Environmental Research Letters

LETTER

Estimating meltwater retention and associated nitrate redistribution during snowmelt in an Arctic tundra landscape

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Keywords: nitrate, arctic, snow water equivalents, UAV, hydrology, surface flow, snow volume

Abstract

Nitrogen availability in Arctic ecosystems is a key driver for biological activity, including plant, growth and thereby directly linked to the greening of the Arctic. Here, we model the redistribution of meltwater following spring snowmelt as well as the accumulation of meltwater and dissolved nitrate at landscape scale. By combining snow mapping with unmanned aerial systems, snow chemistry, and hydrological modelling, we argue that the majority of nitrate in the snowpack is flushed out of the landscape due to the limited storage capacity of meltwater in the early growing season frozen soil. We illustrate how landscape micro-topography is a crucial parameter to quantify storage capacity of meltwater at landscape scale and thereby the associated pool of soluble compounds such as nitrate. This pool will be available for plants and may be important for plant diversity and growth rates in the wettest part of the landscape. This study illustrates that the evenly distributed nitrate input during the Arctic winter may be redistributed during the initial snowmelt and lead to marked differences in biologically available nitrate at the onset of the growing season, but also that the majority of deposited nitrate in snow is lost from the terrestrial to the aquatic environment during snowmelt.

Introduction

There is a current focus on understanding the varied responses of Arctic terrestrial ecosystems to climatic changes, specifically the net effect of an increasing (Forkel et al 2016) or a decreasing carbon sink strength (Nauta et al 2015, Dahl et al 2017). Nitrogen (N) in a plant available form is a key component for these responses since N is considered a limiting factor for plant growth in the Arctic (Shaver et al 2006). Future warming and changes in precipitation patterns are likely to catalyze mineralization of stored N, but also potentially increase other sources such as atmospheric deposition, which could lead to alterations in Arctic vegetation dynamics (Rousk et al 2017a, Bokhorst et al 2018, D’Imperio et al 2018). Main sources of plant-available N at catchment scale in most pristine Arctic ecosystems include redistributed internal N from mineralization of soil organic matter and inputs from fauna, and external input from atmospheric deposition and N2 fixation (Skrzypek et al 2015). Mineralization is limited in poorly aerated soils and atmospheric N2 fixation may therefore play an important role, particularly later in the season when fixation rates increase with higher summer temperature (Rousk et al 2017b). It also means that early season N availability in landscape depressions may rely on external N sources in contrast to aerated soils relying more on internal N (Semenchuk et al 2015).

A marked part of the atmospheric N is deposited into a winter snowpack as plant-available nitrate (NO3−), particularly at higher latitudes where a substantial part of the precipitation (often >50%) falls as snow (Przybylak et al 2003). In addition, a higher NO3− concentration has been reported in precipitation during winter than during summer in the whole Arctic (Hole et al 2009), and locally in e.g. Svalbard

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(Kühnel et al. 2011). This increase is partly related to anthropogenic sources, which is evident in the Greenland Inland Ice Sheet snowpack (Hastings et al. 2009) and in cores from Arctic lakes (Holmgren et al. 2010, Holtgrieve et al. 2011). When focusing on the spatial distribution of NO$_3^-$ in the snowpack in Greenland, concentrations in the Inland Ice Sheet seems to increase towards the southern and western regions due to an enhanced effect of anthropogenic sources, with the highest degree of variation found in low accumulation zones (Burkhart et al. 2009). When observed at a smaller scale as coastal-inland gradients, Curtis et al. (2018) reports decreasing concentrations of deposited NO$_3^-$ in snow towards the coast, yet a higher net deposition than inland due to higher precipitation.

The winter snowpack melting and the subsequent runoff is a decisive annual hydrologic event in Arctic terrestrial ecosystems, during which soluble ions in the meltwater are redistributed over time and space. Studies of snowmelt and subsequent runoff at catchment scale traditionally combine in situ observations of snow parameters or snow distribution model outputs with energy-based snowmelt models (Kane et al. 1997, Bruland et al. 2001, Liston and Elder 2006) and raster- or tile-based hydrologic routing schemes (Zhang et al. 2000, Dornes et al. 2008). Two advantages of such approaches are estimates of snowmelt and runoff over time, and the possibility to add levels of soil infiltration. Modelling the winter snow, including redistribution, requires sophisticated coupling of meteorology, topography and energy-balance data. Moreover, it is demanding in processing power, particularly when using high spatial resolution, and would have the inherent uncertainty of pure model studies. And while the simplest of snowmelt models can be forced with temperature data only, most of them require complete energy-balance datasets (Pohl et al. 2005). Similarly, runoff-routing with infiltration capability require processing power and relies on detailed mapping of soil characteristics over time, particularly soil moisture and structure; datasets which are often scarce in remote areas. This calls for an efficient way to actually measure snow depths and an optimized method to quantify runoff routing.

