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Predicting Glacier Distributions: Local Climate Predictions

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ABSTRACT

The distribution of glacier accumulation areas in the Jotunheim, Norway has been predicted where glacier initiation is expressed as a function of the glacier's mass balance including gains and losses of snow by wind and avalanches. With the increasing global coverage of local scale digital elevation data remote and inaccessible areas are now able to be investigated. The model was designed to allow mass balance studies to be performed without the need for infield measurements and only requires a digital elevation model (DEM) and regional climate data to make accurate predictions.

A 100 m DEM provided the topographic data and was used in conjunction with regional climate data to create a GIS of local scale high altitude climate variables. These were used in conjunction with predicted global radiation to model snow accumulation. A suite of geomorphologically significant measures was extracted from the DEM to increase the accuracy of these local datasets. Results show that it is essential to include these topographic parameters in climate predictions and reject standard lapse rate models. Best results were found when a seasonal lapse rate model was adopted.

The applications of the model allow the reconstruction of past climate and predictions of how glacier systems will react to future climate change scenarios. Providing greater understanding of earth surface systems and their interaction with our changing climate

Keywords: Glacier mass balance, digital elevation model, climate predictions, modelling

1. INTRODUCTION

The distribution of glaciers in upland environments is predominantly controlled by spatial variations in climate and topography. It is only through the analysis of the interactions of these variables that accurate predictions of glacier distributions can be made. This research aims to predict contemporary glacier distributions in the Jotunheim Range, Norway by modelling the dynamic interaction of glaciers with their topographic and climatic environments. As spatial analysis is the key component to the model it will lie within a Geographical Information System (GIS) facilitating the manipulation of multiple layers of data for the same spatial area. The appreciation and quantification of the geomorphological significance of landscape position linked with a methodology that predicts glacier distributions as a joint function of mass balance and surface processes makes this research project both original and innovative.

Early attempts to spatially delineate and define glacier distributions adopted a simple approach of calculating the altitude above which snow will accumulate. The most commonly used method

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identifies the glacier equilibrium line altitude (ELA), which provides the altitude at which losses through ablation are equal to gains through accumulation (Benn and Evans, 1998). This approach commonly only uses altitude as a predictive variable sometimes supplemented by precipitation and consequently fails to incorporate most of the major controls on glacier distributions. Olyphant (1986), Wendler *et al*. (1978) and Essery (1997) identified these controls as the radiation incident on the surface, local slope, aspect and curvature and gains and losses of snow by wind and avalanches. These can be subdivided into factors that directly alter the energy flux for melting at a location and those that alter the transfer of material into or through a location.

The advance in glacier distribution prediction models and mountain climate research has been limited both by technical inadequacies of workstations, the complexity of empirically representing climate and topography interactions and the lack of high altitude climate data. Recent research in this field has focused on modelling the individual controls discussed above, however few have attempted to combine these separate modules to create a holistic approach to glacier mass balance modelling (Dubayah and Rich, 1995).

This research examines new methods of predicting local scale climate data. Mountain environments are characterised by their highly variable local topography that creates strong localised gradients in climatic variables (Barry, 1992). Standard lapse rate models predict a decrease in temperature and an increase in precipitation with altitude and fail to account for these strong local trends. Standard lapse rates are only useful over small spatial and temporal scales where the adiabatic process is the primary control on altitudinal variations. Complex valley and continentally patterns obscure these standard lapse rates trends and require more complex prediction methods.

2. STUDY AREA AND DATA

The model has been developed and tested in a series of study areas in Norway with the Jotunheim region as a major study area (Figure 1). The sites were selected on the basis that they currently contain numerous small glaciers, closely related to topography and climate. The sites extend from latitudes of 60^{o}N to 71^{o}N. The research presented here will be predominantly looking at an area in the central Jotunheim inset in Figure 1. The site covers an area of 400 km^2 and has an altitudinal range of 1572 m, from 900 m to 2472 m. The study area contains over 30 small valley glaciers and the local ELA is around 1600 m . The climate in Norway can largely be classified (excluding the west coast) as Boreal Forest by the Koppens system where the mean temperature of coldest month is below 0^{o}C and there is snow cover every year.

A 100 m DEM provided the topographic data and was supplied by the Norwegian Mapping Agency Statens Kartverk. The interpolation procedures performed by the Statens Kartverk left both spectrally and spatially dominant artefacts in the dataset. These were removed with respect to their spatial and spectral structure using a Fast Fourier Transform to avoid a global smoothing operation. Regional climate data from Norwegian Meteorological Institute was collated for all climate stations in the study areas. Thirty year normals for temperature, precipitation, cloud cover and local and radiosondes wind speed and direction were used in the model to predict local scale (100 m) climate surfaces. Local climate predictions in mountainous areas are inherently difficult due to the lack of high altitude climate stations (Figure 2).

