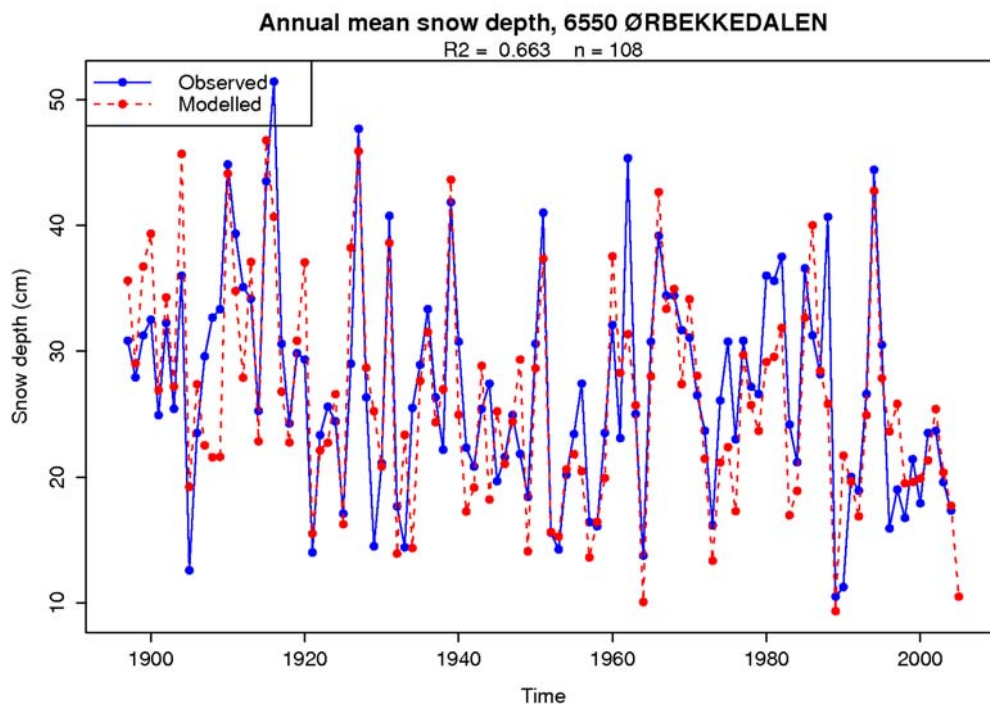





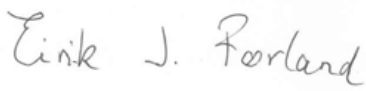
# A simple station-based empirical model for local snow conditions

Herman Farbrot and Inger Hanssen-Bauer





<b>Title</b> A simple station-based empirical model for local snow conditions	<b>Date</b> 12.02.2009
<b>Section</b> Climate	<b>Report no.</b> 03/2009
<b>Authors</b> Herman Farbrot and Inger Hanssen-Bauer	<b>Classification</b> <input checked="" type="checkbox"/> Free <input type="checkbox"/> Restricted
	<b>ISSN 1503-8025</b>
	<b>e-ISSN 1503-8025</b>
<b>Clients</b> The Norwegian Research Council and The Norwegian Meteorological Institute	<b>Client's reference</b>
<b>Abstract</b> This report describes a simple empirical model for estimating monthly change in mean snow depths with monthly average temperature (TAM) and monthly precipitation sum as input variables. The model is developed and tested on weather and precipitation stations in mainland Norway and in the Norwegian Arctic. For precipitation stations TAM is derived from daily temperature maps and standardised regional temperature series. The snow model is well adapted to stations with a stable winter snow cover, but is less adapted to maritime stations in Southern Norway and stations in the Arctic. For stations with an adequate fit, the model can be used to project future snow conditions if monthly temperature and precipitation scenarios exist.	
<b>Keywords</b> Monthly mean snow depth, Empirical model for local snow conditions, Norway	

<b>Disiplinary signature</b>	<b>Responsible signature</b>
	
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# 1 Introduction

Local snow conditions largely affect terrestrial biota as well as human activities and infrastructure. Snow cover variability further feeds back on the climate because of its effect on the albedo. Thus, possible changes of snow cover and -depth are of large interest in the context of global warming (e.g. ACIA 2005). Global climate models, however, have too coarse spatial resolution to give useful information for impact studies concerning these variables. Even in regional models, valleys and mountains are not resolved sufficiently to allow for realistic estimation of local snow conditions, especially in rough terrain. Realistic snow scenarios can be achieved by first running a regional climate model, then adjusting daily precipitation and temperature scenarios from regional models to local conditions, and finally to feed these into a water balance model (Vikhamar Schuler et al. 2006), but this procedure is very resource demanding, and can be followed only for selected climate projections. The aim of the present study is to develop a simple empirical model for calculating the local monthly averaged snow depth, based upon monthly mean temperature and precipitation sum. Running such a model will be very simple. Further, local projections of monthly temperature and precipitation will then allow producing local snow projections. Ensembles of projections of local temperature and precipitation can easily be made by statistical downscaling (e.g. Benestad 2004). Thus, the present model development will make it possible to produce – in an easy way – probabilistic scenarios for local snow conditions. The model development and the input data are described in section 2. The results are presented in section 3, and discussed in section 4.