When linking meltwater runoff with nutrient reallocation, an important component is the ionic pulse occurring during snowmelt (Rasch et al. 2000, Elberling et al. 2007, Boucher and Carey 2010), which reflects that most water-soluble ions in a snowpack are flushed out in the early phase of snowmelt leaving the remaining snow drifts with almost distilled water and solid particles behind. The specific ratio of percent snowmelt to flushed ions will be site- and species-specific. Due to this ionic pulse, the movement of early meltwater and water storage capacity in the landscape during early spring with completely frozen tundra may be critical for the overall redistribution of winter-deposited N species. Previous studies from terrestrial Arctic sites have successfully linked the loss of N at catchment scale to snow meltwater runoff over time (e.g. Jones et al. 2005, Boucher and Carey 2010). While these studies focus on the temporal component of loss of soluble ions such as NO$_3^-$, a combined spatio-temporal approach describing NO$_3^-$ redistribution is for instance given for Nowak and Hodson (2015). However, Nowak and Hodson (2015) do not link the spatial distributions to specific measurements of deposited NO$_3^-$ in snow or the landscape water retention capacity. To increase our understanding of this mechanism, access to high spatial resolution data of snow distribution is one key aspect, alongside detailed topographic representations to evaluate meltwater runoff patterns, and ground-based measurements of snow chemistry.

Recent development in lightweight drones and increased computer processing power has revolutionized the use of unmanned aerial systems (UAS) in biogeosciences within the last decade. When focusing on small drones (<5 kg), aircrafts with high-quality consumer cameras can acquire overlapping aerial photos allowing the use of structure-from-motion techniques to photogrammetrically derive 3D point clouds of the photographed surfaces (James and Robson 2012, Lucieer et al. 2014a). Subsequent digital surface models (DSM) and orthophotos are then created by interpolating planes between points, thereby reproducing topography typically at 1–20 cm spatial resolution. In remote areas such as the Polar regions, this data source is highly versatile for describing the heterogeneity and topography of natural landscapes and has for instance been used to map micro-topography of specific vegetation types (Lucieer et al. 2014b) and evaluate surface heterogeneity at landscape scale (D’imperio et al. 2017). Although such high-resolution DSMs are clearly advantageous to quantify runoff routing in permafrost landscapes where vegetation is absent or low, and would be a novel use of the technique, one limitation with traditional raster-based runoff approaches is that they are inefficient on high-resolution datasets.

When combined with cm-precision ground control points (GCP), the surface models have moreover been found to offer sufficient spatial accuracy to map snow depths using subtractions of co-located snow-covered and snow-free surfaces. Vander Jagt et al. (2015) showed that this approach can provide snow depths with <10 cm error in a naturally vegetated local (<1 ha) alpine area. Harder et al. (2016) reports a similar <10 cm accuracy in an alpine site, as well as for a prairie site, however, the snow depth accuracy was lower at sites with taller vegetation. This observation is supported by Bühler et al. (2017) who achieve accuracies ~7 cm in sparsely vegetated areas, and up to ~30 cm accuracy in areas with vegetation of that particular average height. Consequently, auxiliary data on surface classes and vegetation heights are important for the precision of snow depth estimates.

In summary, the spatial fate and retention of snowpack NO$_3^-$ in Arctic landscapes during snowmelt is uncertain and dependent on micro-topography.
High spatial resolution surface models and snow measurements are needed to capture this topography, but can be achieved with UAS. The subsequent runoff modelling and landscape retention capacity requires new efficient network-based models due to the high spatial resolution. Here we present a new integrated approach to assess the landscape retention capacity of meltwater and dissolved NO$_3$ within a catchment. This includes (1) assessing the spatially distributed concentrations of NO$_3$ in the snowpack, (2) quantifying 3D snow depths using UAS, and (3) quantifying the run-off pattern and retention-capacity of topographic dips, using a high-resolution digital surface model coupled with a high-efficiency surface runoff model. Our aims are to show the ability of this approach as a precise and efficient screening tool, and show for an Arctic tundra site how much NO$_3$ is likely lost from the melting snowpack.

