Weather Analysis of Greater Victoria

Richard Williams

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1 Introduction

The climate of Greater Victoria was investigated using temperature data recorded from various locations in the Vancouver Island School-Based Weather Network. The data was used to compare seasonal and geographic variations in the climate of the region.

Greater Victoria lies at the Southern end of Vancouver Island. Southern Vancouver Island is bounded by the Juan de Fuca Strait to the west and the Haro Strait to the East (fig 1). The Olympic Peninsula and Pacific Ocean are located to the west of the region, and North America to the east.

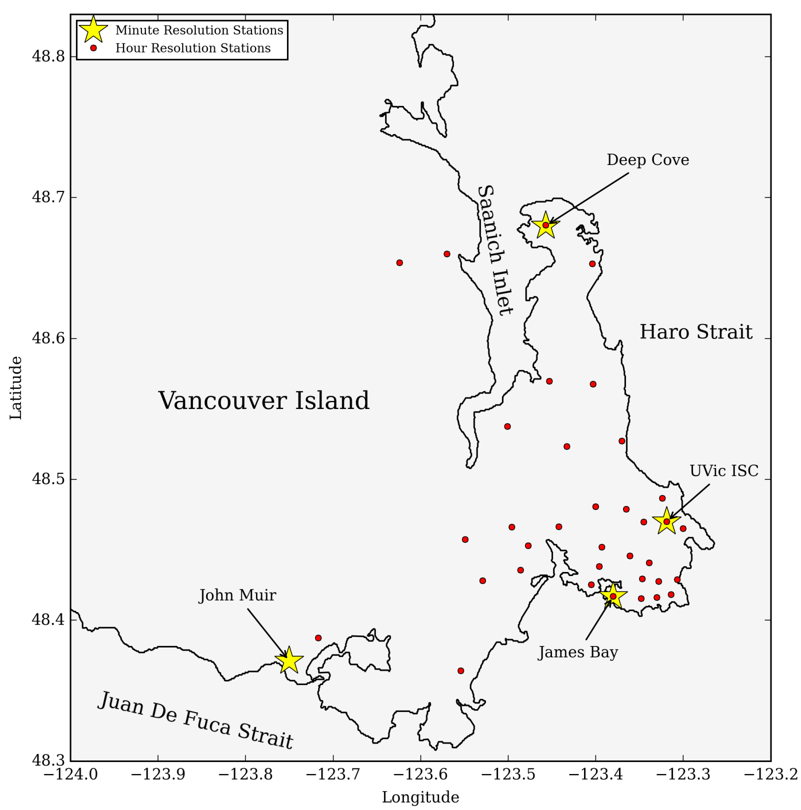

Figure 1: Geographic setting and location of weather stations in the Vancouver Island School-Based Weather Network.

2 Methods

Temperatures were recorded over a three year period between January 1, 2008 and Jan 1, 2012. Minute-resolution data was collected from four school based weather stations: Deep Cove Elementary, James Bay Elementary, John Muir Elementary and the University of Victoria Ian Stewart Complex. Hour-resolution data was collected from 35 weather stations at various locations in Greater Victoria. The location of the stations were plotted on a map (fig 1).

Temperature data was missing from some of the stations at different times, and for various durations, leaving gaps in the time series. These gaps were filled using a linear interpolation of the time series.

3 Results/Discussion

3.1 General Overview of Data

On a yearly scale, the overall shape of the raw time series at the minute-resolution stations (fig 2) appeared to be very similar. This similarity in the time series would be expected for weather stations in close geographic proximity, as the overall climate is likely to be similar. The time series showed a clear seasonal pattern, with higher temperatures in the summer months and lower temperatures in the winter months. These observations were consistent with expectations, as the region is at a relatively high latitude and is therefore likely to show strong seasonal temperature variations.

