# Small-scale variations of climate change in mountainous-forested terrain 

A study from the H.J. Andrews Long Term Ecological Research site, Oregon, USA

Master's Thesis

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## Abstract

The influence of topography on regional climate change remains a poorly understood phenomenon. In this thesis, long-term temperature records from the H.J. Andrews Experimental Forest (HJA), Oregon, USA and six stations from the Snotel network at a distance $20-50 \mathrm{~km}$ from the HJA were analyzed. Temperature patterns of the study area were investigated, with a focus on comparing valley and ridge stations. In particular, trends of the last day of frost, length of the vegetation period, temperature and the annual number of cyclonic, anti-cyclonic and zonal winds were explored. Additionally, the effect of homogenization of the temperature time series prior to analysis was considered. During the study period (1958-2011), the valley stations considered showed more consistent trends of an earlier last day of frost and warming daily minimum temperatures compared to stations at higher elevations. Changes in synoptic forcing towards more cyclonic activity and hence less cold air pooling in spring could serve as a reasonable explanation of these results. Data homogenization was found to considerably affect the temperature trends obtained. Further research and more data are needed.

## Contents

1 Introduction ..... 1
1.1 Motivation ..... 1
1.2 Objectives ..... 1
1.3 Hypothesis ..... 2
2 Theory ..... 3
2.1 Factors affecting surface and near-surface temperature in a mountain- ous terrain ..... 3
2.1.1 Wind and topography ..... 3
2.1.2 Other factors ..... 4
2.2 Predictions ..... 5
2.2.1 Temperatures ..... 5
2.2.2 Synoptic patterns ..... 6
3 Materials and Methods ..... 7
3.1 Study site ..... 7
3.2 Data and variables ..... 8
3.2.1 HJA ..... 8
3.2.2 Snotel ..... 8
3.3 Data quality and homogenization ..... 11
3.3.1 Datasets ..... 12
3.4 Software ..... 13
3.5 Last day of frost (LDOF) ..... 13
3.6 Length of the vegetation period (LOVP) ..... 14
$3.7 T_{\text {min }}$ and $T_{\max }$ trends ..... 14
3.8 Synoptic patterns ..... 15
3.9 Wind speed and direction ..... 17
4 Results ..... 19
4.1 Last day of frost (LDOF) ..... 19
4.2 Length of the vegetation period (LOVP) ..... 21
$4.3 T_{\min }$ and $T_{\max }$ trends ..... 25
4.3.1 LSR PDF maxima ..... 25
4.3.2 Other parameters ..... 28
4.4 Synoptic patterns ..... 29
4.5 Wind speed and direction ..... 32
5 Discussion ..... 35
5.1 Temperature patterns ..... 35
5.2 Synoptic patterns and wind ..... 35
6 Conclusions ..... 37
A Appendix ..... 38
Bibliography ..... 45

## Acknowledgements

I would like to thank my family and friends for their support and encouragement.
I would also like to thank my advisors, Dr. Peter Hoffmann from the Potsdam Institute for Climate Impact Research, especially for his help with the Python programming language and his support and encouragement and Prof. Dr. Christoph Thomas for sharing his knowledge, enthusiasm and for organizing our group visit to the European Geosciences Union Conference. Finally, I would like to thank BAYHOST for their financial support.

## 1 Introduction

### 1.1 Motivation

A mountainous terrain covers 20-25\% of the Earth's surface, depending on which definition is used (Barry \& Blanken, 2016) and mountain-based resources indirectly sustain most of the global population (Beniston, 2006). With climate change threatening global population as well as ecosystems, knowledge about responses of mountain climates on a regional scale is becoming crucial. For example, to predict streamflows, it is necessary to know where precipitation will fall as rain and where as snow, which could be predicted if one knows the temperature distribution (Minder et al. 2010). Accurate climate change predictions would enable us to better predict responses of ecosystems, e.g. an upward motion of species.

It is known that climate change has a high spatial variability (IPCC 2007, Daly et al., 2010). However, climate models are mostly too crude to account for smaller scale features such as topography or to resolve sub-km scale air temperature distribution relevant to biota living in narrow mountain valleys (Holden et al., 2011).

### 1.2 Objectives

In this study, long-term temperature records from the H.J. Andrews Experimental Forest (HJA), Oregon, USA and six stations from the Snotel network at a distance of $20-50 \mathrm{~km}$ from the HJA (Fig. 3.1 and 3.3) were analyzed. Temperature patterns were investigated with a focus on comparing valley and ridge stations' responses to climate change. Specifically, trends of the last day of frost, the length of the vegetation period and temperature trends were explored.

There are many factors affecting near surface temperature patterns (see Chapter 2). This thesis attempts to explain some of the temperature trends by investigating synoptic wind patterns (in particular the annual number of cyclonic, anti-cyclonic and zonal days) and wind speed and direction.

### 1.3 Hypothesis

The hypothesis was that the stations located at mountain ridges will show more pronounced warming trends compared to stations located in valleys. As suggested by e.g. Daly et al. (2010), valley stations are more decoupled from the free troposphere above compared to ridge stations due to a temperature inversion created when cold air pooling occurs. This could lead to a less prominent climate warming signal in valleys.

## 2 Theory

### 2.1 Factors affecting surface and near-surface temperature in a mountainous terrain

There are many factors affecting the surface and near-surface temperature. Wind facilitates thermal convection on and near the surface. Radiative heat transfer is governed by the radiation budget of solar (short-wave) and terrestrial (long-wave) radiation. Heat is transferred from and into soil layers by thermal conduction. Also phase changes play a role - latent heat is absorbed during ice melting and vaporization and released during condensation and freezing.

### 2.1.1 Wind and topography

In this thesis, 'wind' refers to motion of air. This could be at various scales and speeds. Topographic characteristics such as slope, aspect and exposure of surface to solar radiation and to winds affect local climates (Beniston, 2006; Smith, 2002; Geiger et al., 1995). Topography is also influencing the airflow near the surface (Smith, 2002). Vice versa, temperature gradients cause pressure gradients, which drive winds. Here, two phenomena specific for mountainous regions are considered: cold air drainage and pooling.

Cold air drainage and pooling were described by Daly et al. (2010) and other studies, dating back to 1914 (Marvin, 1914). On a clear day, when the radiation balance is negative ${ }^{1}$ (i.e. the surface is warming, $\sim$ day-time), the air near the surface is warming faster than the air at the same elevation further away from the surface. The warmer air will rise and, on a slope, an up-slope flow forms. However, when the radiation balance is positive ( $\sim$ night-time $)$, the air near the surface is cooling faster and when there is a small amount of vertical mixing (i.e. weak winds) a down-slope flow forms, referred to as cold air drainage. This diurnal pattern of up- and downslope flow is present in all mountain regions (Beniston, 2006; Lundquist et al., 2008). Similarly, in a valley with an altitudinal gradient, there are up-valley flows during

[^0]the day and down-valley flows during the night. These winds are the strongest when skies are clear and the synoptic winds are weak, since diurnal mountain circulation patterns can be disturbed by interference with synoptic winds (Whiteman, 2000).

As the air drains down the slope, it can form cold air pools in valleys, referred to as cold air pooling, which causes local temperature inversions. When this occurs, the warmest air of a valley is found in a thermal belt at the top on the inversion, midway up the slope (Whiteman, 2000). Due to a lack of vertical mixing, a cold air pool within a valley is effectively decoupled from the free troposphere above (Daly et al., 2010). The temperature difference between the valley bottom and an adjacent hill slope can be 6 K or even more (Bootsma, 1976; Whiteman, 2000). Actual drainage flows are often intermittent (Mahrt et al., 2010).

Although cold air drainage and pooling are widespread even on weak slopes (Mahrt et al., 2010), their responses to climate change are largely unknown. General circulation models (GCMs) are too crude ( $\sim 50 \mathrm{~km}$ resolution) to account for topography and hence not useful to simulate future cold air drainage and pooling. Moreover, due to the decoupling from the free atmosphere, cold air pools might respond differently to climate change than what would be typical for a given region (Daly et al., 2010).

Valley geometry needs to be considered as well. Cold air drainage on a slope that gets steeper with increasing elevation creates a horizontal pressure gradient that drives nocturnal down-valley winds. On the other hand, when the steepness decreases with elevation there are stable conditions and cold air pooling. The situation is also different for channel-like valleys with a preferred wind direction (along the channel) and cone-like valleys (no preferred wind direction) as the former will likely experience stronger winds and hence more mixing (Lundquist et al., 2008).

Synoptic winds also need to be taken into account. Daly et al. (2010) found out that anti-cyclonic flows with a low flow strength lead to more pronounced cold air pooling and hence stronger temperature inversions, whereas cyclonic flows with a high flow strength showed the steepest temperature drop with altitude (Fig. 3.8). Therefore, regions with a predicted increase in the number of cyclonic days are likely to experience less cold air pooling and valleys might experience greater degree of warming than hill slopes and crests.

### 2.1.2 Other factors

There are other factors affecting the near-surface temperature. For example, vegetation cover affects the amount of solar radiation reaching the surface and also airflows in its proximity (Smith, 2002). Clouds affect the radiation budget by absorbing part of the solar radiation and also emitting radiation themselves. Surface emissivity, the albedo and thermal conductivity also play a role.

