The ability of MODIS land surface temperatures to simulate cold air drainage and microclimates in complex Arctic terrain

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Abstract

The Arctic has experienced the most rapid warming in the world in recent decades. Complex topography combines with low solar elevation to create distinct microclimates in Arctic regions, and for many applications such as ecological response and cryospheric change it is critical to obtain reliable temperature trends at the local scale. Due to lack of weather stations, satellite land surface temperature (LST) is increasingly important as a proxy for air temperature (T_{air}), but how accurately it can represent microclimates is unknown. For the first time, we compare 10 years (2007-2017) of T_{air} recorded over a dense network of 65 sites ($\sim 25 \text{ km}^2$) around Kevo Subarctic Research Station in Finland with equivalent MODIS LST at 1 km resolution from MOD11A2/MYD11A2 8 day products. We assess whether LST can pick up the extreme local gradients in air temperature ($>20^\circ\text{C}/\text{km}$) caused by cold-air drainage. Although there is a high correspondence between LST and T_{air} anomalies on a synoptic timescale, small scale patterns in T_{air} (lapse rates, aspect contrasts) are not picked up by LST. Temperature gradients in T_{air} become positive (temperature inversions) in winter, and at night, but LST gradients show almost the reverse. Aspect contrasts in T_{air} peak in spring and autumn during the day, but LST shows biggest differences in the evening. Land cover has a large influence on LST, tundra heating up/cooling down more than birch or pine forest. The conflation between land-cover and elevation means that differential land-cover response dominates the elevational LST signal. Contrasts between T_{air} and LST cannot be explained by the number of stations measuring T_{air} in a pixel, elevation error, timing differences or the frequency of cloud cover within the 8 day composite. Important features of the Arctic climate such as micro-scale cold-air drainage are thus potentially obscured by land cover effects.

1. Introduction

Recent climate change is known to be amplified in the Arctic regions (Serreze & Francis 2006), not least because of the roles of many feedback processes, including the decline of snow and ice cover (Serreze et al. 2007, Brown & Robinson 2011, Kunkel et al. 2016) and poleward movement of vegetation boundaries (Chapin et al. 2005, Harsch et al. 2009). Although not the case everywhere (Epstein 2015, Pheonix et al. 2016), many analyses have shown that the Arctic is on average greening (Swann et al. 2010, Pearson et al. 2013, Ju et al. 2016), with consequences for associated albedo feedbacks (Sturm et al. 2005). Because of this potential enhanced sensitivity of the Arctic region to climate change, it is critical we have good observations of temperature change at all spatial scales.

Air temperature at screen level (usually 2m) (T_{air}) is the global standard for climate change monitoring and the major land surface temperature datasets such as CRUTEM4 (Osborn & Jones 2014) and GHCNv3 (Lawrimore et al. 2011) rely on surface weather stations. However our knowledge of spatial patterns of temperature change is compromised in the Arctic because of a lack of in situ data in many remote regions. Reanalyses are also compromised by coarse resolution and irregular distribution of observations. Sensors on satellite platforms such as AVHRR and MODIS on the other hand potentially provide an excellent source of land surface temperature (LST), and have the advantage that they cover the whole Arctic at frequent temporal resolution (sub-daily). Increasingly therefore satellite data (both infra-red and passive microwave) is being incorporated into climate change assessments (Merchant et al. 2013, Comiso et al. 2014) but there is a danger that this does not represent the full variety of local scale environments. Although there has been a concerted effort to examine how such satellite datasets can be used as a proxy for air temperature at a regional scale in the Arctic (Bosilovich 2006,

Hachem et al. 2012, Urban et al. 2013), there have been limited attempts to examine representativeness at the local scale. The relatively coarse resolution of satellite records in comparison with point data (MODIS output for example commonly has a spatial resolution of 1 km) means that it is unclear whether they can capture the detailed microclimates common in the Arctic and thus fully assess climate patterns and trends.

Arctic microclimates are often extremely distinct, particularly where the terrain is heterogeneous. Wherever there is complex topography, topographic screening of direct radiation is enhanced because of low solar angles. Aspect is a particularly important control on local climate, particularly when the solar elevation is low (Barry 2008, Bennie et al., 2008, Sadoti et al. 2018). The frequent negative energy balance can create local cold air drainage (Pepin et al. 2009, Virtanen et al. 1998), which effectively decouples the surface climate from the free-air above. This can potentially introduce local variability in climate trends, since decoupled environments with distinct microclimates may not respond to global forcings in the same way as the wider region (Daly et al. 2010, Dobrowski 2011). This paper examines whether satellite data can capture local scale cold air drainage. We use the example of complex topography in Finnish Lapland, where past research (Pepin et al. 2009, Pike et al. 2013, Williams and Thorp 2015) has shown intense and localised inversions to develop under the correct synoptic forcing, and to last for several days. Correct simulation of microclimates is critical to understanding many future climate impacts in the region including the invasion of new species such as the moth *Epirrita autumnata* and the migration of the treeline northwards (Virtanen et al. 1998, Ammunet et al. 2012).

Section 2 reviews past studies which have compared MODIS LST and air temperatures in different regions of the world. Section 3 explains the data collection. We compare MODIS LST with 2 m air temperatures in Section 4 and discuss our findings in the wider context of Arctic climate change in Section 5.

2. Previous studies

There are many review papers over the last decade which outline the challenges in measuring the Earth's surface temperature using LST (Kustas & Anderson 2009, Tomlinson et al. 2011, Li et al. 2013). One of the major challenges is how to use LST to obtain information about air temperature. The overlying rationale for most studies is that developing statistical relationships between *in situ* T_{air} and/or T_{surf} (measured surface temperature) and LST allows more effective downscaling of air temperature fields in remote areas where current *in situ* weather stations are lacking. LST is in theory a useful data source, because it has wide temporal and spatial coverage. Thus it could be of particular benefit in locations where climate trends are thought to be amplified such as the Arctic (Serreze et al. 2009) and high mountains (Pepin et al. 2015), but where there is limited observational data.

