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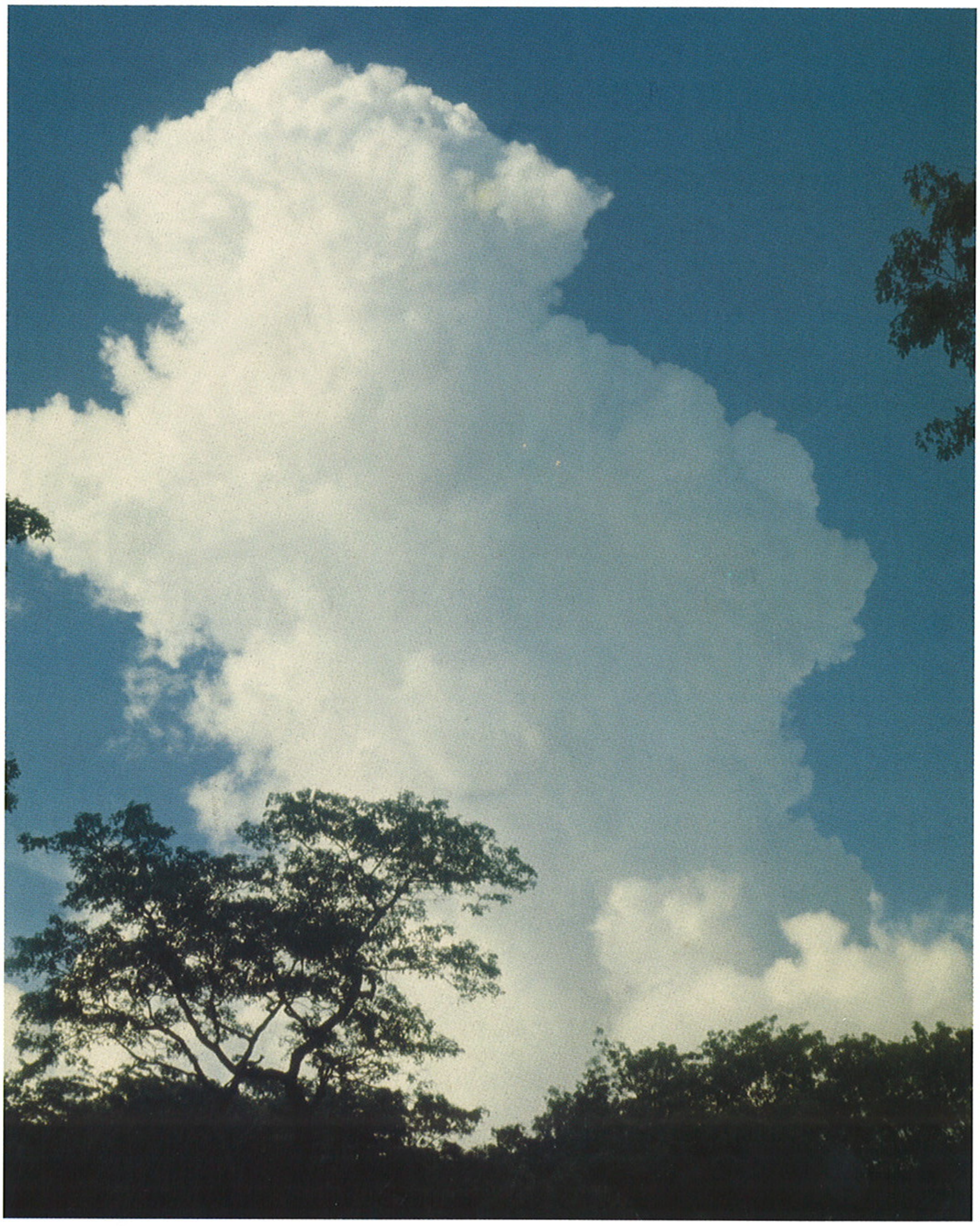
Spatial estimation of mean monthly temperatures by multiple linear regression

REPORT NR. 18/98

Ole Einar Tveito

KLIMA



DNMI-REPORT

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ISBN 0805-9918

REPORT NO.
18/98 KLIMA

DATE:
20.04.98

TITLE:

Spatial estimation of mean monthly temperatures by multiple linear regression.

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PROJECT CONTRACTORS:

Norwegian Electricity Federation (EnFO), (contract no. 55108)

Norwegian Meteorological Institute

SUMMARY:

In this study, multiple linear regression has been applied for estimating maps of mean monthly temperatures for southern Norway. Elevation above sea level and distance to coast are used as independent variables in the regression analysis. The derived regression equations showed good skill, coefficients of determination varied from 0.74 to 0.95. The influence of the independent variables showed a seasonal variation, with distance to coast as the most significant in winter, and altitude in the other seasons.

Verification showed that despite the high coefficients of determination, large deviations from observed temperatures occur in various regions. Linear regression is a regional method, an will not encounter local variability. For a large, inhomogenous area, this method is not a recommended method. However, for smaller and more homogenous regions, this approach may be more applicable.

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DNMI Report 18/98 KLIMA

Spatial estimation of mean monthly temperatures by multiple linear regression

by Ole Einar Tveito

Due to the inscrutable ways of computer systems, figure 4.5 in this report is wrong. The correct figure has been reproduced below.

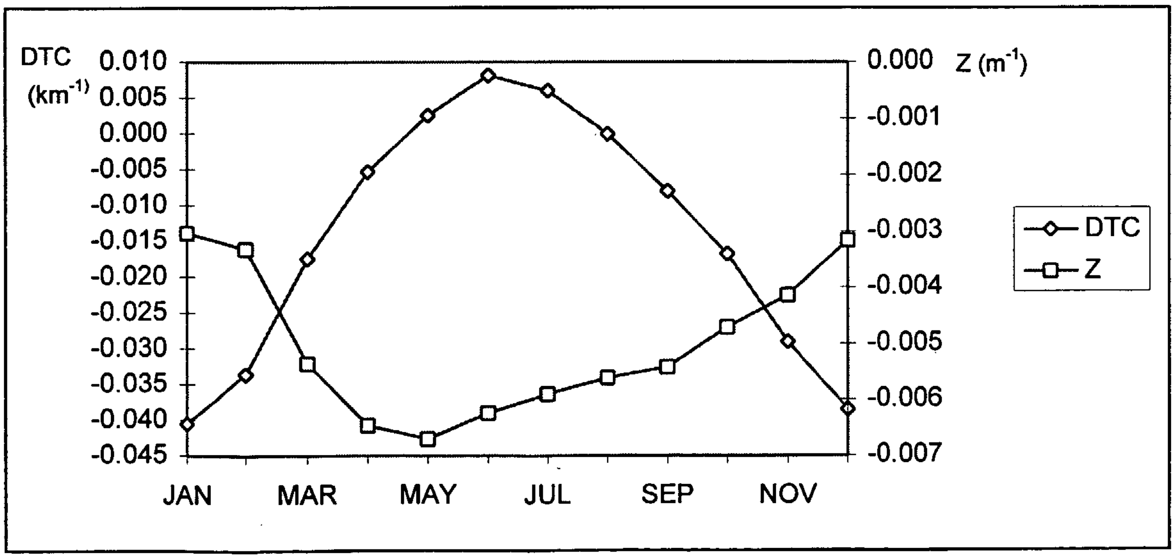

Figure 4-5: Regression coefficients estimating monthly mean temperatures.

Contents

1.Introduction

The spatial distribution of climate elements is important information for many different users. They are input variables to hydrological models, both for energy production and water supply management. Climatology is an important factor to consider in the design of installations which may be affected by weather conditions. Such information should describe both mean conditions as well as extreme conditions, which may cause a safety risk or economic loss. Such installations may be dams, roads and bridges, power lines, tele-towers etc. It has therefore been one of the challenges for climatologists to estimate values of climate elements at locations without measurements.

Traditionally such methods have, from a methodical point of view been quite simple. They have been manual methods, regional averages, nearest neighbour, weighted averages (like Thiessen polygons). During the recent years, the increased computer availability and capacity has made it possible to apply more sophisticated approaches in this field. The introduction of Geographical Information Systems (GIS) has made it easy to combine different types of spatial distributed data, which may describe spatial variations in climatology. This technology have also made areal estimates of climatic

In this paper, the spatial variations of monthly mean temperature is studied. A statistical approach is tested, not only to find the best estimation method, but to examine the statistical properties of the variables expected to explain the spatial variations in temperature.