Methods

Study site
The Bløsedalen valley at 69.26°N 53.47°W located on the southern part of Disko Island in West-Greenland has been ice-free since the last glaciation approx. 10 000 years ago and represents today a heterogeneous mesic tundra landscape. The southern part of the valley is elevated approx. 120 m above sea level, and the studied area is located 500 m north of the coast. Annual mean temperature is $-3.0\, ^{\circ}C$, the warmest month being July at 7.9 $^{\circ}C$ and coldest being February at $-14.0\, ^{\circ}C$ (data from 1991 to 2014; Hollesen et al. 2015), causing the area to be underlain with discontinuous permafrost (Westergaard-Nielsen et al. 2018), with a mean annual soil temperature in the upper 5 cm of $-0.9\, ^{\circ}C$ (data from 1991 to 2004; Hansen et al. 2006). Precipitation data from the area are very scarce, but the annual average has been estimated to $\sim 400\, \text{mm}$ (Hansen et al. 2006). The ratios of land surface classes in Bløsedalen are considered representative for greater parts of Greenland (Karami et al. 2018) and on broader scale substantial parts of the circumpolar Arctic with dominance of dwarf-shrub tundra.

Unmanned aerial system data and ground control points
The UAS-based datasets were collected in the snow-free and snow-covered period, respectively. The snow-free data was collected in 2014 and repeated in 2017 (all in July/August), and the snow-covered data during peak snow depths in 2018 (April 2nd). All flight routes were planned in Mission Planner (ArduPilot Dev. Team) with parallel flight lines and 75% image overlaps. All flights were conducted under clear-sky conditions. Table 1 lists the details of the equipment used and derived products. GCPs were measured to correct the geometry of the DSMs using a differential global positioning system (DGPS, Two Trimble R8 receivers in a post-processing kinematic setup), and distinctive locations estimated to be visible on both the snow-free and snow-covered orthomosaics were selected (abrasion plateaus with distinct corners, centres of boulders, masts etc). A total of 14 GCPs were recorded in the snow-free landscape and initially 10 in the snow-covered landscape. On both occasions, the GCPs were distributed evenly across the study area. DGPS data was postprocessed in Trimble Business Center 3.82, with an average horizontal and vertical precision of 3.4 cm and 6.1 cm, respectively. We added 14 GCPs (giving a total of 24 GCPs to correct the snow-covered DSM) derived from the georeferenced snow-free model from distinct surface features that were also visible on the snow-covered model (barren rocks, masts etc), in order to increase the relative precision between the two surface models.

The imagery from the UAS was postprocessed with Agisoft Photoscan Pro 1.4.5 using a structure-from-motion workflow with GCPs. The workflow can be summarized as: (1) image alignment and sparse point cloud generation (key points), (2) optimization of camera alignment using 14 ground control points (snow-free scene) and 24 ground control points (snow-covered scene), (3) dense point cloud generation, (4) DSM generation based on the dense point cloud and (5) orthomosaic generation based on the DSM.

The images were resampled to half the original pixel resolution during the processing using Photoscan Pro. Trials using full image resolution did not improve the results in this study but increase the processing time substantially. Both the snow-free and snow-covered DSM represented a full catchment, delineated topographically towards north, west, and east. We then subtracted the snow-free DSM from the co-located snow-covered DSM, resulting in a snow depth data layer covering 1.347 km$^2$.