Several studies have compared MODIS LST with either T_{air} or T_{surf} in a range of environments including the Arctic and sub-Arctic (Westermann et al. 2012, Ostby et al. 2014, Williamson et al. 2013, 2014), mid-latitudes (Mostovoy et al. 2005, Shen & Leptoukh 2011, Benali et al. 2012, Shamir & Georgakakos 2014), the tropics (Vancutsem et al. 2010, Maeda & Hurskainen 2014), and at high elevations (Pepin et al. 2016). LST generally on average shows a cold bias in most studies within the Arctic. This is because of the combined effects of surface snow cover and cloud bias effects. Westermann et al. (2012) compared MODIS LST with *in situ* T_{surf} and found MODIS LST systematically underestimated the long term mean surface temperature because of the inherent clear sky bias in the MODIS 8 day

products (cloudy days are not included). Under clear sky conditions in the Arctic and sub-Arctic, it is typically much colder than during cloudy periods, at least for most of the year due to rapid longwave radiation loss. The second issue is that it is difficult for the satellite to distinguish between snow cover and low cloud (cloud-top temperatures are colder than the surface), and so unnoticed cloud contamination can further reduce LST in comparison with in situ surface or air temperature (Westermann et al. 2012, Ostby et al. 2014). In comparisons with T_{air} the presence of snow cover has been shown to reduce LST far more than air temperature so that the underestimation of LST is greater in snow covered regions (Williamson et al. 2017). If snow cover is ephemeral or sporadic then it can cause contrasting trends between LST and air temperature and the relationship between the two changes as snow comes and goes (Shamir & Georgakakos 2014, Pepin et al. 2016). The variable snow effect was even relevant in summer in Yukon above treeline where snow patches remain to various extents throughout most of the growing season (Williamson et al. 2017). In the same study, low elevation sites without snow cover showed much smaller differences between LST and T_{air} . Clearly the presence or absence of snow cover is an important control of the difference between the two measurements.

In mid and low latitudes most studies have concentrated on the effect of vegetation (e.g. Mostovoy et al. 2005, Vancutsem et al. 2010). Generally LST can be higher than T_{air} during the day and under conditions of intense sunlight, especially in open landscapes with little vegetation (Benali et al. 2012, Wenbin et al. 2013). Healthy forest tends to reduce the surface heating effect because it both shades the surface and increases the latent heat flux at the expense of sensible heating. Thus many studies have attempted to use NDVI to correct for the difference between LST and air temperature (Vancutsem et al. 2010, Wenbin et al. 2013, Maeda & Hurskainen 2014). This is the basis of the TVX method which has been applied to correct satellite data in the past (Nemani and Running 1989). At night, differences between LST and T_{air} often decrease in tropical and mid-latitude environments and are more consistent. Thus using nighttime LST as a proxy for T_{air} without correction is more realistic (Maeda & Hurskainen 2014). Work at high elevations on Kilimanjaro up to 5800 m shows that the differences between LST and T_{air} tend to become both larger and more unpredictable at extremely high elevations, because the net radiation balance (Q_n) becomes much more extreme, both in terms of its temporal and spatial variation (Pepin et al. 2016). Because the shortwave component assumes increased dominance at high elevations, scattered cloud creates steep temporal and spatial gradients in Q_n for example. Snow and vegetation effects, combined with solar geometry and aspect, are still the major controls of the differences between LST and T_{air} irrespective of elevation.

Although there have been numerous studies therefore in the Arctic and sub-Arctic, and in landscapes with variable snow cover, and in areas with complex topography, none of these studies to our knowledge has examined the ability of LST to reproduce micro-scale climate effects such as localised aspect effects on T_{air} and the development of small-scale cold air drainage and temperature inversions which are common in Arctic environments. LST was used along with in situ air temperatures by Oyler et al. (2014) to create a combined daily temperature dataset across complex topography in the Western U.S. and there was some improvement in simulating minimum temperatures (controlled in part by cold air drainage) by incorporating LST, but this study was at mid-latitudes.

The aim of this study therefore is to assess the extent to which LST can provide realistic information on micro-climates (at scales of 1 km and less) in a high latitude setting, especially its ability to simulate air temperature patterns controlled by cold-air drainage.

Methods

The field study location is in the vicinity of Kevo subarctic research station (69° 45' N and 27° 01' E) in northern Finnish Lapland (Figure 1). The landscape is dominated by incised valleys which run through a more open fell-field plateau landscape. The site lies almost 300 km north of the Arctic Circle and thus the polar night (absence of direct solar radiation input) lasts for 2 months from mid-November to mid-January. Conversely the polar day lasts from mid-May to mid-July during which the sun doesn't set. The maximum solar elevation at the summer solstice is ~44°. Thus the influence of the diurnal cycle of direct radiation input changes across the seasons with a traditional daily cycle becoming dominant only in spring and autumn. Snow cover lasts from October to May and thus seasonal differences in land cover properties are pronounced. There are also aspect differences, especially in spring and autumn, with north and south facing slopes showing strong contrasts in energy balance regimes (Pike et al. 2013).

Although the elevation range of the study area is relatively small, the highest summits being only 300-400 m above sea-level, the contrast between the open tundra on the hilltops and sheltered boreal forest in the valleys is marked due to the position at the northern edge of the European continent, and the study area includes the boreal forest/tundra transition. The frequent cold air drainage is characteristic of a much larger region on the lee slopes of the Scandes (Zhenlin et al. 2011, Vajda & Venäläinen 2003), and is characteristic throughout Scandinavia (Kotlarski et al. 2015) and the Arctic region (Palo et al. 2017). Past work has demonstrated the existence of intense but temporally variable temperature inversions at this location (Pepin et al. 2009, Pike et al. 2013). Instantaneous temperature differences of over 20°C have been recorded over short distances less than 1 km and over elevation ranges of less than 300 m. Thus the site acts as a useful case study to evaluate the ability of LST to simulate Arctic microclimates.