Many authors have made a contribution in explaining the spatial variations in temperature. Bruun (1957) has given an impressive survey of the Norwegian temperature records up to then. She gave a detailed description of all the stations, and the local effects which may appear. However, the DNMI station-network has changed quite much, so those characteristics are of minor usage nowadays. She also studied the vertical temperature gradient. A number of pairs of stations were studied, divided into groups based on the degree of ventilation in the area. The number of pairs were limited to avoid the problem of the horizontal temperature gradient. She found the vertical gradient to vary throughout the year. The lapse rate is expected to describe a temperature decrease with altitude. Bruun found the lapse rate to be smallest in the winter (typical values -0.3 - -0.4°C/100 m a.s.l.). At some well protected locations, the gradient even appeared to be positive (temperature increase with altitude), an effect of temperature inversions. The highest lapse rates were found in spring and autumn (typical values -0.7 °C/100 m a.s.l.). This was the case for all the groups, but the variance in lapse rate is larger at protected locations compared to locations which are well ventilated.

Utaaker (1963) analysed the climatology at the Nes-peninsula (16 × 10 km) in the Lake Mjøsa. He used a very dense network of temperature and precipitation stations, and even observed temperature profiles from a running car. Analysis of minimum temperatures showed differences up to 8-9 °C over short distances. This particular difference was observed at two stations approximately 3 km apart, with an elevation difference of 170 m, giving a vertical temperature gradient 5.3 °C/ 100 m a.s.l. Maximum temperatures showed less variation, the difference in mean maximum temperature between the stations was measured up to 1.5 °C. For some single days, the local differences in maximum temperature was up to 4 °C. Much of the local variability of temperature is explained by exposition and the nearness to the Lake Mjøsa.

Førland (1984) made an analysis of the climate in a region around Bergen at the Norwegian west coast using a very dense station network. He developed models for temperature, using two parameters, station elevation and distance from a reference line representing the coastline. Expressions for winter, summer and annual mean temperatures were established applying linear regression. The models showed satisfactorily results (correlation coefficients 0.8-0.9).

Carrega (1995) applied a similar approach for the Alpes-Maritime region near the French Mediterranean coast. He stated the distance to coast parameter to be non-linear to temperature, a statement supported by Zheng and Basher (1996), which in their study of New Zealand temperature normals propose a relationship:

$$T = f(e^{-DTC})$$

where DTC is distance to coast. Also Hudson and Wackernagel (1994) suggest the vertical temperature gradient to be non-linear studying Scottish temperature data, but does not verify this suggestion. This view is not supported elsewhere in the literature either.

From litterature the vertical temperature gradient is usually regarded as linear, with a temperature decrease of 0.65 - 1.00 °C/100 m a.s.l., depending on the state of the atmosphere (Pettersen, 1958). In some situations, with negative radiation balance, inversions can be formed. In such conditions, the vertical temperature gradient will be positive (temperature increases with altitude).

The climatological conditions in Norway show a large variation. Southern Norway belongs to (at least) seven climate zones based on Köppens macro-climate classification scheme (Johannessen, 1977). Norway is exposed to westerly winds. As the Atlantic Ocean, North Sea and Norwegian Sea act as heat conservator, the dominating zonal circulation will transport mild, humid air towards the Norwegian coast. At the western and soutwestern coasts, the climate is therefore maritime, with small amplitudes both in diurnal, seasonal and annual temperature amplitudes. Eastern parts however experiences a more continental climate with large temperature amplitudes. This is an effect of both large-scale circulation (blocking anticyclones) and local orographic effects. In the latter westerly winds are lifted by the mountain chain, giving precipitation at the western side. At the eastern side the air-masses will be warmer, and föhn-winds occur regularly. Because of the maritime influence on the coastal climate, a representation of the distance to coast is expected to have significance for temperature estimation. Based on this knowledge, it may be assumed that :

$$T = f(Z, DTC) \tag{1}$$

where T is mean monthly temperature normal, Z is altitude and DTC is distance to coast.

2. Data

The data set analysed consists of 226 temperature normals (1961-90) from southern Norway (Aune, 1992). The location of the stations are shown in figure 2-1. The data set is imported to a geographic information system (GIS), and the parameter «distance to coast», DTC, is calculated as the closest distance from each station location to a coastline, also presented in figure 2-1. The coastline is generated automatically in the GIS. In order to avoid the influence of the fjords, the «coastline» is generated applying the buffer algorithm in ArcInfo® (ESRI, 1997) with a buffer distance of 20 kilometers.

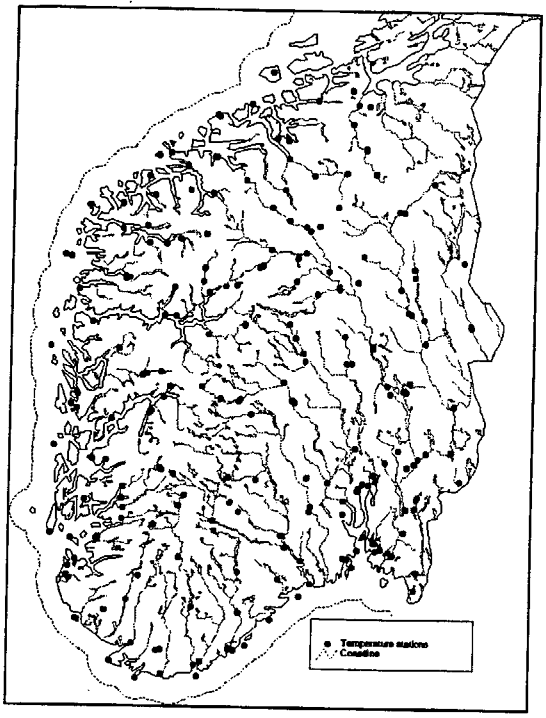

Figure 2-1 Station map

3.Theoretical aspects

In this study, multiple linear regression is used to derive expressions for estimating monthly mean temperatures. Multiple linear regression can be expressed:

$$X = \beta_0 + \beta_1 Y_1 + \beta_2 Y_2 + \ldots\ldots + \beta_n Y_n + \varepsilon \qquad (2)$$

where X is the dependent variable, and $Y_1 \ldots\ldots Y_n$ are the independent variables. $\beta_0 \ldots\ldots \beta_n$ are regression coefficients and ε is the error term.

When applying regression, some assumptions about the populations, in this case the sample of mean monthly temperatures, have to be fulfilled. The dependent variable has to be normally distributed. As a consequence, the variance should be the same for all possible values of X given Y. Another demand is the assumption that the observations of X should be statistical independent.

4. Analysis

4.1 The frequency problem

A problem dealing with all kind of statistical analysis is the representativity of the sample compared to the population to be estimated. For climatological data, the observation network is biased compared to the reality (=nature) which should be estimated. Most of the observations are carried out in populated areas, at lower altitude, while large areas in the mountains are without observations. This phenomena is showed in figure 4-1 and figure 4-2.

As seen from the figures, 85% percent of the climatic stations in Norway are located at altitudes lower than 500 meters above sea level, while 50% of the Norwegian terrain is above this level. Such an bias will lead to an estimation based on the frequency domain for the observation stations. Parts of the process to be described is not covered by observation stations, e.g. at altitudes above 1500 m a.s.l. The sample could be made more unbiased by selecting fewer stations from lower altitudes, but this will reduce the number of stations and the spatial representativity to a level which is not acceptable from neither a climatological nor a statistical viewpoint.

It should be checked if the monthly mean temperatures are normally distributed. Frequency plots based on the 226 stations are shown in figure 4-3.

These figures show that the distribution of air temperature is not normally distributed, and that the distribution varies throughout the year. This is probably both an effect of the climatic variations as well as a consequence of the biased station network (as shown in figures 4-1 and 4-2). This topic is not discussed further in this analysis, but the selection and identification of the best distribution for temperature should be given further attention in future studies.