Vegetation classification
Using structure-from-motion on image data allows for developing a DSM which will not represent the true terrain, unless the barren surface is sufficiently observable in the images. We therefore classified the surface cover types in the area to allow a subtraction of average vegetation heights from the snow-free surface model. In principle, this will result in an actual terrain model. The classification was based on a pan-chromatically sharpened WorldView-2 scene covering the entire study region, acquired on the 12th of June 2012. The scene consists of 5 spectral bands (WorldView-2 band) 2–6 at 0.5 m spatial resolution and 1 pan-chromatic band (for details see www.digitalglobe.com). We used a Maximum Likelihood classifier based on statistics from 11732 training pixels distributed across 7 surface
| Surveys                     | Airframe                                      | Camera                        | Image count | DGPS ground control points | Derived products                                      |
|----------------------------|-----------------------------------------------|-------------------------------|-------------|-----------------------------|-------------------------------------------------------|
| 24th–25th July and 6th August 2014 | Custom Pixhawk-based multirotor flying at 60 m above terrain | Canon sx260hs 4000 × 3000 pixels. Focal length at 5 mm. £ = 1/1250 f-num = 2 ISO = 100 | 442         | 14                          | Orthomosaic (RGB) and Digital Surface Model (DSM) at 10 cm ground resolution |
| 21st—22nd July 2017         | Custom Pixhawk-based fixed wing flying at 100 m above terrain | Canon s100 4000 × 3000 pixels. Focal length at 5 mm. £ = 1/1250 f-num = 2 ISO = 100 | 1362        | 14                          | Orthomosaic (RGB) and DSM at 10 cm ground resolution   |
| 2nd April 2018              | Custom Pixhawk-based fixed wing flying at 100 m above terrain | Canon s100 4000 × 3000 pixels. Focal length at 5 mm. £ = 1/1250 f-num = 2.8 ISO = 100 | 1710        | 24                          | Orthomosaic (RGB) and DSM at 10 cm ground resolution   |
Table 2. Surface classes and corresponding vegetation heights.

| Surface class       | Dominant species and heights                                      | Avg. height |
|---------------------|-------------------------------------------------------------------|-------------|
| Barren              | —                                                                 | 0 cm        |
| Dwarf shrub heath   | Betula nana (7 cm, n = 23), Vaccinium uliginosum (3.9 cm, n = 13), Empetrum hermaphroditum (4.6 cm, n = 21), Cassiope tetragona (10.2 cm, n = 15) | 6.4 cm      |
| Dry heath           | Empetrum hermaphroditum (d.o.), Vaccinium uliginosum (d.o.), Dryas integrifolia (1 cm, n = 6) | 3.2 cm      |
| Copse               | Salix glauca (22.6 cm, n = 45)                                    | 22.6 cm     |
| Fen                 | Carex sp., Eriophorum angustifolium. Surface visible between leaves, so assuming a correct terrain representation | 0 cm        |
| Snow bed slope      | Salix herbacea (2.2 cm, n = 10)                                   | 2.2 cm      |

Validation data of snow properties

Before the UAS survey, we sampled 22 snow cores of the entire snow column along a snow depth gradient using a Snow-Hydro plexiglass probe (www.snowhydro.com) and DGPS measurements for accurate positioning of the sample locations. We wore gloves to avoid contamination of the snow samples, and cleaned the probe with snow between each glove to avoid contamination of the snow samples, rate positioning of the sample locations. We wore gloves to avoid contamination of the snow samples, rate positioning of the sample locations. We wore gloves to avoid contamination of the snow samples, rate positioning of the sample locations.

Table 3. Confusion matrix for surface classification. Overall accuracy is 93.2%, with a Kappa coefficient of 0.91.

| Train class | Barren | Dwarf shrub heath | Dry heath | Copse | Fen | Salix herbacea slope |
|-------------|--------|-------------------|-----------|-------|-----|----------------------|
| Barren      | 4836   | 0                 | 0         | 0     | 4   | 0                    |
| Dwarf shrub heath | 0    | 5717              | 76        | 0     | 0   | 0                    |
| Dry heath   | 0      | 810               | 1100      | 0     | 0   | 0                    |
| Copse       | 0      | 11                | 0         | 1382  | 0   | 39                   |
| Fen         | 0      | 36                | 4         | 0     | 2465| 0                    |
| Snow bed slope | 0   | 3                 | 0         | 187   | 0   | 810                  |

Estimation of runoff streams and landscape water retention

The snow meltwater runoff is modelled following the method developed by Balstrøm and Crawford (2018): the terrain model was examined for the presence of bluespots (landscape depressions) acting as local retention depots for meltwater and soluble ions. Each detected bluespot has a contributing catchment defined by the bluespot’s topographic watershed (figure 1). When a bluespot’s retention capacity is exceeded, the bluespot spills over at its pour point and carries the excess water volume downhill in accordance with the steepest local path. While the lake in the center of the study area is in principle a bluespot, we set its volume to zero assuming that the water table was stable throughout the study period.

When the hydrologic screening is completed the output consists of a number of bluespots, their local contributing watersheds, pour points and streams stored as feature classes in ArcGIS Desktop 10.7 (https://www.esri.com). If two streams merge a pseudo pour point with zero retention capacity is established for the sake of the upcoming tracing procedure. Next, the streams are turned into a topologically...
ordered one-dimensional network stored as an acyclic directed graph based on the open source NetworkX Python module (Hagberg et al. 2008). When starting the flow model, a downstream propagator determines the accumulated, downstream spillover volumes based on the meltwater entering the individual bluespots. The accumulated bluespot water volume represents the expected landscape retention capacity.