Air Temperature (T_{air})

In September 2007, 65 locations were installed with Hobo U23-001 air temperature sensors measuring screen level air temperature (T_{air}) at 1.5 m every 30 minutes (Figure 2). To our knowledge, this is one of the most detailed networks available for such a small area (~25 km²). The accuracy of the sensor is reported as +/-0.2°C at 0-50°C, and slightly worse (+/-0.38°C) at -20°C. All loggers were calibrated at two temperatures before installation and temperature differences were typically less than 0.2°C. The sensor family has been assessed in past papers for accuracy and ability to monitor microclimates (Whiteman et al. 2000, Lundquist et al. 2008). The original station network was designed to monitor microclimates and to cover the various characteristics of the terrain as equally as possible (e.g. transects on different aspects and stations in contrasting elevation zones), rather than provide a match with MODIS pixels so there are variable numbers of stations in each pixel (Figure 1). Figure 2 demonstrates the field set-up. Loggers were screened using a white Stevenson screen to reflect radiation. The bottom of the screen has a lip to reduce reflected radiation but was left partially open to prevent build-up of snow within the screen which otherwise occurred if screens were closed. The snowpack at the location typically reaches a maximum of 60-70 cm in March (Pike et al. 2013) and no screens were buried during the course of the data collection period. However the height of the screen

was not adjusted for the snow level. This is standard climatological practice for most climate stations in snowy environments. We use T_{air} recorded four times daily (at the times of LST data availability) for a 10 year period from September 2007 up to and including March 2017. The patterns of microclimate apparent in the air temperature data have been fully described and explained in a previous publication (Pike et al. 2013).

Satellite Land Surface Temperature (LST)

MODIS LST is taken from the MOD11A2 (Terra) and MYD11A2 (Aqua) 8-day products (v6) https://daac.ornl.gov/cgi-bin/dsvviewer.pl?ds_id=1379 from Oak Ridge National Laboratory Distributed Active Archive Center (ORNL-DAAC) (2017) (Wan et al. 2015). The calculation of LST is based on the split window algorithm (Wan & Dozier 1996). For more information on validation see the papers by Wan et al. (2002, 2004) and Wan (2008). The aggregated 8-day product, https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/myd11a2_v006 reduces missing data in comparison with the 1 day product where cloudy days are missing. It provides the mean LST recorded on clear days over the 8 day period (so could be based on between 1 and 8 days in total). Only pixels which passed quality control (QC flag 0 or 1) were used. Cloud contaminated pixels (QC flag=2) or pixels contaminated for another reason (QC flag=3) were removed. Information on the number of cloud free days in each composite was available. Over the 10 years of the record (September 2007 – March 2017) there are 440 possible 8-day periods. The mean equatorial overpass times of Terra and Aqua are nominally at 1030/2230 and 1330/0130 local solar time respectively. However, because of the convergence of meridians towards the poles the mean times at 70°N converge during the morning (1100 Finnish Standard Time (UTC+0200) for Aqua and 1130 FST for Terra) but diverge in the evening (2000 FST for Terra and 0200 FST for Aqua). These times were assessed as the nearest 30 min interval to the mean times for each pixel calculated from the day and night view time layers (also provided from ORNL). All times listed in this article are Finnish Standard Time.

LST was downloaded for the 23 pixels which contained at least one *in situ* air temperature station. Most pixels cover more than one station (Figure 1 and Table 1). Pixels are labelled from top left to bottom right in Figure 1 and Table 1 for ease of identification. One pixel (14) contains 9 stations but the vast majority of pixels contain between 1 and 4. This variance allows us to assess the influence of station number on the LST vs T_{air} comparison.

Table 1 lists the mean, maximum and minimum elevations of each pixel, along with the elevation range, and mean elevations of the T_{air} stations within the pixel. The elevation error column shows the elevation difference between stations and pixel. This ranges from 75.5 m (stations lower than mean pixel elevation) in pixel 15 to -61.5 m (stations higher than mean pixel elevation) in pixel 6. Many elevation differences are small (<30 m) and the mean difference is less than 10 metres. On average the stations are slightly lower than the pixel elevations because of a concentration of climate stations towards valley sites (rather than on mountain summits). Pixels 4, 8 and 9 cover the lower valley near Kevo lake, dominated by pine forest (Figure 2a). Pixel 2 is a good example of alpine tundra, covering the upper slopes of Jesnalvarri, the highest mountain in the immediate area (Figure 2b). A qualitative assessment of dominant aspect(s) is listed in the penultimate column of Table 1. Pixels 7 and 12 show a good aspect contrast, covering the south and north facing sides of Tsarsejoki valley respectively.

Most of the area has steep slopes, and all pixels show relatively large ranges in elevation (often over 100 m). Thus heterogeneous land-cover and terrain is common.

To compare satellite LST with T_{air} , all stations in the relevant pixel were averaged and the mean air temperatures recorded at the mean overpass times (listed previously) averaged for each 8 day period ($n=440$). We did not attempt to remove cloudy days from the T_{air} calculation, but we do assess the effect of this decision and of cloud on the results in our sensitivity analyses. We calculated the instantaneous differences (LST minus T_{air}) for each 8 day period which we label as ΔT . A positive/negative value means that LST is warmer/colder than T_{air} .

3. Results

a) The Effect of Elevation on Mean Temperature

Since elevation is the main cause of temperature variation within our study area, we first examine the elevational contrasts in both T_{air} and LST, before examining the spatial patterns in ΔT . This is analysed on an annual basis and for different seasons.

Figure 3 shows mean elevational profiles of T_{air} and LST for the four overpass times (FST) based on the whole 10 year record. During the day (top two graphs) there is a weak relationship with elevation for both T_{air} and LST on a mean basis. Strong inversions which occur frequently throughout the year create a weak inversion in T_{air} on a mean basis in the night. This is especially marked at 0200 FST (Figure 3d) when the mean gradient reaches $\sim 10^{\circ}\text{C}/\text{km}$. This means that the usual lapse rate of $-6.5^{\circ}\text{C}/\text{km}$ (Blandford et al. 2003, Minder et al. 2010) is wildly inaccurate at this location, even for mean temperatures. Similar gradients are also shown for MODIS LST (diamond symbol). Unlike for T_{air} the inversion in LST is strongest during the day time (1100 and 1130 LST) rather than the night. Although weak ($\sim 5^{\circ}\text{C}/\text{km}$), this pattern is the opposite to T_{air} .