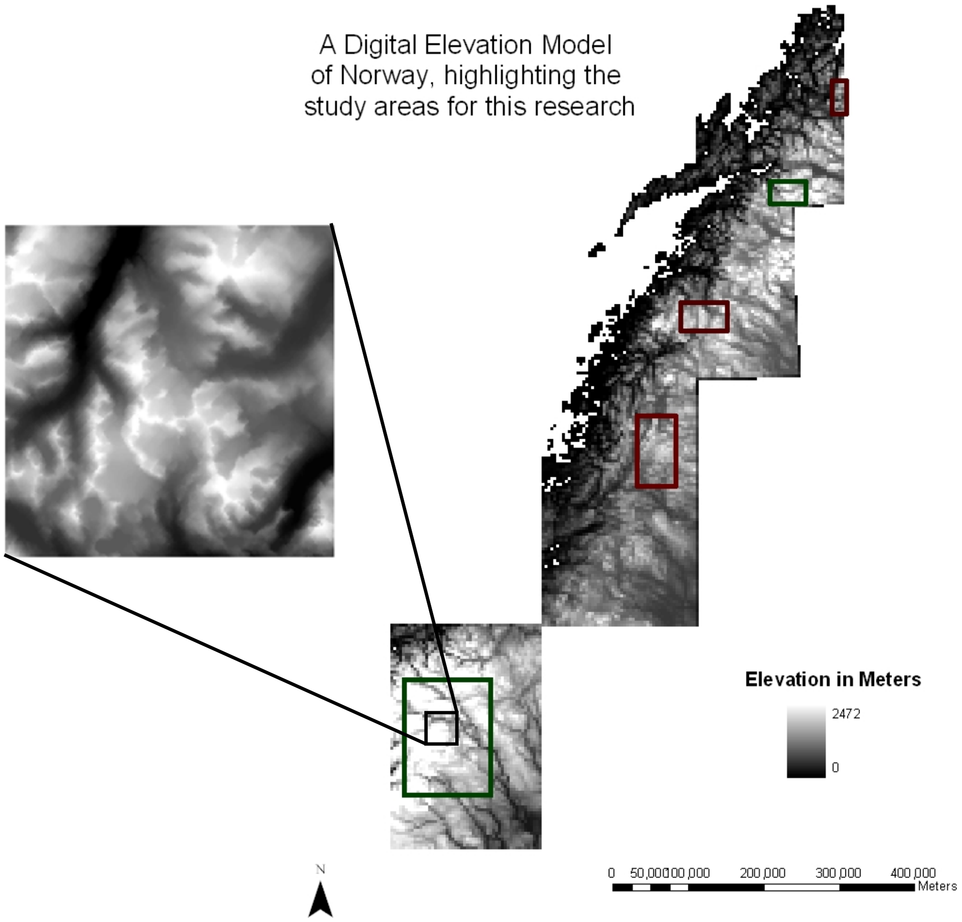

Figure 1: Digital elevation model of parts of Norway, study areas highlighted by red boxes. Primary study area for this research is enlarged inset.

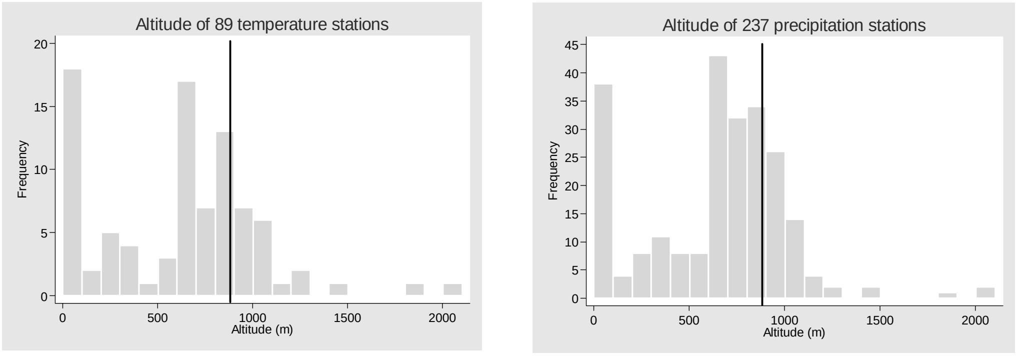

Figure 2: Altitudinal range of temperature and precipitation stations, red line indicates minimum altitude in central Jotunheim study area.

3. MODELLING METHODS

It was necessary to reject several different methods of creating local scale climate surfaces as they were inappropriate for this study. Standard lapse rate models have already been identified as too generalised for this research as they can not replicate topographically induced temperature and precipitation patterns. Downscaling from a global climate model (GCM) was also rejected as the uncertainties and error associated with this procedure are greater than those created by interpolating between climate stations. A quantitative approach to predictions using relationships within the meteorological datasets was also rejected as it failed to account for the modification of lapse rates by the terrain. This research predicted local scale climate by extracting quantitative relationships within and between meteorological and topographical data. This approach quantified the terrain modification of the adiabatic process by characterising geomorphological context.Accurate local scale climate predictions can only be made if the processes controlling the climate variables are parameterised. Therefore, although the model was designed to be flexible and repeatable it was necessary to incorporate local factors to make accurate climate predictions. In Norway these were the strong maritime influence in the West especially evident when considering precipitation. The frequent occurrence of temperature inversions in winter which result in cold valley floor temperatures and the very dominant role that the seasonally variable pressure systems have on the climate.