## 2 Method and data

### 2.1 Method

The idea behind the snow model is that the potential change in mean snow depth from one month to the next ( $\Delta SAM$ ) depends on temperature conditions (represented by the average monthly temperature, TAM) and precipitation (represented by the monthly precipitation sum, RR). Our model may be expressed as:

$$\Delta SAM = f(TAM, RR) = a*RR + b*RR*TAM + c*TAM + d$$

The coefficients of the model (a-d) will obviously depend on temperature, as both precipitation phase and melting conditions depend on temperature. Two threshold temperatures (TT1 and TT2) are thus suggested. When  $TAM < TT1$ , hereafter referred to as COLD, all precipitation is supposed to be solid, and no melting is supposed to occur. When  $TT1 \leq TAM < TT2$ , hereafter referred to as MID, precipitation may be both liquid and solid. When  $TAM \geq TT2$ , hereafter referred to as WARM, all precipitation is supposed to be liquid. Thus:

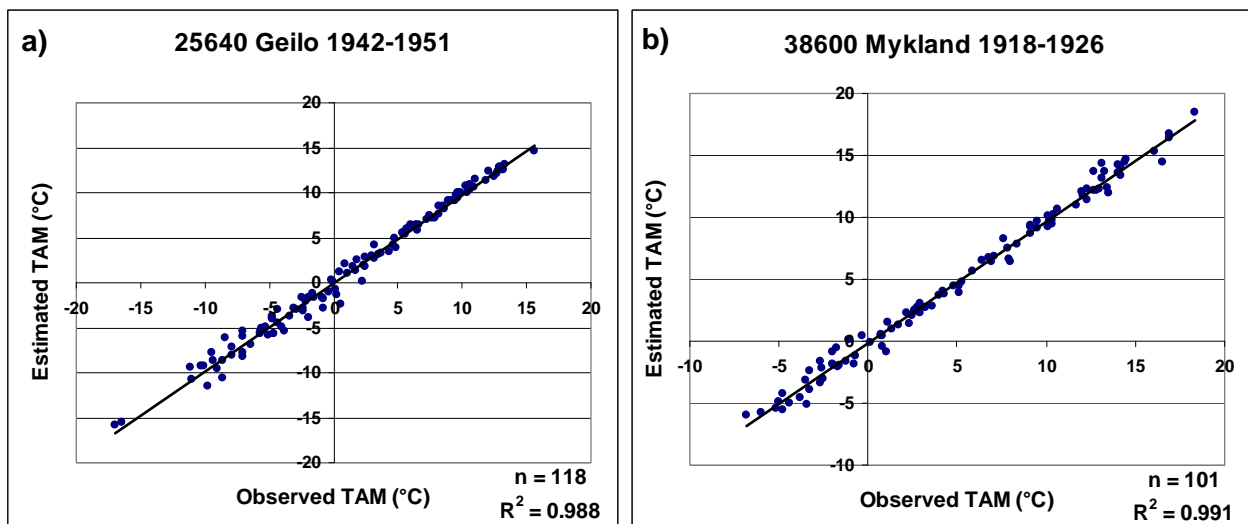
$a1*RR + b1*RR*TAM + d1$	COLD
$a2*RR + b2*RR*TAM + c2*TAM + d2$	MID
$c3*TAM$	WARM

The coefficients of the COLD and MID part of the model are found through linear regression (i.e.  $a_1$ ,  $b_1$ ,  $d_1$ ,  $a_2$ ,  $b_2$ ,  $c_2$  and  $d_2$ ). For WARM linear regression does not fit the data satisfactory due to several data points where  $\Delta\text{SAM}$  is depending on the snow depth of the previous month (i.e. more snow had melted if available). Hence, the melt-rate coefficient  $c_3$  (same length of all months assumed) was used to estimate the potential decrease in the snow depth.

The model was implemented in R (cf. Ellner 2001) with use of the R-package `clim.pact` (cf. Benestad 2003) in the following manner. First RR, TAM and SAM are being read. Erroneous negative SAM values occasionally occurring in the datasets are replaced with NA (not available). Then the monthly change in SAM is calculated. Further, for COLD and MID the change in snow depth is estimated, whereas for WARM the potential decrease in the snow depth is estimated. The first August month of available observations for RR and TAM is found, and here SAM is set to 0 as a starting point for the model. For the next month the estimated SAM,  $\text{est.SAM}_m$ , is found by adding the estimated change in snow depth,  $\text{est.SAM.change}_m$  to the previous estimated SAM,  $\text{est.SAM}_{m-1}$ , i.e.:

$$\text{est.SAM}_m = \text{est.SAM}_{m-1} + \text{est.SAM.change}_m$$

However, in situations where estimated decrease in the snow depth is greater than  $\text{est.SAM}_{m-1}$ ,  $\text{est.SAM}_m$  is set to 0. If  $\text{est.SAM.change}_m$  is NA when RR and/or TAM are missing,  $\text{SAM}_m$  is set to NA. Then SAM is set to 0 for the next August month and the values in between are set to NA. For each station the model was run several times with different choices for  $\text{TT1} = -\text{TT2}$  (1:5) and  $c_3$  (-25:-5). The R-script used to make these computations is given in the Appendix.



