Intercomparison of Snow Melt Onset Date Estimates From Optical and Microwave Satellite Instruments Over the Northern Hemisphere for the Period 1982–2015

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Abstract Robust melt season timing and length estimates are important for hydrological and climatological applications; due to the large area and sparse in situ measurements, snow melt monitoring at the continental scale is only possible from satellites. We intercompared melt onset date (MOD) estimates obtained from optical and microwave satellite sensors over the Northern Hemisphere between 1982 and 2015 and subsequently analyzed the causes of the similarities and dissimilarities found. The optical satellite data are based on the mean surface albedo from the Satellite Application Facility for Climate Monitoring (CM SAF) CLouds, Albedo and RAdition second release Surface ALbedo (CLARA-A2 SAL) data set. The microwave satellite data are based on temporal variations in the differences of the brightness temperature from satellite passive microwave radiometers. The analysis shows that the microwave-based method detects melt onset on average 10 days later than the albedo-based method, which results from the different melt detection methods; the albedo-based method observes the point when the spring snow metamorphosis begins to have a detectable effect on snow albedo, whereas the microwave-based method detects the appearance of meltwater in snowpack. The difference in MOD decreases in forests, because canopy protects snow from sunlight delaying snow metamorphosis. Additionally, we analyzed the MOD estimates for trends across the Northern Hemisphere and separately for Eurasia and North America. A statistically significant negative trend toward earlier melt onset exists in all cases, which is consistent with previous studies.

1. Introduction

Seasonal snow cover of the Northern Hemisphere (NH) is an important part of the global climate system. Snow cover and timing of the melt season affect the surface albedo and, therefore, the surface energy budget. During the cold season more incoming solar radiation is reflected back due to the high albedo of snow, while during the warm season, darker snow-free surface absorbs more solar radiation (Callaghan et al., 2011; Flanner et al., 2011; Qu & Hall, 2005; Trenberth & Fasullo, 2009). Changes in snow cover and timing of the melt season will therefore greatly influence the surface energy budget and, thus, the whole climate system, which in turn makes snow melt onset an important input for climate models (Flanner et al., 2011; Hall & Qu, 2006; Qu & Hall, 2005). Additionally, snow cover greatly influences the hydrological cycle in the high latitudes and mountainous regions (Barnett et al., 2005; Bormann et al., 2018; Callaghan et al., 2011; Douville et al., 2002). During the cold season, seasonal snow cover is a large storage for fresh water limiting water availability, whereas during the warm season water is released and redistributed. Changes in snow cover will influence the hydrological cycle, which in turn affects water availability possibly leading to regional water shortages (Barnett et al., 2005).

Robust melt season timing and length estimates at large scale are important for hydrological and climatological applications, such as spring flood forecasting and climate studies (AMAP, 2017). Spring floods can cause great economical losses; for example, in the United States, spring floods caused $3.365 billion in losses during 1972–2006 (Changnon, 2008). Due to the large area and sparse in situ measurements, melt season monitoring at the continental scale is only possible from satellites; the monitoring can be done by using both optical and microwave satellite methods. One of the optical satellite methods uses changes in snow albedo to detect the melt onset. When the melting starts, the albedo begins to decrease due to snow metamorphism (Colbeck, 1982). Snow metamorphosis is an important source for snow-albedo feedback (SAF), which is one of the primary positive feedbacks contributing to enhanced warming at the northern high latitudes (Pithan & Mauritsen, 2014; Qu & Hall, 2007). The passive microwave satellite method, in turn, uses changes in microwave emissions of snow; the microwave emission depends on the physical properties of snow. The
microwave emissivity increases distinctly from dry to wet snow because of the much higher dielectric constant of water (Ulaby et al., 1982). This makes the microwave measurements highly sensitive to the appearance of liquid water in snowpack and therefore a very good tool for detecting snow melt onset. Microwave satellite data are not affected by clouds and do not depend on sunlight, contrary to optical satellite data. The size and shape of snow grains are constantly changing due to liquid water content, temperature, and temperature gradient (Colbeck, 1982). This process, called snow metamorphism, can be divided into two categories: wet and dry snow metamorphism. Wet snow metamorphism occurs when temperature is above 0 °C, while dry snow metamorphism occurs at lower temperatures. Grain size increases when snow ages, but the growth is slower in dry snow compared to wet snow (Colbeck, 1982). Albedo decreases when grain size increases and grains become more rounded. The incoming solar radiation causes daily variations to the snow surface albedo during subfreezing conditions; albedo decreases during daytime due to snow metamorphism (Dirmhirn & Eaton, 1975; Pirazzini, 2004). A fraction of the energy from the incoming solar radiation is absorbed by the snow cover, which is then used for recrystallization processes (Dirmhirn & Eaton, 1975). The recrystallization results in an increase in grain size, which in turn leads to a decrease in scattering within the snowpack. Thus, radiation can penetrate deeper into the snowpack. A larger fraction of the radiation is absorbed by the snow, which in turn decreases the fraction of the shortwave radiation that is reflected back. When the temperature approaches the melting point, albedo decreases almost linearly (Pirazzini et al., 2006). Thus, the decrease of albedo can be the first signal of the melt onset.