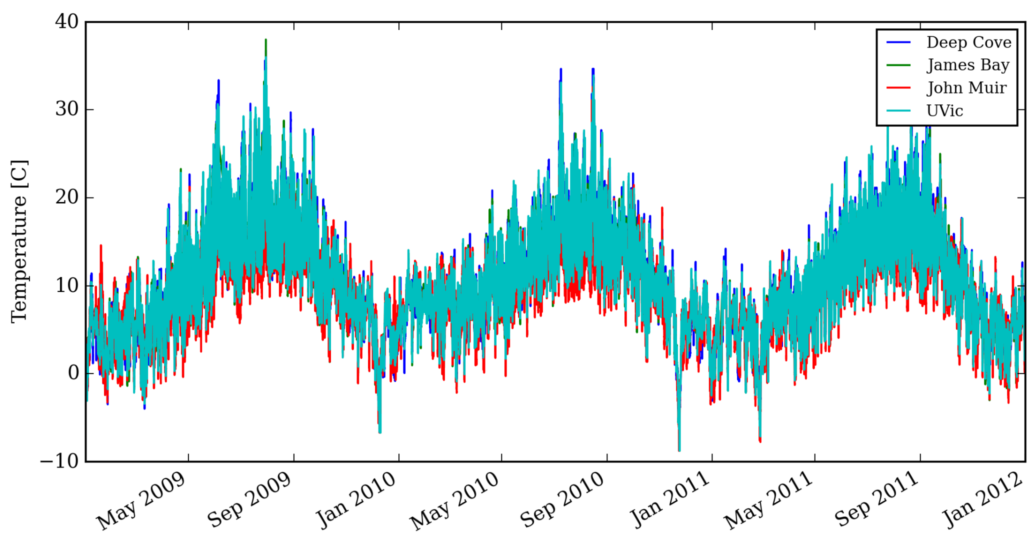

Figure 2: Raw time series for minute-resolution stations.

A plot of the power spectral density of the minute-resolutions stations was made, with a hanning window applied to reduce leakage (fig 3). The spectrum showed a strong signal for high frequency information. This was expected because the temperature is unlikely to change drastically over very short periods, and therefore the temperature data should be highly correlated over small periods. The spectrum did not show a clear yearly signal, but there appeared to be a high degree of correlation for very low frequency information that contained the frequency corresponding to a period of one year.

A yearly signal would be expected because the temperature patterns are likely to be similar from year to year.

The spectrum also showed a clear daily signal and its harmonics. A zoomed-in plot of these signals was made to display these signals with more clarity (fig 4). The daily signal was expected because the temperature from one day to the same time on the following day is likely to be similar. The signal from the daily harmonics grew smaller as the number of days increased. This was also expected because the temperature is less likely to remain similar over the period of multiple days than it is over one day. Daily harmonics for frequencies corresponding to a period greater than 7 days were not really visible in the power spectrum.

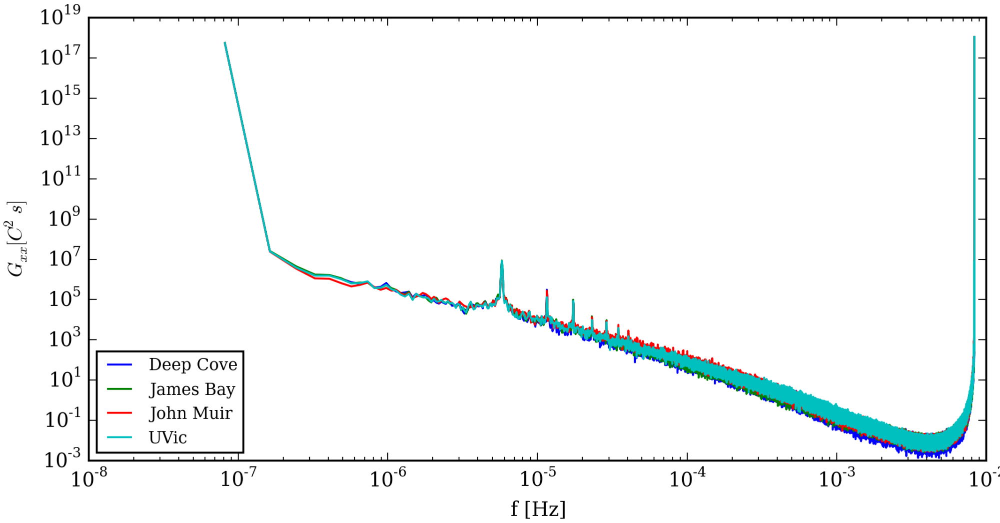

Figure 3: Power spectral density of minute-resolution data.