In the case of the HJA, another factor needs to be considered. There is a water body (Blue River Lake) at the mouth of the valley (Fig. 3.1b). In general, water surfaces take longer to change temperature than land surfaces due to their larger heat capacity (Aguado, 2016). Therefore, the lake has a warming effect on the surrounding area during the periods of positive radiation balance ( $\sim$ night time) and a cooling affect when the radiation balance is negative ( $\sim$ day time). Hence, two competing flows in the HJA valley might occur during the night-time: a down-valley flow caused by cold air drainage and up-valley flow cased by the lake being warmer than the surrounding land surface.

### 2.2 Predictions

### 2.2.1 Temperatures

Globally, on average, both the daily minimum temperature ( $T_{\text {min }}$ ) and the daily maximum temperature ( $T_{\max }$ ) have shown increasing trends since 1950, with most of the increase since 1980 (Vose et al., 2005; Stocker et al., 2013). A number of studies in the US found that $T_{\min }$ records have been showing more pronounced warming trends than $T_{\text {max }}$ records (Easterling, 2002). Greenland (1994) observed an increase in the minimum, maximum and mean temperatures in the HJA in the period 19731991. The greatest increases occurred in spring months (March-May). Jones (2010) studied monthly means of $T_{\min }$ and $T_{\max }$ for some of the HJA stations and found that most of the stations experienced warming trends for the majority of months of the year.

The last day of frost (LDOF) marks the beginning of the vegetation period. The LDOF was defined as the last day when $T_{\min }<0^{\circ} \mathrm{C}$, also referred to as the lastspring freeze (Easterling, 2002) and followed by a frost-free season. In latitudes corresponding to the study region, the LDOF usually occurs in spring, however, at high elevations it is shifted to later dates and it is non-existent in permanently frozen areas. According to Kunkel et al. (2004), the LDOF has been occurring earlier since 1980 in the US on average.

The length of the vegetation period (LOVP), also referred to as the length of the frost-free season (Kunkel et al., 2004), is an important parameter for organisms. Here it was defined as the period where $T_{\min } \geq 0^{\circ} \mathrm{C}$. Since 1980, the LOVP has been increasing the in US on average, and the increase has been greater in the western US (Kunkel et al., 2004).

### 2.2.2 Synoptic patterns

According to the IPCC AR4 (Jones et al., 2007) considering large scale climate models, the annual precipitation will increase and the surface pressure is projected to decrease in the area including the study region. Since anti-cyclonic days are typically dry with high surface pressure (Daly et al., 2010), these changes would indicate a decrease in the annual number of anti-cyclonic days in this area. However, according to the Jones et al. (2007), these projections are still quite uncertain.

## 3 Materials and Methods

### 3.1 Study site

The data was taken from the H.J. Andrews Experimental Forest (HJA), Oregon, US (Figure 3.1) and six stations from the Snotel network at a distance 20-50 km from the HJA.

The HJA is a part of the US Long Term Ecological Research Network (LTER) and it has operated since 1948. It is located on the western slope of the Cascade Mountains in Oregon with elevation ranging from 412 m to 1627 m . It attracts scientists from a variety of disciplines, and provides a unique opportunity to study mountain climate due to its dense network of stations, long-term records and a distinct mountainous topography. Regarding the vegetation, there are conifer-dominated forests, some of which have been growing without human management for several centuries (Daly et al., 2010; Smith, 2002; HJA Website, 2017a). The results could potentially be generalized to other areas since the HJA's climate is representative of mountainous areas of the Pacific Northwest (Smith, 2002; Daly et al., 2010).


Figure 3.1: Location (a) and topographic relief map (b) of the HJA. Sources: Google Maps and Daly et al. (2010), respectively.

The HJA has a Mediterranean climate with wet winters and dry summers and annual precipitation between $2227 \mathrm{~mm} /$ year at 430 m above the sea level (asl) and 2712
$\mathrm{mm} /$ year at 1294 m asl (Daly et al., 2010). It has a pronounced topography with steep slopes and narrow valleys highly susceptible to cold air drainage and pooling, and night-time temperature inversions are common both in summer and winter (Daly et al., 2010; Smith, 2002).

### 3.2 Data and variables

Troughout this text, abbreviated forms of station names are used, e.g. PRIMET instead of Primary Meteorological Station. Stations within the HJA have abbreviations consisting of capital letters and numbers only, whereas Snotel stations are referred to by combinations of upper- and lower- case letters. There are five 'benchmark' stations within the HJA: PRIMET, VANMET, CENMET, UPLMET and HI15MET. For those, measurements at two heights above the ground were included: 150 cm and 450 cm . For example, to refer to PRIMET measurements at height 150 cm , abbreviation PRIMET150 is used and analogously for the height 450 and the other benchmark stations. Please see Table A. 1 in the Appendix for full names of the stations and information about their latitude, longitude, elevation, slope and aspect.

### 3.2.1 HJA

For the HJA, the data used came from six meteorological stations: PRIMET, CS2MET, VANMET, CENMET, UPLMET and HI15MET and 17 reference stands (RS) in forests: RS $1-5,7,10,12,13,15-17,20,24,26,86$ and 89 (Fig. 3.2). Stations were divided into 'valley' and 'ridge' stations, as described in section 3.3.1. For further information about the HJA measurement sites (such as sensors used, canopy, surface and general site characteristics) see the HJA Website (2017a) and Smith (2002), Table F.1., pages 189-211.

### 3.2.2 Snotel

Snotel (short for SNOw TELemetry) is a network of stations primarily aimed at snow monitoring operated by the United States Department of Agriculture Natural Resources Conservation Service (USDA NRCS). For our purpose, daily $T_{\min }$ and $T_{\max }$ data were used. More information about Snotel can be found on their website (USDA NRCS, 2016b). The stations considered were ThreeCreeksMeadow, McKenzie, RoaringRiver, HoggPass, SantiamJunction and JumpOffJoe, at a distance 20-50 km from the HJA (Fig. 3.3).


Figure 3.2: Map showing names and positions of the HJA stations.

The variables considered were $T_{\min }$ and $T_{\max }$ air temperature with daily resolution from 1958 until 2011. The data were provided by C.K. Thomas (2011). During the time period studied (1958-2011), the methods and devices used to measure and record $T_{\min }$ and $T_{\max }$ were evolving. Detailed information about measurement methods and devices for the HJA stations can be accessed on the HJA website, Measurements Information section (2017). For the Snotel network, this information is

## 3 Materials and Methods

available on the Snotel website (2017) under 'Station Information' (station, variable and time-period of interest must be specified first).

Additionally, horizontal wind direction and speed from the benchmark stations were considered. The start of the measurement period was between 1992 and 1996 (depending on the station) and the end date was set to 31. 12. 2011 to correspond to $T_{\min }$ and $T_{\text {min }}$ data. A propeller anemometer at height 5 to 12 m was used to obtain the wind data, available through online application GLITCH (General Linear Integrator for Time CHanging, 2016). More information about the wind data can be found in the section 3.9.


Figure 3.3: Map showing the positions of the Snotel stations and the HJA. It was created using the 3.0 Beta release of the National Water and Climate Center's Interactive Map (USDA NRCS, 2016a).

### 3.3 Data quality and homogenization

Long term datasets are prone to inhomogeneities caused by, for example, a change of devices, station location, or surrounding vegetation (Peterson \& Easterling, 1994). The first step in our work was creating a homogenized dataset. Plausibility tests, despiking and initial quality control tests were performed. The standard Normal Homogeneity Test (SNHT) (Alexandersson, 1986; Alexandersson \& Moberg, 1997) was used to detect breaks and shifts in the time series of the variables considered. A composite climate reference time series based on the Global Historic Climate Network was created and, together with cross-referencing against station records, was used to correct non-homogeneities in the data. The quality control and homogenization procedure was developed in Matlab (The MathWorks, Inc., 2017) by C. K. Thomas (2011) and can be seen in Fig. 3.4. The homogenization is an iterative process it finds and corrects the largest break (shift) in the time series input and then it proceeds iteratively as long as there are breaks above a certain threshold (Fig. 3.5, bottom).


Figure 3.4: Data quality control and homogenization procedure developed by C. K. Thomas (2011).

RS07-tmin Iteration: 1




Figure 3.5: Example of the homogenization procedure for $T_{\min }$ at RS07. From top to bottom: 1. the time series recorded at RS 07 (in blue) and a reference time series (red), 2. the time series of differences between recorded $T_{\min }$ and the reference series (as in 1.) showing a detected shift, 3. the result of the SHNT and a selected threshold for shifts. Shifts smaller than this threshold were not addressed.

### 3.3.1 Datasets

To correct for breaks and shifts in the $T_{\min }$ and $T_{\max }$ time series, a homogenized dataset was created as described above. However, some of the shifts could be a true temperature shifts and might not be caused by a change in devices or measurement methods in general. Most shifts were a part of several bigger clusters, close together in time and magnitude, but there were also outliers. These outlying shifts were not accepted in the 'partially-homogenized' dataset. To determine the effect that data homogenization has on the results, three datasets were analyzed (Table 3.1).

The stations were divided into two groups, according to their relative elevation as estimated from Lidar measurements:

1. Valley stations, here defined as the stations located less than 100 m above the valley bottom, i.e. below 530 asl.
2. Ridge stations - all the other stations.

According to the criteria above, there are five valley stations: PRIMET, RS02, CS2MET, RS01 and RS89. They are all located in the same valley within the HJA.