**Figure 1.** Observed vs. estimated monthly mean temperature (TAM) for two precipitation stations in Southern Norway, a) 25640 Geilo and b) 38600 Mykland. The close fit indicates that the estimated TAM values used as input for the model are reasonable.

## 2.2 Data

The snow model was run for several Norwegian weather stations with long time series of temperature, precipitation and snow depth. For precipitation stations the TAM values had to be estimated. First, daily values for the period 1961-2008 were estimated from daily 1x1 km<sup>2</sup> temperature maps, by algorithms presented in Tveito et al. (2000). Further, these “artificial” time series were extended back to the start of the stations by using standardised regional temperature series (cf. Hanssen-Bauer & Nordli 1998, Hanssen-Bauer 2005). The basis for these series is stations with a long period of temperature observations. Hence, observations of TAM prior to 1961 for the precipitation stations may be used as validation for the estimated TAM series (Fig. 1).

## 3 Results

The fit of the model (coefficient of determination,  $R^2$ ) and the model parameters used for best fit is summarized in Table 1 for weather stations and Table 2 for precipitation stations.  $R^2$  ranges from 0.188 (44560 Sola) to 0.898 (6550 Ørbekkedalen). For the precipitation stations their time series are mainly >100 years. Fig. 2 shows the location of the stations used in this study and their fit to the model ( $R^2$ ). This map demonstrates that the model mainly works satisfactory in mainland Norway, except for the most maritime areas in Southern Norway. In the Norwegian Arctic the model seems to be less adapted. However, in this area there are only four weather stations used and their time series are rather short. Figs. 3 and 4 show some examples of measured vs. estimated SAM, as well time series of measured and estimated annual mean snow depth, for weather and precipitation stations, respectively.

## 4 Discussion

### 4.1 Adjustment of the model

The best fit for the model was mainly found for  $TT1 = -1^\circ\text{C}$  or  $TT1 = -2^\circ\text{C}$ . This limits the MID part of the model with a presumably greater variability of the data due to shifting melting and freezing conditions.

For most stations the choice of the melt-rate coefficient  $c3$  (within reasonable limits) is not too important. This is presumably due to the fact that few stations has great snow thicknesses, so the snow is fairly quickly removed by the model anyway. The best fit is mainly found for  $c3 = 10\text{-}20 \text{ cm}/^\circ\text{C}$ , which fits with measured degree-days factors for snow melt at glaciers in Norway (Laumann & Reeh 1993). That study indicated a decrease in degree-days factors from the west to the east in southern Norway. This trend was explained with higher wind speeds and humidity in the maritime environment in the west compared to the calmer and drier condition in the east, causing higher melt rates for the same temperature in the west than in the east. In our study no such obvious trend is present, but the data’s temporal resolution (monthly values) is probably too coarse for such investigations.

