Drivers of shortwave radiation fluxes in Arctic tundra across scales

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Abstract

Vegetation composition and water surface area are changing in many tundra regions due to climate warming, which is twice as strong in the Arctic as compared to the global mean. Such land cover changes feed back to climate and permafrost thaw through altering the surface energy budget. We quantified the influence of vegetation type, canopy characteristics, and patchiness on the tundra shortwave radiation components. We used in situ measurements and vegetation mapping to parametrise a 3D radiative transfer model (DART) for summer conditions at the Kytalyk test site in northeast Siberia. We analysed model results assessing the most important drivers of canopy albedo, transmittance, and absorptance of photosynthetically active radiation (PAR). Tundra albedo was strongly influenced by the fractional cover of water surfaces. Albedo decreased with increasing shrub cover. However, plant area index effects on albedo were not statistically significant. Canopy transmittance and PAR absorptance (f_{APAR}) were almost entirely controlled by plant area index at the landscape scale. Only about one half of the total plant area index consisted of green leaves, while wood and standing dead leaves contributed equally to the

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other half. While spatial patterns and patch sizes of vegetation types and open water did not significantly influence the radiation budget at the landscape scale, it contributed to the large variability at the local scale. Such local variability of shortwave radiation may impact evapotranspiration and primary productivity at a range of scales. Therefore, the variation of radiation fluxes within single vegetation types potentially affects larger scale energy, water, and carbon fluxes.

Keywords: 3D radiative transfer modelling; DART; In situ data; Vegetation type; Canopy properties; Albedo; Transmittance; Soil shading; fAPAR; Shrub; Sedge; Wood area index; Leaf angle distribution; Spatial heterogeneity

1. Introduction

Vegetation is an important part of the climate system as it reacts to climate drivers and influences climate through changing Earth's surface properties. Arctic greening, in particular the expansion of shrubs in tundra areas, is associated with recent climate warming (Sturm et al., 2001; Myers-Smith et al., 2011; Fraser et al., 2014). This greening directly affects the surface albedo, which feeds back to climate through large scale warming (Chapin et al., 2005; Lorant et al., 2011). Vegetation effects on permafrost thaw are more complex since increased vegetation density not only leads to atmospheric warming but also partly decouple permafrost from the atmosphere through insulation and soil shading (Eugster et al., 2000; Walker et al., 2003; Cannone & Guglielmin, 2009; Briggs et al., 2014).

Encroachment of dense shrub canopies in previously graminoid or lichen dominated tundra reduces the average surface albedo and thus amplifies warming (Thompson et al., 2004; Beringer et al., 2005; Blok et al., 2011b). Furthermore, vegetation alters surface roughness and transpiration, which leads to changes in sensible and latent heat fluxes (Boudreau & Rouse, 1995). Within the canopy, transpiration strongly depends on the light regime, in particular on the small scale heterogeneity (Song et al., 2009; He et al., 2014). Thus, resolving the shortwave energy budget helps understanding and modelling multiple land

21 surface – climate feedback processes.

22 Permafrost is affected by vegetation cover in multiple ways. On one hand,
23 vegetation shades the ground and thus reduces the amount of shortwave radia-
24 tion that is absorbed by the soil (Benninghoff, 1952; Briggs et al., 2014). On the
25 other hand, increasing vascular plant biomass reduces moss abundance through
26 shading and litter production (van Wijk et al., 2003). Decreased moss abun-
27 dance affects the soil heat flux as mosses can strongly insulate the soil from air
28 temperature (Beringer et al., 2001; Blok et al., 2011a). Additional processes,
29 such as trapping of snow by vegetation (Pomeroy et al., 2006), further influence
30 the interaction between vegetation and permafrost thaw.

31 Tundra landscapes typically show small scale patterns, such as hummocks
32 and polygons, which are associated with small water bodies and distinct vegeta-
33 tion types (Walker et al., 2008). Landscape variation and associated differences
34 in soil moisture, nutrients, and pH can lead to different vegetation composition
35 within meters (Walker et al., 2011; Muster et al., 2012). These patterns can
36 either remain stable over decades (Gamon et al., 2012) or change rapidly for
37 example due to permafrost degradation (Schuur et al., 2007). Large scale vege-
38 tation dynamics are also affected by wetland area and the water budget. While
39 an increase in lake and wetland area has been observed in the Siberian tundra
40 (Smith et al., 2005; Lin et al., 2012), the American Arctic shows a drying trend
41 (Oechel et al., 2000; Carroll et al., 2011; Jones et al., 2011; Lin et al., 2012).
42 Shrubs such as dwarf birch (*Betula nana*) profit from warming and fertilisation
43 and become increasingly dominant (Bret-Harte et al., 2001).

44 The radiation budget of patterned tundra landscapes is expected to vary
45 among and within vegetation types at fine scale (few centimetres) due to vari-
46 ations in canopy properties and edge effects. Currently, little is known about
47 the radiation budget of such patterned landscapes, as satellite observations are
48 too coarse to resolve the fine scale differences (Muster et al., 2012). The aim of
49 this study is to analyse the shortwave radiation budget of heterogeneous tundra
50 at the Kytalyk research site in northeast Siberia by using 3D radiative transfer
51 modelling to resolve such fine scales. The focus is on increasing the understand-

ing of drivers of albedo, transmittance, and absorbed radiation of the canopy from patch to landscape scale in summer. Using a 3D radiative transfer model, we provide insights into typical length scales of horizontal interaction between vegetation types and the influence of local land cover variability on the radiation budget at different scales. This is the first time that such a complex 3D radiation model has been parametrised with such high detailed structural and compositional measurements for the tundra.

2. Methods

2.1. Field site

Our field site is the Kytalyk nature reserve located in the Indigirka lowlands, northeast Siberia (70.8°N, 147.5°E, Figure 1a). According to the circumpolar Arctic vegetation map, vegetation is classified as tussock sedge, dwarf shrub, moss tundra (Walker et al., 2005). Low shrub tundra (mainly *Salix pulchra*) occurs along rivers and at lake shores. The area is dominated by continuous permafrost of several hundred meters depth (Romanovskii et al., 2004) with an active layer thickness of 12 to 50 cm (Mi et al., 2014). The Kytalyk field site is described in more detail in van der Molen et al. (2007); Nauta et al. (2015) and Juszak et al. (2016). The size of our study area is 1.4 km × 2 km (Figure 1b).

2.2. Remote sensing data and products

We used a ground referenced orthomosaic from a UAV (unmanned aerial vehicle, eBee, senseFly), acquired with digital cameras in four spectral bands (red, green, blue, and near infra-red (NIR)) to generate a NDVI (Normalized Difference Vegetation Index) map, a DSM (digital surface model), and a land cover map of dominant vegetation types. The map products have a spatial resolution of 5 cm and an extent of 1.4 km × 2 km.

2.2.1. Orthomosaic, NDVI, and DSM

The orthomosaic, which we obtained from the drone flights between 10 July and 10 August 2014, revealed some artefacts due to inhomogeneous illumination

Figure 1: (a) Location of the study site in northeast Siberia (extent of Arctic tundra from Walker et al., 2005) and (b) orthomosaic of the study site including measurement locations of vegetation properties (red) and reference points for vegetation mapping (yellow, point size indicates represented area).

during and between flights (Figure 2a). As these artefacts propagated to the NDVI map, spatial input variables, and the vegetation map (Figure 2b), we chose the sub-sets for modelling in the least affected area (Section 2.4.3). We estimated the NDVI from the red (ρ_{red}) and NIR reflectance (ρ_{NIR}):

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (1)$$

The DSM was generated from the point cloud which was created during the image matching. Interpolation was performed using inverse distance weighting, minimizing artefacts (Chaplot et al. (2006); Postflight Terra 3D, Version 4.0.83). The DSM represented a level between the top of canopy and the soil surface. The uncertainty is due to variability in canopy height and not related to topography. Since the vegetation was low ($< 0.8\text{m}$) and mostly sparse (average LAI of all vascular vegetation types < 1.5), some of the reference points for the DSM may have been mapped at the soil surface. Thus we considered the DSM an appropriate approximation of the ground elevation and used it as topographic

Figure 2: (a) Orthomosaic of the study area (1.4 km × 2 km) including the locations of 21 strip transects and (b) vegetation map.

input for modelling. The elevation difference between the river and the highest area of the ridge was about 23 m. Fine scale drainage patterns could be detected in the DSM, for example in the area of the drained thaw lake bed. The DSM showed small scale height differences between the elevated shrub patches and wet sedge depressions.