Length of the melting season varies regionally, and the length depends on the intensity of melting, snow thickness, and the turbulent and radiative surface fluxes (Pirazzini et al., 2006). Snowfall can interrupt the melting, but during melt season snow also often undergoes cycles of melting and freezing (Colbeck, 1982). During melting, snow metamorphism is rapid, when the grain size increases quickly and the meltwater further decreases the albedo (Pirazzini et al., 2006).

The extent and duration of the NH seasonal snow cover show negative trends (Bormann et al., 2018; Derksen & Brown, 2012; Hernández-Henríquez et al., 2015; Kunkel et al., 2016). Snow cover in spring is especially sensitive to warming (Brown & Mote, 2009; Derksen & Brown, 2012; Déry & Brown, 2007), and therefore, monitoring timing and length of the melt season is important for climate change monitoring. Recent studies show clear trends toward earlier melt season (Huang et al., 2018; Mao et al., 2015; Metsämäki et al., 2018; Takala et al., 2009; Tedesco et al., 2009).

Timing of the melt season has been studied in a number of studies, where it is estimated using either optical satellite data (Anttila et al., 2018; Malnes et al., 2016; Manninen et al., 2019; Rinne et al., 2009) or passive microwave satellite data (Markus et al., 2009; Takala et al., 2009; Tedesco et al., 2009; Wang et al., 2013). However, only one prior study exists on intercomparison of the optical and microwave satellite methods; Metsämäki et al. (2018) compared snow melt-off dates derived from optical and microwave radiometer data, but their study only covered Europe for the period of 16 years and did not consider the onset of melt. Thus, our study is to the authors’ knowledge the first, where snow melt onset date (MOD) estimates based on optical and microwave data are intercompared for a time period of almost 40 years over the NH. The main goals of this study are (1) to intercompare state-of-the-art optical and microwave MOD estimates over the NH between 1982 and 2015 and subsequently analyze the causes of the similarities and dissimilarities found; and (2) to analyze the MOD estimates for trends across the NH and separately for Eurasia and North America.

2. Data and Methods

This study uses two different data sets of snow MOD estimates: one from a series of optical satellite instruments and one from a series of passive microwave satellite instruments (Table 1). The data set from an optical satellite instrument is based on the mean surface albedo from the Satellite Application Facility for Climate Monitoring (CM SAF) CClouds, Albedo and RAdiation second release Surface ALbedo (CLARA-A2 SAL) data set derived from the Advanced Very High Resolution Radiometer (AVHRR) data (Anttila et al., 2018). For each grid cell and year, MOD was detected by fitting a sigmoid function to the CLARA-A2 SAL pentad (5-day) mean albedo values using nonlinear regression. MOD was determined to be the day, when the sigmoid reached 99% of its variation range, that is, the sigmoid fit drops 1% from its stable premelt albedo level. By choosing this value, the algorithm is tuned to observe the very beginning of the melt season.
Choosing another threshold, for example, 95%, would affect the ensuing MOD values. Use of the pentad values and the sigmoid fitting gave the advantage that individual erroneous albedo values had only a limited effect on the analysis. The final analyses included only the grid cells for which (1) both the snow melt onset and end days were retrieved successfully; (2) the albedo difference between the start and end date of melt was larger than 5% absolute albedo units; and (3) data meeting these two criteria were available for at least 10 years. Only the grid cells for which $R^2 > 0.95$ and root-mean-square error < 20 for the sigmoid fitting (i.e., 98% of the whole sigmoid data set) were used in the analysis (Anttila et al., 2018). MOD estimates were obtained at the CLARA spatial resolution of 0.25° × 0.25° on a regular latitude-longitude grid.