Table 3.1: Three datasets used.

| Dataset | Description |
| :--- | :--- |
| Raw | Data as obtained from the stations. |
| Homogenized | Created from the raw dataset as shown in the <br> flowchart in Fig. 3.4. |
| Partially-homogenized | Only shifts occurring in clusters were considered valid, <br> outliers were not accepted. |

### 3.4 Software

Apart from the data homogenization, which was done in Matlab (The MathWorks, Inc., 2017), the analysis was performed in Python (Python Software Foundation, 2017), utilizing its many packages, notably scipy. Spyder - Scientific Python Development Environment (2017) was used. Typesetting of this thesis was performed in Texmaker (Brachet, 2014), running pdfTeX (Thanh, 2015).

### 3.5 Last day of frost (LDOF)

It was assumed than the LDOF occurs within the first 200 days of each year. Starting at day of the year (DOY) 1 (i.e. January $1^{\text {st }}$ ), each DOY up to DOY 200 was checked and the last DOY with $T_{\text {min }}<0^{\circ} \mathrm{C}$ was recorded; if there was a gap ( NaN ) between the last DOY with temperature below $0^{\circ} \mathrm{C}$ and DOY 200, the LDOF was set to NaN.

Afterwards, a trend in the LDOF for each station was calculated using a least squares linear fit. To quantify the significance of the trends (by means of their p-values), the Mann-Kendall test was performed. It is a non-parametric statistical test, described e.g. in Yue et al. (2002). A map utilizing the Universal Transverse Mercator (UTM) coordinate system and showing the stations within the HJA together with their LDOF trends was created (Fig. 4.1). At high elevations, frost can occur at any time of the year, therefore the LDOF is not meaningful there.

### 3.6 Length of the vegetation period (LOVP)

The LOVP was defined as the number of consecutive days where $T_{\min } \geqq 0^{\circ} \mathrm{C}$. To calculate it, the LDOF and the first day of frost (FDOF, also referred to as the first autumn freeze) needs to be determined. The LDOF was calculated as described in the previous section. To calculate the FDOF, it was assumed that it occurs annually between the LDOF and the DOY 365. Starting at the LDOF, days were consecutively checked until the first DOY with a temperature below $0^{\circ} \mathrm{C}$ was found, this day was then recorded as the FDOF of the year considered. If a gap ( NaN ) was encountered before finding a DOY with a temperature below $0^{\circ} \mathrm{C}$, the FDOF was set to NaN . Whenever the LDOF or the FDOF for a particular year was NaN, the LOVP was set to NaN.

Otherwise,

$$
\begin{equation*}
\text { LOVP }=\mathrm{FDOF}-\mathrm{LDOF} \tag{3.1}
\end{equation*}
$$

Afterwards, trends in the LOVP were calculated using a least squares linear fit and their p-values were determined.

## $3.7 T_{\min }$ and $T_{\max }$ trends

For each DOY (ranging from 1 to 365) and each station, a least squares linear fit was used to calculate trends in $T_{\min }$ and $T_{\max }$ for this DOY using all available years (Fig. 3.6). Afterwards, a probability density function (PDF) of the DOY trends was constructed using least-squares regression (LSR). The maximum of the LSR PDF is a measure which can be used to quantify a 'net' temperature trend. The distribution of DOY trends differed for each station and was also affected by the dataset used, however, in most cases, the DOY trends had approximately Gaussian distributions.
'Net' trends of $T_{\min }$ and $T_{\max }$ were calculated as described above for all stations and datasets and a comparison between ridge and valley stations as well as among different datasets was made (Fig. 4.4, Tables 4.3 and 4.4). Additionally, means and standard deviations of all 365 DOY LSR trends were calculated.

Apart from the LSR, the Theil-Sen (TS) method was used to get a trend estimate that is less sensitive to outliers. Analogously to the LSR, for all the stations and datasets, the mean, standard deviation and PDF of corresponding DOY trends were calculated. For both of the LSR and TS methods, all trends were considered, regardless of their p-values. Fig. 4.5 shows an example for CS2MET and full results can be found in Tables A. 4 - A. 6 in the Appendix.


Figure 3.6: DOY trends for $T_{\text {min }}$ at CS2MET (in green). A probability density function (PDF) of those trends was constructed using least-squares regression (in cyan). Its maximum corresponds to a warming trend of 0.16 K per decade.

### 3.8 Synoptic patterns

The change in synoptic patterns during the study period was examined. For each day, the mean lapse rate was taken to be the slope of elevation versus $T_{\text {min }}$ plot (least squares linear fit); for example, see Fig. 3.7. Both the HJA and Snotel sites were considered and it was assumed that for each day the synoptic pattern is the same across our study area. This seems to be plausible since the extent of our study area ( $<100 \mathrm{~km}$ ) is small compared to the synoptic scale (order of 1000 km ).

To classify each date, the result obtained by Daly et al. (2010), Fig. 3.8, was used and three cases according to the lapse rate were considered:

1. lapse rate $<-2.8(\mathrm{~K} / \mathrm{km}) \Rightarrow$ cyclonic day
2. $0 \geq$ lapse rate $\geq-2.8(\mathrm{~K} / \mathrm{km}) \Rightarrow$ zonal day
3. lapse rate $>0(\mathrm{~K} / \mathrm{km}) \Rightarrow$ anti-cyclonic day

However, as apparent from Fig. 3.8, the border distinguishing zonal and cyclonic days is not clear cut. In the example of Fig. 3.7a, the lapse rate was approximately $-3.6 \mathrm{~K} / \mathrm{km}$ and according to Daly et al. (2010) this day would be classified as cyclonic (Fig. 3.8). The p-value of the fit was in this case approximately 0.013 .

However, on another date, the situation might be different. There might not be enough stations available and/or the linear fit used to determine the lapse rate might


Figure 3.7: Lapse rate determination, two examples. Each point represents one station.
have a large p-value (e.g. Fig. 3.7b). To address this, three different variants of conditions were employed:
(a) $n_{s} \geq 3$ and $p_{c} \leq 0.05$
(b) $n_{s} \geq 2$ and $p_{c} \leq 0.1$
(c) $n_{s} \geq 2$ and $p_{c} \leq 0.8$
where $n_{s}$ is the number of stations available on the particular date and $p_{c}$ is the maximum accepted p -value. In the case of $n_{s}<2$, the lapse rate was not determined. (a) has the strictest criteria on the $n_{s}$ and $p_{c}$, which leads to a more accurate synoptic pattern classification, however, most of the dates in our date range (1958-2011) did not meet this criteria. (b) and (c) have less strict criteria and hence are applicable to a greater number of dates, but are more prone to a misclassification of synoptic patterns.

Afterwards, for all variants of conditions, each day was classified as cyclonic, anticyclonic, zonal or NaN (if not enough data were available to classify it). Fig. 4.6 shows the results for the homogenized dataset. To be able to compare years with a differing number of NaNs (gaps), the numbers of cyclonic, anti-cyclonic and zonal days obtained were multiplied by a constant (i.e. scaled by the same factor) such that they would add up to 365 days for each year. Afterwards, trends in annual number of cyclonic, anti-cyclonic and zonal days were calculated. Fig. 4.7 shows the results for the raw dataset.


Figure 3.8: Definition of cyclonic, anti-cyclonic and zonal days according to the mean lapse rate. Source: Daly et al. (2010).

### 3.9 Wind speed and direction

This data was only available for the benchmark stations (CENMET, H15MET, PRIMET, UPLMET and VANMET). Mean hourly wind speed and direction data were downloaded from the HJA website. Regarding the data collection, the wind speed and direction were sampled every 15 seconds by a RM Young Model 05103 Wind Monitor with a detection limit of $1 \mathrm{~m} / \mathrm{s}$. It was mounted to a tower at the height of 10 m for CENMET, PRIMET and UPLMET and 5 m for H15MET. For VANMET, the height was changed on 27. 8. 1996 from 6 m to 10 m . Campbell Scientific datalogger was used in all cases (HJA Website, 2017b).

For each value of the wind direction or speed, there was a flag assigned indicating its reliability. Relevant to our case were flags 'A' - Accepted value has passed all QC tests applied as represented by the quality level and ' B ' - Wind magnitude measurement is below the instrument detection limit of $1 \mathrm{~m} / \mathrm{s}$. A full list of flags can be accessed on the HJA website (HJA Website, 2017b). Two cases were considered:

1. Only 'A' flag was accepted for both wind speed and direction.
2. Only ' A ' and ' B ' flags were accepted for both wind speed and direction.

Since cold air pooling occurs at night, mean night-time wind direction was considered.

It was calculated as the vectorial mean of available wind velocities for each night, where the night-time was defined as 19-06 h. In the case of PRIMET, the only benchmark valley station, further analysis was performed. The results were sorted according to their direction: up-valley (NE, 0-90 $)$ and down-valley (SW, 180-270 ${ }^{\circ}$ ). To investigate the effect of night-time wind direction on $T_{\text {min }}$, the mean night-time direction was plotted against $T_{\text {min }}$ perturbation, here defined as the difference from monthly mean (hence independent of season). Mean $T_{\min }$ and its standard deviation for both SW and NE directions were calculated.

## 4 Results

### 4.1 Last day of frost (LDOF)

The valley stations experienced earlier last day of frost (LDOF) trends during our study period for all three datasets, with only one exception (RS89 showed a later LDOF trend, but only when the partially-homogenized dataset was considered), whereas the ridge stations showed an inconsistent pattern (Fig. 4.1, Table A. 2 in the Appendix).