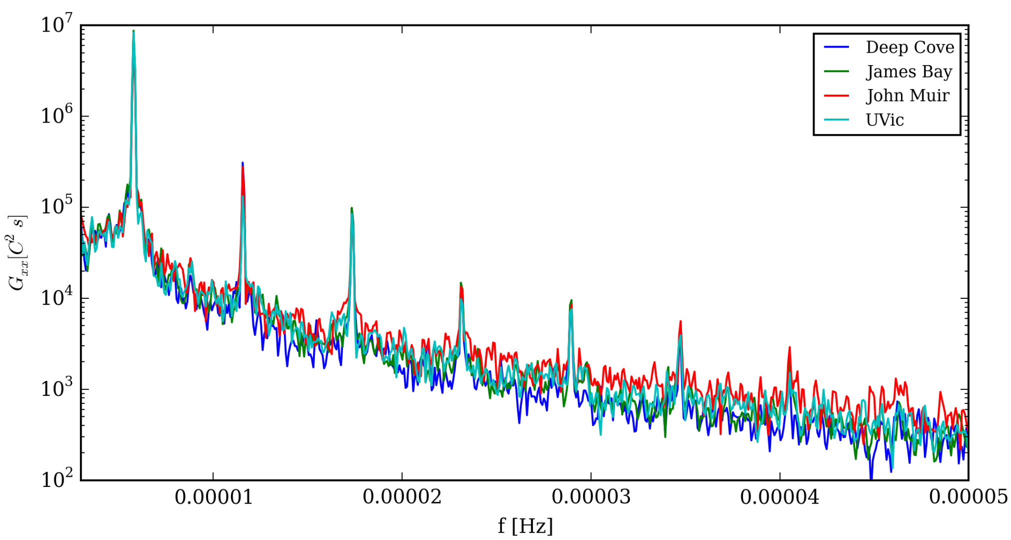

Figure 4: Daily signal and harmonics in the power spectrum for minute-resolution data.

The raw time series (fig 3) appeared as a thick line on the time scale of three years because of the daily temperature variations. These daily variations made it difficult to notice differences between the four stations. The raw time series was smoothed using an elliptical low pass filter, with a stopband of 3.5day^{-1}, to filter out this variation.

A plot was made to show the difference between the raw time series and the filtered time series at Deep Cove (fig 5). The smoothed time series appeared as a thin line compared to the thick line of the raw signal. The overall yearly trends were not lost in the smoothed signal. Other notable events, such as extremely warm periods in the summer and extremely cool periods in the winter, were also preserved in the smoothed time series.

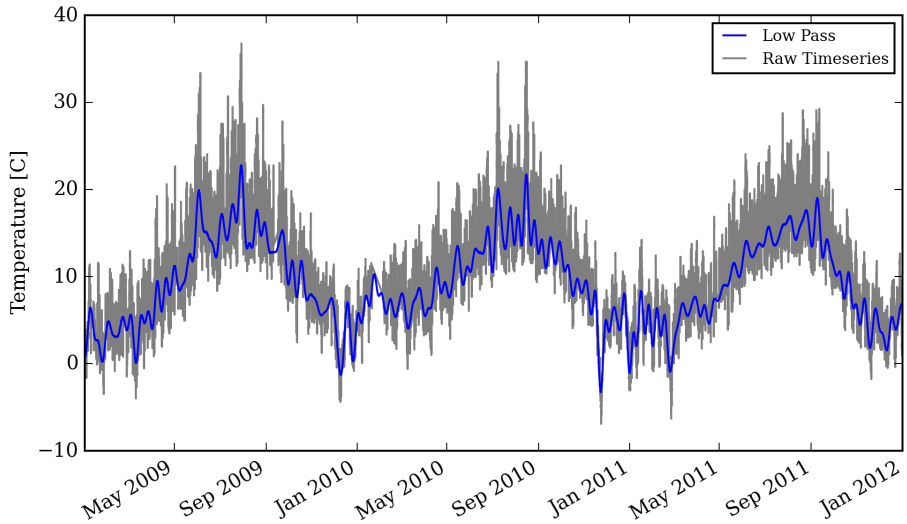

Figure 5: Comparison of raw time series and elliptical low pass filter with 3.5 day^{-1} stop band for Deep Cove temperature data.