The microwave satellite method is based on microwave emission (thermal electromagnetic radiation) from the ground, which is absorbed and propagated through the snowpack, based on its properties. Different frequencies penetrate through snow differently, and the difference in brightness temperature between high and low frequency has been found to be a good indicator for the snow water equivalent of dry snow (Cagnati et al., 2004) and also for snow melt onset (Takala et al., 2009). Usually, 19 GHz is used for a low frequency and 37 GHz for a high frequency. When snow depth, grain size, and snow density increase, the high-frequency signal attenuates more than the low-frequency signal due to scattering. Therefore, a large difference in microwave emission between a high and a low frequency indicates a greater snow volume (Kelly et al., 2003). Liquid water greatly influences the propagation of microwaves through snow cover, which makes this method well suited for detecting the appearance of meltwater in snowpack. At melt onset, the high emissivity of liquid water causes the microwave emissions to increase especially at high frequencies and the difference between the high- and low-frequency signals drops close to 0 (Cagnati et al., 2004). This is the basis for melt detection algorithm development in Wang et al. (2013), which is used to generate the microwave-based data set in this study. The algorithm used daily brightness temperatures from the scanning multichannel microwave radiometer (SMMR, 1979–1987), the special sensor microwave/imager (SSM/I, 1987–2008), and the special sensor microwave imager/sounder (SSMIS, 2009–2015) mapped to a 25-km EASE-Grid. The gaps in the SMMR data (due to a narrower swath and availability of every other day) and SSM/I and SSMIS data are filled by linear interpolation from adjacent days. The algorithm used temporal variations in the differences of the brightness temperature (Tb difference) between 19 and 37 GHz (vertical polarization) to detect MOD associated with the main melt event. A unique feature of the algorithm is its ability to distinguish early periodic melt onset from the main seasonal melt onset; the algorithm compared the daily Tb difference to the previous 3-day average, and MOD was detected, if the difference between these two values was for 4 days in a row greater than a threshold (Wang et al., 2013).

Figure 1a shows pentad mean surface albedo and daily Tb difference time series of one grid cell in 2005 and a sigmoid function fitted to the albedo values, following Figure 1 of Wang et al. (2013) for the microwave part (Tb difference). Figure 1b shows daily surface air temperature and snow depth at the nearby Dudinka station in 2005. The surface albedo begins to decrease after Day of Year (DOY) 115 and reaches 99% of its variation range at DOY 126, which is determined to be the MOD. For the microwave-based data set, two melt events are detected before the main melt event: The Tb difference drops at DOY 109 and DOY 128 but returns back

| Table 1                                                                 | Data Sets Used In This Study                                                                 |
|------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Product                                                                | Source                                         | Resolution                                      | Reference                                      |
| Albedo-based MOD                                                       | CLARA-A2 SAL                                   | 0.25° × 0.25° 5 days                           | Anttila et al. (2018)                           |
| Microwave-based MOD                                                    | SMMR, SSM/I, and SSMIS                         | 25 km × 25 km Daily                             | Wang et al. (2013)                             |
| Land cover                                                             | GLC2000                                        | 0.009° × 0.009°                                 | Bartholome and Belward (2005)                   |
| Elevation                                                              | GMTED2010                                      | 0.25° × 0.25°                                  | Danielson and Gesch (2011)                     |
| Standard deviation of the elevation                                   | GMTED2010                                      | 0.25° × 0.25°                                  | Danielson and Gesch (2011)                     |
| Air temperature at 2 m                                                 | ERA-Interim                                     | 0.25° × 0.25° 6 hr                             | Dee et al. (2011)                              |
| Fractional cloud cover                                                 | CLARA-A2 CFC                                    | 0.25° × 0.25° Daily                            | Karlsson et al. (2017)                         |