The valley stations had negative median and mean values of the LDOF trends for all three datasets (indicating earlier LDOF), while the ridge stations had positive mean values and both positive and negative median values, depending on which dataset was used (Table 4.1). Overall, the majority of the stations showed an earlier LDOF trend and the trends differed depending on whether the raw, homogenized, or partially-homogenized dataset was used. Table 4.1 summarizes the LDOF trends, listing the median, mean, standard deviation, maximum and minimum trend values obtained. LDOF trends together with their p-values for all stations and all three datasets can be found in Table A.2. Most trends had p-values $>0.05$.


4 Results
(b)

(c)


Figure 4.1: Trends of last day of frost (LDOF) for the HJA stations for (a) raw data, (b) homogenized data and (c) partially-homogenized data displayed on a topographic map of the HJA. The red-colored markers indicate earlier LDOF (i.e. 'warming') trends, whereas the blue ones indicate later LDOF ('cooling') trends. The valley and ridge stations are marked by circles and triangles, respectively. A Universal Transverse Mercator (UTM) coordinate system is used. The Snotel stations are not included in the picture.

Table 4.1: The median, mean, standard deviation, maximum and minimum values of the LDOF trends for all three datasets. Numbers are in days/year and rounded to two decimal places. Negative numbers indicate an earlier LDOF, whereas positive ones a later LDOF.

|  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Valley stations | Median | Mean | St. dev. | Maximum | Minimum |
| Raw | -0.75 | -0.81 | 0.27 | -0.53 | -1.33 |
| Homogenized | -0.15 | -0.17 | 0.17 | -0.01 | -0.40 |
| Partially-homogenized | -0.38 | -0.33 | 0.60 | 0.70 | -0.97 |
| Ridge stations | 0.16 | 0.24 | 0.90 | 2.94 | -0.98 |
| Raw | -0.01 | 0.26 | 0.94 | 2.94 | -1.04 |
| Homogenized | -0.05 | 0.12 | 0.98 | 2.94 | -1.33 |
| Partially-homogenized | -0.05 | 0.06 | 0.91 | 2.94 | -1.33 |
| All stations |  |  |  |  |  |
| Raw | -0.02 | 0.19 | 0.87 | 2.94 | -1.04 |
| Homogenized | -0.14 | 0.04 | 0.93 | 2.94 | -1.33 |
| Partially-homogenized |  |  |  |  |  |

### 4.2 Length of the vegetation period (LOVP)

For all three datasets, there seems to be no distinct patterns in the LOVP for the valley and ridge stations (Fig. 4.3, table 4.2). As mentioned in the Materials and Methods section, for the benchmark stations there are two measurement heights 150 cm and 450 cm and the trends for these two hights may differ (this is indicated in Fig. 4.3 by purple markers). For UPLMET and CENMET, the LOVP trends differed for the two heights for all three datasets. For PRIMET, increasing LOVP trends were observed except for the homogenized dataset at measurement height 150 cm .

The LOVP trends' magnitudes are summarized in Table 4.2, which lists the minimum, mean, median and maximum trend values obtained. One can see that the dataset used had an impact on the results; in some cases using a different dataset resulted in a different sign of the LOVP trend. Table A. 3 in the Appendix lists the LOVP trends together with their p-values for all stations and all three datasets. Most trends had p-values $>0.05$.

The LOVP is more sensitive to the accuracy of, and the gaps, in the data, as both the LDOF in spring and the first day of frost (FDOF) in autumn need to be determined. For some of the stations (e.g. UPLMET, Fig. 4.2b, or VANMET150), gaps in the temperature data led to few LOVP data points available, which might have caused unreliable trend outcomes.



Figure 4.2: Hovmöller plots showing the first day of frost (FDOF, in blue), the last day of frost (LDOF, in cyan), the length of the vegetation period and its trend (both in green) using the homogenized dataset at (a) CS2MET (valley station, longest continuous record at the HJA), (b) UPLMET150 (ridge station) and (c) McKenzie (ridge, Snotel station). Black fields indicate no available data.
(a)


## 4 Results



Figure 4.3: Trends of the LOVP for the HJA stations for (a) raw data, (b) homogenized data and (c) partially-homogenized data displayed on a topographic map of the HJA. The red-colored markers indicate increasing LOVP ('warming') trends, whereas the blue ones indicate decreasing LOVP ('cooling') trends. At stations with two measurement heights ( 150 and 450 cm ) with opposite signs of the LOVP trends, blue and red combined to make purple. The valley and ridge stations are marked by circles and triangles, respectively. The Snotel stations are not included in the picture.

Table 4.2: The median, mean, standard deviation, maximum and minimum values of the LOVP trends for all three datasets. The numbers are in days/year and rounded to two decimal places. The negative numbers indicate a shortening of the LOVP, whereas the positive ones increasing LOVP trends.

|  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Valley stations | Median | Mean | St. dev. | Maximum | Minimum |
| Raw | 0.44 | 0.60 | 1.25 | 2.82 | -0.65 |
| Homogenized | -0.01 | 0.25 | 0.60 | 1.44 | -0.14 |
| Partially-homogenized | 0.36 | 0.64 | 1.31 | 2.82 | -1.06 |
| Ridge stations | 0.00 | -0.41 | 3.92 | 3.97 | -18.71 |
| Raw | -0.17 | -0.81 | 3.74 | 3.89 | -18.71 |
| Homogenized | 0.04 | -0.44 | 3.94 | 3.97 | -18.71 |
| Partially-homogenized | All stations |  |  |  |  |
| Raw | 0.01 | -0.24 | 3.61 | 3.97 | -18.71 |
| Homogenized | -0.03 | -0.63 | 3.42 | 3.89 | -18.71 |
| Partially-homogenized | 0.05 | -0.26 | 3.64 | 3.97 | -18.71 |

## 4.3 $T_{\min }$ and $T_{\max }$ trends

### 4.3.1 LSR PDF maxima

Here, only the $T_{\min }$ and $T_{\max }$ trends as assessed by the LSR PDF maxima are presented. For both of $T_{\min }$ and $T_{\max }$, the majority of the stations exhibited a net warming trend for all three datasets. The choice of a dataset played a role. Fig. 4.4 shows the $T_{\min }$ and $T_{\max }$ trends for the HJA stations for all datasets, plotted on a topographic map of the HJA. The $T_{\min }$ and $T_{\max }$ trends are summarized in Tables 4.3 and 4.4, respectively.

For $T_{\text {min }}$, the valley stations showed a slightly more consistent warming signal than the ridge stations. For the raw and homogenized datasets, all of the valley stations showed a warming trend, with the exception of PRIMET450. The records for PRIMET150 spanned the period 1975-2011, whereas for PRIMET450 the span was only 1996-2011 and the standard deviations for PRIMET450 were also larger than for PRIMET150, as can be seen in Tables A. 4 - A. 6 in the Appendix. When the partially-homogenized dataset was used, the largest number of stations ( 25 out of 35 , regarding the two heights of a benchmark stations as two stations) exhibited a warming trend, compared to the raw dataset ( 22 stations showed a warming trend) and the homogenized dataset ( 20 warming trends).

For $T_{\max }$, the choice of the dataset played a considerable role. For the partiallyhomogenized dataset, all of the valley stations except PRIMET450 showed a warming trend, whereas in the case of the raw dataset, four out of six stations showed a cooling trend. Overall, when the partially-homogenized dataset was used, 25 out of the 35 stations showed a warming trend, compared to 19 and 18 warming trends in case of the homogenized and the raw dataset, respectively.


Figure 4.4: The $T_{\min }$ and $T_{\max }$ trends for the HJA stations, all datasets.

Table 4.3: The $T_{\min }$ trends minimum, mean, median and maximum values for all three datasets. The numbers are in K/decade and rounded to two decimal places. The negative numbers indicate cooling trends, whereas the positive ones warming $T_{\text {min }}$ trends.

|  | Median | Mean | St. dev. | Maximum | Minimum |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Valley stations | 0.13 | 0.16 | 0.38 | 0.72 | -0.42 |
| Raw | 0.11 | -0.01 | 0.38 | 0.24 | -0.78 |
| Homogenized | 0.20 | 0.15 | 0.36 | 0.63 | -0.42 |
| Partially-homogenized | 0.13 | 0.08 | 0.54 | 0.77 | -1.19 |
| Ridge stations | 0.01 | -0.11 | 0.42 | 0.60 | -1.11 |
| Raw | 0.14 | 0.05 | 0.49 | 0.82 | -1.19 |
| Homogenized | 0.13 | 0.09 | 0.51 | 0.77 | -1.19 |
| Partially-homogenized | 0.60 | -1.11 |  |  |  |
| All stations |  |  |  |  |  |
| Raw | Homogenized | 0.04 | -0.09 | 0.41 | 0.60 |
| Partially-homogenized | 0.15 | 0.07 | 0.47 | 0.82 | -1.19 |

Table 4.4: The $T_{\max }$ trends minimum, mean, median and maximum values for all three datasets. The numbers are in K/decade and rounded to two decimal places. The negative numbers indicate cooling trends, whereas the positive ones warming $T_{\text {max }}$ trends.

|  |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Valley stations | Median | Mean | St. dev. | Maximum | Minimum |  |
| Raw | -0.03 | -0.19 | 0.60 | 0.27 | -1.36 |  |
| Homogenized | 0.12 | -0.13 | 0.62 | 0.29 | -1.36 |  |
| Partially-homogenized | 0.21 | -0.04 | 0.66 | 0.39 | -1.36 |  |
| Ridge stations | 0.01 | 0.08 | 0.61 | 1.35 | -0.92 |  |
| Raw | 0.02 | -0.10 | 0.58 | 1.15 | -1.95 |  |
| Homogenized | 0.11 | 0.09 | 0.51 | 1.15 | -0.92 |  |
| Partially-homogenized |  |  |  |  |  |  |
| All stations |  |  |  |  |  |  |
| Raw | 0.01 | 0.04 | 0.61 | 1.35 | -1.36 |  |
| Homogenized | 0.03 | -0.11 | 0.58 | 1.15 | -1.95 |  |
| Partially-homogenized | 0.15 | 0.07 | 0.53 | 1.15 | -1.36 |  |

### 4.3.2 Other parameters

Apart from the LSR PDF maxima, the Theil-Sen (TS) method was also used to analyze the trends in $T_{\min }$ and $T_{\max }$. The maxima of PDF of DOY trends as well as means of DOY trends were considered for both the LSR and TS methods. An example result of the $T_{\text {min }}$ and $T_{\max }$ trends at CS2MET for all three datasets can be seen in Fig. 4.5. There was a large variability among the DOY trends for both of the LSR and TS methods, with no clear seasonal patterns. The results for all stations and all datasets can be seen in Tables A. 4 - A. 6 in the Appendix.