3.1 Temperature

Two different conceptual approaches were used for predicting temperature. An annual lapse rate model and a seasonal lapse rate model. The former identifies months as arbitrary divisions that have no meteorological significance as the 1st January is not climatically different from the 31st December and should therefore not be treated as such. This approach predicts using every months data and does not identify boundaries between months. The seasonal lapse rate model accepts that months are arbitrary boundaries but recognises that there is a seasonality to the processes that control air temperature. This seasonality was used as the basis for the second type of predictive model which predicts using only months within the same season.

3.1.1 Annual Lapse rate model

The annual lapse rate model simulated the annual cycle in temperature using a sine and cosine function:

$$\text{Cosine function} = \text{Cosine}\,(2\,\Pi\,(\text{month} - 0.5)/12)$$

$$\text{Sine function} = \text{Sin}\,(2\,\Pi\,(\text{month} - 0.5)/12)$$

Where month is the month number where December is month 1.

3.1.2 Seasonal Lapse rate model

The seasonal lapse rates predicted temperature using topographical predictors. These characterised the geomorphological context of a pixel and used this information in addition to altitude to predict temperature. Topographic measures used included curvature and average gradient and altitude. These parameters were calculated at a number of different scales and over different numbers of pixels to find the most representative scale for the terrain. The temperature dataset was explored and topographic exposure was found to be the dominant variable controlling terrain modification of adiabatic process. Two types of exposure were identified, exposure due to surface roughness (Type 1) and exposure to channelised air flow (Type 2). The exposure measures were calculated in Arc/INFO for every pixel in the DEM.

A high or low surface roughness identifies sheltered or exposed sites that are warmer or cooler than they would be if altitude was the only control. This roughness can either be at a focal (surrounding pixels) scale where the pixel is identified as higher or lower than the surrounding area, or at local scale where the altitude of the climate station (used in predictions) is higher or lower than the pixel it is located within.

Type 1. Exposed to air as a result of high surface roughness.
Degree 1 = Station altitude higher than pixel altitude
Degree 2 = Pixel altitude higher than surrounding pixels
Quantification:
Degree 1 = Difference between pixel and station altitude
Degree 2 = Difference between buffer mean and pixel

Type 2 exposure quantifies how exposed a pixel is to channelised air flow. Valley winds can have a strong cooling effect which is larger further down the valley and nearer the valley center. This exposure measure also identifies valley floors which are frequently subject to temperature inversions where air temperatures are colder than they would be if altitude was the only control.

Type 2: Orientated in direction of channelised / constricted flow
Quantification:
Degree 1.Direction of channel in relation to pixel
Degree 2.Distance from channel center
Degree 3.Distance down valley
Degree 4.Distance from ridge

Type 1 and 2 exposure parameters were used with altitude in a multiple regression, like the topographic parameters the area over which these measures were calculated was varied to find the most representative scale for the terrain.

3.2 Precipitation

Three different approaches to predicting precipitation were adopted. Precipitation is significantly more difficult to predict than temperature, summer is characterised by localised convection events and winter precipitation is predominantly fed by arriving pressure systems.

3.2.1 Dual Lapse rate model

The strong maritime influence in the West of Norway weakens the altitudinal increase in precipitation with altitude ($R^2 < 0.01$), making any local predictions using altitude very difficult (Figure 3). However dividing the climate stations by easting reveals two distinct altitudinal relationships, a dual lapse rate model was developed to account for these two trends (Figures 4 and 5).

3.2.2 Generalised linear model (GLM)

Examination of all of the precipitation climate stations reveals that there is strong easting component to the data (Figure 6). Although there is a topographic barrier through Southern Norway linear divides and steps are not realistic and a less disjointed model than described in 3.2.1 is needed to replicate the nonlinear decrease in precipitation. A regression on a transformed data scale might allow this, however a GLM does the transformation and back transformation in one. A GLM can also be set up to ensure physically meaningful predictions, i.e. precipitation can always be positive. A GLM with a reciprocal link function was used to predict precipitation using a single lapse rate. The reciprocal link function was chosen as it accounted for the non-linear decrease in precipitation with easting.