Note. MOD = melt onset date; CLARA-A2 SAL = CLouds, Albedo and RAdition second release Surface ALbedo; SMMR = scanning multichannel microwave radiometer; SSM/I = special sensor microwave/imager; SSMIS = special sensor microwave imager/sounder; CFC = fractional cloud cover.
to the premelt level. At the same time, the temperature rises close to 0 °C but returns quickly back to the previous below freezing values. The main melt event starts at DOY 134, which is determined to be the MOD. While both microwave- and albedo-based observations of snow cover change contain noise, the respective MOD estimation methods feature means to distinguish the main melt event. The albedo-based method uses pentad albedo values and the MOD is determined by fitting a sigmoid to the albedo values, and therefore, individual erroneous albedo values and small fluctuations in the time series do not affect much the analysis. The microwave-based method detects the timing when the Tb difference between the two frequencies drops close to 0, but additionally, it compares the daily Tb difference to the previous 3-day average. MOD is detected only when the difference between these two values is for 4 days in a row greater than a threshold, which minimizes false detection from fluctuations not due to melt.

Additionally, we used Global Land Cover 2000 data (GLC2000; Bartholome & Belward, 2005) and elevation and standard deviation (σ) of the elevation data sets from the Global multiresolution terrain elevation data 2010 (GMTED2010; Danielson & Gesch, 2011) to study the impact of land cover and topography on the difference in MOD between the data sets. The σ of the elevation was calculated by first dividing the elevation raster into blocks. The σ for the specified cells were then defined by the neighborhood blocks, and after that, the output was generalized to the desired output resolution (Danielson & Gesch, 2011). The ERA-Interim reanalysis data (Dee et al., 2011) for air temperature at 2 m and CM SAF CLARA-A2 fractional cloud cover data (Karlsson et al., 2017) were also used to assess the difference in MOD. The spatial resolution of temperature and cloudiness data sets was 0.25° × 0.25°.
Our study covered the land areas between latitudes 50°N and 80°N and the melting seasons between 1982 and 2015. Regions with ephemeral snow cover in, for example, central Europe are not analyzed, however, as both optical and microwave-based MOD estimations require continuous snow cover from winter to spring (Anttila et al., 2018; Wang et al., 2013).

We used the nearest neighbor method to resample the albedo-based MOD data set, the GMTED2010, the ERA-Interim and CLARA-A2 fractional cloud cover data to the 25-km equal-area projection. The simple nearest neighbor resampling was sufficient for our study, because the native grid resolutions of the data sets were already very similar. The higher-resolution GLC2000 data were resampled to the 25-km EASE-Grid by choosing the dominant land cover class within one 25-km × 25-km grid cell. Additionally, the fractional forest cover was calculated as the fraction of GLC2000 tree cover grid cells of all appearing cells within one 25-km × 25-km grid cell.

We compared the MODs grid cell by grid cell. The difference between MODs was calculated as microwave-based MOD minus albedo-based MOD for each grid cell, which means that positive difference indicates that the microwave satellite method detects MOD later than the optical satellite method.

To detect trends in MOD during the study period, we used the Theil-Sen estimator (Sen, 1968; Theil, 1950) besides the ordinary least squares (OLS) linear regression. Theil-Sen estimator is the median of all slopes between paired values and it is less sensitive to outliers than the OLS method. To study if there are significant monotonic trends, we used the Mann-Kendall test (Kendall, 1975; Mann, 1945), which analyses the difference in signs between earlier and later data points.

3. Results
3.1. Difference in MOD

Figure 2a shows the mean difference in MOD between microwave-based and albedo-based data sets during the whole study period 1982–2015. The difference is mostly positive, which means that the microwave-based method systematically lags the albedo-based method. This phenomenon results from the different melt detection methods. The microwave-based method detects the timing when the Tb difference between the two frequencies drops close to zero, that is, when meltwater appears in snowpack. The albedo-based method, in turn, is tuned to observe the point when the spring snow metamorphism begins to have a detectable effect on snow albedo. The snow metamorphism causes the albedo to decrease before any meltwater appears in the snowpack (Pirazzini, 2004; Roesch et al., 1999; Ross & Walsh, 1987), which is why the optical satellite detects MOD first. The difference varies mostly between 0 and 30 days, and the spatial variability is large. The difference in MOD is largest over Rocky Mountains, in northern Canada and in Mongolia (Boxes a–c in Figure 2a). In Siberia (Box d in Figure 2a), where there are vast forests, the difference is closer to 0. The difference is negative in only a few small areas. The spatial variability of the difference suggests that land cover and topography may
have an impact on the difference between the data sets; the difference seems to decrease in forests and increase in high altitudes. To study if the difference is significant, we used the Student’s $t$ test. The difference is significant ($p < 0.05$) mainly in the northern parts of the study area, whereas in forested areas the difference is not significant (Figure S1 in the supporting information).