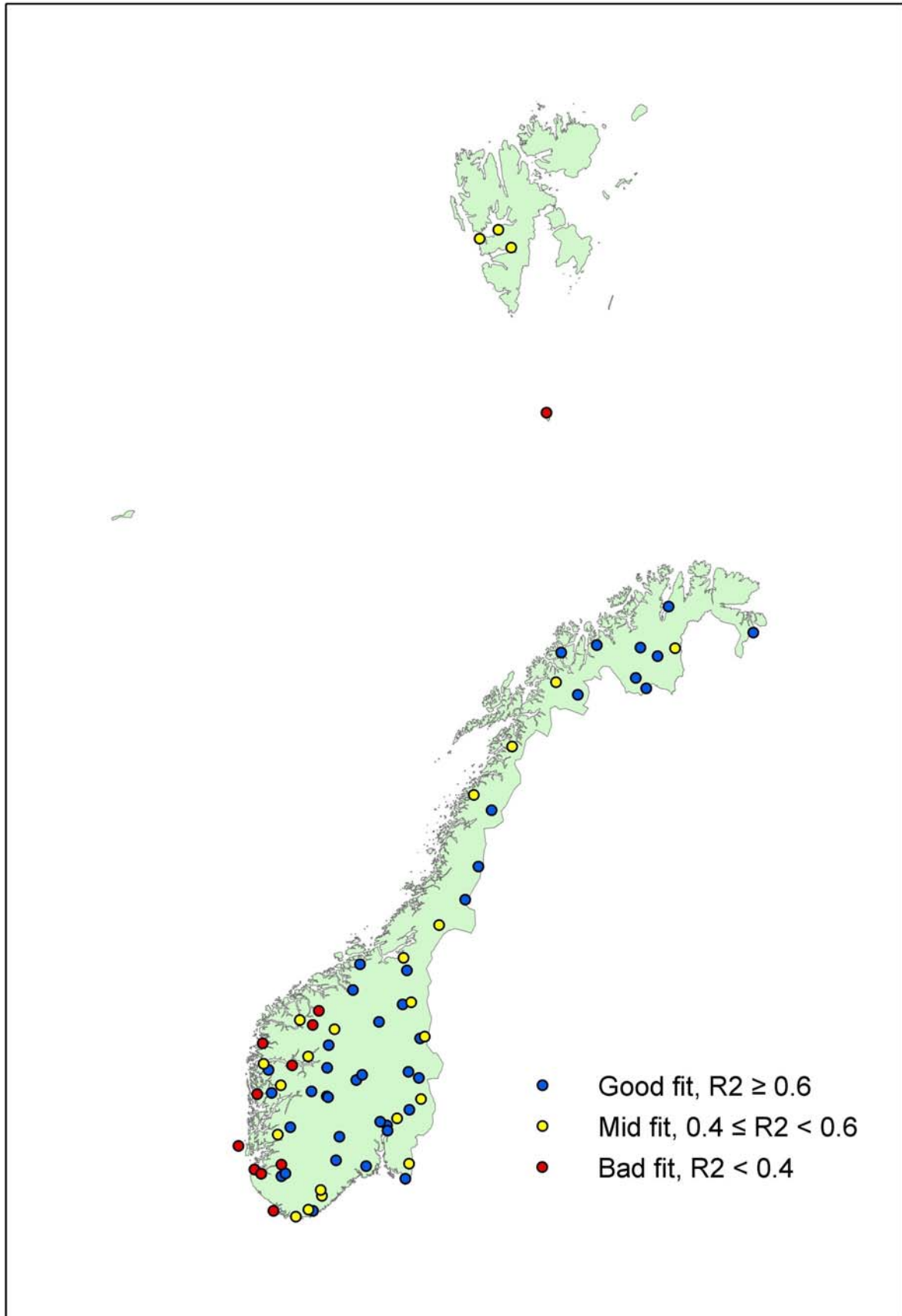


**Table 1.** Maximum fit of the model for different weather stations and the model parameters used. See text for details. The model gives an over all high coefficient of determination ( $R^2$ ) for stations with a fairly stable winter snow cover (e.g. 18700 Oslo – Blindern and 90450 Tromsø), but is less adjusted to the data at stations along the coast (e.g. 44560 Sola) and in the Arctic (e.g. 99710 Bjørnøya).