A plot of the smoothed time series at all four locations was made (fig 6). The smoothed time series showed the long-term temperature trends more clearly than the raw time series. It allowed for comparisons to be made between the weather stations, which were not clearly visible in the raw series. One particular difference in the smoothed time series was the apparent lower temperature at John Muir Elementary, particularly during the summer months.

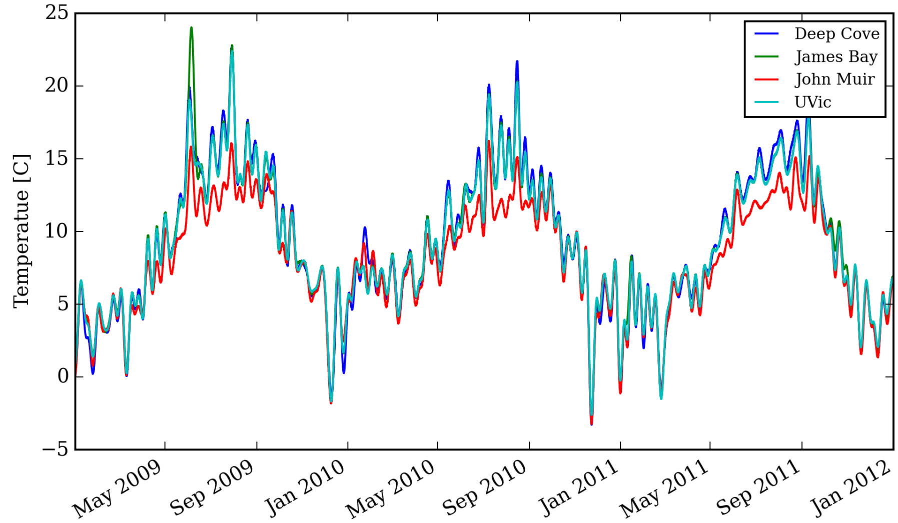

Figure 6: Elliptical low pass filter applied to temperature data with 3.5 day^{-1} stopband.

The temperature anomaly at John Muir was investigated by looking at the probability distributions of the yearly temperature data (fig 7), and by computing the univariate statistics of the raw time series (table 1).

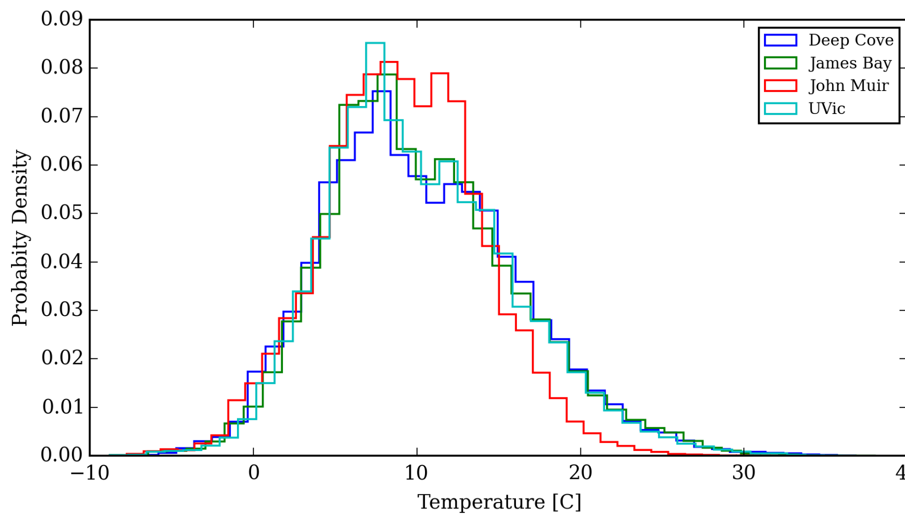

Figure 7: Normalized probability distribution function for minute-resolution stations.

Table 1: Summary of annual temperature statistics for locations around Victoria.