3.2.3 Power function

A power function was developed with altitude, easting and the sine and cosine functions (see 3.1.1) to try and account for the non-linear decrease in precipitation with easting as an alternative to the GLM. Where the log of monthly precipitation is given by:

$$\text{Log}P = a \cdot \text{alt} + b \cdot \log X + c \cdot \text{sine} + d \cdot \text{cosine}$$

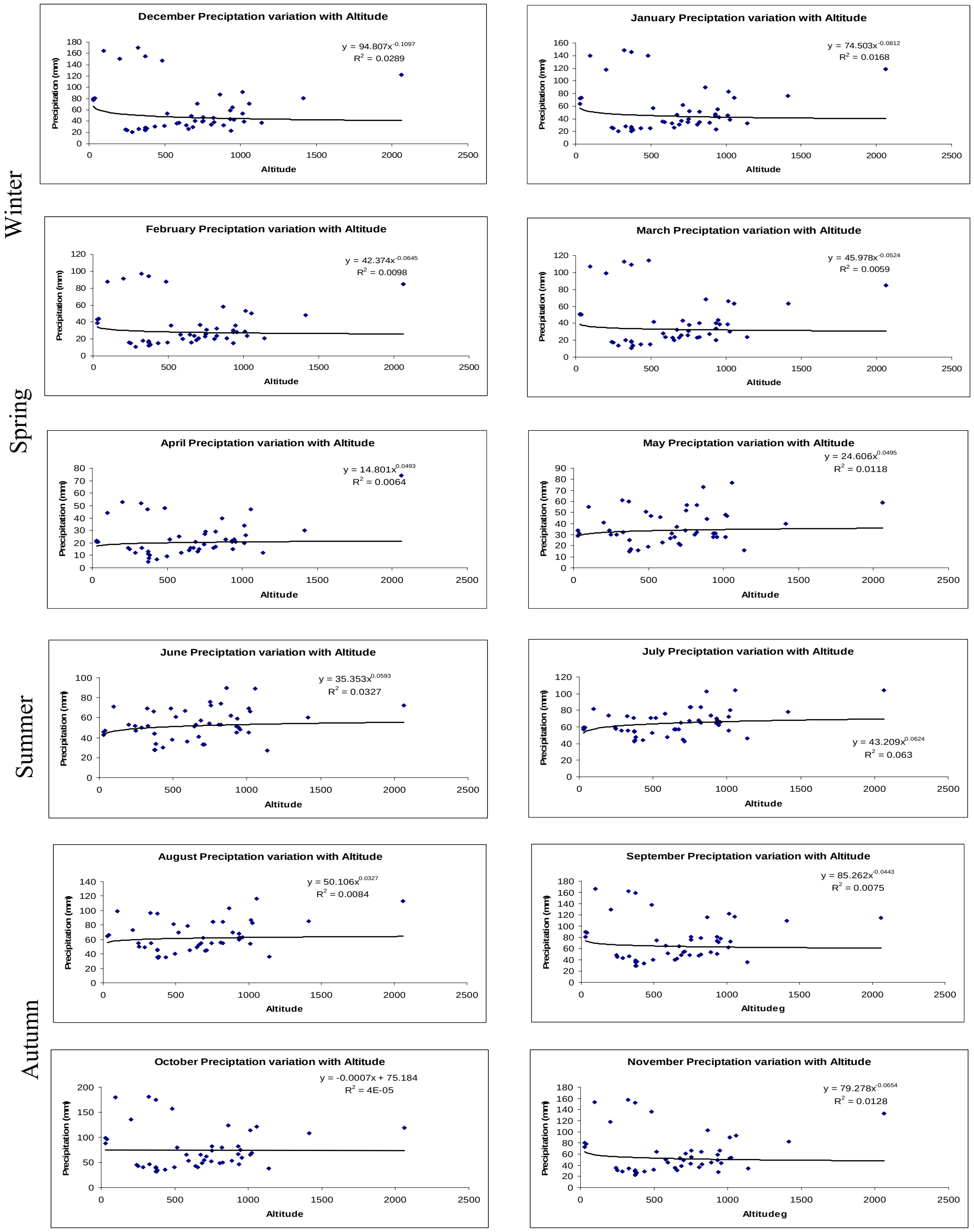

Figure 3: Seasonal trends in altitudinal variation in precipitation for all climate stations.

