# **GLACIER RECESSION**

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### INTRODUCTION

Using satellite images to analyze the mountain glaciers' variation over time and investigate the potential relation to climate factors, including temperature, CO2, and precipitation.





## **GLACIER BASICS**

#### Accumulation vs. Ablation Periods



#### **Glacier Terminal Point**



### LITERATURE REVIEW

**Quantifying Area:**" *Localization of mountain* glacier termini in Landsat multi-spectral images "



#### **Modeling**: "Multivariate models for predicting glacier termini"

#### Environmental Earth Sciences (2017) 76:80 https://doi.org/10.1007/s12695-017-7135-2

ORIGINAL ARTICLE

#### CrossHad

#### Multivariate models for predicting glacier termin

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Concerns over the rapid retreat rates of mountain glaciers have been rising as global temperatures have continued to increase The extent of variation in the retreat of mountain glaciess can provide information about changes to different climatic conditions. Assessing the retreat rates of glaciers is crucial to assess the continuing existence of mountain glaciers and the ramifications of those retreats on water security for human societies. Therefore, mathematical and statistical models for the quantification of glacier dynamics in response to climate change are in high demand. In this research, we propose a multivariate regression model that estimates glacier change and predicts the location of glacier terminus over time, based on observed climate factors. The proposed method is applied to temporal sequences of ground observations for a number of glaciers around the globe. This model can potentially be used for monitoring glacier systems using climatic factors.

Keywords Climate change · Mountain glaciers · Statistical analysis · Regression · Multivariate models · Correlation Prediction · Terminus location · Climate factors

#### Introduction

than any individual Landsat spectral band. A constrain bandwidth selection method using local polynomial regres In our previous work (Kachouie et al. 2013, 2015) we pro- sion was also introduced for the detection of glacier to posed a statistical method for estimating the location of a minus. Here we propose a model for predicting the glacie placier terminus over time, from a sequence of Landsat malpercental statistics of the statistic of (NDTSI) was introduced using B62 and NDSI for elacier climatic factors The definition of climate change varies from any change studies via remote sensing that provides a better estimation in climate over time (Solomon et al. 2007) to changes in climate that result from human activity (UNFCCC 1995) Electronic supplementary material The online version of this Climate change is used synonymously with global warn article (https://doi.org/10.10078/12665-017-7135-2) contains supplementary material, which is available to authorized users. ing, referring to the observed rise in global surface air tem peratures during the past century (Hansen et al. 2010). In their most recent and Fifth Assessment Report of the Intersita Onyejekwe, Bryan Holman, and Nezamoddin N. Kacheuie governmental Panel on Climate Change (IPCC), a body of

work by thousands of scientists worldwide concluded that "Human influence on the climate system is clear, and recent [5] Nezamodéin N Kachonie nezamoddin@fit.edu Osita Onyejekwe oonyejekwe2010@fit.edu anthroporenic emissions of greenhouse pases are the high est in history. Recent climate changes have had widespre Bryan Holman bholman2013@fit.edu impacts on human and natural systems" (Pachauri et al. 2014). These impacts include global sea-level rise; ocean acidification; shrinking glaciers; changes to hydrologic cycles; smaller crop yields; more heat waves, droughts, and floods; and numerous other changes to natural and biologica Department of Ocean Engineering and Sciences, Florida Institute of Technology, Melbourne, FL, USA

### DATASETS

#### Landsat 8 Satellite Images

Processed as a tif file without geographical information



Bands	Wavelength (µm)	<b>Resolution (m)</b>
Band 1 – Blue	0.45 – 0.52	30
Band 2 – Green	0.52 - 0.60	30
Band 3 – Red	0.63 – 0.69	30
Band 4 – Near Infrared	0.77 – 0.90	30
Band 5 –		
Shortwave Infrared	1.55 – 1.75	30
1		
Band 6 – Thermal	10.40 - 12.50	60
Band 7 –		
Shortwave Infrared	2.09 – 2.35	30
2		
Band 8 –		
Panchromatic	0.52 - 0.90	15
(entire visible)		



L to R: Google Earth image of Franz Josef, blue band, green band

L to R: red band, near infrared (IR) band

L to R: shortwave (SWIR) band 1, thermal band, SWIR band 2, panchromatic band (entire visible spectrum)

## CLIMATE DATA

We gathered daily climate data from a weather station closest to each glacier from NOAA.