For $T_{\text {min }}$, the valley stations showed a more consistent warming trend (considering the PDF maxima and means using the LSR and TS methods) than the ridge stations. For $T_{\max }$, this was also true for the homogenized and partially-homogenized datasets, where at least four out of the six valley stations showed a warming trend. Similarly as in the case of the LSR PDF maxima, the TS method results were considerably affected by the choice of the dataset.

In the vast majority of cases, the standard deviations were larger than the absolute values of the corresponding trends, both for the LSR and TS methods, indicating a large spread of the trend values. There were differences between the results obtained by LSR and TS methods. Full results can be seen in Table A. 4 in the Appendix.



Figure 4.5: The LSR (in red) and TS (blue) $T_{\min }$ and $T_{\max }$ trends at CS2MET for all three datasets. Various parameters were used: LSR PDF (red, approximately Gaussian curve); mean of DOY trends, LSR (pink vertical line); LS PDF (blue, approximately Gaussian curve); mean of DOY trends, TS (light blue vertical line). The pink and blue colored belts indicate the areas of $\pm$ one standard deviation from the LSR and TS methods means, respectively.

### 4.4 Synoptic patterns

As described in the section 3.8, for each year, the numbers of cyclonic, anti-cyclonic and zonal days were calculated. Three different variants were used for daily synoptic pattern classification: (a) $n_{s} \geq 3$ and $p_{c} \leq 0.05$, (b) $n_{s} \geq 2$ and $p_{c} \leq 0.1$ and (c) $n_{s} \geq 2$ and $p_{c} \leq 0.8$, where $n_{s}$ is the number of data points (corresponding to stations) for a given date and $p_{c}$ is the maximum accepted p-value. Fig. 4.6 shows Hovmöller diagrams for the cyclonic, anti-cyclonic and zonal days for the homogenized dataset. The results were similar for the raw and partially-homogenized dataset. There was a larger proportion of cyclonic days in the period March - May, compared to June - September.

Afterwards, for each year and each variant of conditions, the numbers of cyclonic, anti-cyclonic and zonal days obtained were multiplied by a constant such that they would add up to 365 days and trends in the annual number of days for each synoptic pattern were investigated. For the raw data, the annual numbers of cyclonic and zonal days exhibited positive trends and the annual number of anti-cyclonic days showed negative trends (Fig. 4.7). Likewise, in the case of the homogenized and partiallyhomogenized datasets, the annual number of anti-cyclonic days had negative trends, whereas the annual numbers of cyclonic and zonal days showed positive trends.

4 Results


Figure 4.6: Synoptic patterns for the study area (the HJA and Snotel) showing cyclonic (blue), anti-cyclonic (red) and zonal days (grey) for homogenized data for (a) $n_{s} \geq 3$ and $p_{c} \leq 0.05$, (b) $n_{s} \geq 2$ and $p_{c} \leq 0.1$ and (c) $n_{s} \geq 2$ and $p_{c} \leq 0.8$. Black fields indicate no available data.
(a)

(b)

(c)


Figure 4.7: Trends of cyclonic (blue), anti-cyclonic (red) and zonal (grey) days over the study area (the HJA and Snotel) for the raw dataset and for (a) $n_{s} \geq 3$ and $p_{c} \leq 0.05$, (b) $n_{s} \geq 2$ and $p_{c} \leq 0.1$ and (c) $n_{s} \geq 2$ and $p_{c} \leq 0.8$.

### 4.5 Wind speed and direction

Wind speed and direction data were only available for the benchmark stations. A time series of mean night-time wind direction was plotted for all of the benchmark stations; Fig. 4.8 shows an example for PRIMET and Table 4.5 shows a summary for all of the benchmark stations.

Out of the benchmark stations available, PRIMET was the only valley station. When plotting the mean nigh-time wind direction at PRIMET, one can clearly see two main flows (Fig. 4.8), channeled along the valley. These were noted as the North-East (NE, here $0-90^{\circ}$ ) and South-West (SW, 180-270 $)$ flows.


Figure 4.8: The mean nigh-time wind direction at PRIMET

Table 4.5: Mean night-time wind direction at benchmark stations.

| Station | Wind direction |
| :--- | :--- |
| PRIMET | Two main flow directions can be seen: NE and SW, corresponding <br> to up- and down-valley direction. Large proportion of the records <br> have wind magnitudes $<1 \mathrm{~m} / \mathrm{s}$. |
| VANMET | Two main wind directions: around $200^{\circ}$ (approximately SSW) and <br> around $90^{\circ}(\mathrm{E})$ |
| UPLMET | One main wind direction: around $210^{\circ}$ (approximately SSW) |
| CENMET | One main wind direction: around $35^{\circ}($ approximately NE) |
| H15MET | A large proportion of the data has a wind magnitude $<1 \mathrm{~m} / \mathrm{s}$. <br> Considering wind direction when flags 'A' and 'B' are accepted, <br> there is a main flow at about $150^{\circ}$ (approximately SSE), which <br> weakened around 2005. |

To investigate whether the nigh-time wind direction at PRIMET affects $T_{\text {min }}$, the mean night-time direction was plotted against $T_{\min }$ perturbation - here the difference
from the monthly mean (hence independent of the season). As Fig. 4.9 shows, the mean perturbation had higher value for the SW flow than for the NE flow, suggesting the days with prevailing NE flows had on average colder night temperatures than those with prevailing SW flows. The difference between SW mean $T_{\text {min }}$ and NE mean $T_{\text {min }}$ was especially pronounced when only the 'A' flags were accepted.

The values for the NE and SW mean and standard deviation were exactly the same for all three datasets. This was because only the differences from monthly temperature means were considered, hence shifting the temperature time series by a constant did not affect the results.

(b)

Night-time wind direction vs. temperature,


Figure 4.9: The difference from the monthly mean $T_{\min }$ (taken at height 4.5 m ) as a function of mean night-time wind direction for PRIMET.

## 5 Discussion

### 5.1 Temperature patterns

The valley stations experienced a more pronounced LDOF trend compared to the ridge stations, contrary to the hypothesis. For most of the stations, an earlier LDOF was observed, in agreement with Kunkel et al. (2004) and results predicting increasing $T_{\text {min }}$ trends (section 2.2.1).

There seems to be no distinct patterns in the LOVP for the valley and ridge stations, which does not support or undermine the hypothesis. Overall, it was found that the LOVP was increasing at the majority of the stations during the study period, in agreement with what was found by Kunkel et al. (2004). The records suffered from gaps that limited the analysis. In some cases, e.g. for UPLMET150, Fig. 4.2b, there were not enough data points to get a significant trend. At high elevations, frost can occur at any time of the year, therefore the LOVP is not meaningful there. A few of the stations studied, especially McKenzie, had a very short LOVP (Fig. 4.2c). Also, the differences in results for the two different heights ( 150 and 450 cm ) for the benchmark stations seem to be relatively large (in some cases, the trends between the two heights at a benchmark station differed more than between one height and another station hundreds of meters away).

For both $T_{\min }$ and $T_{\max }$, the majority of the stations exhibited a warming trend for all three datasets, which is in agreement with what was observed by others (section 2.2.1). For $T_{\min }$, the valley stations showed a more consistent warming trend than the ridge stations, contrary to the hypothesis. However, in most cases, the p-values of the temperature trends considered were $>0.05$. The resulting trends for the raw, homogenized and partially-homogenized datasets exhibited considerable differences, indicating that the presence of breaks in the raw time series affected the results, and this should not be neglected in future climate research. Good quality long-term datasets are highly valuable for climate change studies.

### 5.2 Synoptic patterns and wind

For all datasets, the annual number of anti-cyclonic days was decreasing, as indicated by the models considered in the IPCC AR4 2007. Anti-cyclonic flows with low flow
strength seem to lead to a more pronounced cold air pooling and hence stronger temperature inversions (Daly et al., 2010). Therefore, the more pronounced warming trends of the valley stations could be explained by a decreasing number of anticyclonic days, which leads to less cold air pooling. This then causes a net warming at the valley stations. The ridge stations are likely less affected by the changing cold air pool patterns, as indicated by the results, especially for the LDOF and $T_{\text {min }}$ trends. In future research, seasonal changes in the number of cyclonic, anti-cyclonic and zonal days could be considered.