Of perhaps more interest is the relationship between ΔT and elevation (Figure 4). LST is uniformly lower than T_{air} on a mean basis, and the differences are typically $2-3^{\circ}\text{C}$ in the day and $4-5^{\circ}\text{C}$ at night. This agrees with past studies in similar environments that have all shown a negative mean bias for LST (Ostby et al. 2014, Williamson et al. 2017). However, the elevational gradient in ΔT reverses between day and night with high elevations showing an increased diurnal cycle in ΔT and valley sites showing less contrast. Thus in summary there are systematic differences between the mean daily cycles of T_{air} and LST which are conflated with elevation.

Annual analysis conceals marked seasonal contrasts. Figure 5 shows mean values of ΔT for each 8 day period over the course of the year for a high elevation tundra site (represented by pixel 2: mean elevation 273.5 m) and a low elevation valley lakeside site (pixel 8: mean elevation 99 m). The summit pixel is dominated by arctic/alpine tundra and the valley pixel by pine forest and a small (10-15) % of water during the summer. Vertical lines represent the start and end of the polar day and polar night periods (from mid-May to late July, and from late November to mid-January respectively). We chose these pixels because a) both have more than 5 T_{air} stations, b) there is limited elevation difference between mean pixel and station elevations for each pixel (Table 1), and c) the elevation range between the two pixels is large enough to create a fairly stable temperature gradient between them.

In general ΔT for both pixels is negative, especially at night. During the short Arctic summer ΔT becomes positive during the daytime (Figures 5 a, b), as the snow-free surface heats up under positive

radiation balance. The tundra pixel (mixture of bare rock and grass/shrubs) heats up more than the low elevation forested pixel. This is unsurprising, since the tundra will have lower biomass, lower heat capacity, and reduced latent heat flux (increased sensible heat flux) in comparison with the forest. In addition the pine forest has a large surface area in contact with the air which likely makes it faster to equilibrate with T_{air} . (Lundquist et al. 2018). Heating for both locations peaks in early summer when the solar elevation is highest and then decreases gradually during July and August. Night time differences (Figures 5 c and d) are uniformly negative (LST colder than T_{air}) but more so in the winter when there is snow cover. The summit pixel shows a slightly stronger seasonal contrast in ΔT than the forested one, especially by day, and the most positive/negative night-time differences occur in summer/winter at the summit. In contrast, in the lower forested (valley) pixel, ΔT is consistently negative throughout the year, and although there is more variability in the winter from week to week, the mean difference is less dependent on season.

The mean temperature gradient ($^{\circ}\text{C}/\text{km}$) was calculated for both T_{air} and LST by dividing the difference in temperature between the two pixels (high minus low elevation) by the elevation difference (0.1745 km). In common with much of the climatological literature (Rolland et al. 2003, Marshall et al. 2007, Blandford et al. 2008, Kattel et al. 2015), positive gradients represent an inversion situation, and negative gradients the usual lapse (decrease) in temperature with height. Since our temperature gradients are measured along the Earth's surface (and have a horizontal component as well as a vertical one), they are not strictly the same as the free-air lapse rates discussed in meteorology so we avoid the use of the term.

Figure 6 shows the annual patterns for T_{air} and LST gradients for the 4 times of day. They are very different, meaning that LST is not effectively simulating the microclimates of the Arctic. Air temperature gradients are most negative in spring and summer and in the daytime. The steepest negative gradients (equivalent to a superadiabatic lapse rate: $<-9.8^{\circ}\text{C}/\text{km}$) occur in daytime in April and May (Figure 6a and 6b) when there is strong sunlight combined with snow cover. This steep gradient probably occurs due to the vegetation contrast and subsequent albedo contrast across the treeline and has been identified in previous research (Pike et al. 2013). The lower lying forested areas heat up by day more than the high elevation snow covered tundra, confirming how warming due to greening of the Arctic, common in the growing season (Jeong et al. 2012) is also present with deep spring snow cover.

In common with other studies (Marshall et al. 2007, Zhenlin et al. 2011), the most positive gradients in T_{air} are measured in winter when strong inversions are likely. During the polar night intense inversions can occur at any time with extreme positive gradients $>20^{\circ}\text{C}/\text{km}$ reported in December and January at all four times of day (Figure 6). This is because the diurnal cycle in T_{air} tends to be irrelevant in the polar night (December and January). Inversions that form in spring and autumn however show a strong diurnal cycle and usually disperse through solar heating a few hours after dawn. Thus strong positive gradients in T_{air} are only seen at 0200 FST (Figure 6d) in spring.

In summer there is not much evidence of a reduction in air temperature gradients during the day due to lake effects. The T_{air} stations are all on land and, although there may be localised lakeshore effects due to the lake breeze mechanism, and these can influence daytime temperature gradients in T_{air} to some extent (Pike et al. 2013), low elevation cooling in the T_{air} data in summer is limited.

Unfortunately LST gradients are markedly different, with no strong seasonal pattern at night, no spring maximum, an absence of very intense inversions in winter, and inversions most likely during the daytime in summer, often $>10^{\circ}\text{C}/\text{km}$, especially at 1100 FST (Figure 6a). This summer reduction could arise because grass/rock in the tundra pixel heats up more than the lower elevation pixel dominated by pine forest and/or water. The tundra will have lower specific heat capacity due to lower biomass, and increased rock as opposed to vegetation. Differential energy partitioning with increased latent heat flux over forests and water, and increased sensible flux in the tundra is also likely to be a major contributor to the weakened summer LST gradient. Because pine forest is predominantly at low elevation, and tundra at high elevation (i.e. land cover and elevation gradients are conflated), the effects of land cover on LST response appear to act in a way to reverse (or at least obscure) the regular seasonal and diurnal cycles of air temperature lapse rates expected in an Arctic environment (Marshall et al. 2007, Pike et al. 2013). In summary therefore, the seasonal and daily contrasts in elevational temperature gradients show a strong contrast between T_{air} and LST.