2.2.2. Vegetation map

The reference points for training and validation of the vegetation map were acquired in the field 04 – 08 July 2015 (Figure 1b). We defined eight vegetation types based on the class definition in the circumpolar Arctic vegetation map (Walker et al., 2005) which we split into sub-classes depending on species composition and canopy properties (Table 1). We performed supervised classification (ENVI, Version 5.2) as described in more detail in the appendix (Section A.1). To assess the classification accuracy, we took a random subset of the validation points with an equal amount of pixels per vegetation type (732 pixels). We computed the confusion matrix, user’s accuracy, producer’s accuracy, and the Kappa coefficient (Congalton, 1991).

2.3. Vegetation characteristics used as model input variables and parameters

The above vegetation classes were modelled in the 3D radiative transfer model DART based on vegetation type specific input variables and parameters. We use the term ‘variable’ for spatially varying model input data and the term ‘parameter’ for spatially invariant model input within a given vegetation type. The variables are green and standing dead leaf, and wood area index as well as canopy and standing dead leaf height.

For each vegetation type, we either measured the variables in the field during the peak growing season or compiled values from literature (see Section A.2 for details). We computed spatially varying green leaf area index (LAI) from NDVI following Street et al. (2007); Campioli et al. (2009):

$$\text{LAI} = a \cdot \exp(b \cdot \text{NDVI}). \quad (2)$$

Table 1: Vegetation classes from the circumpolar Arctic vegetation map (Walker et al., 2005) and sub-classes as defined for this study; the background colours indicate the colour used for this vegetation type in maps and graphs.

Class	Sub-class	Description
G4		Tussock sedge (<i>Eriophorum vaginatum</i>), dwarf shrub, moss tundra
S1		Erect dwarf shrub tundra (< 40 cm)
	S1-1	Dwarf birch (<i>Betula nana</i>) dominated
	S1-2	Lichen-rich shrub, <i>Vaccinium</i> spp. dominated
S2		Low shrub tundra (> 40 cm, <i>Salix pulchra</i>)
W2		Sedge, moss, dwarf shrub (< 40 cm) wetland
	W2-1	Wet sedge, <i>Eriophorum angustifolium</i> dominated, dense, green
	W2-2	Dry sedge, <i>Eriophorum angustifolium</i> and <i>Sphagnum</i> spp. dominated
	W2-3	Peat moss (<i>Sphagnum</i> spp.) dominated
	W2-4	Waterlogged sedge, <i>Carex</i> spp. dominated, few standing dead leaves
Water		Open water

120 We obtained a and b by fitting the exponential relationship on five quantiles
121 (0.05, 0.25, 0.50, 0.75, and 0.95) of the in situ LAI measurements and UAV-
122 derived NDVI of all pixels within the vegetation type in question (see Appendix,
123 Table A1).

124 We used linear regressions with observed LAI to spatially extrapolate wood
125 and standing dead leaf area index as well as canopy and standing dead leaf
126 height:

$$x = p \cdot \text{LAI} + q \quad (3)$$

127 where x is the extrapolated variable and p and q represent vegetation type
128 specific parameters (see Appendix, Table A1). The average and standard devi-
129 ation of all variables for each vegetation type were computed for the entire strip

transects (Table 2).

Table 2: Summary of canopy properties used as model input; for plant area index and canopy height mean $\pm$ standard deviation of all cells are provided; the species column indicates which species was used for measuring the input parameters inclination angle and optical properties.

Class	Description	Input variables					Input parameters	
		Area index		Height (cm)			Species	Back-ground
		Green leaf	Wood	Standing dead leaf	Canopy	Standing dead leaf		
G4	Tussock sedge	0.24 $\pm$ 0.10	-	-	12.2 $\pm$ 0.0	-	<i>E. vaginata</i>	S1-2
S1-1	Dwarf birch	1.08 $\pm$ 0.16	1.02 $\pm$ 0.09	-	26.6 $\pm$ 1.2	-	<i>B. nana</i>	S1-1, removal
S1-2	Lichen-rich shrub	-	-	-	-	-	-	S1-2
W2-1	Wet sedge	1.32 $\pm$ 0.33	-	1.53 $\pm$ 0.38	47.6 $\pm$ 5.4	22.1 $\pm$ 2.6	<i>E. angustifolium</i>	Water
W2-2	Dry sedge	0.55 $\pm$ 0.23	-	0.64 $\pm$ 0.26	24.4 $\pm$ 1.9	15.8 $\pm$ 1.8	<i>E. angustifolium</i>	W2-3
W2-3	Peat moss	-	-	-	-	-	-	W2-3
W2-4	Waterlogged sedge	0.46 $\pm$ 0.12	-	-	33.2 $\pm$ 2.0	-	<i>E. angustifolium</i>	Water
Water	Shallow water	-	-	-	-	-	-	Water

An example of all input variables for one strip transect is shown in Figure 3. The LAI included *Betula* and *Salix* shrubs as well as *Eriophorum* and *Carex* sedges but neither dwarf shrubs < 5 cm such as *Vaccinium* spp. and *Ledum palustre*, nor grasses nor forbs. The LAI only made up for about half of the total plant area index (PAI) with about one fourth being wood and one fourth standing dead leaves. The average canopy height was 25.3 cm in the study area.

Figure 3: Input variables for one strip transect (10 m × 25 m) as an example; (a) RGB image, (b) near infra-red image, (c) vegetation map, (d) digital surface model, (e) canopy height, (f) standing dead leaf height, (g) green leaf area index, (h) standing dead leaf area index, and (i) wood area index.

137 Input parameters were the angular distribution and the optical properties of
 138 green leaves, standing dead leaves, and wood and the background reflectance.
 139 We measured the input parameters during the peak growing season. We esti-
 140 mated the leaf angle distribution with the method by Pisek et al. (2011) and
 141 applied a correction for green and standing dead sedge leaves and wood (Ap-
 142 pendix, Figure A2). The correction was necessary because it was not possible
 143 to identify wood or sedge leaves that were perpendicular to the image plane (see
 144 Section A.3 for details).

145 Optical properties of green and standing dead leaves and wood were mea-
 146 sured in the field with a dual integrating sphere design for reflected and trans-
 147 mitted light in the spectral range from 400–950 nm (Jaz & SpectroClip, Ocean
 148 Optics). From 950–2500 nm, we used dwarf birch (*Betula nana*) optical proper-
 149 ties measured at the same field site for leaves, standing dead leaves, and wood
 150 of all species (Fieldspec4, ASD Inc., Juszak et al., 2014, Appendix, Figure A3a).

151 We measured spectral background reflectance on canopies lower than 5 cm
 152 and on shallow water 13 – 23 July 2008 (Fieldspec4, ASD Inc.). Reflectance
 153 measurements of *Vaccinium* dominated lichen-rich shrub communities (S1-2)
 154 were selected as background for tussock sedge tundra as the species composition
 155 was similar. Peat moss (W2-3) dominated below dry sedge vegetation and was
 156 thus used as background for modelling. For wet and waterlogged sedges we
 157 used measurements of shallow water as background (Table 2). Additionally, we
 158 used the background reflectance below dwarf birch (S1-1) after removing the
 159 shrubs (see Juszak et al., 2014). At least four measurements were averaged per
 160 background type (Appendix, Figure A3b).

161 2.4. Radiation budget simulations with DART

162 We simulated the radiation budget using the DART 3D radiative transfer
 163 model (Gastellu-Etchegorry et al., 1996; Grau & Gastellu-Etchegorry, 2013;
 164 Gastellu-Etchegorry et al., 2015, Version 5.6.1). The DART model tracks ra-
 165 diation fluxes within the 3D canopy including multiple reflections and mutual
 166 shading (Schneider et al., 2014). This model has been applied and validated

extensively, for example for forest canopies (Malenovsky et al., 2008; Schneider et al., 2014), crops (Duthoit et al., 2008), and tundra dwarf shrubs (Juszak et al., 2014). The DART model formed part of the radiation transfer model intercomparison (RAMI) (Pinty et al., 2001; Widlowski et al., 2015).

2.4.1. Model configuration

We parametrised the DART radiative transfer model for 21 strip transects and 9 homogeneous cover types for one point in time in the peak growing season. Vegetation was parametrised in a voxel grid filled with turbid media scatterers (Schneider et al., 2014). Three types of turbid media were simultaneously considered: green leaves, dead leaves, and wood. Each turbid medium was simulated as a vertically homogeneous column within its respective height. However, standing dead leaves of wet and dry sedges were implemented with a lower height than green leaves (Table 2). Thus, voxels at low height were dominated by standing dead leaves and higher voxels by green leaves in these two vegetation classes. For the strip transects, we used the DSM as topography while we simulated the homogeneous cover types without topography (Table 3).