At PRIMET, the only valley station with wind data, the mean night-time wind direction was largely channeled along the valley. It could be expected that during nights with a dominant cold air drainage and pooling, the wind direction was downvalley (SW), whereas during nights with dominant warm-air flows from the lake the direction was up-valley (NE). As Fig. 4.8 shows, a proportion of the nights had a mean night-time wind direction in between these two directions, indicating that the wind direction was likely changing during those nights.

Regarding the relationship between $T_{\min }$ and mean night-time direction, the days with prevailing NE flows had on average colder night temperatures than those with prevailing SW flows. The exact reason for this is unknown, however, one explanation could be that the area around PRIMET needs to be considerably colder than the lake for a SW flow of a detectable magnitude to be formed. Or, it could be due to the fact that flows with low strengths were not detected, which could introduce a considerable error in the mean night-time wind direction, especially for nights without any stronger flows. One could expect colder $T_{\text {min }}$ for nights with prevalent cold air pooling, however, low flow strength is needed for a cold air pool to form, which might then go undetected by the wind monitors.

As Daly et al. (2010) found out, synoptic patterns affect formation of cold air pools, and anti-cyclonic patterns are most favorable for cold air drainage and pooling. However, as Fig. 4.7 shows, the anti-cyclonic days were in the minority compared to cyclonic and zonal days. Therefore, the overall mean of $T_{\text {min }}$ perturbation (Fig. 4.9) was mostly affected by cyclonic and zonal days, with only shallow or absent cold air pools. Future research could address this by separating the anti-cyclonic, zonal and cyclonic days and calculating the mean $T_{\min }$ perturbation for each of these three synoptic patterns and the two identified wind directions at PRIMET. Also, wind monitors capable of detecting flows with lower strengths would be helpful in clarifying the observed temperature changes in the valley.

## 6 Conclusions

The hypothesis was not confirmed. In the case of the LDOF, the contrary seems more likely, as the valley stations experienced an earlier LDOF trend, whereas the ridge stations showed an inconsistent pattern. In the case of the LOVP, no distinct patterns were found. For $T_{\min }$, the valley stations showed a more consistent warming trend than the ridge stations. For $T_{\text {max }}$, the same was true only for the partially-homogenized and homogenized dataset. The majority of the stations had temperature trends with p -values $>0.05$.

Three datasets were used: raw, homogenized and partially-homogenized. The choice of dataset played a role in the results. In a number of cases, an observed trend a had smaller absolute magnitude than the change to its value when calculated using a different dataset. The effect of shifts and breaks in a time series should not be neglected in future climate research.

The annual numbers of cyclonic and zonal days showed increasing trends, whereas the annual number of anti-cyclonic days showed a decreasing trend. The exact mechanism is still debated, but changes in synoptic forcing towards more cyclonic activity and hence less cold air pooling in spring could serve as an explanation. In the HJA valley studied, two competing flows channeled along the valley were detected: NE down-valley flow and SW up-valley flow. Days with prevailing NE flows had on average colder night temperatures than those with prevailing SW flows. Further research and more data gathered over a longer period records are needed.

## A Appendix

Table A.1: Stations' names (abbreviated and full) and geographical and topography information. The stations located less
than 100 m above the valley bottom, i.e. below 530 asl, were marked as valley stations; all the other stations were marked as ridge stations. The geographical and topography information was provided by C. K. Thomas (2011).

| ation name abbr. | Station name full | Latitude | Longit | Northing UT | Easting UTM | (m | pect | ope | Va./Ri. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| PRIMET ( 150,450 ) | Primary Meteorological Station | 44.2119 | -122.2558 | 4895461 | 559454.7 | 430 | 0 | 0 | Valley |
| RS02 | Reference Stand 2 | 44.217055 | -122.2439 | 4896042.5 | 560400.9 | 480 | 285 | 22 | Valley |
| CS2MET | Climatic Station at Watershed 2 | 44.215 | -122.2492 | 4895805.5 | 559451.56 | 485 | 55 | 5 | Valley |
| RS01 | Reference Stand 1 | 44.202089 | -122.2572 | 4894370 | 559349.4 | 499 | 200 | 41 | Valley |
| RS89 | Reference Stand 89 | 44.216742 | -122.26 | 4895996 | 559188.3 | 514 | 315 | 37 | Valley |
| RS17 | Reference Stand 17 | 44.220111 | -122.2404 | 4896384.5 | 560678.1 | 534 | 315 | 14 | Ridge |
| RSO7 | Reference Stand 7 | 44.212599 | -122.2488 | 4895544 | 560016.56 | 586 | 1 | 19 | Ridge |
| RS86 | Reference Stand 86 | 44.218849 | -122.2579 | 4896231.5 | 559276.44 | 594 | 215 | 28 | Ridge |
| RS10 | Reference Stand 10 | 44.233571 | -122.2191 | 4897895 | 562360.56 | 621 | 170 | 6 | Ridge |
| RS24 | Reference Stand 24 | 44.1711 | -122.4236 | 4890821.5 | 546080.75 | 651 | 30 | 28 | Ridge |
| RS20 | Reference Stand 20 | 44.221909 | -122.2503 | 4896577 | 559886.44 | 712 | 180 | 34 | Ridge |
| RS16 | Reference Stand 16 | 44.212326 | -122.2402 | 4895527.5 | 561502.25 | 732 | 202 | 29 | Ridge |
| RS15 | Reference Stand 15 | 44.209253 | -122.239 | 4895179 | 560800.8 | 755 | 350 | 33 | Ridge |
| RS05 | Reference Stand 5 | 44.221416 | -122.2027 | 4896558 | 563684.25 | 907 | 10 | 12 | Ridge |
| H15MET (150, 450) | High 15 Meteorological Station | 44.2642 | -122.1739 | 4901332.5 | 565939.44 | 922 | 240 | 15 | Ridge |
| RS03 | Reference Stand 3 | 44.258862 | -122.1585 | 4900752 | 567177.5 | 978 | 315 | 5 | Ridge |
| RS12 | Reference Stand 12 | 44.22586 | -122.1207 | 4897118.5 | 570233.9 | 987 | 282 | 11 | Ridge |
| CENMET ( 150,450 ) | Central Meteorological Station | 44.243 | -122.1417 | 4899038 | 568533.6 | 1018 | 260 | 12 | Ridge |
| RS26 | Reference Stand 26 | 44.268287 | -122.1736 | 4901787 | 565956.2 | 1054 | 180 | 20 | Ridge |
| Jumpoffjoe | Jump Off Joe | 44.383 | -122.167 | 4914751 | 566354 | 1073 | NaN | NaN | Ridge |
| SantiamJunction | Santiam Junction | 44.4333 | -121.95 | 4920319.5 | 583570.5 | 1140 | NaN | NaN | Ridge |
| VANMET ( 150,450 ) | Vanilla Leat Meteorological Station | 44.2717 | -122.1494 | 4902186 | 567886.25 | 1273 | 180 | 23 | Ridge |
| UPLMET $(150,450)$ | Upper Lookout Meteorological Station | 44.2072 | -122.1194 | 4895046.5 | 570357.25 | 1294 | 72 | 13 | Ridge |
| RS04 | Reference Stand 4 | 44.272716 | -122.1371 | 4902309 | 568864.8 | 1302 | 270 | 27 | Ridge |
| RS13 | Reference Stand 13 | 44.3439 | -122.1233 | 4910227 | 569883.56 | 1350 | 270 | 20 | Ridge |
| RS14 | Reference Stand 14 | 44.327 | -122.094 | 4908592 | 572238 | 1430 | 1 | 32 | Ridge |
| McKenzie | McKenzie | 44.2167 | -121.8667 | 4896349.5 | 590532.8 | 1454 | NaN | NaN | Ridge |
| HoggPass | Hogg Pass | 44.4167 | -121.85 | 4918582.5 | 591555.4 | 1460 | NaN | NaN | Ridge |
| RoaringRiver | Roaring River | 43.9 | -122.028 | 4861086 | 584326.94 | 1509 | NaN | NaN | Ridge |
| ThreeCreeksMeadow | Three Creeks Meadow | 44.15 | -121.6333 | 4889225 | 609300.94 | 1734 | NaN | NaN | Ridge |

