1.0 d after the 50% snowmelt date had been reached according to the ground truth data (figure 5). The satellite-based estimates showed significantly earlier male settlement relative to the 50% snow cover dates (MODIS_L2: −5.3 d, $t_{81} = -15.74$, $p < 0.001$; MODIS_L3: −5.9 d, $t_{81} = -9.95$, $p < 0.001$; VIIRS_L3: −1.0 d, $t_{81} = -16.68$, $p < 0.001$; Sentinel-2: +0.6 d, $t_{81} = -4.72$, $p < 0.001$; figure 5). Nest initiation occurred on average 5.4 d after the 50% snow cover date at the nest area according to the ground truth data (figure 5). The satellite-based data suggested significantly earlier nest initiation relative to the 50% snow melt date for all datasets (MODIS_L2: +1.7 d, $t_{46} = -9.65$, $p < 0.001$; MODIS_L3: +2.4 d, $t_{46} = -5.11$, $p < 0.001$; VIIRS_L3: +3.4 d, $t_{46} = -27.75$, $p < 0.001$; Sentinel-2: +4.4 d, $t_{46} = -14.74$, $p < 0.001$).

## 4. Discussion

Measurements of snow cover are of interest for many ecological questions. Our results showed that MODIS and VIIRS datasets tended to overestimate the FSC in arctic tundra habitat. As a consequence, an ecological case study based on these datasets produced erroneous results regarding the timing of important biological events relative to the timing of snowmelt. For example, MODIS datasets indicated that male pectoral sandpipers settled in habitat patches with an average of approximately 80% FSC, but in truth this was closer to 36%. In comparison, Sentinel-2 snow cover estimates had higher accuracy, and yielded similar ecological conclusions when compared to the ground truth snow dataset. Errors in FSC estimates were highest at intermediate levels of snow cover, and were minimal when the ground was fully snow-covered or fully snow-free. This study demonstrates that ecologists should consider how research using remotely sensed snow cover datasets may be impacted by measurement error, particularly if important events occur during the period of intermediate snow cover.

A simple yet effective method for measuring snow is calculating FSC using the 'universal' NDSI correction formula from Salomonson and Appel (2006). Substantial work has been done to validate FSC measurements in MODIS snow cover products, and we found comparable levels of overall bias and error compared to previous studies (e.g. Stillinger *et al* 2023 for MODIS_L3, Salomonson and Appel 2004 for MODIS_L2). However, there have been relatively few studies evaluating FSC measurement error in VIIRS and Sentinel-2 datasets. The VIIRS validation by Stillinger *et al* (2023) and in our study both showed similarly low levels of bias (−5% FSC in Stillinger *et al* 2023 and +5% FSC in our study) and similar levels of overall error (RMSE). Our Sentinel-2 validation results were congruent with the study by Aalstad *et al* (2020), but not with Gascoin *et al* (2020), who reported significantly higher levels of RMSE, possibly because the latter was conducted in a mountain catchment (unlike the tundra landscape in Aalstad *et al* and in our study). Alternatively, the higher levels of RMSE in Gascoin *et al* (2020) may be due to the fact that Gascoin *et al* assessed accuracy at 20 m resolution, such that the 10 m geolocational error in this data (Gascon *et al* 2017) would have been more influential. In contrast, Sentinel-2 data were upscaled to approximately 65 m resolution in our study (the scale of a quadrat), and to 100 m resolution in Aalstad *et al* (2020), potentially reducing the influence of the geolocational error.