Daily Temperature Data



**Daily Precipitation Data** 

## HYPOTHESIS

Whether mountain glacier variation is correlated with global temperature, local temperature, precipitation, and CO2 (climate factors).



#### SCHEMATICS





# PART I. DATA COLLECTION



## DATA QUALITY



Gorner, corrupted by a sensor malfunction



Franz Josef, obscured by clouds



Franz Josef, obscured by shadows

Franz Josef – 42 scenes, 37 usable for terminal point detection, 9 usable for area measurement Gorner – 17 scenes, 15 usable for terminal point detection, 10 usable for area measurement

## TERMINAL POINT

#### MATLAB GUI



A graphical user interface (GUI) allows us to plot the satellite images against an arbitrary graph and manually estimate the location

## **TERMINAL POINT VARIATIONS**

We plotted a time series of the distances between consecutive terminal points for both glaciers



# AREA

### **MEASURING AREA**



Simple idea – count pixels that make up the glacier and multiply by image resolution to get area



Images exist as matrices of pixel intensities





Otsu's method





Images are segmented into different regions based on a threshold for the difference between pixel intensities in those regions





Images are segmented into different regions based on a threshold for the difference between pixel intensities in those regions

### **REGION GROWING**



Too little glacier

Good segmentation!

Too many surroundings

Pick a pixel within the glacier and have it grow based on differences in pixel intensity

#### **EDGE DETECTION**



Glacier not fully outlined

Good outline!

Glacier is broken up

Edges are defined by differences in the intensities of adjacent pixels





#### **COMBINING METHODS**



Superimposed scenes show area change – Franz Josef glacier 1990 (green), 2009 (purple)



Gorner blue band, 1985 (top), 2009 (bottom)



#### **COMBINING METHODS**



Superimposed scenes show area change – Gorner glacier 1984 (green), 2009 (purple)

## PROBLEMS



This method allows us to visualize change over time, but leaves holes in glaciers and includes snow or ice outside the glacier

## MULTI-THRESHOLDING



Franz Josef blue band

Two segments

Five segments

Segmentation is good but having the glacier broken into multiple segments actually makes the problem harder

## **BINARY SEGMENTATION**

We need a method that segments images into only two regions (glacier and background) and does not leave holes inside the segmented glacier area or include pixels from the background



## **BLOB DETECTION**



Gorner blue band



Gorner blue band (cropped)



Binarized

Crop the region of interest and then segment it into two regions

## **BLOB DETECTION**



Binarized



Find the largest blob in the binarized image that represents the glacier area

### **SEGMENTED AREA**



Gorner Area vs Time from 1984 to 2009

Superimposed scenes show area change – Gorner glacier 1984 (green), 2009 (purple)

#### **SEGMENTED AREA**



Gorner Area vs Time from 1990 to 2009



Superimposed scenes show area change – Franz Josef glacier 1990 (green), 2009 (purple)



## PART II. MODELING



## **CLIMATE FACTORS**



## FRANZ JOSEF'S TERMINUS

## **MULTIPLE REGRESSION**



Theoretical Quantiles Im(Distance ~ monthly\_average + Global\_Mean + TMAX)

#### **Plots for checking Homoscedasticity**



Fitted values Im(Distance ~ monthly average + Global Mean + TMAX)

Factors	# of Factors	R^2	AIC	SBIC
TMAX + PRCP + CO2	3	0.0864	180.1562	99.0866
TMAX + CO2	2	0.1278	217.1768	116.2774
TMAX + PRCP	2	-0.0513	183.3642	101.7315
$Global\_temp + PRCP + CO2$	3	0.055	187.367	103.4142
$Global_temp + CO2$	2	0.086	224.7852	120.9909
Global_temp + PRCP	2	-0.0737	190.3286	105.8343
$TMAX + Global_temp + PRCP + CO2$	4	0.1147	180.0575	99.7556
TMAX + Global +PRCP	3	-0.0933	185.3631	104.2935
TMAX + Global + CO2	3	0.152	217.0579	116.8533
TMAX + Global	2	-0.0139	222.5972	121.8789

## GENERALIZED ADDITIVE MODEL SUMMARY

Response variable is modeled based on smoothed functions of predictor variables where smoothed functions are obtained using a non-parametric method.