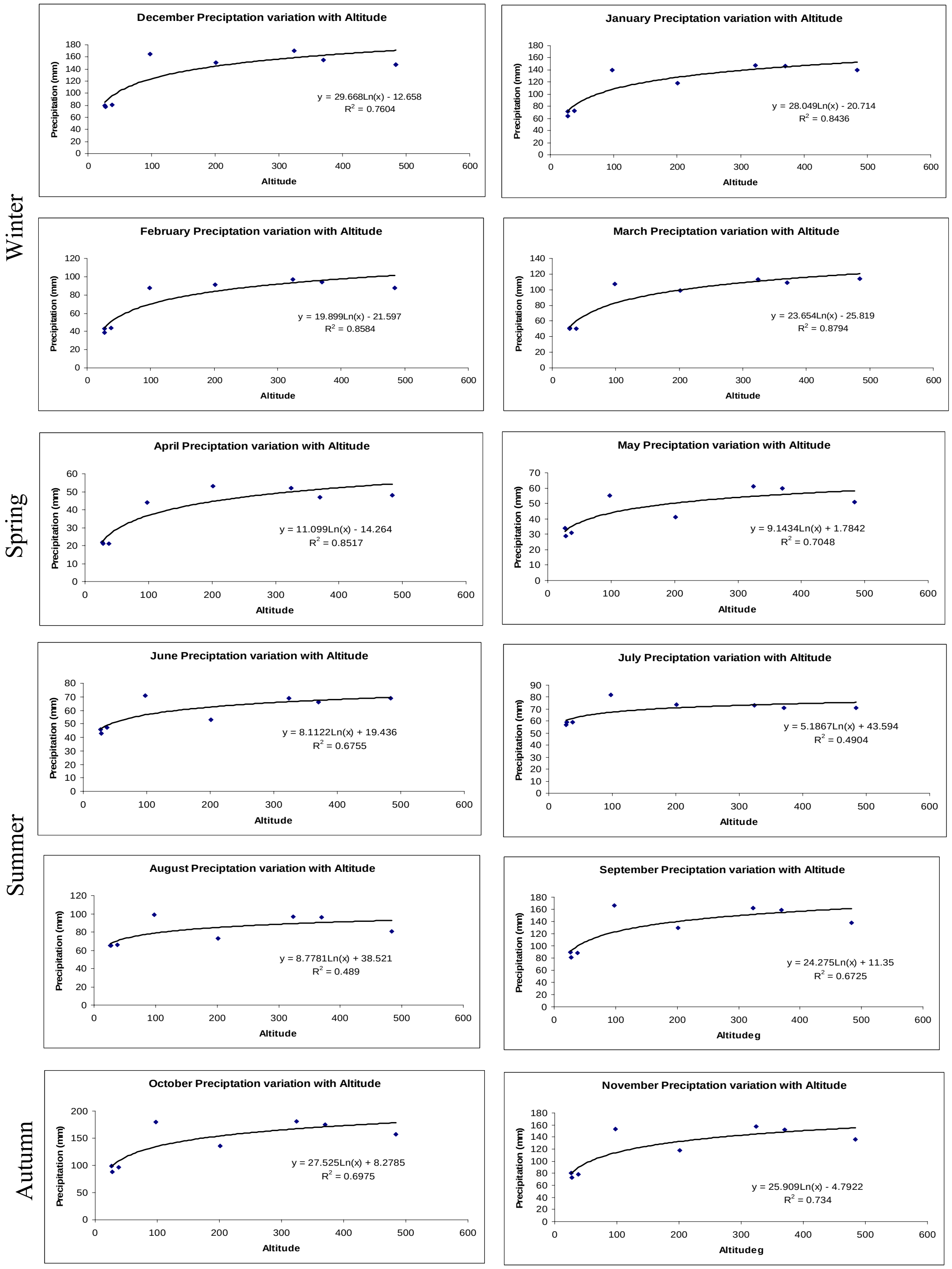

Figure 4: Seasonal trends in altitudinal variation in precipitation for easterly climate stations.