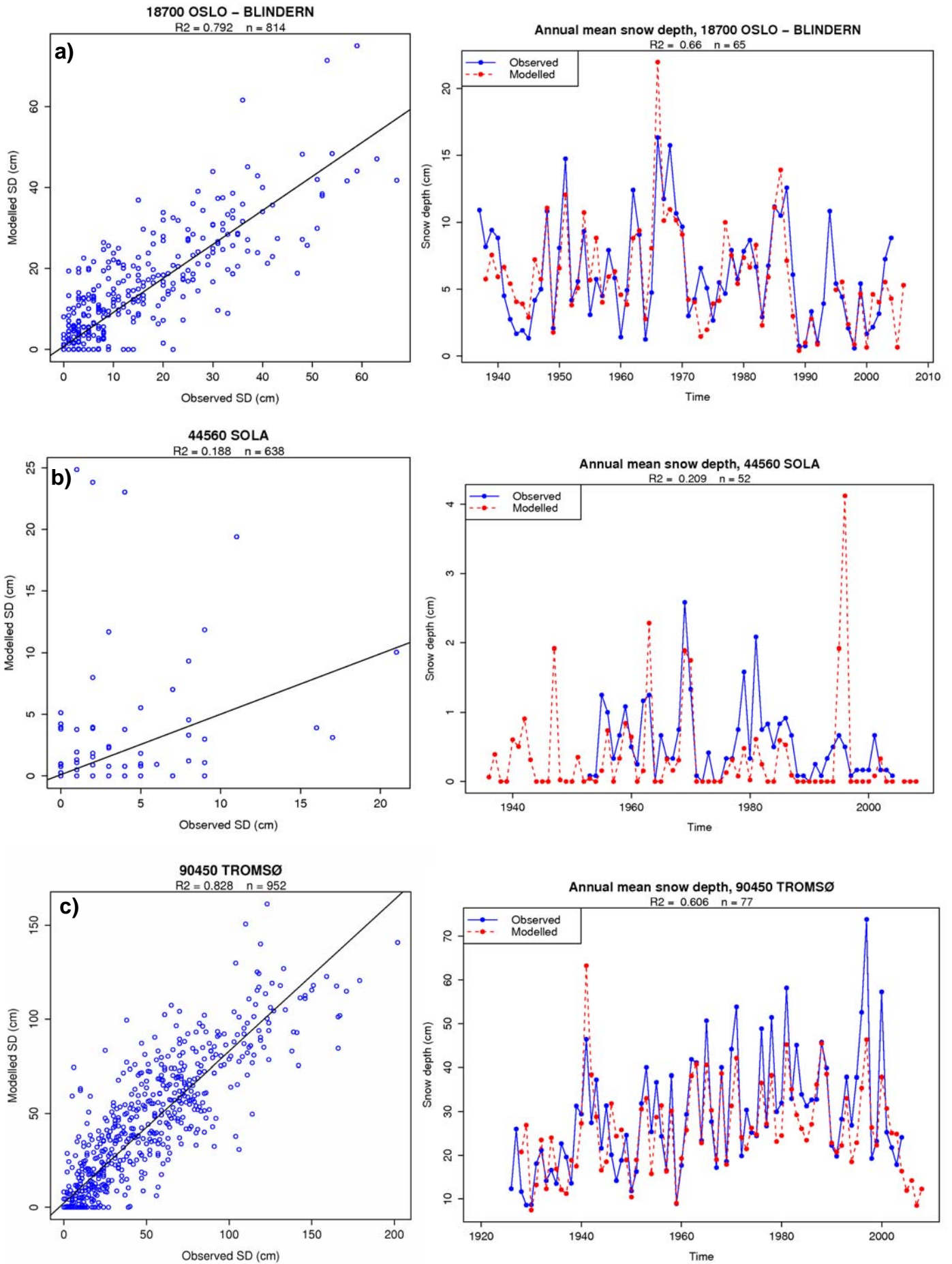
Station number (met.no)	Station name	Altitude (m a.s.l.)	$R^2$	n	c3	TT1
700	DREVSJØ	672	0.602	533	21-25	4
1130	PRESTEBAKKE	157	0.646	461	16-19	1
4780	GARDERMOEN	202	0.444	574	25	3
6040	FLISA	184	0.481	590	10-14	2
7010	RENA - HAUGEDALEN	240	0.834	579	13-15	1
10400	RØROS	628	0.566	578	25	2
18700	OSLO - BLINDERN	94	0.792	814	7-8	1
23160	ÅBJØRSBRÅTEN	639	0.641	623	17-25	3
25590	GEILO - GEILOSTØLEN	810	0.813	448	21-25	1
25840	FINSE	1224	0.698	220	25	1
39040	KJEVIK	12	0.686	708	12	2
41110	MANDAL II	138	0.481	586	7	1
42160	LISTA FYR	14	0.328	605	5-25	3
42920	SIRDAL - TJØRHOM	500	0.797	305	13-14	1
44560	SOLA	7	0.188	638	13-25	1
46610	SAUDA	5	0.524	605	10-11	1
47300	UTSIRA	55	0.290	668	5-25	NA
	BERGEN -					
50560	FREDRIKSBERG	41	0.310	761	5-25	2
52860	TAKLE	38	0.467	592	10-11	1
55290	SOGNEFJELLHYTTA	1413	0.879	118	25	3
58700	OPPSTRYN	201	0.365	402	18-20	1
60500	TAFJORD	15	0.265	629	7	1
69100	VÆRNES	12	0.560	712	6	3
70850	KJØBLI I SNÅSA	195	0.513	622	11-12	1
80700	GLOMFJORD	39	0.439	198	5	2
89350	BARDUFOSS	76	0.578	622	14-17	3
89950	DIVIDALEN	228	0.607	534	11-13	3
90450	TROMSØ	100	0.830	947	14-15	1
93300	SUOLOVUOPMI	377	0.865	431	19-24	2
93700	KAUTOKEINO	307	0.703	325	18-25	3
93900	SIHCCAJAVRI	382	0.758	612	14-21	2
97250	KARASJOK	129	0.550	1224	11	4
97350	CUOVDDATMOHKKI	286	0.838	384	12-13	1
99710	BJØRNØYA	16	0.237	223	19-25	2
99760	SVEAGRUVA	9	0.504	253	24-25	2
99790	ISFJORD RADIO	7	0.458	256	8-25	5
99840	SVALBARD LUFTHAVN	28	0.449	217	5-25	5

**Table 2.** As Table 1, but for precipitation stations. The air temperatures used in these analyses are generated through an objective interpolation technique combined with the use of a GIS (Tveito et al. 2000, 2001).