This novel approach means that beyond the raster based calculations of the overall flow directions and identification of sinks from the terrain model having $\sim 187 \cdot 10^6$ cells, all further computations are handled in a simplified vector space. Thus, the total computation time for this high-resolution dataset in a combined ArcGIS/Python programming environment is only 4-5 CPU minutes on a desktop computer, which is critical to allow iterative sensitivity analyses. Here we run the model five times (measured SWE, plus/minus the SWE uncertainty, and a sensitivity test with plus/minus 50% change in SWE relative to the measured). The hydrologic screening model assumes a Hortonian flow, i.e. surface runoff with no infiltration, which agrees with studies of snowmelt runoff in areas with permafrost and/or frozen ground during initial snowmelt (Kuchment et al. 2000, Johansson et al. 2015). In addition, the period with snowmelt without refreezing of meltwater in the snowpack is only expected to last <9 d (Westergaard-Nielsen et al. 2017). Consequently, we consider the meltwater from the snowpack to be released as one instant pulse and the remaining snow to be depleted with respect to water-soluble ions. In 2018, the majority of snow had melted away on the 10th of June (http://g-e-m.dk), during which the soil temperature in 1 cm depth was 0.05 °C on average (1st–10th of June 2018) (http://g-e-m.dk). Consequently, the active layer was still frozen at that time, supporting our assumption of no infiltration.

Evaluating bluespot locations

Time integrated normalized difference vegetation index (TINDVI) is a commonly used spectrally derived proxy for vegetation productivity (Jia et al. 2009, Westergaard-Nielsen et al. 2015), however it can also serve as an indicator of standing water for which the signal would be low or negative. As an indirect validation of the spatial distribution of bluespots, we computed TINDVI based on the atmospherically corrected L2A products from the Sentinel-2A and 2B satellites (being part of the ESA Copernicus program). The Sentinels are sun-synchronous Polar-orbiting resulting in overpass times $\sim 3–4$ d at 69 °N per satellite. We computed TINDVI using Google Earth Engine (https://earthengine.google.com) as the sum of NDVI values from days with $<20\%$ cloud cover from 10th to 30th of June 2018, corresponding to the melt season and early spring. In total our dataset was based on 15 overpasses. We then extracted TINDVI.
data from the areas outside and inside the bluespots’ coverage for subsequent analyses.

Results

UAS data

The average horizontal error of the snow-free and snow-covered surface models was 32 cm after GCP corrections. From the 22 validation points of snow core measurements (ranging from 0.17 to 1.55 m of snow) with DGPS locations, we had to omit two since they were in the periphery of the UAS-based surface models, where uncertainty is high due to a lack of overlapping images. Using the remaining 20 cores, we estimated the vertical error of the snow depth estimates to a mean absolute error of 9.8 cm (figure 2).

The histogram for the photogrammetrically derived snow depths (figures 3(a) and (b)) shows that most of the depths are in the range of a few centimeters to 2 m, with a right-skewed distribution and a mode around 0.5 m. The average UAS-based snow depth is 1.08 m across the mapped area.

Snow properties

Due to the spatial uncertainty of the MagnaProbe depth measurements, it is not possible to compare those with the UAS-based snow depths. However, the statistical distribution is comparable to the manual probe measurements, although the probe is limited to 120 cm (figure 3(c)).

Using the 22 snow cores from the Hydro-Snow probe, we measured an average snow density of 318 kg m$^{-3}$ ± SD 55. We found a statistically significant linear relationship between snow depths and the snow samples’ water equivalents (figure 4(a)) allowing for a subsequent conversion of UAS-based snow depths into SWE per grid cell (figure 4(b)). Alongside the snow-free terrain model, this SWE data set formed the input to the Hortonian flow model.

The concentration of dissolved NO$_3^-$ in the 30 independent samples was on average 0.095 mg l$^{-1}$ ± SD 0.021, and the reported standard deviation shows that potential spatial differences in the concentrations are negligible. The total estimate of deposited NO$_3^-$ in the snowpack was 12.9 mg m$^{-2}$ ± SD 1.8 or 17.4 kg ± SD 3.9 for the entire catchment. The sensitivity test considering 10% increase or decrease in NO$_3^-$ concentration but the same total amount of snow resulted in ±1.3 mg m$^{-2}$ (0.29 mg N m$^{-2}$), respectively, of NO$_3^-$ change in deposition levels.