The above gradients were calculated based on the two pixels furthest apart in elevation (2 and 8). Choosing two alternative pixels (1 and 4) to calculate gradients had very little influence on the air temperature gradients ($r>0.98$ between the two), but a significant influence on the LST ones (graph not shown). This illustrates that elevation is the main control on T_{air} and the gradient is fairly insensitive to the stations chosen. However LST is influenced by many factors other than elevation and there is more internal variation within the dataset.

b) Aspect Differences in Temperature

As well as elevational differences, aspect will cause localised differences in both T_{air} and LST. Although there is much spatial variance within pixels, pixel 7 is predominantly south-facing (mean elevation 173 m) and pixel 12 north facing (mean elevation 163.5 m) (see figure 1). The influence of aspect can therefore be examined by calculating the temperature difference between the two pixels (elevation contrasts are minimal). For most of the time the differences in T_{air} are relatively small (Figure 7). The exception is the marked peak (positive difference: south warmer than north) in March and April during the daytime (Figure 7a) when the south facing slope heats up and differences of up to 2°C are reported. This effect is caused by the contrast in direct radiation receipt on the two valley sides in spring, is consistent with radiation modelling (Barry 2008), and is absent at night (Figures 7, bottom row). In summer, autumn and winter, aspect differences in T_{air} are smaller. Autumn, despite similar solar geometry, is somewhat cloudier, and there is no snow to enhance slope contrasts.

LST differences on the other hand do not show the same pattern. For much of the time LST on the south facing slope is slightly warmer than on the north facing one, but there is no systematic pattern and there is much fluctuation between adjacent time periods suggesting an influence of synoptic conditions. Changes in cloud cover between periods (cloud will dampen aspect contrasts) could be an obvious influence. Strangely however, the widely variable differences are reported at 2000 FST when solar forcing should be relatively minimal and direct radiation receipt is weak (except in mid-summer). There are also large differences in LST in early January at 1100/1130 FST when there is no direct radiation input.

c) Land Cover Contrasts

The three main land cover types in this region are open tundra (heathland and bare rock), usually at high elevations (>250 m); birch forest (most commonly on intermediate slopes: 150-250 m); and pine forest in the sheltered valley bottoms (<150 m). However there is much intermingling of vegetation types as the forest-tundra ecotone is a broad transition. Figure 8 shows the annual cycles of T_{air} , LST and ΔT averaged for all pixels within each land cover class. 1 km pixels were designated one land-cover only as in Table 1 (last column), based on the MODIS 250 m land cover classification (MCD12Q1: IGBP Land Cover Type 1: 2013). We used woody savanna (class 8) and/or evergreen needle forest (class 1) to represent pine, open shrubland (class 7) to represent tundra, and closed shrubland (class 6) to represent birch. Mixed 1 km pixels (i.e. some 250 m classes were different) were not used in this analysis. Based on our knowledge of conditions on the ground, the MODIS classification picks up the broad differences and dominant land cover types. For details of the land cover classification see https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1 and Friedl et al. (2010).

The tundra (Figure 8 a and d) heats up in the summer daytime with LST exceeding T_{air} . ΔT becomes positive from May to August, often higher than 5°C. The low biomass and presence of bare rock, coupled with absence of surface water and reduced latent heat flux under dry conditions, are all consistent with such heating. For the rest of the year LST is cooler than T_{air} and this is true all year during the night. Patterns for the birch forest (panels b and e) are broadly similar to the tundra. Interestingly the pine forest (panels c and f) heats up less than the other two land cover classes, with LST only reaching around 2-3°C warmer than T_{air} on average, and ΔT peaking earlier in May and then declining earlier during the summer than for the other land cover classes. This could be because most of the low elevation pixels dominated by pine (4, 8, 9, 13, 14, 20, 21 and 22) also contain a large amount of water, which has high specific heat capacity and this increases the latent heat flux and reduces LST once the lakes are unfrozen (June-September). It is hard to separate the vegetation contrast from the lake/land contrast in this instance.

d) Common synoptic variability

Although elevational and aspect differences in T_{air} are not well captured by LST, and different land cover classes appear decoupled from T_{air} by contrasting amounts, overall on a long term basis there are reasonable correlations between LST and T_{air} anomalies for individual pixels over the course of the 10 year record ($n=440$) (Figure 9). Temperature anomalies were calculated with respect to season (i.e. the 8 day period) in order to remove the common seasonal cycle, and capture synoptic variability. Thus LST has some value in monitoring long term variation in T_{air} forced by regional and synoptic climate variability. This does not necessarily mean that climate trends will be similar, but it does illustrate common intra-annual variance. All sites have anomaly correlations above 0.65 and there is relatively little variation in this correlation among locations. Most are above 0.75 meaning that more than half of the short-term variance is common to both datasets. During the day the correlations tend to increase in most of the lower elevation pixels whereas at night the opposite trend is found, although differences in correlation coefficient between pixels are relatively small. The correlation is not related to the number of sites recording T_{air} within the pixel (not shown). Thus increased air temperature sampling does not tend to increase the correspondence between LST and measured T_{air} . The correlation is also only weakly related to the elevation error (pixel minus station elevation).

Scatterplots of individual temperature anomalies for each 8 day period (Figures 10 and 11) are shown for each time of day for the summit pixel (no 2: y axis) vs the valley pixel (no 8: x axis) identified earlier. This shows whether the T_{air} /LST variation is coherent across the domain. For T_{air} (Figure 10) although there is a strong correlation, the graph is stretched along the x axis at the bottom left, meaning that there are some extremely low anomalies recorded in the valley, whilst simultaneous cold anomalies are not so extreme on the summit. This is evidence of cold air drainage episodes common in northern latitudes (Pike et al. 2013, Zhenlin et al. 2011), where trapping of cold air by the topography leads to valley bottom anomalies below -10°C . This happens at all times of day but is most pronounced at night. This feature is not picked up in the equivalent LST anomaly graphs (Figure 11) which do not show similar stretching along the x-axis, evidence that cold air drainage is underestimated by MODIS LST.

e) Case studies of Intense Inversion Events

We examined the ability of the LST data to capture some of the intense air temperature inversion events which occurred on a local scale within the Kevo valley. Two good examples are the 8 day periods of 18-25 February 2010 and 17-24 January 2014. These were selected through calculation of the gradient in T_{air} between pixel 2 (elevation 273.5 m) and pixel 8 (lakeside: elevation 99m). In both cases air temperatures averaged over the 8 day periods fell to around -30°C or lower in the valley bottom but remained above -20°C on the summit of Jesnalvarra in the tundra, meaning that air temperature gradients exceeded $+50^{\circ}\text{C}/\text{km}$ indicating a very strong temperature inversion. Scatterplots of air temperature against elevation at 2000 FST clearly show the influence of topography in confining the cold air to the low elevations in both cases (Figures 12 a, b). The satellite LST plots do not pick this up to the same extent and there is a much weaker positive relationship between elevation and temperature in February 2010 (Fig. 12 c), and even a reversed relationship (or no relationship) in January 2014 (Fig. 12 d).

f) Sensitivity analyses

Further analyses were undertaken to assess how much of the variance in ΔT could be explained by various drivers, including elevation differences between the stations and pixel, the density of air temperature stations within a pixel, timing differences, and cloud influences.