Table A.2: The LDOF trends (in days/year) and their corresponding p-values for all stations and all three datasets. Trends corresponding to an earlier LDOF ('warming') are shown in red and p-values $<0.05$ are in bold

| Station | Elev. (m asl) | Aspect ( ${ }^{\circ}$ ) | Slope ( ${ }^{\circ}$ ) | Raw data |  | Homogenized data |  | Partially-homogenized data |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | LDOF trend ( $\mathrm{d} / \mathrm{y}$ ) | p -value | LDOF trend ( $\mathrm{d} / \mathrm{y}$ ) | p-value | LDOF trend (d/y) | p -value |
| PRIMET450 | 430 | 0 | 0 | -1.33 | 0.010 | -0.40 | 0.835 | -0.97 | 0.111 |
| PRIMET150 | 430 | 0 | 0 | -0.66 | 0.260 | -0.04 | 0.914 | -0.84 | 0.000 |
| RS02 | 480 | 285 | 22 | -0.53 | 0.334 | -0.01 | 0.979 | -0.08 | 0.695 |
| CS2MET | 485 | 355 | 5 | -0.83 | 0.043 | -0.28 | 0.057 | -0.31 | 0.050 |
| RS01 | 499 | 200 | 41 | -0.72 | 0.026 | -0.26 | 0.607 | -0.46 | 0.381 |
| RS89 | 514 | 315 | 37 | -0.78 | 0.014 | -0.02 | 0.960 | 0.70 | 0.074 |
| RS17 | 534 | 315 | 14 | -0.18 | 0.262 | -0.65 | 0.448 | -0.65 | 0.448 |
| RS07 | 586 | 1 | 19 | -0.97 | 0.111 | -1.04 | 0.139 | -1.04 | 0.139 |
| RS86 | 594 | 215 | 28 | -0.50 | 0.021 | -0.14 | 0.563 | -0.14 | 0.563 |
| RS10 | 621 | 170 | 6 | 0.69 | 0.380 | 0.15 | 0.389 | 0.01 | 0.901 |
| RS24 | 651 | 30 | 28 | 0.16 | 0.855 | 0.64 | 0.432 | 0.64 | 0.432 |
| RS20 | 712 | 180 | 34 | 1.25 | 0.047 | 0.92 | 0.079 | 0.92 | 0.079 |
| RS16 | 732 | 202 | 29 | 2.94 | 0.019 | -0.32 | 0.791 | -0.32 | 0.791 |
| RS15 | 755 | 350 | 33 | 1.11 | 0.087 | 0.15 | 1.000 | 0.15 | 1.000 |
| RS05 | 907 | 10 | 12 | 2.12 | 0.133 | -0.01 | 0.987 | -0.01 | 0.987 |
| HI15MET450 | 922 | 240 | 15 | -0.05 | 1.000 | 1.25 | 0.047 | 1.25 | 0.047 |
| HI15MET150 | 922 | 240 | 15 | 1.51 | 0.133 | 2.94 | 0.019 | 2.94 | 0.019 |
| RS03 | 978 | 315 | 5 | -0.98 | 0.227 | -0.27 | 0.956 | -0.67 | 0.546 |
| RS12 | 987 | 282 | 11 | 0.05 | 0.793 | -0.07 | 0.434 | -0.19 | 0.241 |
| CENMET450 | 1018 | 260 | 12 | -0.55 | 0.622 | 0.53 | 0.508 | 0.69 | 0.380 |
| CENMET150 | 1018 | 260 | 12 | -0.30 | 0.251 | 0.16 | 0.855 | 0.16 | 0.855 |
| RS26 | 1054 | 180 | 20 | 0.24 | 0.551 | 0.58 | 0.058 | 0.58 | 0.058 |
| Jumpoffjoe | 1073 | NaN | NaN | -0.44 | 0.869 | -1.03 | 0.134 | -0.78 | 0.014 |
| SaniamJunction | 1140 | NaN | NaN | 0.48 | 0.102 | -0.58 | 0.154 | -0.83 | 0.043 |
| VANMET450 | 1273 | 180 | 23 | 0.41 | 0.549 | -0.05 | 1.000 | -0.05 | 1.000 |
| VANMET150 | 1273 | 180 | 23 | -0.35 | 0.612 | 1.51 | 0.133 | 1.51 | 0.133 |
| UPLMET450 | 1294 | 72 | 13 | -0.05 | 0.514 | 1.11 | 0.087 | 1.11 | 0.087 |
| UPLMET150 | 1294 | 72 | 13 | -0.77 | 0.718 | 2.79 | 0.060 | 2.12 | 0.133 |
| RS04 | 1302 | 270 | 27 | 0.96 | 0.649 | -0.30 | 0.251 | -0.30 | 0.251 |
| RS13 | 1350 | 270 | 20 | -0.51 | 1.000 | -0.21 | 0.940 | -0.21 | 0.940 |
| RS14 | 1430 | 1 | 32 | 0.16 | 0.640 | 0.05 | 0.722 | -0.05 | 0.418 |
| McKenzie | 1454 | NaN | NaN | 0.19 | 0.809 | -0.11 | 0.833 | -0.77 | 0.091 |
| HoggPass | 1460 | NaN | NaN | -0.15 | 0.629 | -0.01 | 0.955 | -1.33 | 0.010 |
| RoaringRiver | 1509 | NaN | NaN | 0.17 | 0.905 | -0.42 | 0.450 | -0.53 | 0.334 |
| ThreeCreeksM. | 1734 | NaN | NaN | 0.28 | 0.297 | 0.06 | 1.000 | -0.72 | 0.026 |

Table A.3: The LOVP trends (in days/year) and their corresponding p-values for all stations and all three datasets. Trends corresponding to an increasing LOVP ('warming') are shown in red and p-values $<0.05$ are in bold.

| Station | Elev. (m asi) | Aspect ( ${ }^{\circ}$ ) | Slope ( ${ }^{\circ}$ ) | Raw data |  | Homogenized data |  | Partially-homogenized data |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | LOVP trend (d/y) | p -value | LOVP trend ( $\mathrm{d} / \mathrm{y}$ ) | p -value | LOVP trend ( $\mathrm{d} / \mathrm{y}$ ) | p-value |
| PRIMET450 | 430 | 0 | 0 | 2.82 | 0.060 | 1.44 | 0.452 | 2.82 | 0.060 |
| PRIMET150 | 430 | 0 | 0 | 0.67 | 0.332 | -0.01 | 0.457 | 1.31 | 0.003 |
| RS02 | 480 | 285 | 22 | -0.41 | 0.233 | -0.03 | 0.787 | 0.05 | 0.989 |
| CS2MET | 485 | 355 | 5 | 0.20 | 0.523 | 0.24 | 0.232 | 0.38 | 0.109 |
| RS01 | 499 | 200 | 41 | 0.95 | 0.972 | -0.01 | 0.897 | 0.35 | 0.745 |
| RS89 | 514 | 315 | 37 | -0.65 | 0.297 | -0.14 | 0.800 | -1.06 | 0.067 |
| RS17 | 534 | 315 | 14 | 0.84 | 0.826 | 1.29 | 0.442 | 1.29 | 0.442 |
| RS07 | 586 | 1 | 19 | 1.54 | 0.807 | 2.31 | 0.101 | 2.31 | 0.101 |
| RS86 | 594 | 215 | 28 | -0.74 | 0.284 | -0.43 | 0.419 | -0.43 | 0.419 |
| RS10 | 621 | 170 | 6 | -0.97 | 0.043 | -0.15 | 0.680 | 0.05 | 0.957 |
| RS24 | 651 | 30 | 28 | -0.28 | 0.552 | -1.31 | 0.112 | -1.31 | 0.112 |
| RS20 | 712 | 180 | 34 | -0.39 | 0.333 | -1.65 | 0.012 | -1.65 | 0.012 |
| RS16 | 732 | 202 | 29 | -1.04 | 0.392 | -0.28 | 0.913 | -0.28 | 0.913 |
| RS15 | 755 | 350 | 33 | 0.01 | 0.754 | -1.22 | 1.000 | -1.22 | 1.000 |
| RS05 | 907 | 10 | 12 | -0.19 | 0.498 | 0.04 | 0.843 | 0.04 | 0.843 |
| HI15MET450 | 922 | 240 | 15 | -2.55 | 0.088 | -2.55 | 0.088 | -2.55 | 0.088 |
| HI15MET150 | 922 | 240 | 15 | -3.67 | 0.764 | -3.67 | 0.764 | -3.67 | 0.764 |
| RS03 | 978 | 315 | 5 | 2.18 | 0.184 | 0.94 | 0.436 | 1.48 | 0.213 |
| RS12 | 987 | 282 | 11 | -0.51 | 0.385 | 0.24 | 0.545 | 0.24 | 0.545 |
| CENMET450 | 1018 | 260 | 12 | -2.56 | 0.308 | -2.13 | 0.462 | -2.56 | 0.308 |
| CENMET150 | 1018 | 260 | 12 | 3.89 | 0.221 | 3.89 | 0.221 | 3.89 | 0.221 |
| RS26 | 1054 | 180 | 20 | 0.34 | 0.476 | -0.74 | 0.159 | -0.74 | 0.159 |
| Jumpoffjoe | 1073 | NaN | NaN | 3.00 | 0.055 | 0.48 | 1.000 | 3.00 | 0.055 |
| SaniamJunction | 1140 | NaN | NaN | 1.68 | 0.021 | 1.14 | 0.093 | 1.68 | 0.021 |
| VANMET450 | 1273 | 180 | 23 | -0.63 | 0.452 | -0.63 | 0.452 | -0.63 | 0.452 |
| VANMET150 | 1273 | 180 | 23 | -18.71 | 0.296 | -18.71 | 0.296 | -18.71 | 0.296 |
| UPLMET450 | 1294 | 72 | 13 | -0.32 | 1.000 | -0.32 | 1.000 | -0.32 | 1.000 |
| UPLMET150 | 1294 | 72 | 13 | 0.00 | 1.000 | 0.00 | 1.000 | 0.00 | 1.000 |
| RS04 | 1302 | 270 | 27 | 0.10 | 0.799 | 0.10 | 0.799 | 0.10 | 0.799 |
| RS13 | 1350 | 270 | 20 | 0.33 | 0.944 | 0.13 | 0.963 | 0.13 | 0.963 |
| RS14 | 1430 | 1 | 32 | -0.55 | 0.440 | -0.66 | 0.416 | -0.53 | 0.646 |
| McKenzie | 1454 | NaN | NaN | 0.96 | 0.424 | -0.17 | 1.000 | 1.15 | 0.209 |
| HoggPass | 1460 | NaN | NaN | 3.97 | 0.003 | 0.54 | 0.656 | 3.97 | 0.003 |
| RoaringRiver | 1509 | NaN | NaN | 1.52 | 0.215 | 1.10 | 0.342 | 1.52 | 0.215 |
| ThreeCreeksM. | 1734 | NaN | NaN | 0.91 | 0.487 | -1.19 | 0.049 | 0.91 | 0.487 |