Water runoff modelling

Bluespot capacities ≤100 l were eliminated in the hydrologic screening considering the digital elevation model’s overall vertical accuracy. From the derived watersheds it was computed whether the local bluespots’ capacities were big enough to retain the meltwater within the bluespots. If not, the spill over was accumulated downstream.

The modelled drainage pattern is presented in figure 5. 12 688 individual bluespots were identified with an average volume of 0.58 m$^3$ meltwater. The total water volume contained in bluespots was 7295 m$^3$, +4 m$^3$ and −10 m$^3$ resulting from the 9.8 cm mean absolute error in snow depths. The disproportionate uncertainty is due to the vast majority of bluespots being filled up to maximum capacity, so increased meltwater will result in increased surface runoff rather than a higher retention. The total surface area of bluespots was 0.116 km$^2$. Assuming equally
Figure 3. Histograms of snow depths sampled with UAS ((a); 50 bins), UAS clipped to the MagnaProbe range ((b); 18 bins) and the MagnaProbe ((c); 18 bins). The MagnaProbe does not extend to >1.2 m depth, hence, the high occurrence of that depth. In both histograms, the peak frequency is found around 0.3–0.6 m, with a right-skewed distribution.
distributed NO$_3^-$ ions in the meltwater, a total of 0.69 kg ± SD 0.15 of NO$_3^-$ is retained in the studied area or 2.0% of the initial deposited pool. Our sensitivity test with a 50% increase in SWE but an unchanged concentration of NO$_3^-$ show that 1.4% of the deposited NO$_3^-$ would be retained, while 4.1% would remain if considering a 50% decrease in SWE. The retained mass of NO$_3^-$ would decrease by <1 g for the entire catchment with 50% less SWE, and increase by ∼3.4 g with 50% more SWE.

From the snow-free terrain model we see that the study site is separated into one prominent drainage catchment concealed by a lateral moraine towards North, a river system to the West (Røde Elv), and bedrock to the South and East (figure 5). Following those delineations, we divided the study area into four regions which drain to different catchments once the active layer thaws and allows for lateral water transport in the soil. The central region retains 3187 m$^3$ or 0.30 kg NO$_3^-$ ± SD 0.063; the North region 269 m$^3$ or 0.03 kg NO$_3^-$ ± SD 0.006; the South region 1871 m$^3$ or 0.18 kg NO$_3^-$ ± SD 0.038; the West region 1971 m$^3$ or 0.19 kg NO$_3^-$ ± SD 0.41.

Relative spatial differences in TINDVI

The extracted TINDVI from the bluespots was significantly different from the average TINDVI in the studied area without bluespots (t-test, $\alpha = 0.05$). The TINDVI outside of bluespots followed a gaussian distribution with a mode at 2.05. However, the distribution for TINDVI from the bluespots was bimodal, with a gaussian mode at −1.34 and 1.73, respectively. Negative NDVI refer to objects with a higher absorption in the near-infrared than in the red part of the electromagnetic spectrum; it usually occurs over water bodies or highly moist surfaces. We found no correlation between TINDVI and area or volume of individual bluespots.

Discussion

The average measured NO$_3^-$ concentration of 0.0945 mg l$^{-1}$ in snow meltwater in this study is similar to measurements at 0.093 mg l$^{-1}$ (1.5 μmol l$^{-1}$) reported by Curtis et al. (2018) from nearby Sisimiut in April 2011. Both Blæsedalen and Sisimiut are subject to a marine environment on the West coast of Greenland. Rather than a marked inter-annual variability, we expect concentrations to vary along coast-inland gradients and geographical location. Higher NO$_3^-$ concentration levels in the snow have thus been reported at similar latitudes but further inland in Greenland (Curtis et al. 2018) where less precipitation than in the coastal areas results in lower dilution effects. In general, the coastal areas of Greenland fall within the lower range of concentration levels in Arctic snow, as shown by e.g. de Caritat et al. (2005) who reported a median of 0.217 mg l$^{-1}$ from 17
different Arctic locations. This pattern is furthermore supported from modelling by Hole et al. (2009).