We simulated shortwave radiation fluxes for MODIS bands 1 to 7 (Table 3) and derived broadband shortwave quantities (full shortwave albedo and full shortwave transmittance) from a linear combination of bands with coefficients by Liang et al. (1999). Additionally, we simulated broadband photosynthetically active radiation (PAR) to assess the fraction of PAR which is absorbed by the canopy (f_{APAR}) and to compare the results with the PAR conversion from three MODIS bands by Liang et al. (1999). In the simulations, the illumination was defined by the total irradiance and the fraction of diffuse light for each spectral band (Table 3). The spectral irradiance was defined as the reflectance of a Spectralon panel measured around solar noon on 11/07/2012 under clear sky conditions using a spectrometer (Fieldspec4, ASD Inc.). All spectrometer measurements within a MODIS full width at half maximum band width or the PAR range were averaged to obtain the irradiance within the band in question. The diffuse fraction in the PAR range was obtained from field measurements

under clear sky conditions (Delta-T Devices, BF3). In other wavebands, diffuse fractions were obtained with DART simulations of atmosphere radiative transfer for conditions at noon mid of July with a subarctic summer atmosphere. We adjusted the aerosol optical depth factor so that the simulated diffuse fraction in the PAR range matched the observations.

Table 3: General model configuration and spectral bands with respective irradiance and diffuse fraction (SKYL); the spectral bands represent the full width at half maximum (FWHM) of the MODIS instrument.

Characteristic	Value							
Mode	Flux-tracking							
x, y, z resolution (voxel grid)	5.0 cm							
Scene size								
- homogeneous cover type	1 m $\times$ 1 m							
- strip transects	10 m $\times$ 25 m							
Scene type	Repetitive							
Topography								
- homogeneous cover type	no							
- strip transects	yes							
Vegetation representation	Turbid media							
Sun position	15/07/2015, 1 hour before solar noon							
Atmosphere	Spectral SKYL (from DART)							
No. of directions	193							
Wavelengths (nm)	400–700	459–479	545–565	620–670	841–876	1230–1250	1628–1652	2105–2155
MODIS bands	-	3	4	1	2	5	6	7
Irradiance ($\text{W m}^{-2} \mu\text{m}^{-1}$)	968	1079	1044	930	636	310	154	58
Diffuse fraction (%)	19.0	25.4	13.5	13.2	7.5	3.6	2.0	1.3

202 2.4.2. Model outputs

203 We analysed three major model outputs. The first output was the short-
204 wave albedo one metre above the soil surface, which we converted from spectral
205 to shortwave albedo (Liang et al., 1999). The second output was shortwave
206 irradiance at the soil surface divided by above canopy shortwave irradiance.
207 We call this variable ‘transmittance’, which equals to ‘1 - soil shading’ (Ben-
208 ninghoff, 1952). Canopy transmittance influences soil heat flux and permafrost
209 thaw (Briggs et al., 2014). We considered the fraction of photosynthetically ac-
210 tive radiation absorbed by the canopy (f_{APAR}) as the third output. We defined
211 the canopy as vascular vegetation parametrised in the radiative transfer model.
212 Therefore, mosses, lichen and vascular plants lower than 5 cm, which we treated
213 as background, did not contribute to f_{APAR} and soil shading. Although f_{APAR}
214 is closely linked to canopy transmittance, it provides additional information as
215 it is associated with photosynthesis and thus the carbon cycle (Ruimy et al.,
216 1994; Huemmrich et al., 2010). Before analysing the model output, we removed
217 2 m borders on all sides of the strip transects to eliminate edge effects. Thus
218 the remaining strip transect size was 6 m $\times$ 21 m (120 $\times$ 420 pixels).

219 2.4.3. Selection of subsets for modelling

220 Model simulations were done with two different land cover complexities.
221 First, we simulated homogeneous land cover types without topography and sec-
222 ond, we simulated the radiation budget of 21 strip transects including hetero-
223 geneous tundra vegetation. We refer to this complex 3D simulation at the
224 landscape scale as *direct* 3D simulations. For both complexities, we used the
225 same average canopy variables and parameters (Table 2).

226 To quantify the shortwave radiation budget of heterogeneous tundra, we se-
227 lected subsets of the study area on the vegetation map (Figure 2b). We chose
228 strip transects within a single flight area (flown twice, 23 and 31 July 2014)
229 because of artefacts due to inhomogeneous illumination (Figure 2a). Due to
230 the low vegetation height of the tundra in our study area (Table 2) and the
231 small scale spatial variability of vegetation type, we selected 21 strip transects

232 of $10\text{ m} \times 25\text{ m}$ representative of the landscape scale. Each strip transect repre-
233 sented a transition between dwarf birch dominated vegetation (S1-1) and other
234 vegetation types or water (Figure 4). As low shrub tundra (S2) was restricted to
235 lake and river banks, we did not choose strip transects in this vegetation type.
236 The remaining six vegetation types and water were each dominating three strip
237 transects. Additionally, all vegetation types were represented in smaller frac-
238 tions also in the other strip transects. The patch size distribution differed among
239 the strip transects.

240 We computed explanatory variables at two different levels, for the whole
241 strip transects and for each vegetation patch. For the strip transects, we used
242 the explanatory variables (I) average PAI including green leaves, standing dead
243 leaves, and wood, (II) fractional cover of each vegetation type, and (III) mean
244 characteristic length, which we defined as mean ratio of patch area to patch
245 perimeter. We used the characteristic length as proxy for edge effects, which
246 are more important for strip transects with a small mean characteristic length.
247 The radiation budget of a single patch is influenced by its vegetation type, PAI,
248 canopy height, neighbouring vegetation, and topography. Topography influences
249 the radiation budget more at the patch scale than at the transect scale, because
250 the strip transects are mostly flat on average while mounds and tussocks influ-
251 ence local slope and exposition. We assessed the influence of local variability
252 and edge effects using the characteristic length of the single vegetation patches
253 in relation with their radiation budget.

Figure 4: Vegetation maps of 21 strip transects ($10\text{ m} \times 25\text{ m}$); the rows represent different major vegetation types sorted by the mean characteristic length of the major type with simple polygons on the left and more complex polygons on the right.

254 2.5. *Weighted averages*

255 In addition to the direct 3D radiative transfer simulations, we estimated the
256 radiation budget of each strip transect using weighted averages. The weighted
257 averages were calculated using the radiation budget for each land-cover type,
258 weighted by the fraction of the cover types within each strip transect. The
259 weighted averages were computed in two steps. In a first step, we computed
260 the 3D radiation budget of homogeneous vegetation types with DART using the
261 same mean vegetation type specific variables as for the strip transect simulations
262 in a small and repetitive scene (Table 2). DART was configured in the same
263 way as for the strip transects, but the scene was smaller and did not include
264 topography (Table 3). In a second step, we computed the average albedo,
265 transmittance, and f_{APAR} weighted by land cover type fraction for each strip
266 transect. Thus the weighted averages are an easy and fast method to estimate
267 radiation quantities, which does not take into account the spatial distribution
268 of the land cover types or any other interactions between them.

269 2.6. *Statistical analysis*

270 We estimated the importance of different strip transect characteristics on the
271 mean radiation budget using an analysis of variance (ANOVA, f-test) (R Core
272 Team, 2015, Version 3.2.3). The response variables were strip transect albedo,
273 transmittance, and f_{APAR} . The explanatory variables of each strip transect
274 were the fraction of shrub cover (S1-1), the combined fraction of water and
275 waterlogged sedges (W2-4), mean PAI, and mean patch characteristic length.
276 We did a 4-way ANOVA per response variable without taking into account
277 interactions between explanatory variables. Our model first accounted for the
278 explanatory variable with the highest correlation coefficient with the response.
279 We changed the order of the other three response variables in the model to
280 assess the robustness of the model results and possible relationships among
281 the explanatory variables. The radiation budget simulated directly with the
282 3D radiative transfer model was compared with the weighted averages using a
283 paired t-test (R Core Team, 2015, Version 3.2.3).

