## GEOG309-23S2

### Research for resilient environments and communities

# ANALYSIS OF WEATHER DATA AT MT HUTT AND THE WIDER CANTERBURY ALPINE REGION



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# Executive summary

The research question for this project is: How can we better understand the synoptic and microscale weather processes at Mt Hutt?

This report discusses the technical data manipulation techniques used to identify weather processes. Different datasets provided from our community partner were wrangled using R studio. Visualisation of the data was done using R studio & Excel. Analysis was also completed to validate our community partners weather stations

Figure 1: Map representing the study site. Mt Hutt found within the subset.

### 3. Stake Holders

Our primary stakeholder is Dave Kelly (member of the Cass Research Area Management Group). They provided valuable temperature and rainfall measurements to better understand weather patterns. A key focus was automation of data wrangling to validate the weather station readings because this process is currently labour intensive.

This project has significance for local Iwi in future research because climate data can be used to understand ecological processes that implicate food security and biodiversity. Climate data also informs research around potential health and wellbeing issues derived from climate change. The information validated during this study can be used to gain insights of how the local environment has been affected over time.

### 4. Background Information

#### 4.1 Scales

It is important to understand micunimate

Figure 2 shows the first stages of the data wrangling for all three stations. This code takes two



Figure 3. Flow diagram of steps used in data wrangling.

One gross error that has been identified is due to recurring battery failures. This sometimes produces a repetitive extreme reading for the panel sensors which are filtered out of the dataset (Figure 4). For this reason, it is helpful to record the status of the battery, because it can be an indicator of poor hardware performance. The last three steps are statistical comparisons of readings, first within the primary data set and then to the averaged values of the secondary dataset. Thresholds are set based on the maximum difference between stations after a correction for bias has been applied. Values are only modified if they will not intersect with their corresponding minimum, mean, and maximum daily readings. This was an issue which arose when applying spatial correlation analysis over larger distances. This is due to higher variability in the data, which lead to greater processing error.

#### 5.4 Wind

To analyse wind in the Mt Hutt area, 3 NIWA stations were gathered (Rakaia, Snowdon, Winchmore)\* n TJETQqWQqWMadfm7882.16 1o2n21t



Figure 8. The gradient of 0.8084 means that for every increase in temperature in Rakaia of 1 degree, temperature increases by 0.8084 degrees in Winchmore. The y-intercept of 8.8505 means that when the temperature in Rakaia is 0 degrees, the temperature in Winchmore is 8.8505 degrees.



Figure 9. The gradient of 0.8068 means that for every increase in temperature in Winchmore of 1 degree, temperature increases by 0.8084 degrees in Snowdon. The y-intercept of 1.4675 means that when the temperature in Winchmore is 0 degrees, the temperature in Snowdon is 1.4675 degrees.

Figure 10. The gradient of 0.8679 means that for every increase in temperature in Rakaia of 1 degree, temperature in Snowdon increases by 0.8679 degrees. The y-intercept of 8.0032 means that when the temperature in Rakaia is 0 degrees, the temperature in Snowdon is 8.0032 degrees.

6.2 Rainf



Figure 11. Line graph showing the accumulation of rainfall recorded at the mid elevation site alongside the recordings from the ECan Mt Hutt Station. The recordings shown are during 1/01/2005-1/01/2023.



Figure 12. Line Graph showing the accumulation of rainfall recorded at the mid elevation site alongside the recordings from the ECan Mt Hutt Station. The recordings shown are during 1/01/2016-1/01/2023.



Figure 13 Line graph showing the accumulation of rainfall recorded at the low elevation site alongside the recordings from the mid elevation site. The recordings shown are from 1/01/2006-31/12/2013.



Figure 14. Line graph showing the accumulation of rainfall recorded at the low elevation site alongside the recordings from the mid elevation site. The recordings shown are from 1/01/2016-1/01/2023



Figure 15. Line graph showing the accumulation of rainfall recorded at the low elevation site alongside the recordings from the ECan Mt Hutt station. The recordings shown are from 1/01/2017-1/01/2023

#### 6.3 Wind

Figures 16 & 17 show how topography can alter the local wind patterns in an area. Figure 13 (Rakaia) shows that NW winds tend to produce the highest windspeeds, there seems to be much lower wind speeds at all the other wind directions. Comparing summer and winter plots in Figure 16, there tends to be lower winds speeds during the cooler winter months. This is supported by Figure 7¢ kernel density plot. N/NE winds tend to have the highest windspeeds in summer whereas the NW winds dominate during the winter months. Winchmore's site has little to no topographical relief which can interfere with wind patterns thus becoming more susceptible to large scale wind patterns rather than dynamic small-scale patterns.