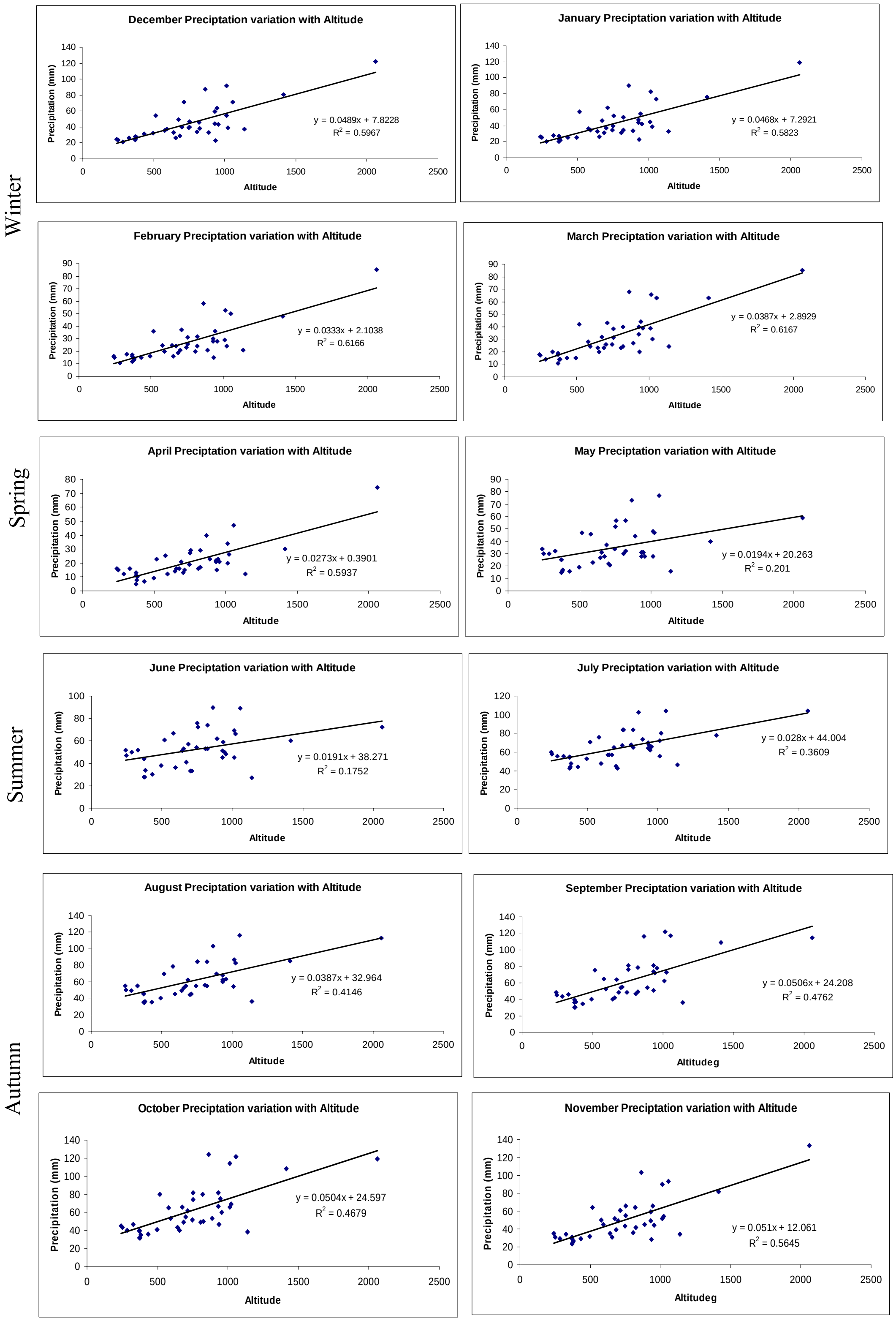

Figure 5: Seasonal trends in altitudinal variation in precipitation for westerly climate stations.

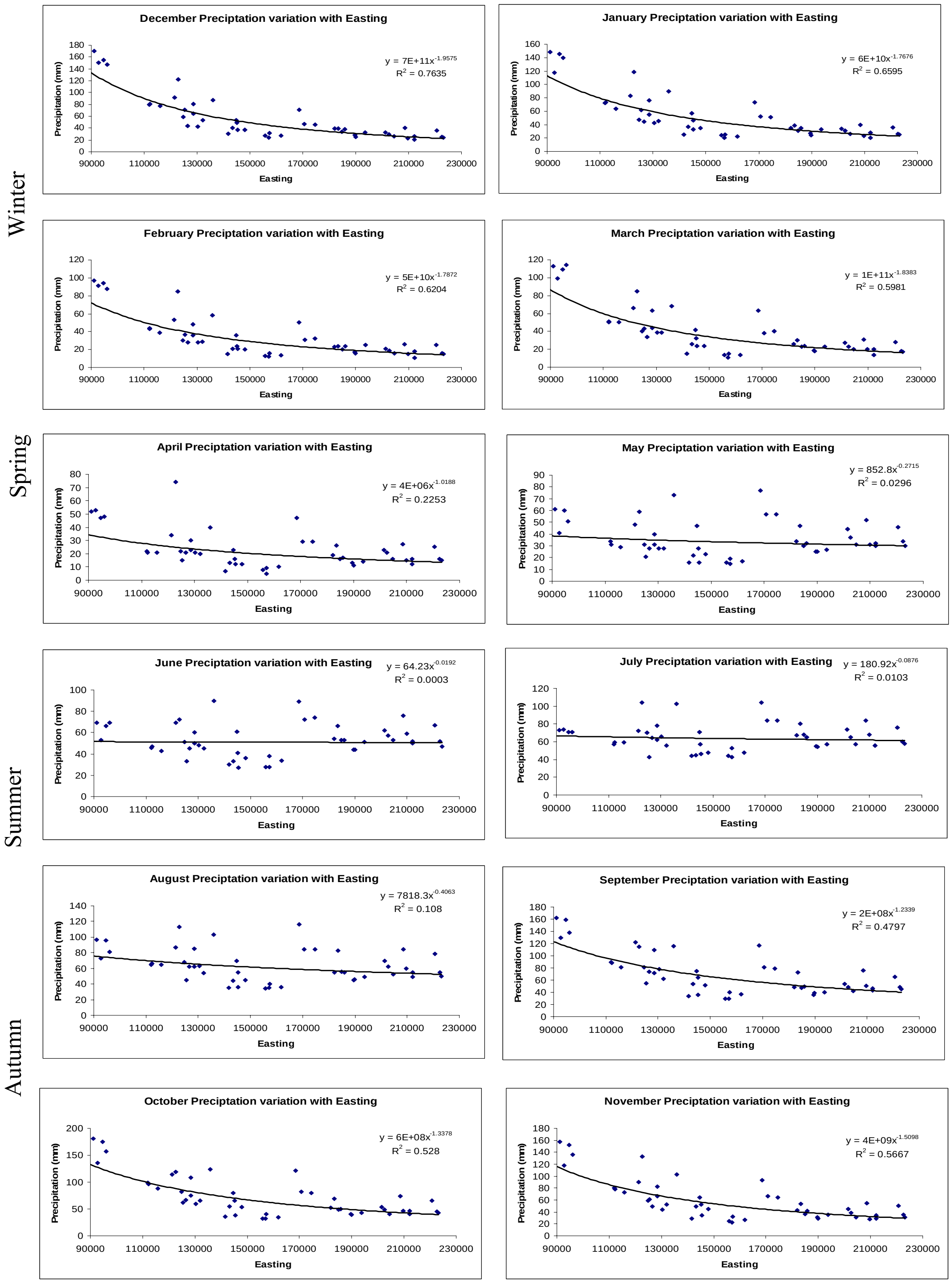

Figure 6: Seasonal trends in variation of precipitation with easting for all climate stations.