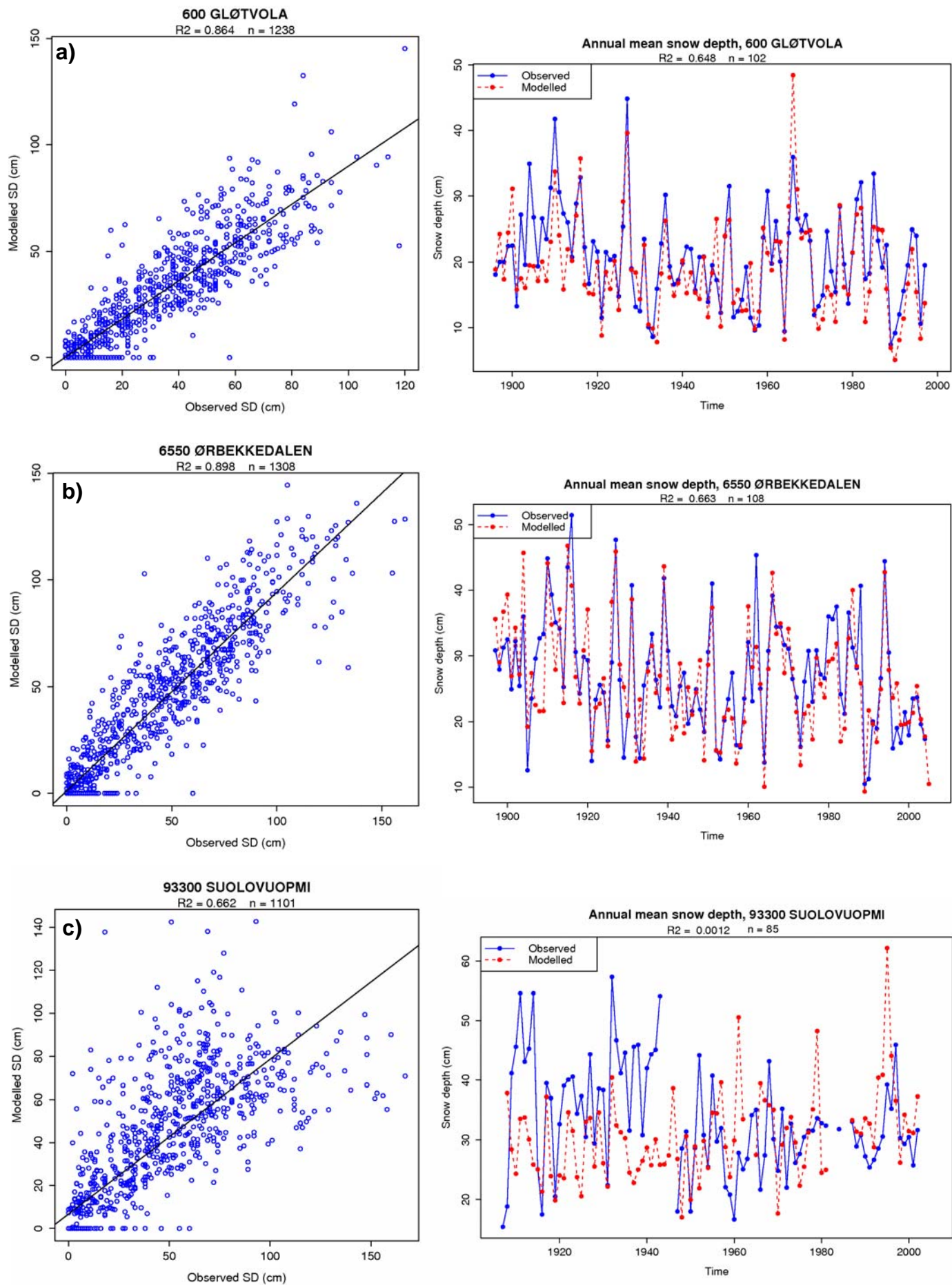
Station number (met.no)	Station name	Altitude (m a.s.l.)	R <sup>2</sup>	n	c3	TT1
600	GLØTVOLA	696	0.864	1238	23-25	2
1650	STRØMSFOSS SLUSE	113	0.444	1336	15	3
5350	NORD-ODAL	147	0.828	1330	12-13	1
655	ØRBEKKEDALEN	513	0.898	1308	19-22	1
9100	FOLLDAL	709	0.733	1324	23-24	1
10100	OS I ØSTERDAL	788	0.680	1313	16-18	2
15660	SKJÅK	432	0.544	1333	23-25	1
18500	BJØRNHOLT	360	0.645	1103	12	2
20120	STUBDAL	442	0.758	1073	21-25	1
21880	NORDRE ETNEDAL	679	0.896	863	22-25	2
25640	GEILO	841	0.648	1337	25	1
27800	HEDRUM	31	0.731	1321	10-11	2
31900	TUDDAL	464	0.816	1321	10-12	1
34900	POSTMYR I DRANGEDAL	464	0.819	1336	23-25	1
38450	HEREFOSS	85	0.482	1280	9-10	1
38600	MYKLAND	245	0.522	1342	15-17	1
39220	MESTAD I ODDERNES	151	0.575	1281	8-9	1
42890	SKREÅDALEN	474	0.680	1328	8-9	1
44800	SVILAND	230	0.322	1334	6-10	1
45350	LYSEBOTN	9	0.342	1322	7-25	1
46450	RØLDAL	393	0.751	1247	11-12	1
50350	SAMNANGER	370	0.703	1198	11-12	1
51470	BULKEN	323	0.592	1344	11-12	1
52700	MASFJORDEN	357	0.623	956	7	1
53070	VIK I SOGN III	65	0.284	1328	5	1
54600	MARISTOVA	806	0.774	1338	19-22	1
55550	HAFSLO	246	0.556	1330	6	1
57110	OSLAND VED STONGFJORDEN	119	0.302	1140	12-19	1
58960	HORNINDAL	340	0.511	1339	12	1
64700	INNERDAL	403	0.702	1231	20-24	1
65220	HEMNE	133	0.695	1232	8	1
68330	LIEN I SELBU	255	0.625	1344	11-12	1
73800	TUNNSJØ	376	0.732	1203	21-25	1
77850	SUSENDAL	498	0.840	1310	18-20	1
79740	DUNDERLANDSDALEN	155	0.760	1295	15	1
83500	KRÅKMO	76	0.542	1326	12-14	1
91750	NORDREISA	1	0.643	1076	13-15	1
93300	SUOLOVUOPMI	377	0.662	1101	17-25	2
95600	BØRSELV	10	0.694	1027	13-15	3
99450	BJØRNSUND	28	0.865	1298	16-18	1