Location	Deep Cove	James Bay	John Muir	UVic
Mean	10.30	10.31	9.12	10.24
Standard Deviation	5.98	5.84	4.84	5.70
Skewness	0.444	0.449	0.064	0.491
Kurtosis	0.113	0.229	0.141	0.288

The overall shape of the probability distributions at Deep Cove, James Bay, and UVic all appeared to be very similar, while John Muir was different. The mean temperatures at the similar stations were all within $0.07°C$ of one another, while the mean temperature at John Muir was almost $1°C$ lower. The distributions at Deep Cove, James Bay, and UVic were all asymmetrical with similar positive skewness (within $0.047°C$). John Muir had a much more symmetrical distribution, with a skewness of only 0.064.

Two maps of mean annual temperatures were produced using temperature data from the hour-resolution stations. One used a global interpolation (fig 8), and the other used a linear interpolation (fig 9). Both maps suggested that the mean temperatures are higher on the east side of the region than they are on the west. This was consistent with the observation of John Muir being colder than the other minute-resolution stations. This temperature anomaly may be a result of the most common direction of weather movements. If weather generally moves from the west, John Muir would not be exposed to land-heating because the Juan de Fuca strait lies to its west. All of the other minute-resolution stations have land to the west of them, which could lead to higher temperatures for weather moving from the west.

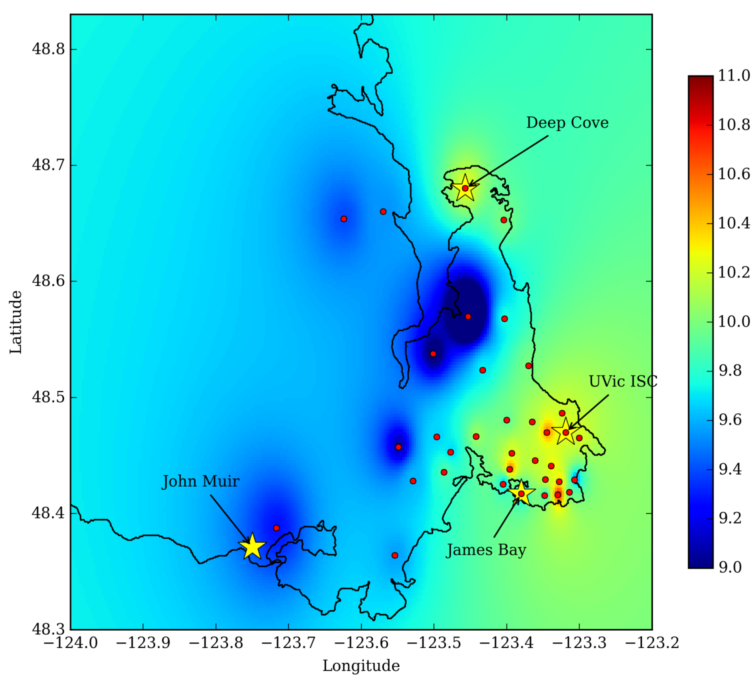

Figure 8: Average yearly temperature for hour resolution stations (Global Interpolation).

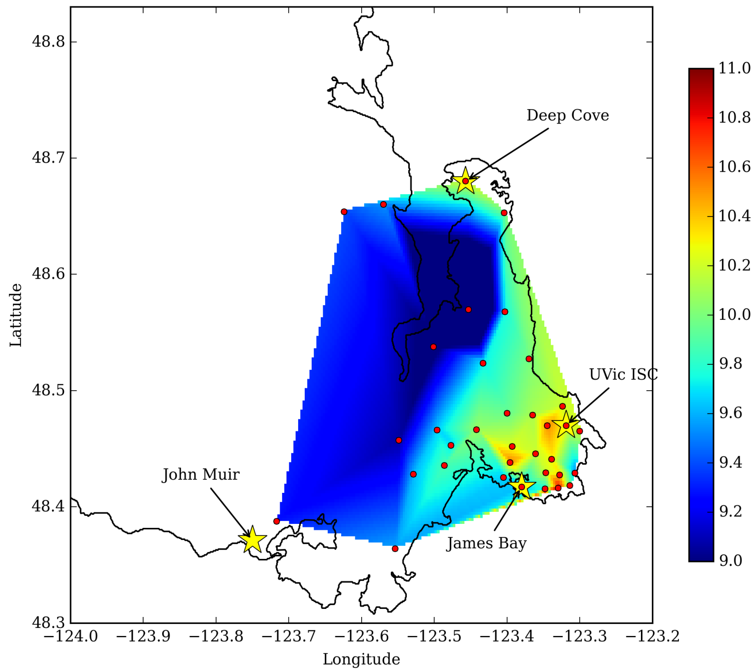

Figure 9: Average yearly temperature for hour resolution stations (Linear Interpolation).