Using UAS data to estimate snow depths introduce uncertainty at several levels, including the precision of the structure-from-motion technique. Being a numerical optimization technique, the derived products are rarely 100% reproducible, and the precision depends on camera and image quality, image overlap, image contrast, type of surface features, and sensor-to-object distance (James and Robson 2012, Lucieer et al. 2014a). The volume of bluespots derived from the snow-free terrain model (i.e. the surface model subtracted by vegetation heights) is consequently affected by this. In addition, the uncertainty in vegetation classification and heights should be considered. In this study area, the vegetation is <20 cm, with the exception of Salix glauca reaching up to 70 cm in certain spots. The terrain features, which the low vegetation generally follows, often have a greater difference in elevation across distances of a few meters, and the total elevation difference measured by the UAS is 183 m, illustrating that the bluespots are not a product of the photogrammetric surface model’s vegetation canopy but rather the general terrain. Moreover, it is the relative elevation difference between the snow-free and snow-covered period that is important, which is ultimately reported by the validation against ground truth measurements of snow depths.

We found our uncertainty in snow depth estimation on par with previous studies (Vander Jagt et al. 2015, Harder et al. 2016, Bühler et al. 2017). More importantly, there is no significant difference in the estimates of retained snow meltwater in the landscape when taking the uncertainty in snow depths into account in the SWE-modelling. This results from the bluespots in the area being filled to maximum capacity already from 2% of the estimated meltwater volume in 2018.

The measured snow density was only acquired at one point in time, although it is known to increase throughout the winter season due to compaction and refreezing of meltwater (Pedersen et al. 2016). Here, we measured late-season densities which may overestimate the annual mean. To meet this, we measured densities in a transect of snow depths with an expected variation in compaction level. The linear correlation between depths and water content (figure 4(a)) suggests that such compaction was likely linear when the samples were taken. While the sample range cover <580 mm SWE and the modelled range is 0–2203 mm (figure 4(b)), our sample range is covering 83% of the modelled SWEs. Hence, we argue to have a representative SWE dataset.

Figure 5. Modelled streams based on the Hortonian flow model using the UAS-based surface model having vegetation heights subtracted. The water input consists of a single pulse of snow meltwater derived from UAS-based SWE. Main streams representing inputs from >200 000 grid cells.
The precision of the hortonian flow model is fully dependent on the accuracy of the terrain model, which in our case is a combination of uncertainty related to photogrammetry, vegetation heights, and a surface classification. Here, we validate the result based on two factors. Firstly, the modelled streams generally follow the visible streams in the area (figure 5) as well as the micro topography (e.g. lower lying routes between elevated patches with exposed bedrock). Secondly, the bluespots resulting from the flow model are co-located with negative TINDVI in early spring, which we interpret as presence of standing water. The lake is drained towards West, into the major river system denoted as ‘Main westward streams’ on figure 5. From visual inspection the lake had spill-over through these streams during and after snowmelt in the study period, and precipitation data show that the previous autumn had normal rainfall (Zhang et al. 2019). We therefore assume that the lake was filled to maximum capacity throughout the study period.

Climate model projections of precipitation patterns in the Arctic suggest higher winter atmospheric moisture levels, with a possibility of increased snowcover (Cohen et al. 2012). Yet, a trend analysis from regional climate model data of snowfall (MAR v3.6.4; Fettweis et al. 2017) did not show any statistically significant changes in the period 1985–2016 for the studied site. The SWE sensitivity test showed that a higher ratio of the total deposited NO₃ would run off with a 50% increase in SWE. However, the retained meltwater volume would only increase by 8 m³ and the associated increase of NO₃ less than 4 g for the total catchment. That means more snow with an unchanged mg l⁻¹ NO₃ concentration would not lead to a marked increase in N input to the terrestrial ecosystem in a landscape such as Blæsedalen because >95% of the nitrate-pool in the snow pack is lost to streams, lakes and other aquatic environments.