3. Results

3.1. Vegetation map

Betula dwarf shrubs (S1-1) and *Salix* low shrubs (S2) covered about 20% of the landscape, another 39% was covered by densely vegetated wetlands (W2-1, W2-2, W2-3) and 8% by water bodies and waterlogged sedges (W2-4). The remaining area was classified as either tussock sedge (G4) or lichen-rich dwarf shrub tundra (S1-2). The Kappa coefficient of the vegetation classification was 0.44, the overall accuracy was 50%. The confusion matrix (Table 4) indicates that tussock tundra (G4) was similar to lichen-rich shrub tundra (S1-2). Therefore, large parts of the tussock tundra in the area of the ridge were misclassified as S1-2 (Figure 2b). Furthermore, dry sedges (W2-2) and peat moss tundra (W2-3) resembled each other in appearance and (shallow) water was often classified as waterlogged sedges (W2-4).

Table 4: Confusion matrix of the vegetation map calculated from a random subset of the validation data with an equal number of validation pixels per class.

		Map									Producer's
		G4	S1-1	S1-2	S2	W2-1	W2-2	W2-3	W2-4	Water	accuracy (%)
Ground truth	G4	160	41	468	0	47	6	10	0	0	22
	S1-1	133	297	240	0	43	15	0	4	0	41
	S1-2	54	43	483	0	99	37	16	0	0	66
	S2	1	27	2	652	19	2	0	28	1	89
	W2-1	18	104	14	0	338	188	49	21	0	46
	W2-2	18	0	162	0	17	407	128	0	0	56
	W2-3	0	0	78	0	0	424	230	0	0	31
	W2-4	19	27	0	0	10	3	0	654	19	89
	Water	0	0	4	0	15	1	0	629	83	11
	User's accuracy (%)	40	55	33	100	57	38	53	49	81	Overall 50%

297 *3.2. Small scale spatial variation in albedo, transmittance, and f_{APAR}*

298 At the patch scale, variations in PAI, canopy height, topography, and neigh-
 299 bouring vegetation type led to considerable variation in albedo, transmittance,
 300 and f_{APAR} among cells of the same type (Figure 5). Albedo was on average
 301 lower in the direct 3D simulation as compared to the simulation of single vege-
 302 tation types (Figure 5a). However, this was not the case for the vegetation types
 303 with relatively low albedo (dwarf birch (S1-1), waterlogged sedges (W2-4)) and
 304 water. While the transmittance of highly transmitting vegetation types was
 305 reduced due to edge effects, it was increased in denser vegetation (Figure 5b).
 306 Edge effects strongly increased f_{APAR} , especially for vegetation types with dense
 307 canopies that absorb much radiation anyway (Figure 5c).

Figure 5: Modelled radiation budget components for all cells of all strip transects, (a) albedo, (b) transmittance, and (c) fraction of PAR absorbed by the canopy (f_{APAR}); the boxes indicate the 0.25, 0.5, and 0.75 quantiles, the whiskers are the 0.02 and 0.98 quantiles; red dots indicate the modelling results using homogeneous cover types.

308 At the patch scale, albedo was not related to transmittance ($R = 0.00$) or
 309 f_{APAR} ($R = -0.05$, results not shown). While transmittance and f_{APAR} were
 310 highly negatively correlated at the landscape scale, the negative correlation
 311 between them was reduced to $R = -0.43$ at the patch scale. Patch f_{APAR} was
 312 highly positively correlated with PAI ($R = 0.96$). However, the correlation

313 between patch transmittance and PAI was less strongly negative ($R = -0.57$)
314 than at the landscape scale.

315 The larger the patch area was in relation to its perimeter, the smaller was the
316 influence of bordering vegetation, LAI variation, and topography on the patch
317 average albedo, transmittance, and f_{APAR} (Figure 6). The characteristic length
318 at which a radiation budget component is independent of edge effects can be es-
319 timated from the convergence of an upper and a lower hull curve. Depending on
320 the vegetation type, variation in patch albedo and f_{APAR} was small for patches
321 with characteristic lengths above 0.5 m on average, while patch transmittance
322 was variable until 0.7 m. However, the variability among vegetation types was
323 large (Figure 6). Thus, the characteristic length scale depended on the radiation
324 quantity in question and on vegetation type. In terms of patch area, converging
325 hull functions indicated small edge effects for patches of 7 m² or more for albedo
326 and f_{APAR} and 10 m² area for transmittance, respectively. Although only 2%
327 of the patches were larger than 7 m², such large patches represented 65% of the
328 total area in the modelled strip transects.

Figure 6: Mean patch (a,b) albedo, (c,d) transmittance, and (e) fraction of PAR absorbed by the canopy (f_{APAR}) as a function of characteristic length (patch area to perimeter ratio) for wet sedges (W2-1) and lichen-rich shrubs (S1-2); one point per patch; the green lines represent exponential curves fitted to the outer points as hull curves and converging at the indicated point (threshold = 0.001).

3.3. Drivers of the radiation budget at the landscape scale

We compared modelled radiation budgets of different strip transects to estimate the importance of different landscape elements. Strip transect albedo was strongly negatively related with water fractional cover (including waterlogged sedges (W2-4), Pearson correlation $R = -0.91$, Figure 7b). Shrub cover significantly affected the albedo when the statistical model accounted for the water effect first (Table 5). Higher shrub cover was associated with lower albedo values. If all data were taken into account, the relationship between shrub cover and albedo was concealed by the strong influence of water cover ($R = 0.19$, Figure 7a). However, excluding the strip transects with more than 20% water cover (coloured red in Figure 7a), the relationship was more clear ($R = -0.91$). After accounting for water cover, neither PAI nor the average patch characteristic length were significantly related to strip transect albedo, even if the model did not account for shrub cover first. The correlation between each pair of explanatory variables was less than $|R| = 0.55$. Landscape albedo was only weakly related with transmittance ($R = -0.40$) and f_{APAR} ($R = 0.38$).

Table 5: The effect of strip transect characteristics on simulated albedo and transmittance expressed as ANOVA results; water cover includes waterlogged sedges (W2-4). Each characteristic takes one of 20 degrees of freedom (df); please note the different variable order; *** $P \leq 0.001$; ** $P \leq 0.01$; ns: not significant.

	df	F	P
Albedo			
Water cover	1	277.90	***
Shrub cover	1	38.15	***
Plant area index	1	0.01	ns
Characteristic length	1	0.89	ns
Transmittance			
Plant area index	1	617.38	***
Shrub cover	1	9.71	**
Water cover	1	2.13	ns
Characteristic length	1	0.91	ns

345 Modelled strip transect f_{APAR} and shortwave transmittance were strongly
 346 negatively correlated ($R = -0.99$). PAI strongly reduced canopy transmittance
 347 ($R = -0.98$, Figure 7g) and increased f_{APAR} ($R = 0.98$, Figure 7k). The
 348 second most important driver of both variables was shrub cover ($R = -0.34$
 349 and $R = 0.28$ for transmittance and f_{APAR} , respectively, Figure 7e, i), which
 350 significantly influenced transmittance but not f_{APAR} when PAI was accounted
 351 for (Table 5). Water cover and average patch characteristic length did not
 352 significantly affect transmittance and f_{APAR} .

Figure 7: Modelled DART strip transect (a–d) albedo, (e–h) transmittance, and (i–l) fraction of PAR absorbed by the canopy (f_{APAR}) as a function of (a, e, i) shrub fractional cover (S1-1), (b, f, j) combined fractional cover of water and waterlogged sedges (W2-4), (c, g, k) plant area index, and (d, h, l) average characteristic length; regression lines are included for data with $|R| > 0.5$; in (a) and (b) strip transects with water cover above 20% are highlighted in red.

3.4. Influence of spatial distribution and interaction of land cover types

We analysed results of direct 3D radiative transfer simulations as compared to a weighted average of the radiation budget with given fractional cover per vegetation type and average type properties. While the direct 3D simulations included the spatial distribution and interactions between land cover types, such effects were not accounted for in the weighted average approach. Using the 3D model, strip transect albedo values were significantly lower than the weighted average ($p < 0.001$, Figure 8a). On average, the albedo reduction when using the direct 3D approach was 0.004, corresponding to 3% of the average albedo, and the maximum absolute difference was 0.01.

Figure 8: (a) Albedo, (b) transmittance, and (c) fraction of PAR absorbed by the canopy (f_{APAR}) modelled for each strip transect with DART and computed with weighted averages of the radiation quantities of land cover types occurring in the strip transect; each point represents one strip transect, the mean of all strip transects is the red square, the line represents a 1:1 relationship.

Canopy transmittance was on average 3% higher in the direct 3D model results as compared to the weighted average (Figure 8b). However, this was not the case for all strip transects. For single strip transects, the absolute transmittance difference was between -0.06 and 0.09. The 3D model results were significantly different from the weighted averages ($p < 0.05$). Transmittance modelled with the 3D approach was generally higher than with the weighted

average for strip transects with low PAI and low shrub cover (results not shown).