3.2 Single Weather Front

A single weather front was found in the data, and its temperature information was used to determine the direction of its movement. The time series of the minute-resolution stations for the weather front was plotted (fig 10), and it showed a clear time lag of about 2 hours between John Muir and James Bay/UVic, as well as another clear time lag of about 2 hours between James Bay/UVic and Deep Cove. This could indicate a movement of cool air from the southwest to the northeast. Six maps were created using a linear interpolation of the hour-resolution data to show temperature changes in the region over the time period (fig 11). The maps showed a clear temperature drop, starting in the southwest and moving towards the northeast. These observations support the postulation that cool air moved from the southwest.

I was unable to produce a lag-correlation plot to quantify the observation of a time-lag for the time series in figure 10. If I had been able to produce this plot, I would have liked to do the same for a whole year to determine the dominant weather direction. This could have explained why John Muir had a lower temperature, because of the land-heating effects discussed in section 3.1.

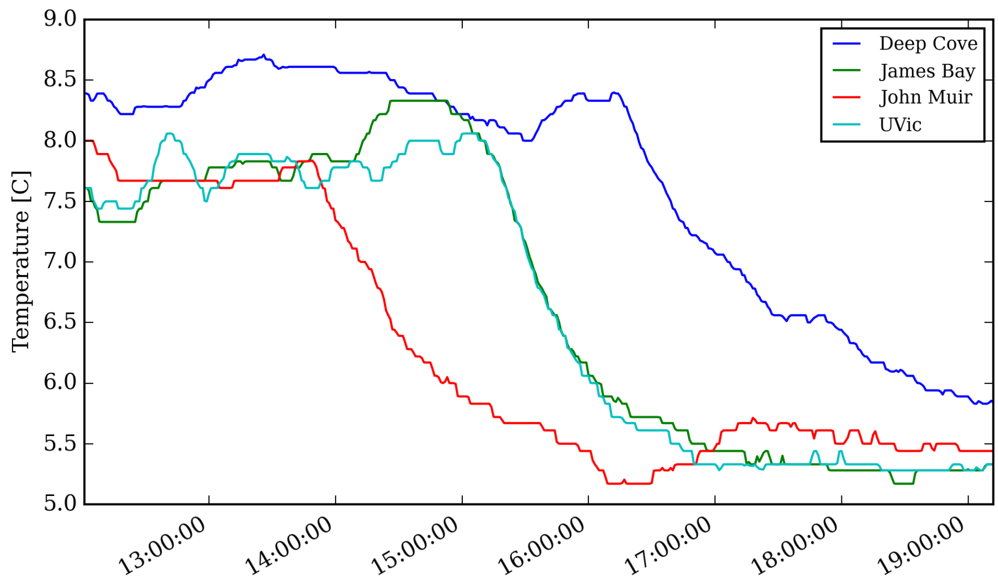

Figure 10: Minute-resolution time series for single weather front.