If we assume that the total pool of nitrate in the snowpack is relocated to bluespots, the estimated total mass of retained NO₃ will be ~0.69 kg, corresponding to 11.7 mg m⁻² if we consider the surface area of the bluespots only. The 10% sensitivity test of NO₃ concentration change then results in ± 1.2 mg m⁻² change. These numbers are considerably less than the suggested annual fixation levels of 100–700 mg N m⁻² year⁻¹ (Steward et al. 2011, Rousk et al. 2016a), but on par with the fixation in early spring which can be as low as 8–39 mg N m⁻² month⁻¹ in similar ecosystems (Lett and Michelsen 2014, Rousk et al. 2016b). This illustrates that a concentration change in the snowpack from increased atmospheric deposition would lead to slightly more NO₃ and likely other dissolvable compounds being trapped in lowlands in spring. It also illustrates that the retained NO₃ can still be critical for early season plant phenology in areas where biologically available N otherwise can be limited due to slow mineral weathering and decomposition of soil organic matter under poorly drained anoxic lowlands, and in a period where the otherwise dominant N₂ fixation process (Lett and Michelsen 2014, Rousk et al. 2017b) is temperature-prohibited. The combination of both meltwater and nitrate fluxes across the landscape may further partly explain hotspot measurements of high denitrification rates and the associated N₂O emissions in the Arctic reported from anaerobic lowlands (Maruschak et al. 2011). Without receiving meltwater from the surroundings, high rates of N₂O emissions would quickly decrease with the depletion of nitrate over time.

It is important to note that the previously mentioned ionic meltwater pulse is likely to have much higher ion concentrations in the first quarter of the meltwater (Rasch et al. 2000, Elberling et al. 2007, Boucher and Carey 2010). This suggests that the initial meltwater filling the bluespots can have a higher concentration of e.g. NO₃ than the total meltwater volume on average. Therefore we may underestimate the levels of retained NO₃ using our integrated method.

Future climate changes could also result in increased autumn rainfall as shown by Bintanja and Andry (2017). Such rain events can be important for input and redistribution of NO₃ and other nutrients partly due to soil infiltration but cannot be treated as simple as the initial meltwater, since infiltration may influence the vertical and horizontal fluxes. The effect of rain events in terms of NO₃ wet-deposition will greatly depend on the timing and intensity. High-intensity rain would result in substantial runoff on the surface, while low intensity rain during the growing season could result in increased plant uptake.

Another scenario with increased occurrences of winter warming events (Pedersen et al. 2015) could lead to brief melt and runoff during winter. Under such circumstances our approach is expected to perform well, since the runoff would be hortonian on top of a frozen active layer.

The presented new combination of field measurements with UAS-based surveys and subsequent efficient runoff modelling show, that the spatial redistribution of NO₃ can be estimated based on short field campaigns, which can aid the closure of the N budgets at catchment scale. The approach was successful used at the study site with a moderate topography and several gradients with more than 10% slope. The approach may not perform similarly well in large-scale catchments with flat topography due to the challenges in collecting precise ground control points for the UAS-survey, as well as the chance for meltwater infiltration. We therefore encourage testing of our approach on several contrasting sites with differences in topography and snow-cover to assess cross-site variability.

**Conclusions**

In this study, we successfully estimated a 3D snowpack at an Arctic tundra site, using UAS. We achieved a sufficient accuracy to model surface runoff pathways and
landscape retention capacity of snow meltwater during spring thaw using a novel highly efficient network-based flow model. We measured similar nitrate concentrations in the pre-melt snow to other reported levels, and up-scaled to a total nitrate stock in the snowpack. We found that the majority of the meltwater is drained from the terrestrial zone to streams and lakes, and with that, more than 95% of the atmospherically deposited nitrate in snow and likely other soluble nutrients. From this we conclude that future potential increases in snowfall does not necessarily lead to increased input of plant-available nitrate, as opposed to changes in atmospheric deposition rates or autumn rainfall which could potentially increase inputs. The method is generally applicable in environments with snowmelt occurring before the soil thaws to locate surface stream pathways and aid a closure of annual N budgets. We encourage use of this method in other landscape types to assess the variability of nitrate loss during spring thaw in permafrost areas.

Acknowledgments

We acknowledge the Danish National Research Foundation (CENPERM DNRf100), and University of Copenhagen, for funding this study. Also, we acknowledge the infrastructural support provided by Arctic Station, University of Copenhagen, the NVIDIA Corporation for GPU hardware support, the TerraLuma group at UTAS for valuable inputs, and Greenland Ecosystem Monitoring for data. Thanks to journal reviewers for helpful and constructive comments.

Author contributions

Bo Elberling (BE) and Andreas Westergaard-Nielsen (AWN) designed the study in collaboration with Thomas Balstrøm (TB). AWN and BE collected the bulk of data, TB performed the hydrological modelling, Urs A Treier (UAT) and Signe Normand (SN) provided ground truth data with vegetation heights and corresponding positioning data. AWN wrote the manuscript with significant contributions from all authors.

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Environ. Res. Lett. 15 (2020) 034025