 $g(\mathrm{E}(Y)) = eta_0 + f_1(x_1) + f_2(x_2) + \dots + f_m(x_m).$ 



~ "GAM: The Predictive Modeling Silver Bullet", *MultiThreaded* 

### **GENERALIZED ADDITIVE MODEL**

#### Plots of the Factors in the Multiple Additive Model



#### **Graph of Predicted Values from the Model**



Factors	# of Factors	R^2	AIC
TMAX + PRCP + CO2	3	0.422	369.8605
TMAX + PRCP	2	0.216	376.764
TMAX + CO2	2	0.296	457.4287
Global_temp + PRCP +CO2	3	0.244	386.8718
Global_temp+ PRCP	2	-0.0737	394.4011
$Global\_temp + CO2$	2	0.268	471.386
$TMAX + Global\_temp + PRCP + CO2$	4	0.201	375.3042
TMAX+Global_temp + PRCP	3	-0.0591	382.9207
TMAX+Global_temp + CO2	3	0.253	459.6973
TMAX+Global_temp	2	-0.012	467.5875

## FRANZ JOSEF'S AREA

### **MULTIPLE REGRESSION**



Factors	# of Factors	R^2	AIC	SBIC
TMAX + PRCP + CO2	3	-0.0342	115.0206	98.3176
TMAX + CO2	2	0.1218	131.6565	108.6156
TMAX + PRCP	2	0.1718	113.0285	94.3215
Global_temp + PRCP +CO2	3	-0.0897	115.4389	98.7359
$Global\_temp + CO2$	2	0.1271	131.602	108.5611
Global_temp + PRCP	2	0.1074	113.628	93.805
$TMAX + Global_temp + PRCP + CO2$	4	-0.3572	116.8935	105.3016
TMAX + Global +PRCP	3	-0.0222	114.9274	99.9869
TMAX + Global + CO2	3	-0.0381	133.5215	113.1006
TMAX + Global	2	-0.0756	133.481	110.4401

#### **GENERALIZED ADDITIVE MODEL**



#### **Graph of Predicted Values from the Model**



Factors	# of Factors	R^2	AIC
TMAX + PRCP + CO2	3	0.309	112.1162
TMAX + PRCP	2	0.172	113.0287
TMAX + CO2	2	0.193	131.5022
Global_temp + PRCP +CO2	3	-0.0897	115.4391
Global_temp+ PRCP	2	0.107	113.6282
Global_temp + CO2	2	0.167	131.6321
TMAX + Global_temp + PRCP + CO2	4	NA	NA
TMAX+Global_temp + PRCP	3	-0.0222	114.9275
TMAX+Global_temp + CO2	3	0.0867	132.9009
TMAX+Global temp	2	-0.0121	133.4584

#### GORNER GLACIER'S TERMINUS

GSB Photography -

## **MULTIPLE REGRESSION**



#### **Plots for checking Homoscedasticity**



Theoretical Quantiles lm(Distance ~ monthly\_average + Average\_PRCP + Average\_TMIN + Global\_Mean)

Fitted values Im(Distance ~ monthly average + Average PRCP + Average TMIN + Global Mean)

Factors	# of Factors	R^2	AIC	SBIC
TMIN + PRCP + CO2	3	0.9592	161.3541	121.4306
TMIN + CO2	2	0.9576	161.2273	119.7976
TMIN + PRCP	2	0.3306	202.6117	161.4185
Global_temp + PRCP +CO2	3	0.9532	163.3948	123.4713
$Global\_temp + CO2$	2	0.9526	162.9085	121.7153
Global_temp + PRCP	2	0.6122	194.4261	153.233
$TMIN + Global\_temp + PRCP + CO2$	4	0.9604	161.4673	123.3991
TMIN + Global +PRCP	3	0.6285	194.4752	154.5516
TMIN + Global + CO2	3	0.9586	161.5526	121.6291
TMIN + Global	2	0.6591	192.4898	151.2966