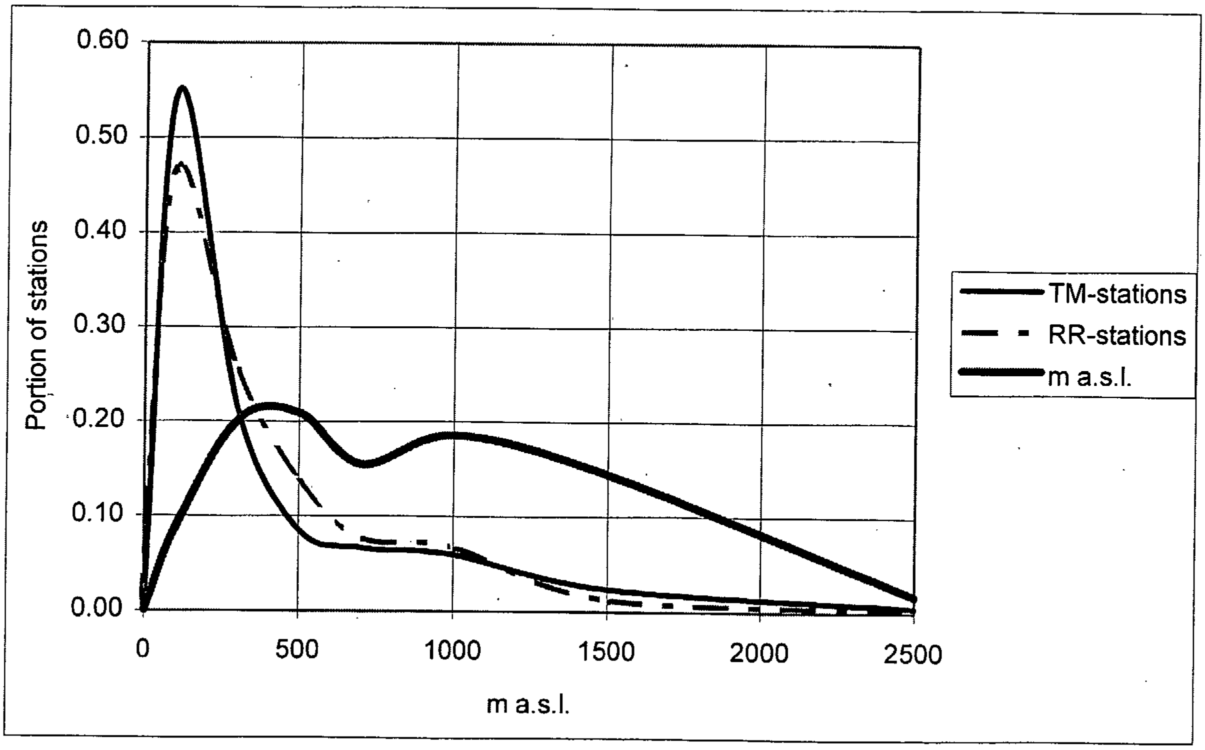

Figure 4-1: Distribution of climatological stations and terrain by altitude in Norway (TM = temperature, RR=precipitation).

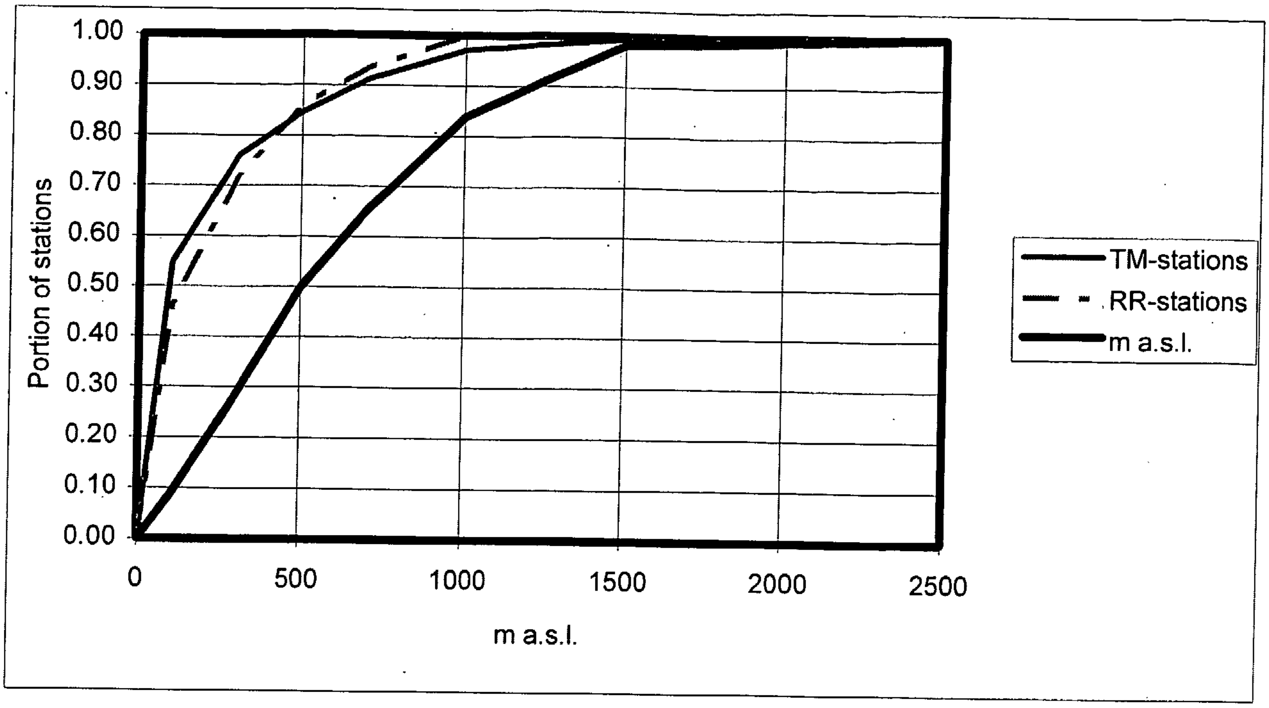

Figure 4-2: Cumulative distribution of climatological stations and terrain by altitude in Norway.

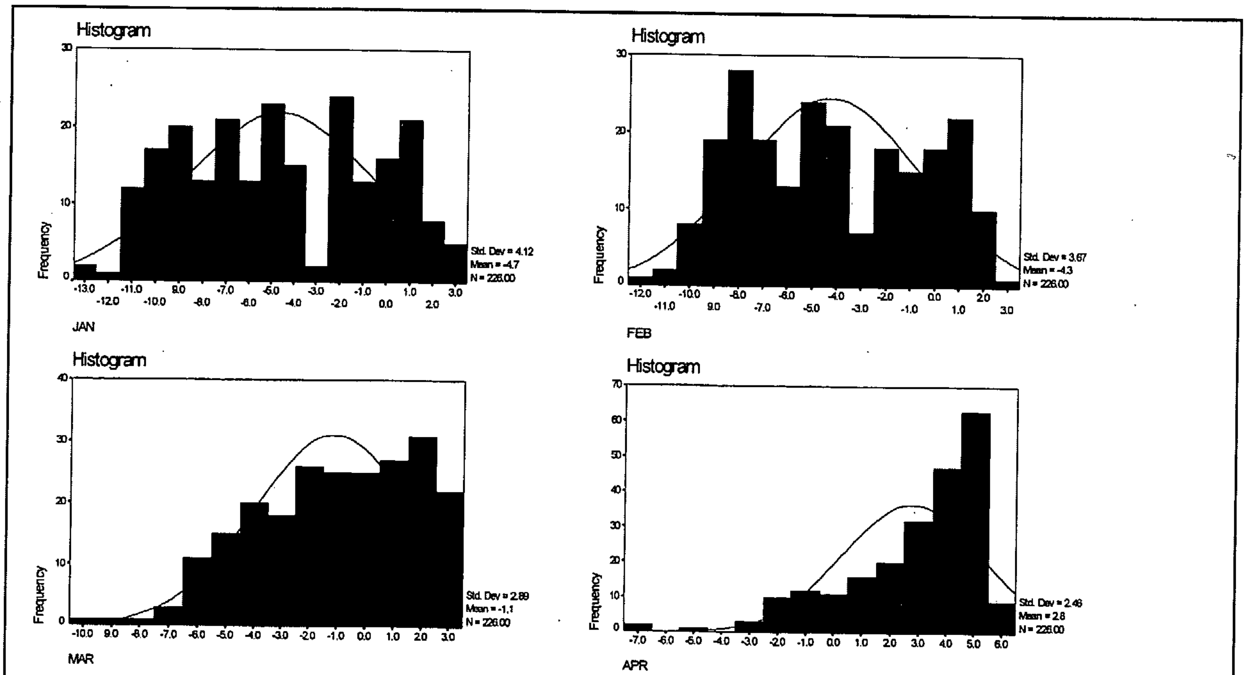

Figure 4-3 Frequency of monthly normal temperatures in southern Norway 1961-90. (Continues at next page.)