4.0 RESULTS

4.1 Annual lapse rate model for temperature

The sine and cosine functions were used in a multiple regression with altitude, the model predicted temperature well (adjusted $R^2 = 0.97$, RMSE = 1.2 °C) but predicted a constant monthly range, failing to account for the variability in the dataset. An interaction term was created to try and account for some of this variability. The most useful term was month * altitude. The coupled model (sine and cosine and interaction term) accounted for more of variation within the dataset (adjusted $R^2 = 0.98$); but despite a reduction in RMSE (1.15°C) the model still performed consistently poorly for some stations.

The inclusion of type 1 and 2 exposure variables improved station predictions although their usefulness was varied. Distance from valley centre was the most successful and created the best predictions (adjusted $R^2 = 0.98$, RMSE = 1.15°C), the other measures were useful for predicting other climatic variables especially wind. Distance from channel centre identified areas that were subject to cooling by temperature inversions and valley winds. Although the model accounted for more of the variability within the data it still under predicted monthly range with the coldest and warmest station temperatures not being predicted.

4.2 Seasonal lapse rate model for temperature

In Norway the processes that control temperature are not constant through the year. Therefore it was not possible to accurately predict temperature using an annual lapse rate. Only summer temperatures can be accurately predicted using altitude, winter temperatures are controlled by a more complex suite of factors. The annual variation in RMSE and R^2 for temperature predictions using altitude shows that there is a large seasonal disparity with very poor predictions found in winter. Comparison of the RMSE and R^2 after the inclusion of topographic and exposure parameters shows that there is a reduction in this seasonal disparity as the accuracy of winter predictions has increased where sites liable to temperature inversions are predicted (Figure 7).

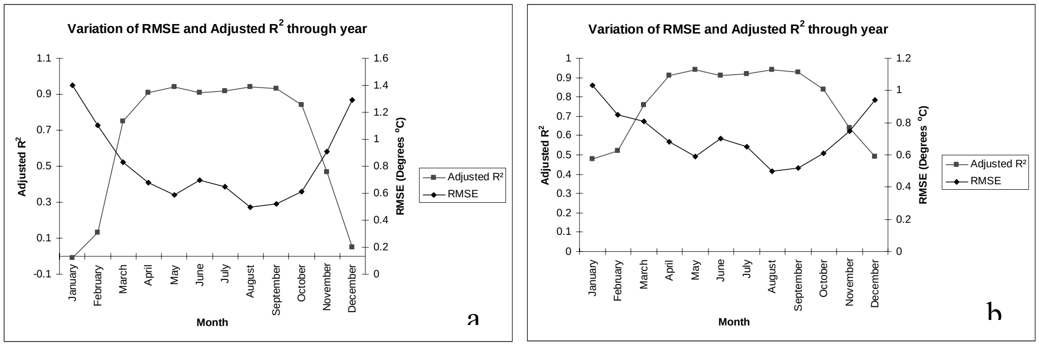

Figure 7: Annual variation in RMSE and adjusted R^2 for temperature predictions using a) altitude and b) altitude and extracted topographic parameters.

The seasonal lapse rate model provided the best predictions. Profile curvature, average altitude and gradient and distance to valley centre were significant when predicting temperature in all of the winter and spring months. Altitude alone was used to predict temperature in summer and autumn (Figure 8). The seasonal lapse rate model accounted for the monthly range and terrain modification of the adiabatic process better than the annual lapse rate model.