Elevation error

At 0200 FST about half of the variance in ΔT can be accounted for by the difference in elevation between the mean of the stations and the pixel ($r=0.768$). Thus compensating for the elevation error could remove some of this variance. However there is still a consistent offset of around $4\text{-}5^{\circ}\text{C}$. During the day however, and at 2000 FST an elevational correction would not help to account for variance in ΔT , and thus it is likely that other factors (aspect, snow cover fraction, vegetation type) are of more importance.

Spatial and temporal mismatch: Number of stations and timing errors

LST represents an average value over 1 km^2 , and having more observations of T_{air} within a pixel could be assumed to lead to a more spatially representative air temperature measurement, and thus potential greater similarity between the two. However, there is no relationship between the number of stations measuring T_{air} within a pixel and the mean ΔT or its variance (figure not shown). Thus attaining more air temperature stations does not decrease the difference between LST and T_{air} or its

temporal variability. We also examined the influence of timing errors. The mean overpass time for each composite was available from the product average view time layer. For example, although the mean time is 2000 FST for Terra night-time overpasses, and 85-90% of composites are within one hour of this time, individual times range from 1800 to 2230 FST. There was no systematic change or increase in ΔT as the timing error increases (figure not shown). Indeed some of the largest differences occurred when there was little timing error.

Effect of cloud cover

The metadata for each 8 day period includes the number of clear sky days/nights (between 0 and 8) used to calculate LST in each composite. This is available for each pixel individually. Thus we can examine how the difference between LST and T_{air} is influenced by cloud patterns. Although LST is based on cloud-free days only, T_{air} is calculated based on all days (which may include cloudy ones). If this is a cause contributing to ΔT , then ΔT should approach zero as the number of clear days in the composite increases, since fewer “unnecessary” days are being used in the air temperature calculation. Figure 13 shows boxplots of ΔT against the number of clear days in the composite. During the day there is limited evidence, particularly for the valley pixel (Figure 13c), that mean differences decrease when there are more clear days. However at night (Figures 13b, 13d), although the variance tends to decrease, mean values of ΔT remain significantly negative (LST colder than T_{air}) for both pixels, even when there are 7 or 8 cloud free nights, and when in theory correspondence should be good. This suggests that there is a real difference between LST and T_{air} which is not explained by the amount of cloud. Differences in the days used to calculate T_{air} and LST in the composites are therefore not the main cause of the negative difference between the two, particularly at night.

We also analysed the cloud cover data for trends over in the 10 year period or marked seasonal changes in cloud amount (which may help explain patterns in ΔT), but none was found. Seasonal and diurnal contrasts in cloud frequency are subdued at this location (not shown).

4. Discussion

Our main findings are:

a) On a long time scale there is a reasonable correspondence between individual measurements of LST and air temperature for a given pixel (raw correlations are usually above 0.9). Even when the common seasonal cycles are removed, correlations remain above 0.7 in nearly all cases. Thus common synoptic variability in temperature is measured by both LST and T_{air} to a large extent.

b) LST is on average 4-5°C lower than air temperature averaged from stations within the same pixel. During the winter LST is up to 10°C colder, but in summer the difference can temporarily reverse with LST becoming as much as 5°C warmer than T_{air} .

c) The elevational temperature gradients for air temperature show strong diurnal and seasonal cycles, with temperature inversions forming in winter, and at night during spring and autumn. Steepest air temperature gradients form in daytime in spring. LST temperature gradients are almost the reverse, with inversions forming during the daytime in summer, possibly caused by differential response of surface types to solar heating. Most of the low elevation pixels contain forest and water (parts of Kevo lake) and this may explain the low values of LST in summer.

d) The LST for tundra (at high elevations) appears to heat up and cool down more than those for birch and pine covered pixels because of increased sensible heat flux, coupled with lower biomass and lower heat capacity in the tundra.

e) Aspect differences in air temperature become most pronounced in spring when the south facing slopes warm more than north-facing slopes due to contrasts in direct radiation receipt. LST however shows the largest (but also inconsistent) differences at night (2000 FST), the reasons for which are unclear.

f) The differences between the two measurements cannot be accounted for by the number of stations measuring air temperature within the pixel, the elevation error, timing differences or the frequency of cloud cover. Thus differences in spatial and temporal sampling are not the major cause of the differences.

It pays to be critical of both datasets and examine possible errors in both T_{air} and LST. The Stevenson screens used to measure T_{air} are un aspirated, and likely observe a little high during periods of still weather with high incident radiation. Although the screens have a little platform underneath the sensor to limit reflected radiation, this is still potentially an issue in spring (March-May) when strong solar radiation combines with snow cover. However, the absence of a marked discontinuity in ΔT in this period, and calibration against Kevo station run by the Finnish Meteorological Institute: <http://en.ilmatieteenlaitos.fi/observation-stations> (mean differences in T_{max} 0.2°C and T_{min} 0.01°C – $n=3701$: our screen colder) suggest that this problem is minimal. Additionally the air temperature dataset shows a high level of internal consistency, elevational temperature gradients for example showing very little sensitivity to the pixels chosen. Individual spikes in temperature at stations do not appear to be common. Finally any problem due to reflected radiation would be expected to be most serious at the high elevation stations where there is no tree cover. Within the boreal forest on the other hand, the screens are on trees, and the ground beneath is often shaded. However observed day time temperature gradients in air temperature reach their steepest (most negative) in spring, meaning that the low elevation sites heat up much more than the high elevation ones. This is the opposite of what would be expected if reflected radiation was unduly influencing our results. Thus in conclusion we feel the air temperature network closely represents the true air temperature gradients in this region.