As described above, f_{APAR} was strongly negatively related with transmittance. Consequently, f_{APAR} was slightly reduced when using the direct 3D radiative transfer model as compared to the weighted average (Figure 8c). The absolute difference varied between -0.10 and 0.06, on average 3% of the total f_{APAR} . However, the difference between f_{APAR} modelled with DART and f_{APAR} calculated from weighted averages was not significant ($p > 0.1$).

4. Discussion

4.1. Vegetation map and canopy characteristics

Our vegetation map had a Kappa coefficient of 0.44 with the original nine land cover classes. The achieved accuracy was lower than in other studies classifying tundra vegetation using orthomosaics (Lantz et al., 2010; Muster et al., 2012) or high resolution satellite imagery (Atkinson & Treitz, 2012; Virtanen & Ek, 2014; Siewert et al., 2015). The lower accuracies of our classification were mostly due to similar reflectance properties of several classes in the four spectral bands which were available.

The vegetation classification accuracy and the 3D modelling (Figure 5a) indicate that several of the pre-defined vegetation classes have similar reflectance properties. This functional similarity is in contrast to the differences among vegetation types in terms of species composition and canopy properties such as height or PAI. As these canopy properties translate into specific radiation transmittance and absorptance characteristics, they play an important part in the radiation budget at the landscape scale and are thus included in the 3D radiative transfer modelling. Given that several structurally different classes had similar reflectance properties, more information is needed to reliably estimate tundra vegetation distribution and structural complexity. One approach is to use more spectral bands for vegetation mapping. Several studies show that hyperspectral data enable estimates of canopy composition (Antonarakis et al., 2014; Bratsch et al., 2016) and structure (Asner, 1998). At the local scale,

the use of LiDAR to estimate canopy structural properties could be considered (Antonarakis et al., 2014; Schneider et al., 2014).

Model input variables and parameters were subject to uncertainties based on the field measurements and the spatial extrapolation. Despite our correction, the Ocean Optics leaf optical properties measurements were affected by the small size of the two integrating spheres (Section A.3). Furthermore, we used optical properties of a single species for all species in the three near-infrared wavebands (Figure A3). However, pre-experimental tests with the DART model showed that leaf optical properties were generally less important than other factors, in particular the leaf angle distribution, PAI, and leaf to wood ratio. Thus, we expect that other differences between the vegetation types, such as the LAI, are more important controls of the (broadband) radiation budget.

We used field observations of spatial LAI variability within vegetation classes and an NDVI map to extrapolate LAI over the whole study region. Several studies have shown strong relationships between NDVI and LAI in Arctic tundra (Shippert et al., 1995; Riedel et al., 2005; Campioli et al., 2009), especially if each vegetation type was treated separately (Street et al., 2007). Williams et al. (2001) estimated a mean error of prediction of around 16% when extrapolating tundra LAI based on NDVI. However, we were not able to validate the spatial LAI distribution due to a lack of observations in the same time period as the orthophotos. All other input variables, namely wood area index, standing dead leaf area index, canopy height, and standing dead leaf height, were extrapolated based on linear relationships with LAI. We are not aware of any other study which spatially extrapolated these canopy characteristics in a tundra ecosystem. Given the uncertainties in the field measurements, the NDVI, and the vegetation map, the spatial distribution of LAI and the other canopy variables is uncertain. However, we ensured that the range, mean values, and variability were well-represented in the modelling. While the uncertainty of input variables limits our ability to predict the radiation budget at specific locations, it still allows us to investigate the importance of different drivers for the radiation budget at local and landscape scale as well as the role of the spatial vegetation distribution.

429 We found that green leaves only contributed about one half to the total
 430 PAI. The importance of wood for Arctic shrub canopies has been highlighted
 431 by Thompson et al. (2004) who measured larger wood area indices than leaf
 432 area indices in tundra shrubs. Juszak et al. (2014) emphasised the role of wood
 433 for the radiation absorption of tundra dwarf shrubs. The large area of standing
 434 dead sedge leaves found at our study site is relevant for the radiation budget,
 435 as dead leaves can contribute significantly to canopy reflectance (Chapin et al.,
 436 2000) and shading (Caldwell et al., 1974). We included all vegetation above 5 cm
 437 height (cell size) as turbid media in the radiative transfer model, while lower
 438 vegetation and mosses were included as background and thus did not contribute
 439 to f_{APAR} and soil shading. Therefore, we likely underestimate f_{APAR} at most
 440 vegetation types as moss and lichen cover is very common. However, understory
 441 light extinction is not commonly included in the f_{APAR} definition (Huemmrich
 442 et al., 2010). As mosses may account for a significant part of tundra absorbed
 443 radiation and gross ecosystem production (Huemmrich et al., 2010), further
 444 research is required on how to accurately represent mosses in radiation transfer
 445 and land surface models.

446 4.2. Small scale spatial variation in albedo, transmittance, and f_{APAR}

447 In agreement with Oliphant et al. (2006), we found that at the 5 cm pixel and
 448 the patch scale albedo, transmittance, and f_{APAR} can be substantially different
 449 from mean values of the respective vegetation types (Figure 5). We found that
 450 the scale of the variability in radiation budget components is much smaller
 451 than what we can observe from satellites, posing challenges for driving models
 452 from conventional remote sensing. The suitability of satellite observations for
 453 shortwave radiation budget studies is also limited by the low correlation between
 454 albedo and transmittance or f_{APAR} , in particular at the local scale. This weak
 455 relationship between the more easily observable albedo and transmittance is
 456 relevant for permafrost research. Shading (i.e. inverse of transmittance) by
 457 shrubs has been found to influence permafrost thaw locally (Briggs et al., 2014)
 458 through the amount of solar energy at the soil surfaces. Canopy transmittance

also affects soil surface temperature (Smith, 1975) and thus longwave radiation and sensible heat fluxes (Ni-Meister & Gao, 2011). Our results concerning transmittance indicate, that the shortwave radiation budget at the soil surface is highly variable, strongly related to plant area, and only weakly related with canopy reflectance.

Several studies have shown that the heterogeneity of the light regime within the canopy affects ecosystem processes. In particular, f_{APAR} and its variability affect the canopy energy, water, and carbon budget of tundra ecosystems (Caldwell et al., 1974; Huemmrich et al., 2010; Tagesson et al., 2012; Huemmrich et al., 2013). For example, evapotranspiration is sensitive to spatial heterogeneity of radiation within the canopy (Song et al., 2009; He et al., 2014). He et al. (2014) simulated lower water stress in a forest with a model that included 3D radiative fluxes and canopy structure as compared to a homogeneous case due to the light limited vegetation in shaded areas. Furthermore, the carbon budget is influenced by spatial heterogeneity of radiation. Light Use Efficiency not only depends strongly on vegetation type and related hydrological conditions (Huemmrich et al., 2013), but also on light heterogeneity caused by self-shading (Huemmrich et al., 2010; Williams et al., 2014). Consequently, Sprintsin et al. (2012) showed strong effects of the radiation scheme on modelled gross primary production. Thus, the high local variability of the shortwave radiation budget is relevant for a number of land–climate feedbacks.

Edge effects extended to larger patches for canopy transmittance as compared to albedo and f_{APAR} . This may be a consequence of the different heights being relevant for each radiation process. While albedo and f_{APAR} are determined by the mean scattering centre of the canopy, transmittance is defined below canopy. Thus lateral shading may affect the radiation at soil level further away from the tall elements. The characteristic length scale differed between vegetation types, which indicates complex interaction between the spatial vegetation distribution and the radiation budget.

The edge effects and length scales found in this study likely depend on the irradiance conditions. Our work was conducted for a unique illumination con-

490 figuration. While we simulated clear-sky conditions, a higher fraction of diffuse
 491 light generally lowers the albedo (Eugster et al., 2000), an effect observed more
 492 strongly in wet sedge tundra as compared to dwarf shrub tundra (Juszak et al.,
 493 2016). Cloud cover also increases wet sedge transmittance more strongly than
 494 dwarf shrub transmittance (Juszak et al., 2016). Therefore changes in irradi-
 495 ance conditions will likely have different effects on the spatial variability of the
 496 radiation budget, depending on vegetation type. Furthermore, the time within
 497 the growing season influences sun angles and canopy and background properties
 498 and thus the radiation budget. Field measurements generally show an increase
 499 in tundra (and shrub specifically) albedo in the course of the summer (Lafleur
 500 et al., 1997; Lloyd et al., 2001). This seasonal albedo variation is influenced
 501 by vegetation development, structure, and background properties, and there-
 502 fore depends on vegetation type (Juszak et al., 2016). As our study focusses on
 503 a single time-point, this temporal evolution is not included. Further research
 504 and temporally-resolved input and validation data are needed to quantify the
 505 seasonal cycle of all radiation budget components for each vegetation type.