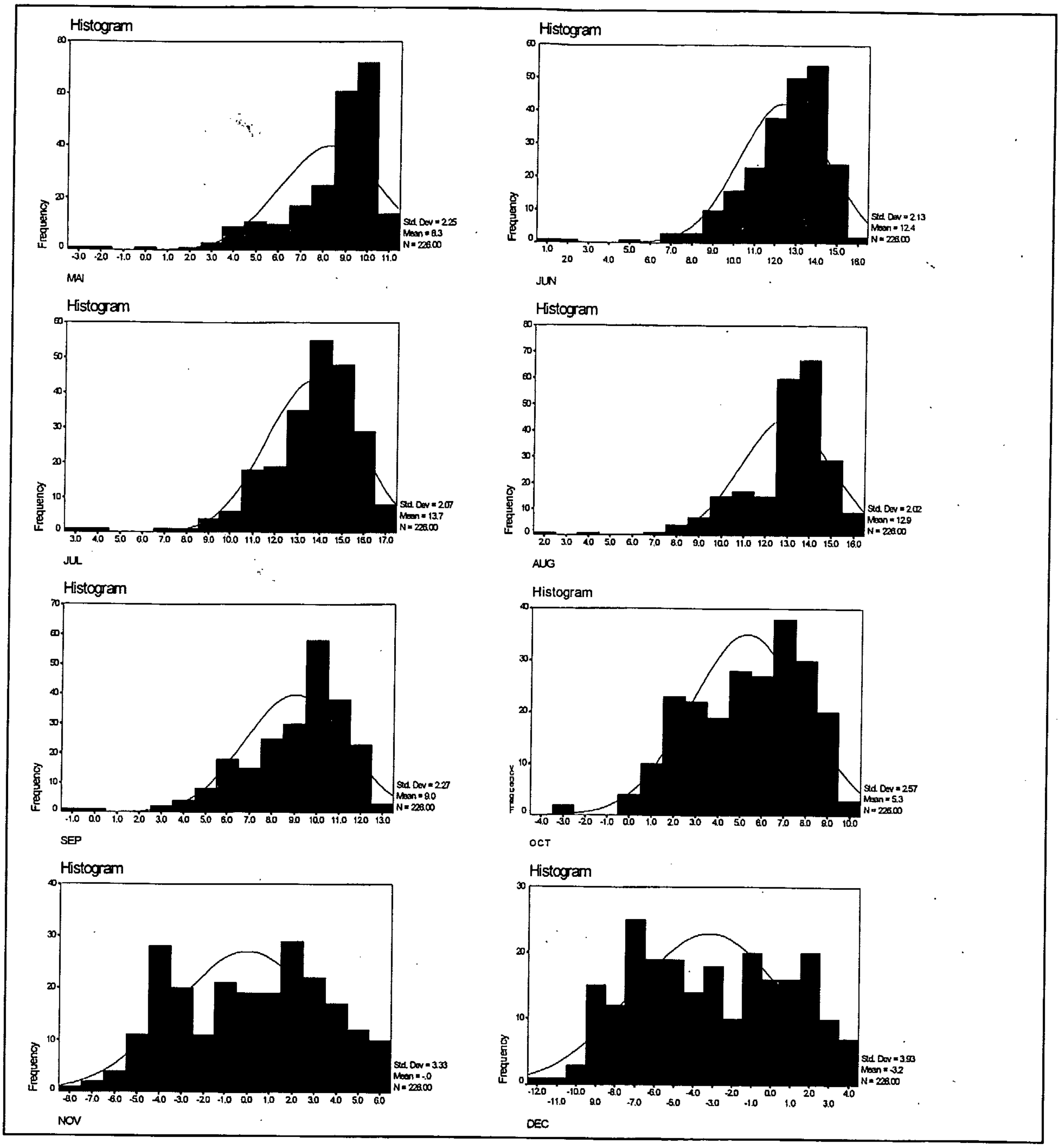

Figure 4-3: Frequency of monthly normal temperatures in southern Norway 1961-90.

4.2 Monthly mean temperatures

Regression analysis was performed for each month applying station altitude (Z) and distance to coast (DTC) as independent variables. The resulting correlations and coefficients of determination (R^2) as well as the regression coefficients are shown in table 4-1. The dependence between the normal temperature and both altitude and distance to coast shows a seasonal variation. This variation is shown graphically in figure,4-4. Notice that the left y-axis is showing negative correlation. The axis is turned for easier interpretation.

Table 4-1: Correlation coefficients between normal monthly temperature and distance to coast and station altitude, regression coefficients and coefficient of determination.

	Correlations		Regression coefficients			Coeff. of determ.
	DTC	Z	Const.	DTC	Z	R^2
JAN	-0.85	-0.64	0.80	-0.04053	-0.00304	0.76
FEB	-0.83	-0.66	0.47	-0.03360	-0.00333	0.75
MAR	-0.78	-0.86	2.33	-0.01750	-0.00536	0.87
APR	-0.64	-0.97	5.11	-0.00529	-0.00646	0.95
MAY	-0.46	-0.96	9.87	0.00255	-0.00670	0.92
JUN	-0.26	-0.84	13.14	0.00810	-0.00624	0.75
JUL	-0.31	-0.84	14.58	0.00598	-0.00590	0.74
AUG	-0.51	-0.93	14.44	-0.00002	-0.00561	0.87
SEP	-0.69	-0.94	11.41	-0.00801	-0.00542	0.93
OCT	-0.81	-0.87	8.50	-0.01680	-0.00471	0.92
NOV	-0.85	-0.76	4.43	-0.02900	-0.00414	0.85
DEC	-0.86	-0.66	2.05	-0.03850	-0.00316	0.78

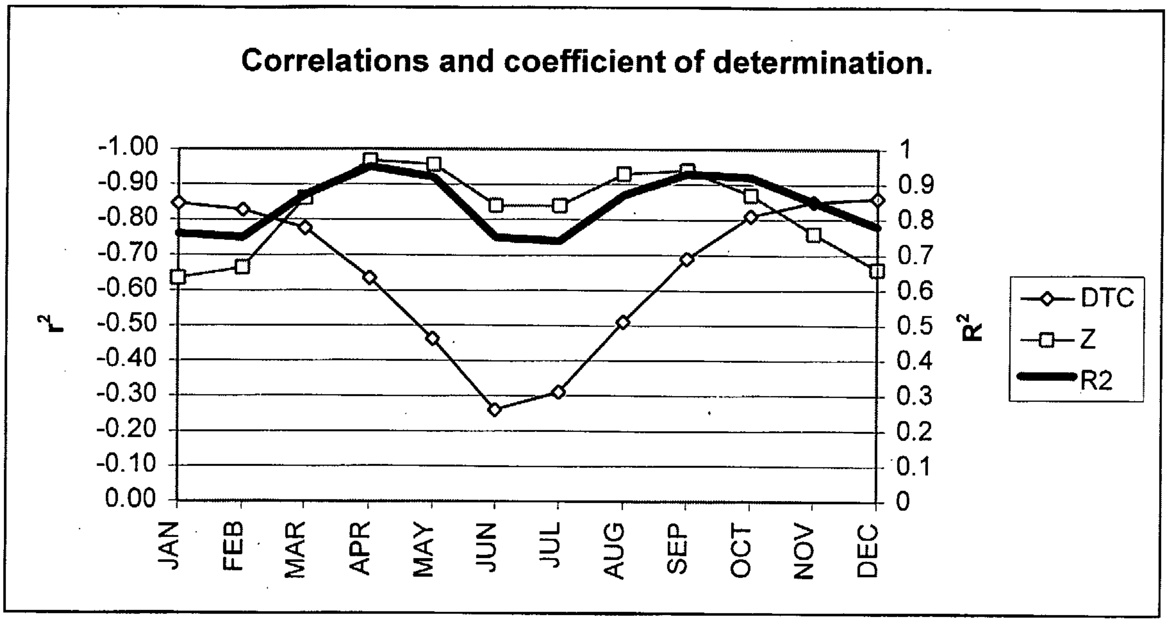

Figure 4-4 Correlation coefficients (r^2) between monthly mean temperature and station altitude (z) and distance to coast (dtc), and the coefficient of determination (R^2)estimating monthly temperature applying z and dtc as independent variables.