**Figure 2.** Map showing the location of the stations used in this study and their fit to the model based on their coefficient of determination ( $R^2$ ). Three classes are present: Bad fit ( $R^2 < 0.4$ ), mid fit ( $0.4 \leq R^2 < 0.6$ ) and good fit ( $R^2 \geq 0.6$ ).



**Figure 3.** Observed vs. estimated monthly mean snow depth (SAM; left) and time series of observed and estimated annual mean snow depth (right) for some selected weather stations. a) 18700 Oslo – Blindern; b) 44560 Sola; c) 90450 Tromsø.

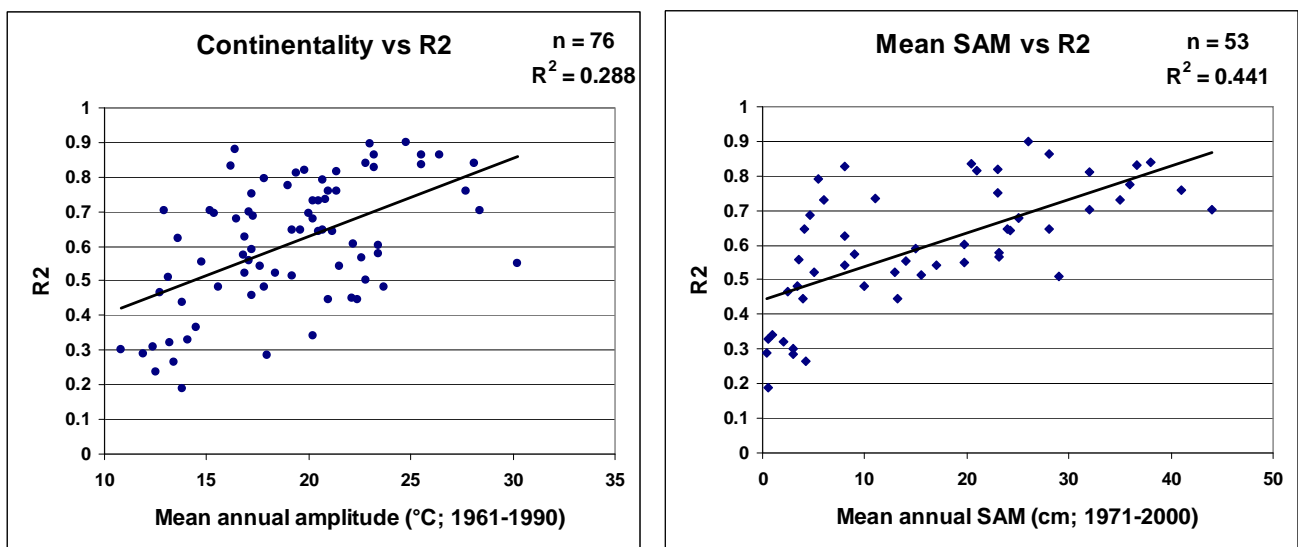


**Figure 4.** As Fig. 3, but for precipitation stations. a) 600 Gløtvola; b) 6550 Ørbekkedalen; c) 93300 Suolovuopmi. See text for details concerning the latter station.