Figure 16. Wind rose plots for Rakaia WS representing Windspeed vs Direction (Left, 2023 Winter / Right, 2023 Summer)

![](_page_16_Picture_0.jpeg)

Figure 17. Wind rose plots for Winchmore WS representing Windspeed vs Direction. (Left, July 2022 / Right, December 2022)

## 7. Discussion

#### 7.1 Lapse rates on Mt Hutt

13 15310	42	11 26	i <mark>66</mark> 1	<u>67</u>
128888410	.930	17082	2 7	1.16
17.49 18	3.28	5395	8	
15.03	15.	5902	5	
666667 13	3.87	5687	5 1	13.1
166667 <mark>5</mark> .	7114	5835	5	.414
	792	127		
25290 <i>0</i> .2	-92.3			66
103636	20.5		36	i î î
Sa militza	203	ii ni		
2133644	<b>T</b> SA		u.	666
8.9754583	311		17	.71
5-9091454	22	1.100	660	674
1166663	19.4	6068	75	.17
0.396666	342	1312	121	3.1
	2.499	n		and a

Interlinking with the data provided by Tim Kerr and Heather Purdie has created a guided understating of how air temperature lapse rate occurs on Mount Hutt. Shown Figure 18, data in the left column represents 1090m (Kerr and Purdie) and 1070m data in the right column (Kelly). Although there are some days where the 1090m site experiences higher temperature recordings, the difference between the sites is insignificant. When the 1090m sight recorded cooler temperatures, it reflects active air temperature lapse rates that occurred

*Figure 18 (to the left). Snapshot of the conditionally formatted data in excel showing the differences in temperature for the 1090m and 1070m sites. Specific to the first few days of January 2022.* 

#### 7.2 Microclimates at Mt Hutt

Understanding microclimates at our community partners sites can build trust in the data to be representative. The first site at 450m is raised on a mound above a paddock with a line of trees towards the south that shelter it from strong wind. At 450m, snow is rare which keeps annual temperatures consistent with the wider region. From installation in 2005 to Feb 2020, a handful of eucalyptus trees shaded the weather station during winter months. At Noon sun was halfway up the tree when seen from solar panel. This is an environmental factor which may affect the representation of data for the wider region. These trees were cut down in February 2020.

Figure 21. MSLP charts show the large high-

```
summarise(
    site_avg = mean(!!sym(nearestSite), na.rm = TRUE),
    site_max = max(!!sym(nearestSite), na.rm = TRUE),
    site_min = min(!!sym(nearestSite), na.rm = TRUE)
)
day_values$day <- day_values$day + days(1)
# Apply lapse rate correction
day_values[, -which(names(day_values)
```

```
# remove max panel default failure values
Reliable_data <- Reliable_data %>%
  mut at e (Max. panel = i f el se (Max. panel ==35.44 & Bat t Fai l ed ==TRUE,
NA, Max. panel ) )
#####
# Average across different sensor readings
# M N
min_columns <- Reliable_data %>%
 sel ect (cont ai ns ("M n"))
row_averages1 <- min_columns %>%
  rowwise() %>%
  mut at e(M n = mean(c_across(), na.rm = TRUE))
Rel i abl e_dat a$M n <- row_aver ages1$M n
# MEAN
mean_col umns <- Rel i abl e_dat a %%
  sel ect (cont ai ns ("Mean"))
row_averages2 <- mean_columns %>%
  rowwise() %>%
  mut at e(Mean = mean(c_across(), na.rm = TRUE))
Rel i abl e_dat a$Mean <- row_aver ages2$Mean
# MAX
max_columns <- Reliable_data %>%
  sel ect (cont ai ns ("Max"))
row_averages3 <- max_columns %>%
  rowwise() %>%
  mut at e (Max = mean (c_across(), na. r m = TRUE))
Reliable_data$Max <- row_averages3$Max
Rel i abl e_dat a$dat e <- dat a_set $dat e
day_values <- day_values %>%
  mut at e (day = for mat (day, for mat = "% - % m % d"))
Reliable_data <- Reliable_data
```

```
mut at e(Mean_diff = st at i ons_dat a_set $sit e_avg - st at i ons_dat a_set $Mean)
av_bi as
                                                                                               sum(stations_data_set $Mean_diff, na.rm
                                                             =
TRUE)/l engt h(st at i ons_dat a_set $Mean)
stations_data_set <- stations_data_set %>%
       mut at e(MeanBi asCorrection = stations_data_set $site_avg - av_bi as)
stations_data_set <- stations_data_set %>%
       mutate(Mean_diff
                                                                                         =
                                                                                                              stations_data_set $MeanBiasCorrection
                                                                                                                                                                                                                                                                                      -
st at i ons_dat a_set $Mean)
av_bi as
                                                                                                     sum(st at i ons_dat a_set $Mean_di ff, na. r m
                                                                                                                                                                                                                                                                                      =
                                                             =
TRUE)/l engt h(st at i ons_dat a_set $Mean)
threshold_mean = max(stations_data_set $Mean_diff, na.rm=TRUE)
mean_columns <- Reliable_data %>%
       sel ect (cont ai ns("Mean"), -Mean)
mean_col ums <- mean_col ums %>%
       mut at e(across(everything(), ~ if else((.x > .x+threshold_mean | .x < .x-threshold_mean | .x 
threshold_mean), NA, .x)))
```

mx_bias	=	sum(st at i ons_	_data_set <b>\$</b> Max_	_diff,na.rm
TRUE)/				

=

# Write data to an Excel file with multiple sheets

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