Distance to coast (DTC) have high correlation to winter temperatures and low correlation in summer. The problem with this parameter is the seasonal variation of temperature due to continentality. The gradient shifts from a decreasing temperature with distance to coast relation in winter to a positive gradient in summer. In summer, however, some mountain stations will still be colder than coastal stations and disturb the statistical relation. This is partly the explanation for the low correlation.

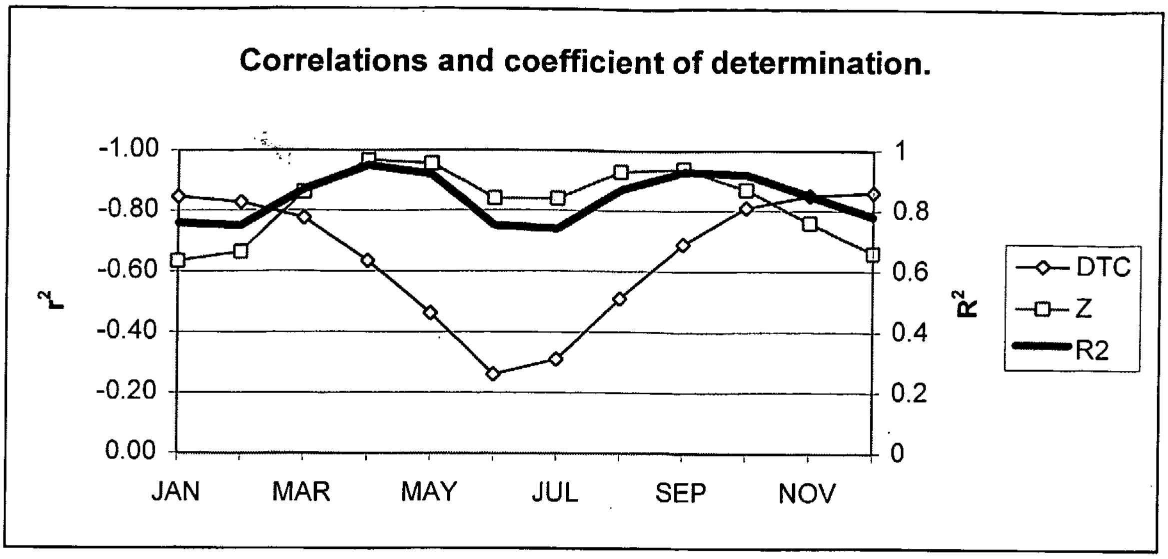

Figure 4-5: Regression coefficients estimating monthly mean temperatures.

Figure 4-5 shows the seasonal variation of the regression coefficients, describing the gradients.

The temperature has a high correlation to altitude in spring and autumn, and low in winter. This is reasonable, since the low winter correlation are due to inversions at many stations in the valleys. In spring and autumn there is generally good ventilation at most locations, preventing inversions to be formed. These season also have the smallest horizontal temperature gradients.

The curve showing the relation between altitude and temperatures varies between 0.30 and 0.67°C/100 m a.s.l. decrease (notice that the axis are related to altitude in meters!). These numbers are very similar to the vertical gradients found by Bruun(1957) for well ventilated locations. She studied the vertical difference of pairs of neighbouring temperature stations. Her data-material was sparse, only 15 pairs, 6 of them categorised as well ventilated. The regression coefficients for Z are somewhat lower than Bruun's vertical gradients. This is probably a result of the influence from «protected» stations. These stations may have inversions both in winter and summer.

The regression coefficients do not coincide very well with the results of Førland (1984) concerning the winter altitude relation. This is due to the fact that his study area is very close to the coast, and thereby less influenced by inversions. His gradients are close to 0.6°C/100 m a.s.l. for both summer and winter. The data sample used in this analysis cover a much larger and in-homogenous area. The stations are a mixture of very exposed, moderately exposed to very protected locations with respect to ventilation. Specially in winter time, inland stations will reduce the vertical temperature gradient, or in this case the regression coefficient. In summer this effect is not that much pronounced. The DTC relation is quite similar to the linear relation found by Førland (1984).

The coefficient of determination is highest in spring (March and April) and in autumn (September and October). All months have acceptable regression models considering the large area studied, covering several different climatic regions.

4.3 Non-linear response.

Zheng and Basher (1996) used a non-linear distance to coast relation ($T = f(e^{-DTC})$). Their model was tested for non-linear response by applying Akaike's information criterion (AIC). This criterion is known from time-series analysis, where it is used to determine number of time lags to be used in autoregressive (AR) models. Autoregressive models can be considered as equal to linear regression in its basic structure. AIC is a measure of goodness of fit, but does in addition to standard maximum likelihood estimates (minimum variance) also punish models by giving them a penalty depending of the parametrization. More parameters gives a larger penalty. The AIC favours simplicity by taking both the residual and the model complexity into account. AIC applied to multiple linear regression can be expressed as:

$$AIC(x_1, x_2, \ldots, x_n) = \left\{ n(\log 2\pi) + n \log \frac{1}{n} \sum_{i=1}^{n} \hat{\varepsilon}_i^2 \right\} + 2(m+2) \qquad (3)$$

where $\hat{\varepsilon}_i$ is the least square estimate of ε in equation (2). The criterion is used to compare the efficiency of different models belonging to the same class of models, e.g. different regression models. The best model is defined as the model with the lowest (or more negative) AIC-value.

Different versions of regression model set-ups, varying the response of *DTC*, was tested by using AIC as test criterion. Two different non-linear representations of DTC were tested:

A: $\sqrt{DTC}$

B: $e^{-0.1 \cdot DTC}$

The model used as reference was the model including linear DTC described in chapter 4.2:

C: ***DTC*** (reference model)

The difference in AIC between the reference model C and the test models A and B was calculated, and the difference is shown in table 4-2 and figure 4-6. The results applying AIC suggests that the distance to coast is weakly non-linear, and best represented by $\sqrt{DTC}$. AIC gives most credit to model A in October, and figure 4-7 shows the difference in estimated temperatures applying model A and model C. The difference between the models are up to 0.7 °C, and the map shows that the difference depends on the distance from coast. The largest negative differences occur close to the coast and far away, while the largest positive differences occur some 100 km from the coastline.

Table 4-2: Difference in AIC between the reference model C and the models A and B.

AIC	J	F	M	A	M	J	J	A	S	O	N	D
Model A	6	5	9	7	-7	-4	-1	0	-27	-31	-12	-1
Model B	177	156	146	64	-10	30	20	-3	34	177	192	181