The standard deviation ($\sigma$) of the difference (Figure 2b) shows quite similar spatial variations: $\sigma$ of the difference is large over areas where the difference in MOD is large. We investigated the $\sigma$ for both data sets separately, and the $\sigma$ of the albedo-based data set is larger than the $\sigma$ of the microwave-based data set. Albedo-based MOD varies, especially, over mountainous terrain. Microwave-based MOD varies over Rocky Mountains more than in other areas, but the variability is smaller than the variability of albedo-based MOD. Therefore, the large $\sigma$ of the albedo-based MOD dominates the spatial variations of the $\sigma$ of the difference.

### 3.1.1. Impact of Land Cover on the Difference in MOD

Figure 3 shows the mean difference in MOD between microwave-based and albedo-based data sets for diverse land cover classes during the whole study period 1982–2015. The mean difference varies between 2.5 and 22 days depending on the land cover class. In forests, the difference in MOD varies between 2.5 and 12 days (shaded with gray in Figure 3) and in other land cover classes between 8 and 22 days. Figure 3 shows the same pattern as Figure 2a: The difference between microwave-based and albedo-based MOD estimates decreases in forests compared to open areas.

Figure 4 shows the dependency between forest cover from GLC2000 and the mean difference in MOD. Figure 4 is consistent with Figures 2a and 3: The larger the fractional forest cover, the smaller the mean difference in MOD. The correlation between the variables is almost linear when the forest cover is over 20%.

A likely explanation for this effect was indirectly given by Colbeck (1989), who argued that the penetration of solar radiation into a snowpack provides energy for an increase in subsurface water vapor flow rate (also in subfreezing conditions), which in turn accelerates snow metamorphism. Malle et al. (2019) also found that shading effect of the canopy has a large effect on the shortwave radiation budget. This is consistent with our finding that in forests, where the canopy reduces the insolation of the underlying snow surface, dry snow metamorphism is weaker than in open areas, delaying the date when the induced albedo decrease is
detectable by the algorithm. However, the canopy cannot shield the snow from the increasing air temperatures, which strengthen the vertical temperature gradient in the snow and thereby increase the subsurface water vapor flow, causing grains to grow and albedo to decrease. This triggering of the albedo-based MOD detection would occur at a date closer to the melt water-triggered microwave MOD detection, as shown here, and at warmer air temperatures, as we will demonstrate in section 3.2. However, it also needs to be noted that the canopy itself may interfere with the MOD detection algorithms via, for example, sporadic on-canopy snow cover and the microwave emissions generated by the canopy and tree trunks themselves.

3.1.2. Impact of Topography on the Difference in MOD

Figure 5 shows how the mean difference in MOD depends on elevation and on $\sigma$ of the elevation. When the altitude is between 0 and 500 m (Figure 5a), the difference is approximately 10 days and there are no significant changes. With higher altitudes the difference increases almost linearly. With altitudes higher than 2,200 m, the variables do not correlate clearly with each other.

Figure 5b shows a clear correlation between difference in MOD and the $\sigma$ of the elevation: The difference in MOD increases linearly, when the $\sigma$ increases from 0 to 350 m. With larger $\sigma$ values the variables do not have any clear correlation. Usually, the elevation is large where the $\sigma$ of the elevation is large, as well, which could explain the similar correlations in both Figures 5a and 5b.

Mountainous areas complicate the derived Tb interpretation, because the spatial resolution of the radiometer data is so modest. For the albedo retrieval, the spatial resolution of individual images is better and a topography correction is made. However, large variation in the albedo value is typical in spring, when the northern and southern slopes may have systematically different snow albedo. For these reasons large MOD differences are natural in roughest terrain. Also, the sample sizes for high-elevation mountainous areas are very small (as illustrated), which degrades the statistical viability of the analysis.