Table A.4: Statistics of DOY trends, raw data. Positive ('warming') trends are shown in red

|  |  |  |  | $\mathrm{T}_{\text {min }}$ trends (K/decade) |  |  |  |  |  | $\mathrm{T}_{\text {max }}$ trends (K/decade) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Station | Elev. (m asi) | Aspect ( ${ }^{\circ}$ ) | Slope ( ${ }^{\circ}$ ) | LSR max | LSR mean | LSR std | TS max | TS mean | TS std | LSR max | LSR mean | LSR std | TS max | TS mean | TS std |
| PRIMET450 | 430 | 0 | 0 | -0.418 | -0.005 | 1.477 | -0.335 | -0.023 | 1.494 | -1.361 | -1.239 | 2.249 | -1.491 | -1.178 | 2.402 |
| PRIMET150 | 430 | 0 | 0 | 0.376 | 0.442 | 0.477 | 0.376 | 0.418 | 0.455 | 0.265 | 0.319 | 0.722 | 0.265 | 0.278 | 0.751 |
| RS02 | 480 | 285 | 22 | 0.022 | 0.131 | 0.398 | 0.070 | 0.114 | 0.374 | 0.239 | 0.445 | 0.681 | 0.282 | 0.426 | 0.707 |
| CS2MET | 485 | 355 | 5 | 0.160 | 0.094 | 0.293 | -0.001 | 0.081 | 0.261 | -0.055 | -0.054 | 0.424 | 0.003 | -0.051 | 0.437 |
| RS01 | 499 | 200 | 41 | 0.719 | 0.755 | 0.958 | 0.824 | 0.729 | 0.927 | -0.013 | 0.379 | 1.709 | 0.094 | 0.362 | 1.729 |
| RS89 | 514 | 315 | 37 | 0.094 | 0.054 | 0.528 | 0.094 | 0.027 | 0.501 | -0.227 | -0.419 | 0.806 | -0.227 | -0.443 | 0.854 |
| RS17 | 534 | 315 | 14 | 0.130 | 0.242 | 1.032 | 0.130 | 0.232 | 0.955 | -0.461 | -0.566 | 1.605 | -0.672 | -0.589 | 1.672 |
| RS07 | 586 | 1 | 19 | 0.094 | 0.298 | 0.955 | 0.094 | 0.283 | 0.912 | -0.330 | 0.133 | 1.459 | -0.238 | 0.112 | 1.493 |
| RS86 | 594 | 215 | 28 | -0.051 | -0.030 | 0.484 | 0.031 | -0.037 | 0.471 | -0.075 | 0.201 | 0.864 | 0.192 | 0.187 | 0.938 |
| RS10 | 621 | 170 | 6 | -0.175 | -0.106 | 0.404 | -0.201 | -0.137 | 0.381 | 0.177 | 0.159 | 0.702 | 0.177 | 0.155 | 0.733 |
| RS24 | 651 | 30 | 28 | 0.742 | 0.764 | 0.795 | 0.914 | 0.753 | 0.799 | 1.294 | 1.482 | 1.242 | 1.217 | 1.463 | 1.330 |
| RS20 | 712 | 180 | 34 | 0.442 | 0.385 | 0.563 | 0.410 | 0.386 | 0.567 | 0.933 | 0.946 | 0.998 | 1.108 | 0.941 | 1.066 |
| RS16 | 732 | 202 | 29 | -0.020 | 0.296 | 1.256 | 0.113 | 0.252 | 1.212 | 0.797 | -0.008 | 2.043 | 0.561 | -0.037 | 2.104 |
| RS15 | 755 | 350 | 33 | 0.623 | 0.795 | 1.427 | 0.537 | 0.714 | 1.352 | 0.012 | 0.112 | 2.061 | 0.270 | 0.103 | 2.095 |
| RS05 | 907 | 10 | 12 | -0.013 | 0.105 | 0.473 | -0.128 | 0.050 | 0.478 | 0.339 | 0.293 | 0.741 | 0.244 | 0.283 | 0.784 |
| HI15MET450 | 922 | 240 | 15 | -0.674 | -0.568 | 1.370 | -0.763 | -0.548 | 1.381 | -0.711 | -0.875 | 2.130 | -0.574 | -0.921 | 2.186 |
| HI15MET150 | 922 | 240 | 15 | -0.287 | -0.104 | 1.628 | -0.001 | -0.093 | 1.617 | -0.517 | -0.714 | 2.263 | -0.802 | -0.678 | 2.463 |
| RS03 | 978 | 315 | 5 | 0.775 | 0.922 | 1.500 | 0.868 | 0.885 | 1.465 | 0.690 | 1.024 | 2.137 | 0.450 | 0.951 | 2.214 |
| RS12 | 987 | 282 | 11 | -0.071 | -0.087 | 0.418 | -0.071 | -0.090 | 0.382 | 0.177 | 0.422 | 0.747 | 0.228 | 0.408 | 0.775 |
| CENMET450 | 1018 | 260 | 12 | -1.185 | -1.264 | 1.820 | -0.967 | -1.152 | 1.855 | -0.133 | -0.777 | 3.058 | 0.220 | -0.709 | 3.186 |
| CENMET150 | 1018 | 260 | 12 | -1.045 | -0.746 | 1.801 | -1.163 | -0.677 | 1.817 | -0.375 | -0.876 | 2.931 | -0.709 | -0.730 | 3.108 |
| RS26 | 1054 | 180 | 20 | 0.643 | 0.384 | 0.683 | 0.156 | 0.396 | 0.674 | 0.612 | 0.684 | 0.998 | 0.612 | 0.660 | 1.056 |
| JumpOffJoe | 1073 | NaN | NaN | 0.443 | 0.336 | 0.960 | 0.012 | 0.293 | 0.796 | -0.238 | -0.184 | 1.516 | -0.044 | -0.170 | 1.506 |
| SaniamJunction | 1140 | NaN | NaN | 0.344 | 0.481 | 0.938 | 0.022 | 0.435 | 0.816 | 0.289 | -0.123 | 1.325 | 0.069 | -0.130 | 1.294 |
| VANMET450 | 1273 | 180 | 23 | 0.140 | -0.162 | 1.305 | -0.076 | -0.161 | 1.297 | 0.007 | -0.161 | 1.874 | 0.112 | -0.195 | 1.932 |
| VANMET150 | 1273 | 180 | 23 | -1.034 | -0.839 | 2.552 | -0.744 | -0.882 | 2.622 | -0.702 | -1.316 | 4.161 | -0.425 | -1.077 | 4.433 |
| UPLMET450 | 1294 | 72 | 13 | -0.195 | -0.416 | 1.726 | -0.478 | -0.398 | 1.778 | -0.916 | -0.899 | 2.666 | -1.066 | -0.843 | 2.734 |
| UPLMET150 | 1294 | 72 | 13 | -0.276 | 0.144 | 6.188 | -0.736 | 0.015 | 6.880 | -0.904 | 2.604 | 12.835 | -0.904 | 2.577 | 13.030 |
| RS04 | 1302 | 270 | 27 | 0.042 | 0.193 | 0.558 | 0.101 | 0.179 | 0.539 | 0.577 | 0.559 | 0.707 | 0.538 | 0.523 | 0.738 |
| RS13 | 1350 | 270 | 20 | 0.580 | 0.701 | 0.745 | 0.580 | 0.687 | 0.745 | 1.351 | 1.341 | 0.971 | 1.181 | 1.283 | 1.013 |
| RS14 | 1430 | 1 | 32 | 0.541 | 0.438 | 0.761 | 0.295 | 0.435 | 0.758 | 0.740 | 0.888 | 0.934 | 0.794 | 0.858 | 0.975 |
| McKenzie | 1454 | NaN | NaN | 0.376 | 0.103 | 1.882 | -0.041 | 0.393 | 1.178 | -0.334 | -0.511 | 2.087 | -0.042 | -0.205 | 1.755 |
| HoggPass | 1460 | NaN | NaN | 0.746 | 0.743 | 0.983 | 0.001 | 0.664 | 0.902 | 0.234 | -0.202 | 1.704 | 0.050 | -0.295 | 1.683 |
| RoaringRiver | 1509 | NaN | NaN | 0.250 | 0.520 | 1.423 | -0.010 | 0.509 | 1.167 | 0.074 | -0.071 | 1.771 | -0.018 | -0.042 | 1.815 |
| ThreeCreeksM. | 1734 | NaN | NaN | 0.419 | 0.258 | 1.450 | -0.033 | 0.285 | 1.260 | -0.170 | -0.173 | 1.577 | 0.033 | -0.218 | 1.533 |
| Number of stati | ions with a wa | arming tren |  | 22 | 24 |  | 19 | 24 |  | 18 | 17 |  | 22 | 17 |  |
| Number of stati | ions with a co | ooling trend |  | 13 | 11 |  | 16 | 11 |  | 17 | 18 |  | 13 | 18 |  |

Table A.5: Statistics of DOY trends, homogenized data. Positive ('warming') trends are shown in red.

Table A.6: Statistics of DOY trends, partially-homogenized data. Positive ('warming') trends are shown in red.


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[^0]:    ${ }^{1}$ Here the sign convention as in e.g. Foken \& Nappo (2008), defining fluxes away from the surface as positive and those directed towards the earth's surface as negative, is used.