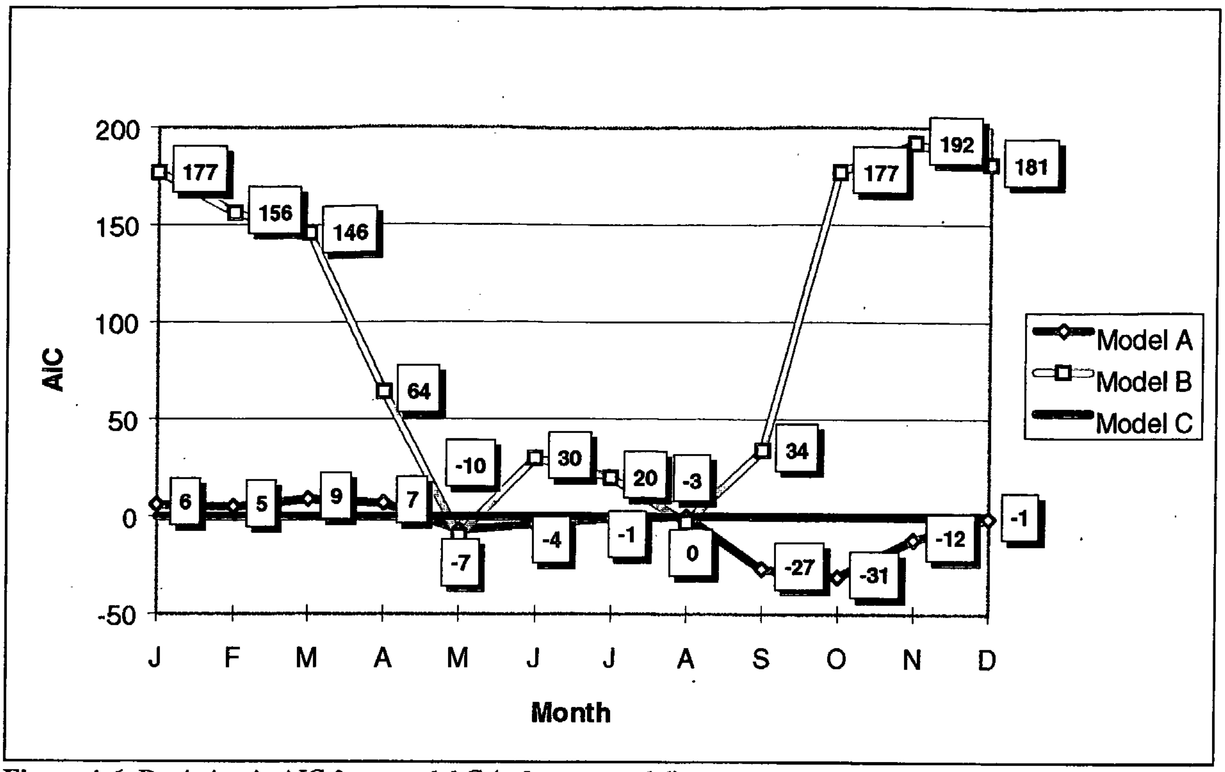

Figure 4-6: Deviation in AIC from model C (reference model).

Figure 4-8 shows maps of the deviation from observed temperatures applying the two models. A closer examination of these results shows that 134 of the 226 station get the best estimate from model A, 89 from model C and 3 stations get exactly the same estimate. However, for 200 of the stations (figure 4-9), the difference between the estimates are less than 0.3 °C. Since the results are not very different, results from applying model C is used in the further discussions.

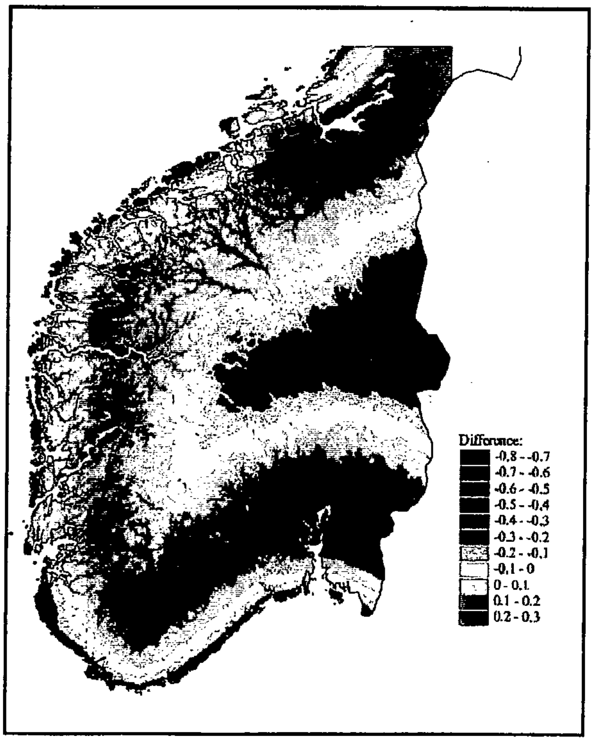

Figure 4-7: Difference in estimated temperature applying model A and C.

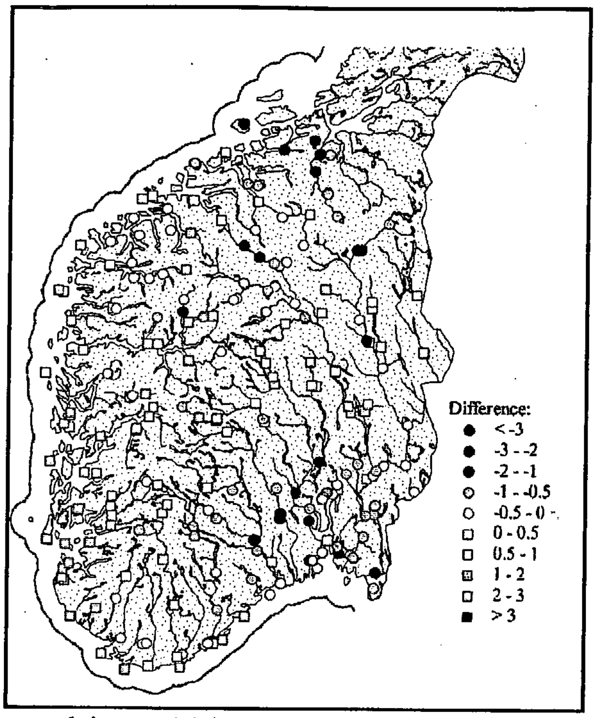

Figure 4-8a (Left): Deviation from observed temperature applying model A.
Figure 4-8b (Right): Deviation from observed temperature applying model C
(Mean monthly temperature, October. A positive residual means that the temperature is underestimated).

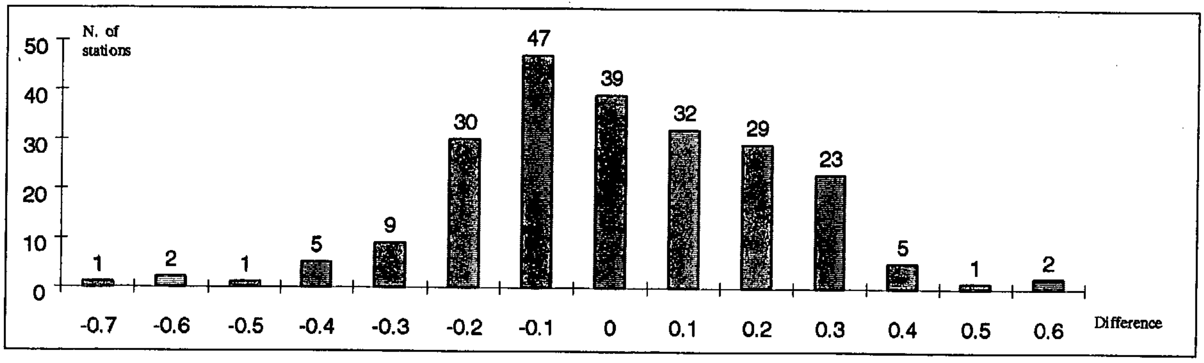

Figure 4-9: Distribution of the difference applying model A and C.

5. Application of the models

Application of the models can be applied to produce maps of monthly temperature normals. The models are implemented in the raster (grid) module of a geographical information system (GIS), applying equation (2). Grids containing the digital elevation model (Z) and distance to coast (DTC) with a 1×1 km resolution are established. By applying the regression coefficients β_0, β_1 and β_2, grids representing monthly temperature maps can easily be created without involving other information than Z and DTC.

The resulting January and June temperature maps for southern Norway are shown in figure 5-1.

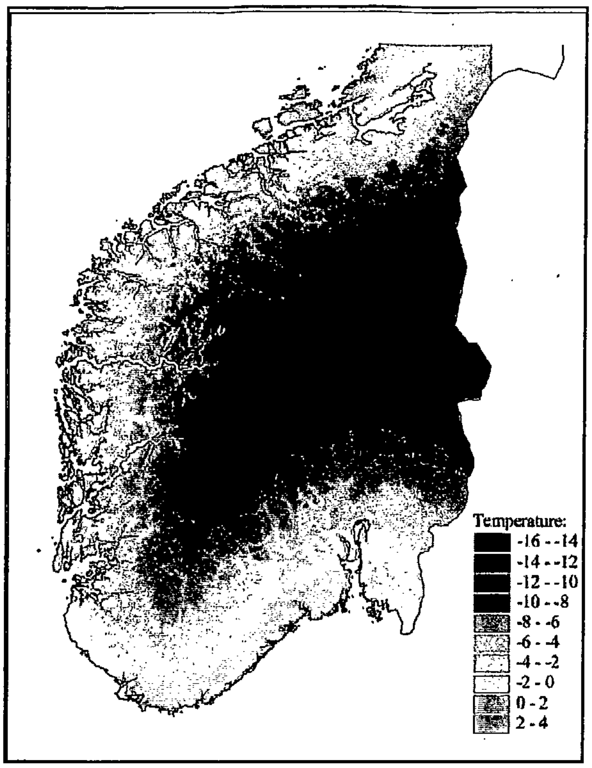

Figure 5-1a: Estimated temperature for January.