LST on the other hand is based on all cloud-free days/nights within an 8-day composite. It is possible that some cloudy scenes are incorrectly identified as cloud-free, particularly at night (Zhang et al. 2016), and when there is snow cover, previous work has shown it is sometimes difficult to tell the difference between snow and cloud (Ostby et al. 2014). If low clouds were inadvertently included this would tend to increase LST and make ΔT less negative (i.e. reduce the difference) because cloudy periods are nearly always warmer in the Arctic. The bad news is therefore that removal of cloud contaminated pixels would likely increase the magnitude of ΔT which is already negative. Unlike air temperature, the LST temperature gradient also shows more sensitivity to the pixels chosen, which illustrates that there is less coherence in the LST data, with elevation playing a reduced role. The extra variance is likely to be due to contrasts in surface characteristics (land cover and its associated properties). This also means that it is likely to be more difficult to upscale LST results to apply to the region since they may be less representative of a wider area.

Sensitivity analyses also suggest that the variance in ΔT we observe is not solely due to limitations caused by differences in days due to cloud cover (Figure 13) or the number of stations in the pixel used to measure air temperature (i.e. inadequate spatial sampling). Neither is ΔT related to timing errors between individual overpasses within an 8-day composite and our allocated mean overpass time. At 0200 FST the elevation difference between the LST pixel and stations accounts for some of the variance in ΔT , but there is still a strong consistent offset, even when this is corrected. At other times of day the elevation difference is of no significance in explaining variance in ΔT . In conclusion it is unlikely that we will be able to correct LST to make it more like T_{air} based on compensating for differences in measurement times and spatial scale.

The failure of spatial, temporal and cloud differences to explain ΔT means that much of the difference between T_{air} and LST must result from fundamental differences between the two, the former being a broad regional response of the lower atmosphere to energy balance (air temperature) and the latter being a highly spatially-variable response of the underlying surface to variations in the surface energy and water budgets (Kustas & Anderson 2009, Li et al. 2013). In regions of complex topography this can add significant spatial variance in LST (Malbeteau et al. 2017). Even though LST is a crude spatial average over the whole pixel, it is not easy to equate this easily to a regional air temperature value.

A 1 km² pixel could contain quite a lot of different land cover types and the final result is an amalgam of these. A good example would be pixel 12 which although classified as north facing and as pine forest, includes low lying areas of pine forest in the Tsarsejoki valley (Figure 14a), open areas surrounding the river itself (Figure 14b), areas of steep rock face covered in birch forest (Figure 14c), and relatively flat mixed slopes of birch and pine (Figure 14d). All of this complexity is averaged out in the LST value. Other pixels such as pixel 6 include pine forest in low lying valley bottoms, birch forest (usually at medium elevations on steep slopes) and arctic tundra at high elevations. The vegetation phenology of birch (seasonal leaves) and pine (evergreen) needs to be considered as contrasting seasonal patterns will be amalgamated. Many low elevation pixels also contain lakes which are ice and snow covered in winter but open water in summer. Further work therefore needs to concentrate on the influence of land-cover variation on LST both within and between neighbouring pixels, so that any non-linearities can be understood. Does a pixel which is half tundra and half forest behave like an average of the two? Can individual temperature values representative of different land-cover types within a pixel be extracted? Recent research is already beginning to ask such questions. Lundquist et al. (2018) have developed a method to separate snow and forest surface temperatures in MODIS pixels for example, in the Sierra Nevada.

There are wider implications of our findings, both in methodological terms and for broader environmental and societal impact. As satellite records lengthen, many assessments of climate change in the Arctic will be increasingly reliant on LST data (Merchant et al. 2013, Comiso et al. 2014). Although these are usually carefully calibrated against in situ weather station data where available, the inability of LST to capture microclimate effects which can be observed by dense air temperature networks is a concern. Any calibration will be influenced by the distribution of sites chosen. One cannot assume that a calibration based on one location can easily be transferred to another area, especially when distinct microclimates are involved. A bias towards locations which are prone (or not) to cold air drainage for example, could influence both any calibration and in theory any regional temperature trend obtained. Cold air drainage is a universal process which occurs across the globe

(Lundquist et al. 2008, Dobrowski et al. 2009, Daly et al. 2010), and although particularly distinct in the Arctic, the implications are not restricted to this region.

Accurate modelling and forecasting of air temperature variability at the landscape level is particularly relevant for infrastructure and transport due to the potential risks of local icing, freezing precipitation, evaluation of permafrost and retention of snow and ice cover (Gustavsson et al., 1998, Whiteman et al., 2001, Lundquist et al., 2008, Lewkowicz & Bonnaventure 2011). Many environmental processes in the Arctic are dependent on microclimates. The example of birch defoliation in northern Lapland is informative (Jepsen et al. 2008, Ammunet et al. 2012) in that the eggs of the larvae of *Epirrita Autumnata* are destroyed at temperatures below -35.5°C. Localised cold air drainage provides the low temperatures necessary to prevent moth populations from expanding into new areas (Virtanen et al. 1998). Freeze up and melt out of lakes (which are usually in valley locations) are often influenced by cold air drainage (French 2007), and topography and lake effects on micro-climate are thus intertwined (Aalto et al. 2014). Cold air drainage has even been shown to influence carbon uptake and ecosystem function in mountain ecosystems (Pykper et al. 2008, Novick et al. 2016). Ecological refugia are frequently contained within areas with distinct microclimates (Dobrowski 2011) or at least enhanced spatial contrast in climate conditions which enables climate velocity to be reduced (Laorie et al. 2009, Dobrowski et al. 2013).

Finally, any processes which would decrease the propensity towards cold air drainage in a warmer climate from example reduced snow cover (Rupp et al. 2013) and/or increased cloud cover (Liu et al. 2008) could amplify warming in such valley locations, but we are unsure at present the extent to which this is the case (Pepin et al. 2011) and up until now projections of climate change in Finland have been at too large a scale to fully consider this matter (Jylhä et al. 2004). If warming were to be enhanced in such locations, then satellite datasets which fail to simulate CAP could underestimate regional warming rates. It is critical we have temperature data relevant to answer such questions. If we are to use satellite records to capture such effects, there is more work to be done to improve their representativeness in Arctic environments.