FSC validation studies usually report overall error statistics instead of quantifying error statistics stratified by FSC. However, for ecologists it is often highly useful to understand how bias differs across the full range of snow cover conditions, depending on the timing of key ecological events relative to snow melt patterns. We found that all datasets gave accurate estimates of FSC when true values were at or near 100% and 0% cover, but overestimated FSC with pronounced error at intermediate levels of snow cover. Using MODIS and VIIRS datasets, FSC was overestimated by as much as 50%. The same pattern was found in the Sentinel-2 dataset, but to a lesser degree. The pattern of bias we found resembles the results of Crawford (2015), who showed that a MODIS_L2 dataset continued to estimate 100% FSC until true FSC was as low as 50%–75%. Our results also partially resemble results from Stillinger *et al* (2023), who reported a similar pattern of overestimation but to a lesser degree in a MODIS_L3 FSC dataset (10% bias instead of 50%). Unlike in our study, Stillinger *et al* (2023) found that a VIIRS_L3 dataset tended to underestimate cover with a negative bias of approximately 10% at intermediate levels of FSC. Given the apparently higher levels of bias at intermediate levels of FSC, one could ask why our overall bias estimates are still comparable to those reported in previous research. The reason may be that there were relatively few satellite retrievals with FSC values at intermediate levels, so that these results were 'diluted' by the more numerous retrievals made at 0% or 100% FSC which are of high accuracy.

One interpretation of why we observed higher bias at intermediate levels of snow cover relative to other studies could be that the 'universal' formula to convert NDSI to FSC (Salomonson and Appel 2006) is not optimal for our particular study plot of arctic tundra. The relationship between NDSI and snow cover varies depending on environmental characteristics such as vegetation cover (Hall *et al* 1998), topography (Zhang *et al* 2021), solar angle, atmospheric conditions, and other factors (Hall and Riggs 2007, Appel 2014, Härer *et al* 2018, Stillinger *et al* 2023). A previous study has also shown that the MODIS data agreed with ground-truth data to varying degrees for different land cover types with higher error for surface snow cover in evergreen forest (Simic *et al* 2004). Although the coastal tundra habitat in the high Arctic—including our study site—can be considered a relatively homogeneous landscape, we observed substantial temporary water cover from pooled melt water during periods of intense snow melt, which could have inflated FSC estimates in our study. Water has similar levels of NDSI compared to snow (Dixit *et al* 2019), and MODIS, VIIRS, and Sentinel-2 snow detection algorithm screens out water using a static map of inland water bodies (Riggs *et al* 2019, Versluijs 2023), but does not account for temporary water bodies. Thus, the bias we observed may not be generalizable across all snow monitoring applications. However, our study suggests that researchers should be aware of variability in the accuracy of remote sensed snow datasets, which may lead to a large degree of bias, and consequently yield misleading ecological conclusions.

We found that snowmelt date was generally estimated within a few days of accuracy. The Sentinel-2 dataset yielded the most accurate estimates of snowmelt date (±1 d of the actual date), whereas MODIS and VIIRS datasets on average made estimates around 3 d later than the actual date, which is similar to levels of error in date estimation reported in previous research using MODIS imagery (e.g. Lindsay *et al* 2015, O'Leary *et al* 2018). A difference of 3 d may be trivial for some studies, but it may be substantial in habitats such as arctic tundra, where seasonal change is rapid and key ecological events may be closely related to the timing of snow melt. For example, 95% of shorebirds within a given breeding population in the Arctic lay their first egg within a span of 10 d (25 taxa reviewed at 16 sites; Weiser *et al* 2018). One of the important questions regarding climate change is whether the reproductive timing of organisms is adequately tracing the advancement of snow melt date (Meltofte *et al* 2007, Grabowski *et al* 2013, Liebezeit *et al* 2014). Here, inaccurately estimating the timing of snow melt by 3 d could falsely assign a large proportion of the population as breeding 'too late' or 'too early'. In our case study, the bias in snow date estimated using MODIS led us to conclude that male pectoral sandpipers settled on average 5 d prior to the 50% melt date, i.e. a largely snow-covered landscape, but the drone-based snow melt data showed that the mean settlement date rather came *after* the 50% melt date, i.e. birds arrived in a relatively snow-free landscape. This error could influence how we understand the species' ecology and lead to the generation of flawed hypotheses.

## 5. Limitations of our study

This study only investigated measurement error in a single season on a single plot of arctic tundra. Levels of bias and uncertainty may differ according to factors such as landscape and habitat characteristics, as described previously. Furthermore, the snow melted relatively consistently and rapidly on our study plot, but different patterns of bias may be observed in years with a slower snow melt (e.g. with additional snowfall events or snow drift after the snow has partially melted), or in areas with larger spatial heterogeneity in the snow melt dates.