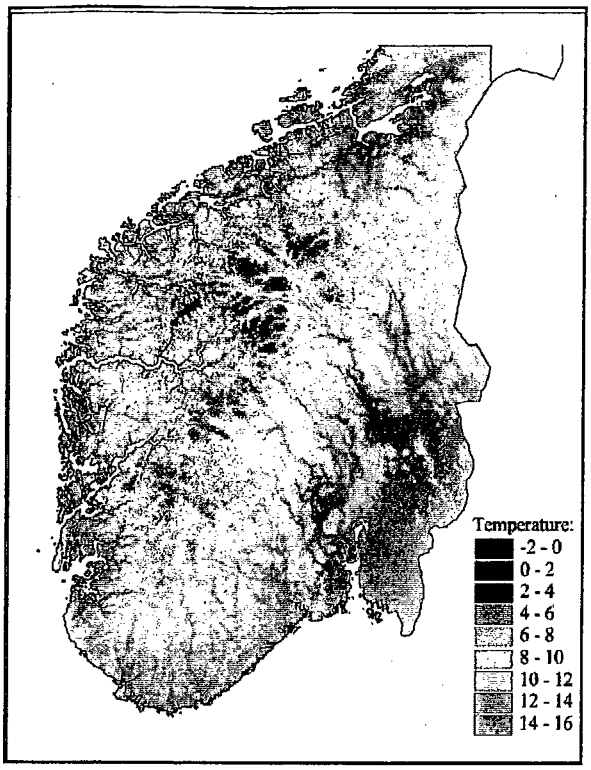

Figure 5-1b: Estimated temperature in June.

These two months have different characteristics concerning the weighting of the independent regression variables, which is reflected by the spatial variation in the maps. In winter, the coefficient of altitude is small, and the spatial variation of temperature is mostly explained by DTC. This is clearly seen in the January map (fig.5-1a). The altitude coefficient is small, and the terrain is weakly represented in the temperature map. In the June map (fig 5-1b), the DTC coefficient is smaller, and the altitude coefficient larger than in winter. This results in a temperature map controlled by the terrain.

6.Verification.

The results are verified by comparing the estimated temperatures with the observed monthly normal at each location. This is expressed in the map showing the residual between observed and estimated temperature. The residuals are calculated as:

$$T_{res} = T - T^* \qquad (3)$$

where T_{res} is the residual, T the observed temperature and T^* the temperature estimate. A positive residual thus means that the temperature is underestimated.

6.1 January & February

The R^2 for January is 0.76, and the residualmap for January is shown in figure 6-1. In the map, positive residuals are marked with squares, negative residuals with circles. One major pattern in the map is positive residuals along the west coast, giving too low temperatures. Exceptions are at some protected locations, e.g. at Voss, ≈ 100 km east of Bergen, which are overestimated. Most of the stations around the Oslofjord have several centigrades overestimation.

Temperatures at stations located in the bottom of the valleys are often overestimated, and vice versa for the stations located at hillsides or on mountains. This may be a result of temperature inversions in the valleys, where the temperature will increase with altitude. In such cases, the regression model, with its negative regression coefficient for the altitude variable will fail. As mentioned above this may be the reason why the correlation coefficients between temperature and altitude for the winter months are low. Regression models are not ideal for January. Despite the overall good statistics, local anomalies will not be represented in the regression model, leading to large estimation errors in such areas.

February have about the same R^2 as January (0.75), and the general patterns of the residual map are the same.

6.2 March

The map for estimated temperatures in March is shown in figure 6-2, and the R^2-coefficient has increased to 0.87. The residuals in this map are much smaller than for the two previous months. Most of the central parts of the study area have residuals less than ±0.5°C. Still there is underestimation in the western parts and overestimation in east.

6.3 April

The regression model for this model shows the best performance in terms of R^2, with a score of 0.95. Most of the stations (figure 6-3) are within a ±0.5°C residual, and very few outside the ±1°C deviation. The largest deviations are found at stations situated at bottom of the westernfjords (underestimated) and in the northern part of the study area (overestimated). The overestimation in the northern parts is probably due to lack of a latitudinal variable in the regression.

6.4 May

This map (figure 6-4) shows new properties compared to the four previous months. One major difference in May is the change of sign in the regression coefficient of DTC. In the period May to July, this coefficient has a positive sign, implying a temperature increase with distance from coast. The effect of this is generally an underestimation of the temperatures around the Oslofjord. At the north-western coast, temperatures are slightly overestimated, so are most of the central parts of the study area. Stations in the valley bottoms suspected to be overestimated due to inversion in the winter, are now underestimated.

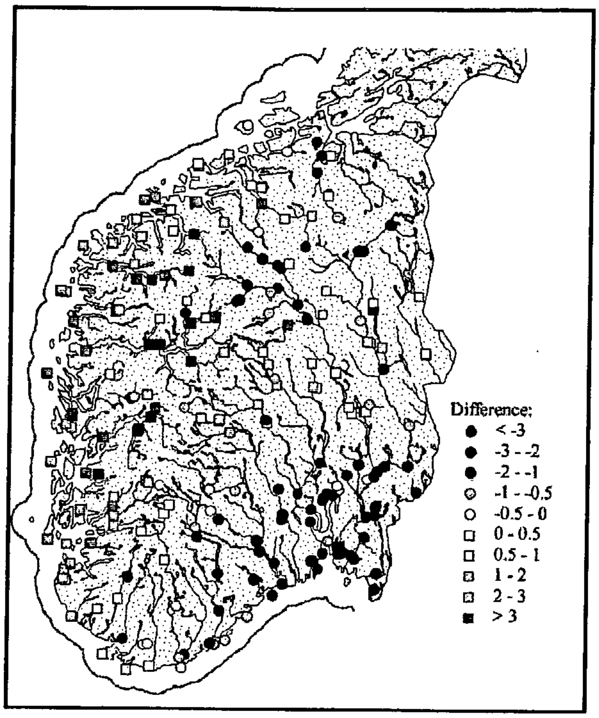

Figure 6-1: Deviation between observed and estimated monthly temperatures in January.

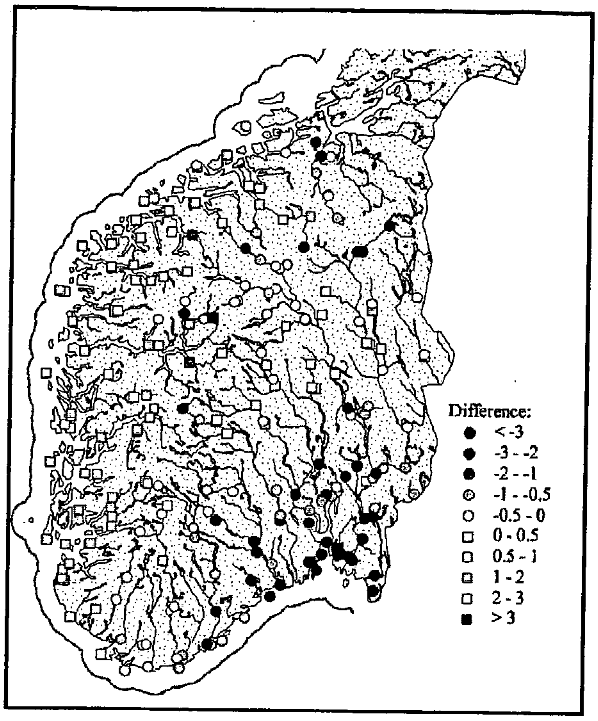

Figure 6-2: Deviation between observed and estimated monthly temperatures in March.