506 *4.3. Drivers of the radiation budget at the landscape scale*

507 We found that the fraction of standing water was by far the most important
 508 driver of landscape albedo (Table 5). Thus, currently observed changes in water
 509 cover (Smith et al., 2005; Carroll et al., 2011; Lin et al., 2012) will likely affect
 510 the tundra energy budget strongly. The importance of standing water for spatial
 511 and temporal tundra albedo variations has been highlighted in several studies
 512 (Lafleur et al., 1997; Gamon et al., 2012) and has been acknowledged by defining
 513 lake area as essential climate variable (Bojinski et al., 2014). However, we
 514 consider water bodies of very small spatial extent, typically covering only a few
 515 square metres. Arctic tundra often comprises such small scale water bodies
 516 that cannot be detected based on medium resolution satellite imagery such as
 517 Landsat-7 (Muster et al., 2012; Virtanen & Ek, 2014). In polygonal tundra,
 518 this can lead to a 35% lower estimate of water surface area and translate into
 519 high uncertainties in energy fluxes, especially evapotranspiration (Muster et al.,

2012). While small water bodies are included in the satellite albedo estimates, they are neglected in medium and large scale land cover maps (such as Gould et al., 2003; Walker et al., 2005). As our modelling results highlighted that the fraction of standing water was strongly influencing tundra albedo, simplified land cover maps and underestimation of the water surface area can affect large scale modelling results, especially in wetlands. Our results showed that wetlands with high cover of peat mosses or dry sedges had the highest albedo within the tundra landscape at our site, while water bodies and waterlogged sedges had the lowest albedo (Figure 5). Land cover and vegetation type in these lowlands are highly dependent on the hydrological conditions. Even under predicted permafrost thaw, the hydrological implications are highly uncertain (Walvoord & Kurylyk, 2016).

The second significant driver of landscape albedo was shrub cover, which was more important than PAI. The importance of shrub cover is well known, as shrub expansion is associated with a positive feedback to global warming (Chapin et al., 2005; Blok et al., 2011b; Lawrence & Swenson, 2011). However, at the larger scales shrub cover and PAI are linked (Thompson et al., 2004; Beringer et al., 2005) and their relative importance for growing season albedo cannot easily be disentangled in modelling studies that increase both values simultaneously (such as in Lawrence & Swenson, 2011; Bonfils et al., 2012).

PAI explained almost all variability in transmittance and f_{APAR} among the strip transects. The importance of PAI for f_{APAR} (Myneni et al., 1997; Asner et al., 1998; Shabanov et al., 2000) and transmittance has been highlighted in other studies (Flerchinger et al., 2009; Juszak et al., 2014). At the landscape scale, edge effects did not significantly influence the radiative budget (Table 5).

Albedo was only weakly related to transmittance and f_{APAR} at the landscape scale and even less at the local scale. An accurate estimate of PAI is important for transmittance estimates and thus for assessing the energy budget at the soil surface.

549 4.4. Influence of spatial distribution and interaction of land cover types

550 At the landscape scale, our direct 3D model results were very similar to
551 the results of the weighted averages and the difference of 3% is likely within
552 the model uncertainty (Figure 8). However, the higher albedo estimate using
553 simple weighted averages in a complex landscape is consistent with studies of
554 the forest and the global radiation budget (Rowe, 1993; Yuan et al., 2014). The
555 small effect may be due to low canopy height in our simulations (Dickinson et al.,
556 2008). The bias in albedo resulting from the direct 3D versus weighted average
557 modelling approaches needs further investigation, such as a comparison to field
558 measurements with fully characterized uncertainties. This detailed validation
559 will help to identify the appropriate model complexity and grain size depending
560 on the scale of interest.

561 Simulations with the direct 3D approach on average increased canopy trans-
562 mittance by only 3% as compared to the simple approach. The lower trans-
563 mittance estimate by simple models is consistent with Knyazikhin et al. (1997),
564 who found that 1D simulations overestimate the decline of solar radiation in a
565 canopy with depth.

566 In line with albedo and transmittance, the f_{APAR} results revealed little differ-
567 ences between the direct 3D model and a weighted average, while other studies
568 report significant underestimation of f_{APAR} using 1D models (Kobayashi et al.,
569 2014; Loew et al., 2014; Yuan et al., 2014). Kobayashi et al. (2014) show that
570 1D simulations in boreal forests underestimate the fraction of light absorbed by
571 the canopy (f_{APAR}) by about 50%. As for albedo and transmittance, the small
572 differences between the direct 3D model and weighted averages that we found is
573 most likely due to the short-statured vegetation at our study site. The tundra
574 canopy in our model is less than 80 cm tall. Additionally, we explicitly include
575 canopy gaps as independent vegetation types in both simulations, direct 3D and
576 weighted averages.

577 Overall, we find that tundra albedo, transmittance, and f_{APAR} are less sensi-
578 tive to the spatial distribution and interaction of land cover types (as indicated
579 by different model complexities) than to land cover type and canopy charac-

580 teristics at the landscape scale. As the effect of different model complexities is
 581 much smaller than the variability among the strip transects, we suggest that
 582 more effort should be made to estimate water cover, shrub cover, and PAI than
 583 toward more physically based modelling at the landscape scale. However, the
 584 3D model results depend on the model parametrisation and may differ more
 585 strongly from weighted averages when plants are simulated as objects instead of
 586 turbid media, or when the turbid media include vertical gradients. Furthermore,
 587 the influence of model complexity on the results strongly depends on the scale
 588 of interest. While direct 3D radiative transfer modelling may not be needed
 589 for radiative fluxes at the landscape scale, we find that at the small scale the
 590 heterogeneity of the radiation budget can be substantial. Thus, 3D modelling
 591 may be required in case of non-linear feedbacks.

592 5. Conclusions

593 Our modelling results show that the surface area of water bodies and water-
 594 logged sedges is the most important driver of tundra albedo in summer, even at
 595 small scales where current Earth observation satellites will not be able to assess
 596 the process of dynamic changes in water body size due to their spatial resolu-
 597 tion. Shrub cover is the second most important control and explains more of the
 598 spatial albedo variations than PAI. Canopy transmittance and absorbed PAR
 599 are almost entirely controlled by PAI at the landscape scale. At the landscape
 600 scale, the effect of model complexities with and without spatial heterogeneity
 601 is much smaller than the variability depending on the cover type and canopy
 602 plant area. Therefore, accurate validation data would be needed to determine
 603 the most suitable model complexity. However, using the direct 3D radiative
 604 transfer model we found considerable variability of albedo, transmittance, and
 605 canopy absorbed PAR at the scale of a few centimetres, which cannot be easily
 606 observed from satellite. As local radiation variability influences photosynthesis
 607 and evapotranspiration, it should be considered in modelling studies of the tun-
 608 dra energy or water budget. If coarse satellite data are the major model input,

the local radiation variability and associated feedbacks should be parametrised using sub-grid scale models. We recommend assessing this local scale radiation variability at large scales as well, to determine if water cover and PAI influence albedo in a similar fashion. Building on our results on the shortwave radiation budget, an analysis of non-linear feedback mechanisms between radiation, evapotranspiration, and photosynthesis is needed to draw conclusions on changes of the Arctic energy budget. Our results highlight the importance of small water bodies, shrub cover, and the PAI, which does not only include green leaves but also standing dead leaves and wood. As very little data on standing dead leaves and wood are currently available, we propose more field measurements of these components to allow for more detailed parametrisations in land surface models. Furthermore, we propose to extend the analysis from spatial to spatio-temporal radiation variability. In this way, vegetation, irradiance, and snow dynamics could be included.

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Appendix. Detailed description of the methods

A.1. Vegetation map

Vegetation reference points. To train and validate the vegetation map, we
visually selected 187 points in the study area which were clearly within one
vegetation type and estimated the radius for which each point was representa-
tive (point size in Figure 1b). As we were using a hand-held GPS with ± 3 m
accuracy, we needed to validate the point locations in comparison with the or-
thomosaic. We removed points that lay outside the vegetation type in question
(22 points) and shifted points which lay on the border of a vegetation patch
(32 points). For 40 points, we reduced the size of the estimated radius because
they intersected with other vegetation types on the orthomosaic. Half of the

1023 points were used for training of the vegetation classifier, the other half for val-
1024 idating the final map. We chose additional water training points based on the
1025 orthomosaic as they were difficult to access in the field.