Our method of snowmelt date estimation does not necessarily reflect the performance of other methods. We modelled snow depletion with a sigmoid-shaped curve, which appeared to be a good representation of the snow ablation process on our study site. However, more flexible models such as generalized additive models could be considered (e.g. as in Versluijs 2023) if the pattern of snow depletion is not smooth or otherwise does not fit a sigmoid pattern. Another common approach for estimating snowmelt date uses an NDSI threshold to classify pixels as snow-covered or snow-free. Then, the first date of crossing below a critical NDSI threshold can be used as the snow melt date (e.g. Curk *et al* 2020). However, NDSI thresholds used for snow classification are typically validated against snow depth measurements from snow stations (e.g. <2 cm depth is considered 'snow-free'), and snow depth measurements do not directly equate to a known level of FSC. Therefore, the translation of NDSI thresholds to FSC levels of ecological interest (e.g. 50% cover) needs to be considered with care. Additionally, methods for estimating FSC that are not based on the NDSI exist, such as spectral unmixing algorithms (Roberts *et al* 1998, Bair *et al* 2021, Rittger *et al* 2021), which may have lower bias for some applications (but see Aalstad *et al* 2020), but are more complex to implement and/or not as readily available as NDSI-based datasets.

## 6. Recommendations

From our results, we can make the following recommendations to ecologists seeking to use remote sensed snow cover products for measuring FSC or snow melt timing.

- FSC estimates from MODIS and VIIRS datasets can be subject to substantial bias and uncertainty at moderate levels of FSC. Therefore, these FSC datasets should be used with caution if the study focuses on ecological events that take place during the period of snow melt. Researchers should ideally collect validation snow cover data at their study site if feasible, or consult validation studies conducted in similar habitat (if available) to ascertain the possible extent of bias.
- Date estimates from MODIS and VIIRS datasets may be in the region of 2–5 d late, so researchers should consider whether this uncertainty has significant implications for their research application.
- VIIRS datasets (available after 2011) are preferable over MODIS datasets, due to improved spatial resolution and similar or lower levels of error.
- Sentinel-2 data may yield more accurate estimates of FSC and snow melt date, and researchers can consider using them. However, the temporal resolution of Sentinel-2 data may be prohibitive at lower latitudes, and relatively few studies have been conducted validating Sentinel-2-based FSC-methods. Furthermore, MODIS and VIIRS have global, ready-prepared snow cover datasets freely available, whereas pre-prepared Sentinel-2 snow datasets have limited spatial extent (e.g. (Gascoin *et al* 2019). Thus, researchers may need to process Sentinel-2 data themselves to produce a usable snow cover dataset, which is more time consuming and requires more technical expertise.
- Ecologists should be aware that several features of a region of interest may impact bias and uncertainty: levels of true snow cover, vegetation/habitat type, the length of the snow melt period, and other landscape properties as well as imaging conditions. Therefore, the reported mean levels of bias may not be relevant or may be misleading for a particular study.

## 7. Conclusion

FSC measurements derived from satellite imagery are valuable in ecological research, particularly as the resolution of satellite datasets continues to increase over time. However, measurement error in these datasets can be large in some conditions, which can lead to erroneous conclusions on the effects of snow cover on ecological processes. Therefore, ecologists using snow cover data should be conscious of these limitations, and where possible consult studies validating snow measurements in environments comparable to that of their study system. We find that the use of Sentinel-2 datasets for FSC measurement seems particularly promising, and we encourage further studies validating the use of Sentinel-2 snow cover data in varied environments.

## Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.17617/3.8WHNS4.

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## Author contributions

B K, M V, and R J H conceived the ideas and designed the methodology; R J H collected the data; R J H and M V analysed the data with input from B K; R J H, B K, and E K led the writing of the manuscript; T V extracted and analyzed the Sentinel-2 data and wrote the supplementary methods. All authors contributed critically to the drafts and gave final approval for publication.

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