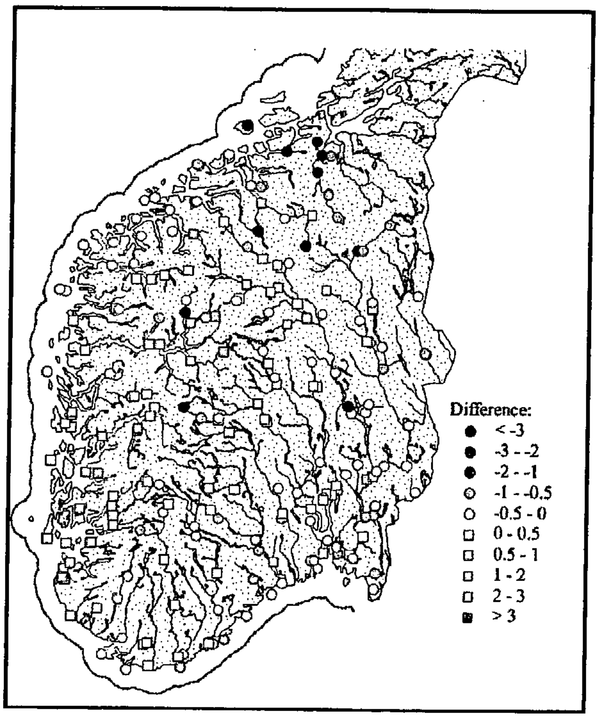

Figure 6-3: Deviation between observed and estimated monthly temperatures in April.

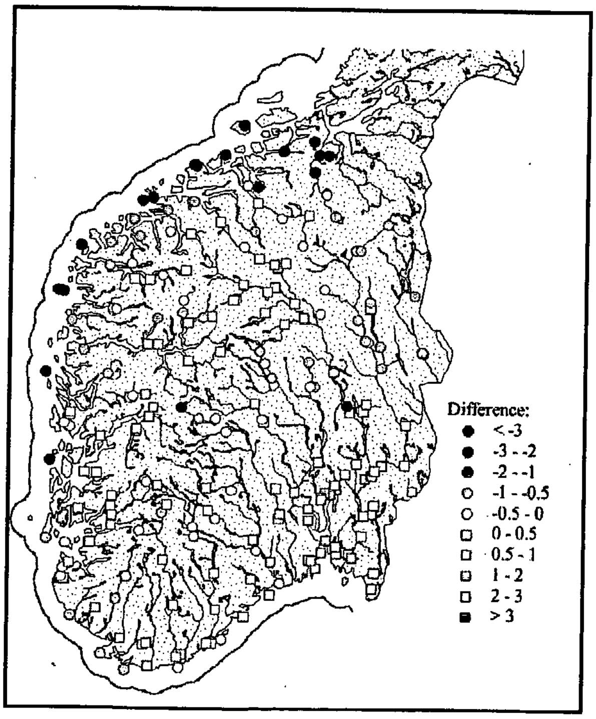

Figure 6-4: Deviation between observed and estimated monthly temperatures in May.

6.5 June, July, August & September

In June (fig. 6-5) the R^2 again sinks to 0.75. The temperatures in the south-eastern areas are underestimated, while the western and north-western stations mostly have an overestimation. July has a R^2-score of 0.74, and have the same residual properties as June.

In August (R^2 = 0.87) the DTC-coefficient is very close to zero, and the regression model is mostly a terrain dependent model. The residuals follow the patterns described in June and July, but temperatures at high altitude stations are overestimated. In the southern parts, positive residuals occur, and in the northern parts dominate negative residuals.

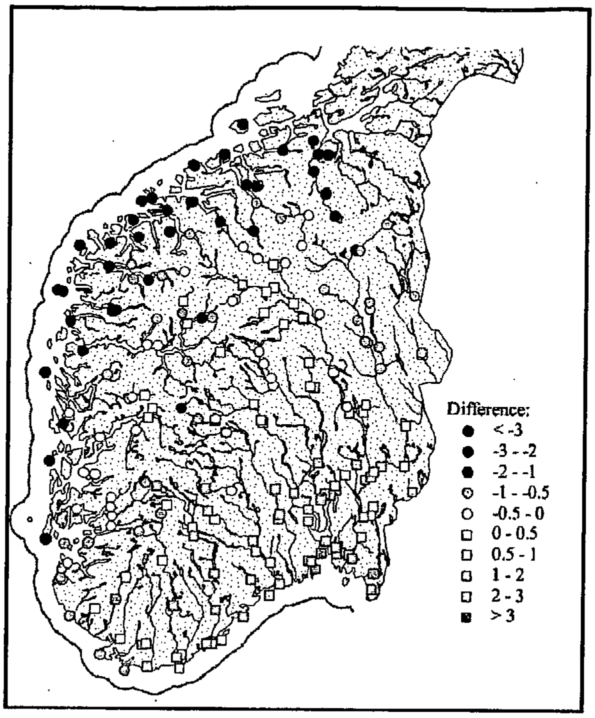

Figure 6-5: Deviation between observed and estimated mean monthly temperature in June.

6.6 October.

Temperatures at stations at the southern and western coasts are underestimated. In the Oslofjord area, temperatures are overestimated. The patterns are generally noisy in this R^2=0.92 map.

6.7 November & December

These two months shows very much of the same properties as January and February. Temperatures are overestimated around the Oslofjord and in the valley bottoms, and underestimated at the west coast and in the southern parts of the mountain region. In the northern part of the mountain region temperatures are overestimated.

7. Discussion and Conclusions

This analysis shows that estimation of normal monthly temperatures applying multiple linear regression is not applicable for a large inhomogenous region as studied here. The results of this study have however contributed to a better knowledge of the influence of altitude and distance to coast as two important variables in spatial temperature modelling.

One of the largest problems using statistical methods like regression is the assumption of the whole population following the same frequency distribution. This assumption is hardly fulfilled for the data sample used in this analysis. Specially values at the tails of the distribution will be burdened with errors.

There are different aspects concerning temperature and the two independent variables used here. Temperature depends very much on local conditions, specially in the winter season.

Inversions will often be formed at well protected locations, like in bottoms of valleys and local terrain sinks. Such areas have different lapse rate close to ground compared to more ventilated (wind exposed) locations. These conditions may change over short distances, disturbing the statistical relations. There are also problems with the DTC-variable, specially in the summer. Our assumption is that there is an increasing or decreasing temperature away from the coast. In summer, high altitude stations may be colder than the observations close to the sea, while the inland stations at low- and mid-altitudes are considerable warmer than at the coast. This effect is probably the reason why the correlation between temperature and DTC is low in summer time. At some locations local effects will cause an enhanced heating also in areas relatively close to the coastline. Local terrain effects can both give «kettle»-effects and favour föhn-winds. This seems however to be well accounted for in the models. Such stations may be considered as inversion stations, as the same terrain effects often occur also at inland stations which are underestimated in winter.

Monthly normal temperatures are difficult to interpolate, because they represent a wide variety of underlying processes during the 30 year period they are based upon. Therefore the coefficients will represent the mean atmospheric situation during this period, and not necessarily a possible synoptic situation.

The analysis shows that there is a systematic variation of temperature explained by altitude and distance to coast. The importance of the two independent variables used here show a seasonal variation, and their importance is alternating. In winter time distance to coast plays a more significant role than in summer, while altitude is most siginificant in spring and autumn. It could be very tempting to apply this approach, since the coefficient of determination (R^2) is high. However, the deviations are too large in many regions to recommend this. The results of this analysis could however be used to reduce the temperature to a reference level, either based on altitude or distance to coast. Then a spatial interpolation could be performed using e.g. residual kriging (Martinez-Cob, 1996) or other interpolation techniques. Other possibilities could be to use regional models. This may ensure better estimates within limited regions. Such models will be difficult to apply in the transition zones between different regions, because there will not be continuity between the models for each region.

Regression is a «global» method, describing the average features for the entire region. It will not encounter regional deviations and anomalies. However, within the frames of geostatistics and GIS, regional parametrization could be applied, based upon regional and local characteristics, e.g. given by terrain parameters, distance to coast etc. This approach is under investigation (Tveito and Førland, 1998). The regression approach may however be applicable for smaller and more homogenous regions than tested here.

8.Acknowledgements

The author is indebted to my colleague and project coordinator Eirik J. Førland, which support and constructive criticism has been invaluable in this study.

The Norwegian Electricity Federations have finacially supported this project, contract no. 55108.

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