3.2. Relationship Between Air Temperature and MOD

Figures 6a and 6b show the daily mean air temperature on MOD for both microwave-based and albedo-based data sets during the entire study period 1982–2015. The microwave satellite method detects melt onset when daily mean air temperature is mostly at or slightly over 0 °C, as expected. There are some areas, especially in Asia, where melt onset is detected at
lower temperatures. The albedo-based method detects melt onset at significantly lower temperatures; the albedo decrease associated with melt onset begins at temperature below 0 °C over all regions of the NH. The coldest temperatures can be found in Mongolia (Box a in Figures 6b), where the temperature can be as low as −8 °C when the melt onset is detected. Due to the different melt detection methods, we can conclude that Figure 6b shows the air temperature on the day, when the large-scale metamorphism of snow begins to be detectable by its albedo signal. Correspondingly, Figure 6a shows the air temperature on the day, when meltwater appears in the snowpack. Figure 6c shows the difference in temperature on MOD between microwave-based and albedo-based data sets. The difference shows very similar spatial variations with the difference in MOD (Figure 2a): The difference in temperature is large over areas where the difference in MOD is large. Over some areas the difference can be as high as 10 °C.

The mean cloudiness between the MODs detected by albedo-based and microwave-based method (Figure 7) is rather low in Mongolia (Box a in Figure 7). We postulate that this is why the albedo-based method detects the melt onset at very low temperatures; the incoming solar radiation is so strong that snow metamorphism effect on albedo is detectable already at very low temperatures. The same phenomenon cannot be seen in northern Canada and northeastern Russia (boxes b and c in Figure 7), where the cloudiness is low too. We hypothesize that because in the north the incoming solar radiation is weaker, the albedo decrease requires higher air temperatures.

Figure 8 shows the mean air temperature on MOD for different land cover classes. The albedo-based method detects melt onset, when the
The temperature is mostly between −4 and −7 °C. The microwave-based method detects MOD, when temperature is mostly between 0 and 2 °C. In the albedo-based data set, more variability appears between the land cover classes, whereas in the microwave-based data set, the differences between diverse land cover classes are quite small.

Table 2 shows a summary of the mean air temperatures on MOD for both data sets and separately for diverse land cover classes of various kinds of forests and for open areas. The mean temperature on MOD in all land cover classes is −5.5 °C for the albedo-based data set and 0.6 °C for the microwave-based data set. In forests, the corresponding values are −4.6 °C for albedo-based data and 0.8 °C for microwave-based data. The values for open areas are −6.2 and 0.5 °C, respectively.

It is noteworthy that in forested areas, the albedo-based MOD detection triggers generally later and at higher air temperatures than in open areas, whereas no such difference is apparent in the microwave-based method. This is consistent with our reasoning in section 3.1.1 on the role of solar radiation in triggering the initial dry-snow metamorphism-induced albedo decrease detected by the algorithm and how forest canopies may shield the underlying snow cover from this effect.

### 3.3. Trends in MOD

Figure 9 shows time series of mean MOD and trends, which are determined using OLS (blue line) and Theil-Sen (red line) methods for the whole study period 1982–2015. The trend in the mean MOD of the NH is negative for both data sets, and it does not depend on the method: the trend is −0.23 day/year for both data sets.
However, the uncertainty is slightly larger for the albedo-based data set. According to the Mann-Kendall test, a monotonic significant trend exists for both data sets.

Figure 10 shows the time series of the mean MOD separately for Eurasia and North America during the whole study period 1982–2015. A monotonic negative trend is significant in all four cases. The trend is more negative in Eurasia than in North America, and similar to Figure 9, the trends between the albedo-based and microwave-based data sets are very similar (Table 3).

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Table 3

| Data Set         | Trend in the NH (day/year) | Trend in Eurasia (days/year) | Trend in North America (day/year) |
|------------------|-----------------------------|-----------------------------|----------------------------------|
| Microwave based  | $-0.23 \pm 0.08$            | $-0.26 \pm 0.10$            | $-0.18 \pm 0.14$                 |
| Albedo based     | $-0.23 \pm 0.11$            | $-0.28 \pm 0.14$            | $-0.16 \pm 0.15$                 |

Note. Trends are determined using Theil-Sen method. All the trends are statistically significant. MOD = melt onset date; NH = Northern Hemisphere.
4. Discussion

Melt season timing has been studied in a number of studies. However, the vast majority of the studies has been conducted using microwave satellite data. The albedo-based data set we used in this study is the first independent control based on optical satellite data that covers almost 40 years (Anttila et al., 2016). Thus, this is the first study where fully independent albedo-based and microwave-based MOD estimates have been intercompared at multidecadal time scales over all land areas of the NH with substantial snow cover persisting from winter to spring.