1026 **Classification.** We classified the vegetation based on the four image bands
1027 (RGB and NIR) as well as hue and saturation, which we calculated from the
1028 RGB image. We additionally used the entropy of the hue image as seventh input
1029 channel. For more robust mapping results, we reduced the image resolution
1030 to 15 cm. The supervised classification was done with a maximum likelihood
1031 classifier (ENVI, Version 5.2). Based on field observations, we restricted low
1032 shrubs (S2) to areas close to rivers and floodplains in a post-processing step.
1033 In order to reduce the number of patches smaller than 4 pixels, we sequentially
1034 assigned those pixels to classes with a similar likelihood if that increased the
1035 patch size.

1036 **Classification accuracy.** For comparison with other tundra maps, we ag-
1037 gregated the nine original classes to four classes as defined by the circumpolar
1038 Arctic vegetation map (Walker et al., 2005). These are tussock- sedge, dwarf
1039 shrub, moss tundra (G4), erect dwarf shrub tundra (S1-1, S1-2), low shrub tun-
1040 dra (S2), and sedge, moss, dwarf shrub wetland (W2-1, W2-2, W2-3, W2-4, and
1041 shallow water). For these four classes we obtained an overall accuracy of 65%
1042 and a Kappa coefficient of 0.53 using an equal amount of validation pixels per
1043 class. The best accuracy was achieved by including the lichen-rich shrub tundra
1044 (S1-2) in the tussock tundra class (G4). The map with four classes aggregated
1045 in this way had an overall accuracy of 74% and a Kappa coefficient of 0.65.

1046 The classification accuracy was lower than in other studies due to three
1047 main reasons. First, we were not able to collect water reference points in deep
1048 ponds or the river. We added additional points representing deep water to the
1049 training data based on visual inspection of the orthomosaic. Thus, the classifier
1050 was trained on points which included deep water bodies in the water class.
1051 Shallow water was mostly classified as waterlogged sedges (W2-4). As we did
1052 not add additional points to the validation data, the classification accuracy of

1053 water was only computed for shallow ponds which we were able to access in the
1054 field. Given the typically low vegetation density of waterlogged sedges and the
1055 strong background effects in both, waterlogged sedges and shallow water, this
1056 classification imprecision is not problematic and mainly due to suboptimal field
1057 sampling of reference points.

1058 Second, the sub-classes dry sedges (W2-2) and peat moss (W2-3) were often
1059 misclassified because they appeared very similar on the orthomosaic. While
1060 peat moss occurred in both classes, the classes could be distinguished in the
1061 field based on the cover of sedges. However, dry sedges have a high cover of
1062 light-coloured standing dead leaves, which have a similar reflectance as peat
1063 moss areas, at least in the four spectral bands covered by the orthomosaic. The
1064 albedo of W2-2 and W2-3 was almost identical (Figure 5). These two sub-classes
1065 were mainly distinguished for modelling canopy transmittance and absorptance
1066 and should be merged in a vegetation map.

1067 Third and most importantly, erect dwarf shrub tundra (S1-1 and S1-2) can-
1068 not be clearly distinguished from tussock sedge tundra (G4) by the classifier.
1069 This difficulty has been pointed out by Siewert et al. (2015) in a classification
1070 of a GeoEye-1 satellite image of the same field site. Several other studies do
1071 not distinguish, or do not have, tussock tundra (Lantz et al., 2010; Atkinson &
1072 Treitz, 2012; Muster et al., 2012; Virtanen & Ek, 2014). The similarity between
1073 lichen-rich shrubs and tussock tundra is a consequence of the similarity of the
1074 two classes in terms of species composition. The major difference is the pres-
1075 ence of *Eriophorum vaginatum*, a tussock forming sedge. However, this sedge
1076 has a low leaf area and canopy height at the site (Table 2) and thus does not
1077 dominate the surface reflectance. As we modelled very similar albedo values for
1078 S1-2 and G4, landscape scale albedo is insensitive to misclassification between
1079 these classes.

1080 The classification accuracy could potentially be improved by including the
1081 NDVI. However, we used the NDVI to spatially extrapolate model input vari-
1082 ables and thus avoided circular reasoning by not including NDVI in the vegeta-
1083 tion classification. A second potential classification input is microtopography.

1084 However, we used topography as input for the radiative transfer model and
1085 thus wanted to keep the vegetation classification independent of the topogra-
1086 phy. Spectrally similar vegetation classes could also have been avoided using an
1087 unsupervised classification approach (Atkinson & Treitz, 2012). However, un-
1088 supervised classification of tundra areas does not necessarily yield homogeneous
1089 vegetation classes (Schneider et al., 2009). Furthermore, we collected input data
1090 for the radiative transfer model for specific vegetation classes in the field and
1091 thus were restricted to those for the modelling.

1092 *A.2. Input variables for radiative transfer modelling*

1093 ***Plant area index.*** We used different methods to measure green leaf area index
1094 (LAI) for shrubs and graminoids in the field in the peak growing seasons 2013
1095 and 2014. *Betula nana* (S1-1) projected LAI and wood area index were measured
1096 non-destructively using 1 m×1 m point quadrat grids where we vertically lowered
1097 a needle at 81 points and recorded all contacts with leaves or wood (Juszk
1098 et al., 2016). We collected in total 25 measurements distributed over 10 plots
1099 within two growing seasons. We computed LAI by dividing projected LAI by
1100 the average point quadrat efficiency. The point quadrat efficiency was estimated
1101 in two destructive harvests to be 0.78 for *B. nana* leaves and 0.76 for *B. nana*
1102 wood. In case of LAI, this estimate contains the total one-sided LAI, while the
1103 wood area index is a projection of the cylindrical elements, approximately the
1104 product of branch diameter and length.

1105 For estimating *Eriophorum angustifolium* (W2-1 and W2-2) LAI, we used an
1106 allometric approach, which involved counting leaves and destructively measuring
1107 single leaf areas (Juszk et al., 2016). For sub-class W2-1, we measured canopy
1108 height and counted all tillers and the number of green leaves per tiller on 16
1109 squares of 100 cm² on 1 m². We collected in total 30 measurements distributed
1110 over 11 plots within two growing seasons. For sub-class W2-2, we measured
1111 canopy height, counted tillers and leaves on four plots of 50 cm × 50 cm. We
1112 combined the information of both *E. angustifolium* sub-classes with destruc-
1113 tively measured leaf sizes. We measured the total standing dead leaf area of *E.*

1114 *angustifolium* on three destructive plots of wet sedge tundra (W2-1) by weighing
1115 all standing dead leaves and scanning a subset.

1116 *Eriophorum vaginatum* (G4) LAI was estimated on seven plots of 50 cm $\times$
1117 50 cm. We counted the number of leaves per plot and multiplied it by the
1118 average area of single leaves that was obtained from scanning.

1119 We extrapolated the LAI spatially using the NDVI and an exponential func-
1120 tion (Equation 2). To avoid unrealistically large LAI values, we reduced all LAI
1121 which were more than 1.5 times higher than the maximum observation to the
1122 maximum observed LAI. The parameters a and b are shown in Table A1 and
1123 the statistics of the modelled LAI per vegetation type in the strip transects in
1124 Table 2. We used literature values of LAI for low shrub tundra (S2) and wa-
1125 terlogged sedge tundra (W2-4). For low shrub tundra we took the minimum
1126 (LAI=0.77) and maximum (LAI=1.95) values from Imnavait creek water tracks,
1127 Alaska by Williams et al. (2006) and fitted them to the 0.05 and 0.95 quantiles
1128 of the NDVI data. The literature LAI values were consistent with other sources
1129 (Beringer et al., 2005). For *Carex* spp. dominated waterlogged sedge tundra we
1130 used LAI=0.4 (*Carex* spp. dominated wetland near Toolik, Alaska, Shaver &
1131 Chapin (1991); McFadden et al. (2003)) as median and took the maximum value
1132 of LAI=0.65 (wet sedges without shrubs, S3, Imnavait creek, Alaska, Williams
1133 et al. (2006)) to fit to the 0.95 quantile.

1134 We used linear regressions with observed LAI to spatially extrapolate the
1135 other input variables (Equation 3, Table A1). Due to the lack of observations
1136 for low shrub tundra wood area index, we used the same parameters that we
1137 obtained from the fit of dwarf birch leaf and wood area index (Table A1). We
1138 estimated standing dead leaf area and green leaf area index destructively at
1139 three plots of wet sedges (*E. angustifolium*, W2-1). Due to the limited number
1140 of observations, we forced the regression through zero assuming that standing
1141 dead leaves are always associated with plants which also have green leaves. We
1142 used the same parameters also for dry sedges (*E. angustifolium*, W2-2).