5. Conclusions

We compared 10 years of air temperatures with simultaneous LST measurements across 23 pixels (based on 65 T_{air} stations) around Kevo Subarctic Research Station. We demonstrated that LST does not represent the microclimate features of the landscape at all well, being a fundamentally different measurement to air temperature.

The problem with a purely statistical comparison of T_{air} vs LST is that it is hard to know what is causing the differences between the two measurements. Field validation via measurement of effective radiative surface temperature in specific locations for different land cover types at the time of specific overpasses is recommended, combined with model simulations. To conclude, long term trends in LST are probably a reasonably good proxy for trends in air temperature at a regional scale. However, if understanding of complexities such as the changing frequencies of inversions and cold air drainage, or changes in elevational gradients (to examine phenomena such as elevation dependent warming) is required, then LST is not currently able to pick up such patterns in an Arctic context and further research efforts are recommended to develop satellite products capable to do this.

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8350 words approx

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Table 1

Pixel No.	Max z	Min z	Range z	Mean z	Mean station elevation	Elevation error (pixel minus stations)	Number of stations	Aspect	Land Cover
1	318	180	138	249	300	-51	1	N, E	Birch
2	329	218	111	273.5	308.4	-34.9	5	Flat, E	Tundra
3	242	120	122	181	225	-44	1	E	Birch
4	138	73	65	105.5	87.5	18	4	Flat	Pine
5	240	206	34	223	218.3	4.7	3	Bowl, W	Tundra
6	303	115	188	209	270.5	-61.5	2	S	Tundra
7	260	86	174	173	140	33	5	S, E	Birch
8	123	75	48	99	85.2	13.8	6	E	Pine
9	173	75	98	124	126.5	-2.5	2	S, W	Pine
10	243	153	90	198	191	7	1	W	Tundra
11	232	112	120	172	130.5	41.5	2	N, E	Mixed
12	228	99	129	163.5	162.5	1	4	N, W	Pine
13	221	76	145	148.5	116.5	32	4	E, Flat	Pine
14	174	75	99	124.5	118.3	6.2	9	N, E	Mixed
15	236	75	161	155.5	80	75.5	1	W	Mixed
16	226	149	77	187.5	148	39.5	2	Bowl, W	Mixed
17	200	75	125	137.5	173	-35.5	2	Ridge	Mixed
18	231	85	146	158	98	60	1	S, E	Pine
19	203	79	124	141	95	46	2	Flat, W	Mixed
20	201	75	126	138	111.5	26.5	2	E	Pine
21	219	78	141	148.5	153.5	-5	2	W	Pine
22	163	78	92	120.5	95	25.5	3	N, E	Pine
23	258	80	178	169	174	-5	1	S, W	Mixed
Mean	224.4	106.0	118	165.2	156.9	8.3

820

821 1. Air Temperature station network surrounding Kevo Sub-Arctic Research Station in Finnish Lapland.
822 The 65 stations are shown with their correspondence to the pixel coverage of MODIS LST (1 km²).
823 Pixels are numbered in Table 1 as shown. The inset shows the position of Kevo in northern Europe.

824

825 2. Pictures showing the temperature logger set up in the field. Stevenson screens were tied to the
 826 north side of trees or other structures (fence posts etc) at a height of 2 metres above ground level, a)
 827 station in pine forest (pixel 8), b) arctic tundra: slopes of Jesnalvarri – pixel 2.

828

829 3. Elevational profiles of mean T_{air} and LST for four times of day, corresponding to mean satellite
 830 overpass times. Data runs from September 2007 to March 2017 inclusive.

831

832 4. Correlations between mean ΔT (LST minus T_{air}) and elevation for four times of day corresponding to
 833 mean overpass times.

834

835 5. Mean annual cycles of ΔT (LST minus T_{air}) for summit (tundra) pixel no 2 (triangles), and valley (pine)
836 pixel no 8 (squares). Pixel details are given in Table 1. Vertical lines represent the start and end of the
837 polar night (late November to mid-January) and polar day (mid-May to late July).

838

839 6. Mean annual cycles of vertical temperature gradients ($^{\circ}\text{C}/\text{km}$) derived from T_{air} and LST.
 840 Temperature gradients across elevation are calculated solely from pixels 2 (high elevation) and 8 (low
 841 elevation), calculating the temperature difference and dividing it by the elevation difference (173.5
 842 m). All stations within a pixel are averaged to calculate T_{air} .

843

844 7. Mean annual cycles of the aspect influence on T_{air} and LST. The aspect effect is derived by
 845 subtracting the temperature for the north facing pixel (12) from the south facing one (pixel 7). A
 846 positive value means that the south-facing pixel is warmer.

847

848 8. Mean annual cycle of T_{air} , LST and ΔT (LST minus T_{air}) for pixels assigned to various land-cover
849 classifications for top row: day (1100 FST) and bottom row: night (0200 FST). Panels a and d) tundra
850 (n=4), b and e) birch (n=3), c) and f) pine (n=9).

9. An assessment of common synoptic variability in T_{air} and LST. Plots show the correlation between T_{air} and LST anomalies calculated for each 8-day period (common seasonal cycle removed) against elevation for four times of day corresponding to mean overpass times.

855

856 10. Scatterplots of tundra (pixel 2) vs valley (pixel 8) air temperature anomalies (common seasonal
857 cycle removed) for four times of day corresponding to mean overpass times.

858

859 11. Same as Figure 10 but for LST.

860

861 12. Scatterplots of T_{air} and LST versus elevation, for two case studies of intense air temperature
 862 inversions in February 2010 (left) and January 2014 (right).

863

864 13. The effect of the number of cloud free days/nights within the LST 8-day composite on the variance
 865 of ΔT (LST minus T_{air}) over the 10 year period, a) Tundra pixel 2 (1130 FST), b) Tundra pixel 2 (2000
 866 FST), c) Valley pixel 8 (1130 FST), d) Valley pixel 8 (2000 FST).

867

868

869

870 14. Differential land cover and topography within pixel 12: a) low lying areas of pine forest in the
871 Tsarsejoki valley, b) open areas surrounding the river itself, c) areas of steep rock face covered in birch
872 forest, and d) relatively flat mixed slopes of birch and pine.