Both methods have relatively large uncertainties in mountainous terrain, and thus, $\sigma$ of the difference in MOD increases in high altitudes (Figure 2b). The microwave measurements usually have large uncertainties in mountainous regions due to deep snow, complex terrain, or dense vegetation (Tong et al., 2010). Additionally, the coarse resolution is not ideal over complex terrain and is likely to cause uncertainties. The range in Tb difference between dry and wet snow can be underestimated, which may result in large uncertainties in MOD from the microwave-based method (Wang et al., 2013). Microwave-based method also has challenges in forests due to the vegetation. For albedo retrieval, mountains pose a challenge due to shadowing, but this is taken into account by making the topography correction for the CLARA-A2 SAL product (Anttila et al., 2016). However, the snow melt onset may differ markedly on the northern and southern slopes, which causes large heterogeneity in the MOD values based on the albedo.

As the albedo-based MOD detection requires a snow cover which is sufficiently continuous and bright (i.e., likely optically semi-infinite) at the grid cell scale to obtain a premelt albedo level for the sigmoid fit, it also appears unlikely that the differences in high-elevation areas would result from cases where premelt variations in albedo result from changes in thin and patchy snow cover, as these would likely render the grid cell too unstable to process. However, considering all the challenges present in both methods in mountainous terrain, it is advisable to treat all high-elevation results and differences with due caution.

When we additionally investigated our results by masking out all grid cells with the $\sigma$ of elevation over 350 m, it had little impact on our results. Even though both methods have challenges over mountains,
mountainous regions represent only a small fraction of the overall study area and, therefore, do not significantly affect the overall results.

The albedo-based MOD was determined to be the day, when the sigmoid reached 99% of its variation range. With other value, for example, 95%, the method would detect MOD later. Thus, changing this threshold value would affect the results; shifting the value onward, would bring the albedo-based and microwave-based MOD values closer to each other. Therefore, one might in principle use this methodology to, for example, try to match the estimates in order to ascertain the mean snow albedo (within the limits of the estimation uncertainty) per land cover class valid for the point during the melt season when liquid water first appears in the snow pack. However, the substantial spatiotemporal variability shown in Figure 2b would place restraints on such an approach. The current threshold is tuned to observe the point when the spring snow metamorphism begins to have a detectable effect on snow albedo, which is the onset timing of the SAF component related to snow metamorphisms (Qu & Hall, 2007). A persistent spread in SAF strength has been found in Phase 3 and Phase 5 of the Coupled Model Intercomparison Project simulations (Fletcher et al., 2015; Qu & Hall, 2014). This spread is largely responsible for uncertainties in simulated 21st century warming at northern high latitudes (Qu & Hall, 2014). The albedo-based MOD data set will be useful to evaluate the onset of the spring snow metamorphism in climate models and thus potentially to gain improved understanding of the spread in SAF in the models.

In our study, we have not accounted for possible changes in land cover, and we used only one land cover classification data set for the whole study period. It is possible that this can cause some minor uncertainties to our results. However, our study concentrates on the northern parts of Eurasia and North America, where man-made land use changes are not as prevalent as in the lower latitudes. Additionally, misclassifications in cloud masking can cause errors to the optical satellite-based albedo estimates. However, the albedo-based method used pentad albedo values and sigmoid fitting, thus, limiting the effect of individual erroneous albedo values on the results.

We found that the mean temperature when albedo begins to decrease is −5.5 °C. This result is an empirical estimate for the temperature, when snow metamorphism begins to have a detectable effect on snow albedo, thus affecting radiative transfer and the surface energy budget. A number of studies have investigated the relationship between albedo and temperature (Pirazzini, 2004; Pirazzini et al., 2006; Roesch et al., 1999; Ross & Walsh, 1987). These studies are based on field experiments, and the results are very similar to our results; snow albedo begins to decrease due to snow metamorphism at about −5 °C. Even though our results are for the NH at coarser resolution, they are still consistent with the previous studies. Additionally, many climate models use similar approach to calculating the surface albedo; for example, in the fifth-generation atmospheric general circulation model (ECHAM5) developed at the Max Planck Institute for Meteorology, the surface albedo is constant below −5 °C and above 0 °C and decreases linearly between those temperatures (Roeckner et al., 2003).