Table A1: Parameters a and b for computing LAI from NDVI with an exponential equation (Equation 2) and parameters p and q for computing other variables from LAI with a linear equation (Equation 3) for each vegetation type; canopy and standing dead leaf height in mm.

Variable \ Type		G4	S1-1	S2	W2-1	W2-2	W2-4
LAI	a	0.00002976	0.02618681	0.05929370	0.01425009	0.00202313	0.01523543
	b	12.6308	4.8927	4.4051	6.1931	8.8501	4.7804
Wood area index	p	0	0.536	0.536	0	0	0
	q	0	0.439	0.439	0	0	0
Standing dead leaf area index	p	0	0	0	1.16	1.16	0
	q	0	0	0	0	0	0
Canopy height	p	0	7.21	80	16.7	8.51	16.7
	q	12.2	18.8	40	25.5	19.7	25.5
Standing dead leaf height	p	0	0	0	8.13	8.13	0
	q	0	0	0	11.3	11.3	0

1143 *Canopy and standing dead leaf height.* We used two different approaches
1144 to measure canopy height in the growing seasons 2013 and 2014. For dwarf birch
1145 (*B. nana*, S1-1) and wet sedges (*E. angustifolium*, W2-1) we measured canopy
1146 height at 25 points of a 1 m $\times$ 1 m point quadrat grid at the same time and plots
1147 as our LAI estimate (Juszak et al., 2016). At the *E. angustifolium* plots, we
1148 also measured standing dead leaf height above the water or wet litter surface
1149 at the same points as canopy height. On the other hand, we measured canopy
1150 height of single individuals on six tussock sedge plots (*E. vaginatum*, G4) and
1151 five dry sedge plots (*E. angustifolium*, W2-2).

1152 We extrapolated canopy height spatially for each type using a linear regres-
1153 sion between canopy height and LAI measured at the same plots at the same
1154 time (Equation 3). For tussock tundra, the linear fit showed a negative rela-
1155 tionship between LAI and canopy height for the six observations. Instead of a
1156 negative slope, we used a constant canopy height independent of the leaf area.
1157 For low shrub tundra we adjusted the parameters p and q in a way that the final
1158 canopy height varied between 1 and 2 m (Table 2), a range that we observed
1159 in the field. We used the parameters of *E. angustifolium* dominated wet sedge

1160 tundra (W2-1) also for *Carex* ssp. dominated waterlogged sedge tundra (W2-4,
 1161 Table A1). We only observed a layer of standing dead leaves below *E. angus-*
 1162 *tifolium*, in the vegetation types W2-1 and W2-2. Standing dead leaf height
 1163 was related to LAI using the same parameters for both types although our field
 1164 measurements covered only type W2-1.

1165 A.3. Input parameters for radiative transfer modelling

1166 **Leaf and wood angle distribution.** We measured the leaf angle distribution
 1167 in three different ways depending on species and organ. For *B. nana* leaves, we
 1168 used the method by Pisek et al. (2011). This method employs carefully levelled
 1169 photography of the vegetation taken from all cardinal directions. In each image,
 1170 we identified leaves which were perpendicular to the image plane. We marked
 1171 these leaves in the image and calculated the leaf inclination angle (Leaf normal
 1172 – nadir, Figure A1a). In total, we measured 1294 *B. nana* leaves. We fitted a
 1173 beta function to the data to reduce the scatter (Figure A2a). Beta functions
 1174 are commonly used for leaf inclination angle distributions (e.g. Goel & Strebel,
 1175 1984; Strebel et al., 1985; Wang et al., 2007).

Figure A1: Sample pictures used for measuring leaf angle distribution of (a) *B. nana* and (b) *E. angustifolium*; red numbers indicate the leaf inclination angle of a leaf or leaf segment.

1176 We had to modify the method by Pisek et al. (2011) for *B. nana* wood and *E.*
 1177 *angustifolium* green and standing dead leaves as it was not possible to identify

1178 cylindrical or triangular objects perpendicular to the image plane. In this case,
 1179 we marked all segments of green leaves, standing dead leaves, and wood that
 1180 were visible on the images, even the segments pointing towards or away from
 1181 the camera, in total more than 8000 per organ (Figure A1b). For leaves that
 1182 were inclined towards or away from the camera, this raw data overestimated
 1183 the leaf inclination angle. We corrected for this effect in three steps. First, we
 1184 weighted the histograms of measured inclination angles by the length of each
 1185 identified segment. We did that for each azimuth view direction separately and
 1186 then took the mean of all probability distributions as we did not identify an
 1187 equal amount of segments in each view direction. Second, we converted the
 1188 observed, projected leaf inclination angle distribution to the real inclination
 1189 angle distribution assuming a random distribution of leaf azimuth angles. This
 1190 step involved binning the leaf inclination angles and computing weights for each
 1191 bin which describe, how much of which original leaf angle has contributed to
 1192 this bin given random azimuth angles. The real leaf angle distribution was
 1193 computed by solving a linear system of equations with the projected leaf angle
 1194 distribution and the weights of all bins. Third, we corrected for the fact that
 1195 leaves appeared shorter on the images if they were not perpendicular to the
 1196 image plane. Finally, we fitted a beta function to the data (Figure A2b–d) in
 1197 the same way as for *B. nana* leaves.

1198 For *E. vaginatum* and *Salix pulchra*, we manually measured the leaf inclina-
 1199 tion angles of 21 and 39 leaves, respectively. As the number of measured leaves
 1200 was small, we did not fit a beta function to the data but selected the best fitting
 1201 standard leaf angle distributions, ‘erectophil’ for *E. vaginatum* and ‘uniform’
 1202 for *S. pulchra* (Figure A2e, f) (de Wit, 1965).

1203 **Leaf and wood optical properties.** We measured optical properties of plant
 1204 organs in the field using an Ocean Optics SpectroClip probe in the peak grow-
 1205 ing seasons 2013 and 2014 (Figure A3). The probe features two integrating
 1206 spheres of about 3.5 cm diameter, one for the reflectance and the second for
 1207 the transmittance of the sample. The sample is fitted between the two spheres

Figure A2: Probability density (bin width: 1 rad = 57.3°) of measured green leaf, standing dead leaf, and wood inclination angle distributions and fitted functions of (a) *Betula nana* leaves, (b) *B. nana* wood, (c) *Eriophorum angustifolium* green leaves, (d) *E. angustifolium* standing dead leaves, (e) *Eriophorum vaginatum* leaves, and (f) *Salix pulchra* leaves.

1208 with a measurement area of 5 mm diameter. In addition to our measurements
 1209 of samples, we regularly took reference measurements with a 99% and a 50% re-
 1210 flectance standard and without sample. The integrating spheres were too small
 1211 in comparison to the sample size to provide data without correction for multiple
 1212 interactions between light and sample (Jacquez & Kuppenheim, 1955). Thus we
 1213 did a first-order correction of the raw reflectance and transmittance measure-
 1214 ments. We estimated the fraction of light that interacted twice with the sample
 1215 before being recorded using a comparison between the readings of the 99% stan-
 1216 dard and the 50% standard. Although we could only calibrate this fraction for
 1217 non-transmitting samples, we used the same value also for the correction of the
 1218 transmittance signal. The correction of the samples transmittance involved as-
 1219 suming equal reflectance and transmittance of both leaf sides. We tested the
 1220 correction for leaves which we measured with the standard procedure, including
 1221 transmittance, and on a black background.

1222 *E. vaginatum* leaves were too thin to be measured with the SpectroClip probe
 1223 in the standard procedure. Therefore, we fixed multiple leaves next to each other
 1224 on a sample holder. As all leaves together covered the measurement area, we
 1225 could use the reflectance measurement without further correction. However, for
 1226 the transmittance measurement, we had to adjust for the reduced transmittance
 1227 due to the holder. We estimated the *E. vaginatum* leaf transmittance (T) from
 1228 the corrected transmittance measurement ($T_{measured}$) and the transmittance of
 1229 the empty holder ($T_{empty\ holder}$):

$$T = \frac{T_{measured}}{T_{empty\ holder}^2} \quad (A1)$$

Figure A3: (a) Upper face reflectance (bottom half) and transmittance (top half) of the major species (bottom face reflectance not shown for clarity) and (b) background reflectance; the grey lines indicate the MODIS bands 1–7 used for modelling.