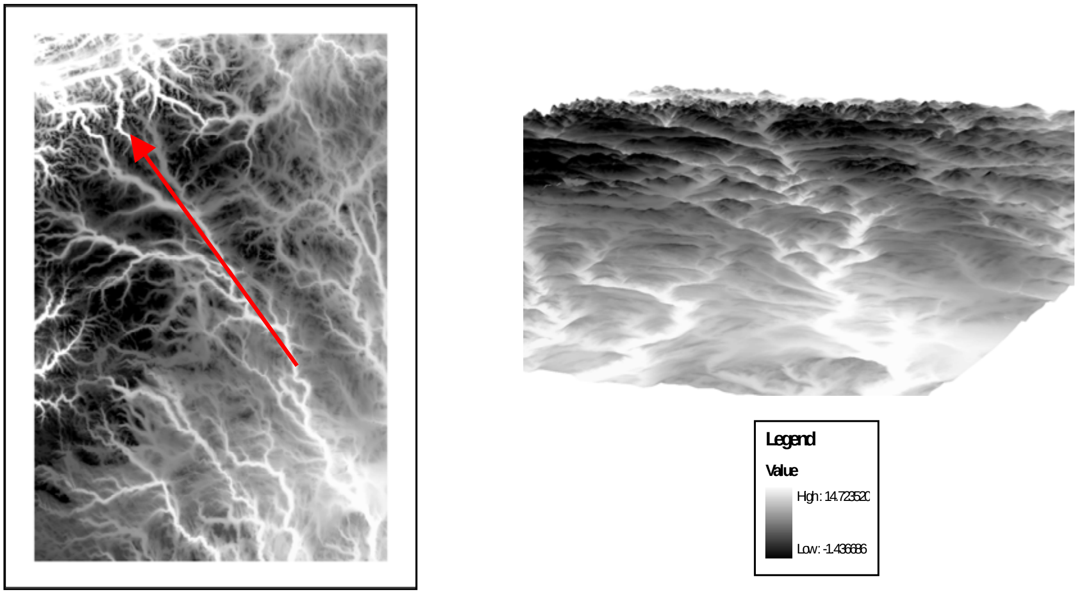

Figure 8: June temperature surface for Southern Norway, 3D view looks down valley towards Fjord system as indicated by the arrow.

4.3 Precipitation dual lapse rate model

The easting coefficient in the regression results was found to decrease through spring to summer and then increase through autumn to winter. This matches changes in pressure systems as westerly winds become less and then more influential in providing precipitation. Summer months are fed by convective rain events which are not as dependent on distance from coast. When the precipitation surfaces from the different lapse rate models were combined an unrealistic surface was created. The dual lapse rate model was rejected as the resultant precipitation surface had a large jump in precipitation at the boundary between the different lapse rates.

4.4 Precipitation single lapse rate model

GLM predicted precipitation well and matched the non-linear decrease in precipitation from the westerly to easterly stations (Figure 9).

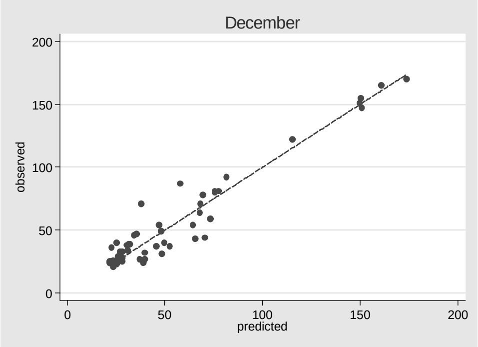

Figure 9: Generalised linear model precipitation predictions for December.

However the model predicted negative precipitation as a result of the reciprocal function being used and had to be rejected. No other link function could predict the non-linear decrease.

4.5 Power function

The power function model provided the best results (average $R^2 = 0.87$) however it failed to predict the high maritime precipitation as well as the GLM. This model was used in the glacier prediction model.

5. CONCLUSIONS

In Norway summer months are characterised by convection where precipitation is hard to predict and temperature is easy to predict. In contrast winter months are dominated by tracking pressure systems facilitating prediction of precipitation events and leading to less predictable temperature lapse rates. Temperature and precipitation in such complex meteorological systems cannot be predicted using standard lapse rates. Accurate predictions can only be made using a suite of topographic parameters that capture geomorphological context and potentially therefore process.

Implications in model output by using different climate surfaces will be small and assessed in sensitivity analysis, the glacier prediction model is working well and results are similar to observed glacier distributions (Figure 10).

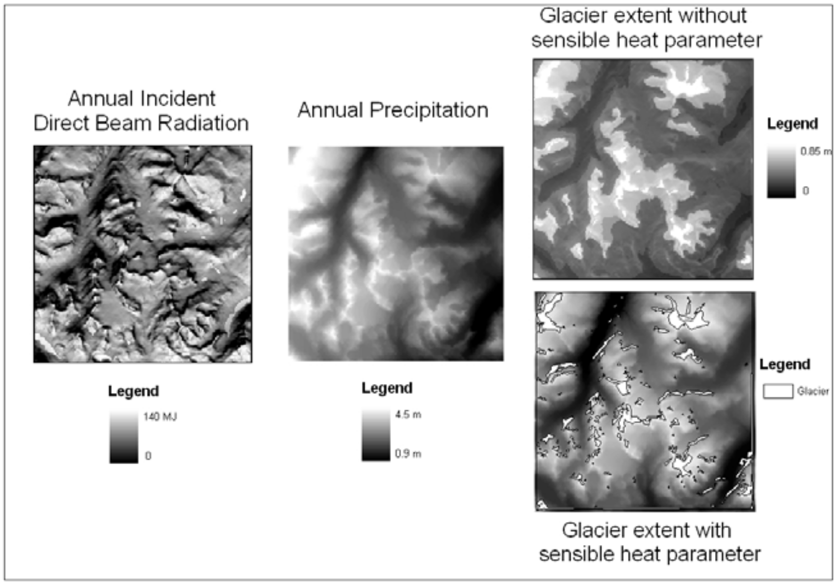

Figure 10: Model prediction results at end of mass balance year.

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