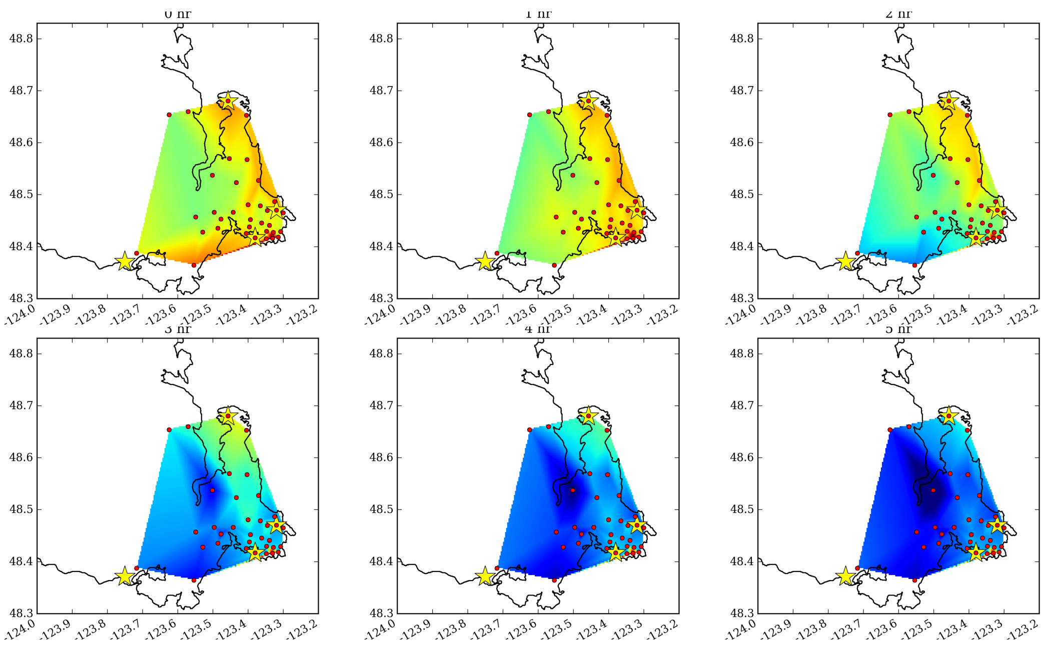

Figure 11: Linear Interpolated map of weather front.

4 Appendix

4.1 Linear Interpolation Example

```
#import data
dc = np.genfromtxt('DeepCoveNew.txt')

#save original time points
tdc = dc[:,0]

#remove points with nan's
dcr = dc[~np.isnan(dc[:,1]),:]

#function for linear interpolation
fdc = interpolate.interp1d(dcr[:,0],dcr[:,1],kind='linear')

#replace nan's with interpolated values
dc[:,1] = fdc(tdc)
```

4.2 Low-Pass Elliptical Filter Example

```
day = 60.*24
df = 1./ (3.5*day) #half week frequency

wp = 0.7*df #passband frequency
ws = 0.9*df #stopband frequency

#run elliptical filter
n,fn = signal.ellipord (wp,ws,0.5,20.)
b,a = signal.ellip (n,0.5,20.,fn)
dcf = signal.lfilter (b,a,dc)
dcf = signal.filtfilt (b,a,dc)
```

4.3 Power Spectral Density

```
files = [dc,jb,jm,uv]
names = ['Deep Cove','James Bay','John Muir','UVic']

dt = 60.
nfft = 2048*100

fig,ax = plt.subplots(1,1,figsize=(7.5,4))

for i in range(0,4):
    minutedata = files[i]
    g,f = mlab.psd(minutedata[:,1],NFFT=nfft,Fs=1./dt,noverlap=nfft/2,window=mlab.
    window_hanning)
    ax.loglog(f,g,label=names[i])

ax.set_xlabel('f [Hz]'); ax.set_ylabel('$G_{xx} [C^2s]$');ax.legend(fontsize='small',
    loc=0)
plt.tight_layout()
fig.savefig('psd.png',dpi=300)
```

4.4 Probability Density Functions

```
bn = 40
fig,ax = plt.subplots(1,1,figsize=(7.5,4))

for i in range(0,4):
    minutedata = files[i]
    temp = minutedata[:,1]
    ax.hist(temp,normed=True,bins=bn,histtype='step',label=names[i])

ax.legend(loc=1,fontsize='8')
ax.set_xlabel('Temperature [C]')
ax.set_ylabel('probabity density')
```