#### **GENERALIZED ADDITIVE MODEL**

#### **Plots of the Factors in the Multiple Additive Model**



#### **Graph of Predicted Values from the Model**



Factors	# of Factors	R^2	AIC
TMIN + PRCP + CO2	3	0.982	151.2125
TMIN + CO2	2	0.974	154.8016
TMIN + PRCP	2	0.419	201.4022
Global_temp + PRCP +CO2	3	0.982	150.8067
Global_temp+ CO2	2	0.974	154.4909
Global_temp + PRCP	2	0.612	194.4265
TMIN + Global_temp + PRCP + CO2	4	0.979	152.8832
TMIN+Global_temp + CO2	3	0.972	156.5745
TMIN+Global_temp + PRCP	3	0.644	194.4644
TMIN+Global temp	2	0.659	192.49

#### GORNER GLACIER'S AREA



## **MULTIPLE REGRESSION**



Factors	# of Factors	R^2	AIC	SBIC
TMIN + PRCP + CO2	3	0.2727	170.5771	150.1562
TMIN + CO2	2	0.3597	169.0711	146.7626
TMIN + PRCP	2	0.1241	171.891	148.8501
$Global\_temp + PRCP + CO2$	3	0.3655	169.349	148.9281
$Global\_temp + CO2$	2	0.0396	191.245	165.0703
Global_temp + PRCP	2	0.2573	170.4059	146.3961
$TMIN + Global_temp + PRCP + CO2$	4	0.3618	169.3921	153.2262
TMIN + Global +PRCP	3	0.4579	167.9325	147.5116
TMIN + Global + CO2	3	0.4892	167.3962	148.7272
TMIN + Global	2	0.5338	166.2156	144.0324

#### **GENERALIZED ADDITIVE MODEL**



Factors	# of Factors	R^2	AIC
TMIN + PRCP + CO2	3	0.995	123.5698
TMIN + CO2	2	0.947	147.3274
TMIN + PRCP	2	0.954	145.8929
Global_temp + PRCP +CO2	3	0.699	163.3429
Global_temp+ CO2	2	0.306	188.7458
Global_temp + PRCP	2	0.728	162.1333
TMIN + Global_temp + PRCP + CO2	4	0.999	105.9211
TMIN+Global_temp + CO2	3	0.937	148.577
TMIN+Global_temp + PRCP	3	0.993	126.458
TMIN+Global_temp	2	0.902	152.9688

#### SUMMARY AND CONCLUSION

## SUMMARY OF WHAT WE DISCOVERED

- Multi-spectral Landsat images and climate factors were used to study glacier variations over time.
- Image processing methods were developed to detect and segment glacier area.
- Our models identified the relationship between glacier changes and some climate factors including global temperature, local temperature, precipitation, and CO2.
- Investigate and model the relationship between CO2 and other climate factors to better understand the impact of CO2 on glacier changes.

# FUTURE PLANS FOR AREA MEASUREMENT

- Our work has brought us to a good basic method, blob detection
- Segmentation can always improve
- Problems:
  - Thresholding
  - Gap filling
  - Preprocessing

### **PROCESSED BANDS**



Higher contrast allows for better segmentation and better area measurements

## THRESHOLDING



#### Each image needs its own threshold

## **GAP FILLING**



Viedma glacier blue band



**Binarized** 



Example of gap filling

We need a method to fill holes in glaciers while minimizing non-glacier pixels added

#### PREPROCESSING







We can train a neural network to classify images by plotting different bands' pixel intensities against each other

Clockwise from top left: FJ green band (good image), NDSI plotted against green for good image, NDSI plotted against green for cloudy image, FJ green band (cloudy image)

#### **RESEARCH TEAM**



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# QUESTIONS?



#### APPENDIX

Add any extra stuff that you might need to reference but it isn't essential to presentation

#### WHAT ARE THEY?

- The set of intensity values from regularly spaced points along a line segment (in our example, that is the glacier path)
- From the Landsat Data, we graphed each separate column and got the intensity profiles for glacier path on each image



#### INFLECTION POINTS

• We found the candidate points from the raw data for the first four paths.