MOD exhibits large annual variability (Figures 9 and 10), and the two data sets show very similar trends. However, there are differences in trends between Eurasia and North America; the trend toward earlier melt onset is larger in Eurasia than in North America. The trend estimates observed in our study are consistent with previous studies: Takala et al. (2009) observed statistically significant negative trends in MOD in Eurasia, and Kim et al. (2012) found that spring thawing trend is −0.233 day/year in tundra and −0.196 day/year in boreal forest, which are very similar to the trend estimates we observed. Mioduszewski et al. (2015), Kim et al. (2012), and Tedesco et al. (2009) observed that negative trend in MOD is larger in Eurasia than in North America, which is consistent with our results. However, Tedesco et al. (2009) found that spatially averaged trend in the NH was −0.47 day/year, which differs from our result (−0.23 day/year). Additionally, trend estimates for sea ice melt onset are very similar to our results (Markus et al., 2009; Stroeve et al., 2014), consistent with studies documenting the link between earlier terrestrial snow melt and associated atmospheric circulation changes across the Arctic impacting the sea ice cover (Matsumura et al., 2014). However, we note that there is not yet a clear picture on the identification of the dominant underlying mechanisms or in the cause-effect delineation between the various emerging signals (Gao et al., 2015).

Additionally, we investigated the connection between the trends in MOD and the trends in spring temperature. Figure 10 shows that the melt onset occurs mostly between DOY 95 and DOY 130, so we
calculated the mean air temperature during this period for each year. We studied the correlation between the mean temperature and MOD values and found that there is a statistically significant negative correlation between these variables (Figure S2). Given the straightforward causal connection between air temperatures and snow metamorphism and melt, it is very likely that rising spring temperatures earlier are a major driver in the trend toward earlier melt. However, temperature is not the only driving force, but, for example, precipitation and clouds affect the melt onset, too. Mioduszewski et al. (2015) found that temperature is one of the strongest predictors for early MOD anomalies, and also, atmospheric thicknesses, water vapor, and downward longwave radiation play significant roles in the timing of melt onset.

Multiple studies have observed negative trends in snow cover extent in spring (Brown & Robinson, 2011; Derksen & Brown, 2012; Déry & Brown, 2007; Hernández-Henríquez et al., 2015; Mudryk et al., 2017). Decreasing snow cover extent in spring is likely to result from earlier melt onset, which is consistent with our results.

5. Conclusions

We have intercompared MOD estimates obtained from microwave and optical satellite sensors over the NH between 1982 and 2015. The main findings in our study are as follows:

1. Microwave satellite method detects MOD on average 10 days later than the optical satellite method. In some regions, the difference can be several weeks. This results from the different melt detection methods; the albedo-based method detects the point when snow metamorphism begins to have a detectable effect on snow albedo, whereas the microwave-based method detects the appearance of meltwater in snowpack.

2. The difference in MOD decreases in forests; canopy protects snow from sunlight delaying snow metamorphism. However, the canopy cannot protect snow from increasing air temperatures, thus bringing the MODs closer together.

3. Statistically significant trends exist toward earlier melt onset in the NH and in North America and Eurasia over the 1982–2015 period. The trend estimates are very similar for both melt onset estimation methods; we observed a trend of −0.23 day/year, for both assessed methods for NH.

All in all, differences in MOD exist between the data sets, but they can be explained due to the different melt detection methods. Additionally, the trend estimates are very similar, even though the methods are independent of each other. This consistency suggests that the trend estimates are reliable and the recent developed albedo-based method is effective for MOD detection. The consistency between the two methods also suggests that the present methods and data sets should be applicable to evaluate the treatment of seasonal snow cover and its annual melt in climate models. Given the albedo-based method detects the timing, when snow metamorphism begins, the data set can be used to evaluate the onset of SAF related to the snow metamorphism component in climate models. In future work, the albedo-based method could be used for MOD detection using data from other optical sensors at improved spatial resolutions, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) surface albedo products, which may improve MOD estimates in mountainous regions.

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