4.5 Plot Coastline

```
#coastal data
coast = np.genfromtxt('Coast.txt')
N = np.size(coast)
coastlon = coast[:N/2]
coastlat = coast[N/2:]

#hour-resolution stations
hour = np.genfromtxt('HourlyCoords.txt')
hourlon = hour[0,:]
hourlat = hour[1,:]

#minute-resolution stations
minstat = (
    ('Deep Cove', 236.543-360., 48.680,40,40),
    ('James Bay', 236.620-360., 48.417,-50,-40),
    ('John Muir', 236.250-360., 48.371,-60,40),
    ('UVic ISC', 236.681-360.,48.470,15,30),
)

#arrows adds labels for minute stations
#geog adds geographic names
#legend adds a legend for the points

def plotMap(lonmin,lonmax,size,arrows=False,geog=False,legend=False,axislabel=True):
    #set correct scale
    lonrange = lonmax-lonmin
    latrange = lonrange*np.cos(48.5*np.pi/180.)
    latmin = 48.3
    latmax = latmin+latrange

    #fig,ax = plt.subplots(1,1,figsize=(size,size))

    #plotcoastline data
    ax.plot(coastlon,coastlat,color='black',rasterized=True)

    #plot minute resolution stations and arrows
    for name,mlon,mlat,textx,texty in minstat:
        ax.plot(mlon,mlat,'.',marker='*',markersize=20.0,color='yellow',
                label='Minute Resolution Stations')
        if arrows==True:
            ax.annotate(
                name, xy=(mlon, mlat), xytext=(textx, texty),
                textcoords='offset points', fontsize=10,
                arrowprops=arrow_properties,)

    if geog==True:
```

```
        #annotate geography
        ax.text(-123.9,48.55,'Vancouver Island',fontsize='16')
        ax.text(-123.35,48.6,'Haro Strait',fontsize='13')
        ax.text(-123.97,48.34,'Juan De Fuca Strait',fontsize='13',rotation=-13)
        ax.text(-123.54,48.7,'Saanich Inlet',fontsize='13',rotation=-80)

    #plot hour resolution stations
    ax.plot(hourlon,hourlat,'o',markersize=4.0,color='red',
        label='Hour Resolution Stations')

    if legend==True:
        #display minute resolution only once
        handles,labels = ax.get_legend_handles_labels()
        display = (0,4)
        ax.legend([handle for i, handle in enumerate(handles) if i in display],
                  [label for i, label in enumerate(labels) if i in display],
                  loc=2,fontsize='8',numpoints=1)

    #remove relative axis shift
    ax.get_xaxis().get_major_formatter().set_useOffset(False)

    if axislabel==True:
        ax.set_xlabel('Longitude');ax.set_ylabel('Latitude');

    #other plot formatting
    ax.set_xlim(lonmin,lonmax); ax.set_ylim(latmin,latmax);
    plt.tight_layout()
```

4.6 Global Interpolated Map

```
def globalInterpMap(z,res,cbar=False,tmin=0,tmax=10):
    x = hourlon
    y = hourlat
    xi = np.linspace(np.amin(coastlon),np.amax(coastlon)+0.2,res)
    yi = np.linspace(np.amin(coastlat)-0.1,np.amax(coastlat),res)

    nx = len(xi)
    ny = len(yi)
    Zi = np.zeros((ny,nx))

    for i in range(nx):
        for j in range(ny):
            w = 1./((xi[i]-x)**2+(yi[j]-y)**2)
            w=w/np.sum(w)
            Zi[j,i]=np.sum(w*z)
    pcm = ax.pcolormesh(xi,yi,ma.masked_invalid(Zi))
    pcm.set_clim([tmin,tmax])

    if cbar==True:
        plt.colorbar(pcm,shrink=0.8)
```

4.7 Linearly Interpolated Map

```
def localInterpMap(z,res,cbar=False,tmin=0,tmax=10):
    x = hourlon
    y = hourlat
    xi = np.linspace(np.amin(coastlon),np.amax(coastlon)+0.2,res)
    yi = np.linspace(np.amin(coastlat)-0.1,np.amax(coastlat),res)
    Xx = np.vstack((x,y)).T
```

```
    Xi,Yi=np.meshgrid(xi,yi)
    Zi = interpolate.griddata(Xx,z,(Xi,Yi),method='linear')

    pcm = ax.pcolormesh(xi,yi,ma.masked_invalid(Zi))
    pcm.set_clim([tmin,tmax])

    if cbar==True:
        plt.colorbar(pcm,shrink=0.8)
```