Intensity Profile of Path IV



#### POLYNOMIAL REGRESSION

• On the first four paths, we ran polynomial regressions of degree 1 to 10.



#### CUBIC SPLINES

• On the first four paths, we fit cubic splines.









#### COMPARISON OF THE PARAMETRIC REGRESSIONS

• We wanted to compare each regression's performance of estimating the intensity profile using R^2.



#### NON-PARAMETRIC REGRESSIONS

 We specifically chose the LOESS method in R when creating our nonparametric regression.



#### REGRESSION'S INFLECTION POINTS

• We see that the non-parametric regression finds a more closer approximation for the terminal point than other regressions.



#### SUMMARY OF INTENSITY PROFILES

01

I. We can find the terminal point in intensity profile by using inflection points. 02

II. It is better to find terminal points from regressions than from the raw data for future predicting purposes.



III. A non-parametric regression is the best method of estimating and prediciting future terminal point locations.

#### LINEAR MODELS FOR FRANZ JOSEF

#### **Terminal Point**

Factor	P-value	R^2
Average Monthly Temperature	0.993	3.77E-06
Average Minimum Temperature	0.872	0.001327
Average Maximum Temperature	0.278	0.03453
Average Precipitation	0.94	0.000204
Average Monthly Co2	0.0382	0.117
Average Global Temperature	0.485	0.01405

Factor	P-value	R^2
Average Monthly Temperature	0.131	0.5872
Average Minimum Temperature	0.0939	0.0939
Average Maximum Temperature	0.239	0.1913
Average Precipitation	0.128	0.3422
Average Monthly Co2	0.0991	0.3405
Average Global Temperature	0.34	0.1301

# LINEAR MODELS FOR GORNER

#### **Terminal Point**

Factor	P-value	R^2
Average Monthly Temperature	0.0176	0.3623
Average Minimum Temperature	0.00858	0.4238
Average Maximum Temperature	0.0331	0.3039
Average Perciptation	0.645	0.01681
<b>Cumulative Monthly Perciptation</b>	0.6178	0.01971
Average Monthly Co2	3.22e-10 *	0.9563,
Average Global Temperature	0.000201	0.6674

Factor	P-value	R^2
Average Monthly Temperature	0.166	0.2541
Average Minimum Temperature	0.125	0.3028
Average Maximum Temperature	0.323	0.1392
Average Perciptation	0.117	0.3138
Cumulative Monthly Perciptation	0.112	0.3211
Average Monthly Co2	0.363	0.104
Average Global Temperature	0.20391	0.193

#### ADDITIVE MODELS FOR FRANZ JOSEF

#### **Terminal Point**

Factor	P-value	R^2
Average Monthly Temperature	0.59	0.0238
Average Minimum Temperature	0.733	-0.00962
Average Maximum Temperature	0.387	0.0159
<b>Average Precipitation</b>	0.94	-0.0355
Average Monthly Co2	0.0103	0.29
Average Global Temperature	0.285	-0.0141

Factor	P-value	R^2
Average Monthly Temperature	0.13	0.45
Average Minimum Temperature	0.127	0.587
Average Maximum Temperature	0.239	0.0757
Average Precipitation	0.127	0.233
Average Monthly Co2	0.149	0.295
Average Global Temperature	0.38	0.137

#### ADDITIVE MODELS FOR GORNER

#### **Terminal Point**

Factor	P-value	R^2
Average Monthly Temperature	0.0173 *	0.313
Average Minimum Temperature	0.00832	0.379
Average Maximum Temperature	0.0329 *	0.25
Average Precipitation	0.646	-0.0588
<b>Cumulative Monthly Precipitation</b>	0.618	-0.0556
Average Monthly Co2	<2e-16	0.986
Average Global Temperature	0.000139 ***	0.642

Factor	P-value	R^2
Average Monthly Temperature	0.0221	0.638
Average Minimum Temperature	0.0136	0.686
Average Maximum Temperature	0.04	0.566
Average Perciptation	0.0113	0.704
Cumulative Monthly Perciptation	0.00954	0.718
Average Monthly Co2	0.254	0.213
Average Global Temperature	0.204	0.0922