## 4.2 Regional fit of the model

Fig. 5a shows a plot of the  $R^2$ -fit of the model vs. mean annual SAM (1971-2000), whereas Fig. 5b shows the  $R^2$ -fit vs. mean annual range of temperature (highest – lowest monthly normal values (1961-1990)) as a proxy for continentality for the different stations. A linear regression model with mean annual SAM (1971-2000) and the continentality proxy as independent variables, explains 56% of the variance in the  $R^2$  values ( $n = 53$ ). The plots indicate that the model is best fitted for the inner parts of Norway with stable snow conditions during winter, whereas in areas along the coast the fit is worse. This pattern fits with investigations by Linge Lystad (1977) on linear regression of mean annual SAM with functions of temperature and precipitation as independent variables. This is probably due to the fact that a greater portion of the data belongs to MID. The model fit of these data are not too good since weather conditions of shifting melting and freezing are more prominent. Not surprisingly 60500 Tafjord, situated in the inner part of Storfjorden in Sunnmøre, has a limited fit of the model, presumably due to the common mid-winter melting conditions associated with föhn-winds. Further, the model has limited fit to data from stations in the Norwegian Arctic. This may be caused by heavy redistribution of snow by the wind, so that observed SAM does not represent the solid precipitation received (cf. Humlum 2002). Also, the precipitation undercatch, depending on precipitation type and temperature, is extensive (Hanssen-Bauer et al. 1996, Førland & Hanssen-Bauer 2000) presumably leading to lower fit of the model.



**Figure 5.** Plots of (a)  $R^2$ -fit of the model vs. mean annual SAM (1971-2000) and (b)  $R^2$ -fit vs. mean annual range of temperature (highest – lowest monthly normal values (1961-1990)) as a proxy for continentality for the different stations. A linear regression model with mean annual SAM (1971-2000) and the continentality proxy as independent variables, explains 56% of the variance in the  $R^2$  values ( $n = 53$ ). The plots indicate that the model is best fitted for the inner parts of Norway with stable snow conditions during winter, whereas in areas along the coast the fit is worse.

### **4.3 Possible future use of the snow model**

For stations with a limited amount of SAM observations, but extended observations of RR and TAM, the model can be used to estimate missing SAM values. Also the model may be used for homogeneity testing of uncertain SAM series, e.g by splitting the data series in half and evaluate the differences in linear regression coefficients and coefficient of determination ( $R^2$ ). E.g. the station 93300 Suolovuopmi was a precipitation station until it became a full weather station in 1963. As for most stations in Finnmark, Northern Norway, 93300 Suolovuopmi has no observations of snow depths for the latter part of World War II, and it has been discussed if the snow depth measurements are inhomogeneous, as the site of the measurements may have changed and the surrounding buildings certainly have changed after World War II. The rather different results for this station in Table 1 (including only the data from 1963 and on) and in Table 2 (including the whole series from 1906) indicate that there is a homogeneity break at the station. This is supported by Fig. 4c, which shows observed and estimated annual mean snow depth at the station according to the model based upon the entire period. There is a clear tendency that the model underestimates the snow depth before World War II, while it tends to overestimate the snow depth during the later decades.

More importantly, the snow model may be used for projections of future snow conditions (cf. Vikhamar Schuler et al. 2006) if monthly temperature and precipitation scenarios exist. Monthly scenario data are more easily available than daily data, and they may be applied as input data in the snow model as suggested by Hanssen-Bauer (2004).

## **5 Conclusions**

This report describes a simple empirical model for estimating monthly change in mean snow depths with average monthly temperature and monthly precipitation as input variables. The model is developed and tested on station data from mainland Norway and in the Norwegian Arctic. The model is well adapted to stations with a stable winter snow cover in mainland Norway, but is less adapted to stations along the coast and in the Arctic. For stations with an adequate fit, the model can be used to project future snow conditions if monthly temperature and precipitation scenarios exist.

## **6 Acknowledgements**

This study was funded by the Norwegian Research Council through the research projects Éalat (Contract no. 178278) which is part of the International Polar Year programme and NorClim (Contract no. 178246) which is part of the program NORKLIMA.

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## Appendix

### R-script

Below is the listing of the R-script used to derive the results for most of the weather stations (file name is `snomodell_KDVH.R`). Note that the program crashes if one of the temperature classes has no observations, e.g. there are no TAM values below  $-5^{\circ}\text{C}$  for the model period at 60500 Tafjord. In such cases the script needs to be run with fewer threshold temperatures (in the case of 60500 Tafjord  $\text{TT1} = -\text{TT2}$  (1:4)). The R-script used to run the model for precipitation stations (`snomodell_nedbor.R`) is slightly different.

```
library(met.no) # Activates the R-package met.no

library(clim.pact) # Activates the R-package clim.pact

library(stats) # Activates the R-package stats

sink("snomodell5.txt") # Prints the output to a txt-file

stnr <- c(700, 1130, 4780, 6040, 7010, 10400, 18700, 23160, 25590, 25840, 39040, 41110, 42920, 46610,
55290, 58700, 69100, 70850, 89350, 89950, 90450, 93300, 93700, 93900, 97250, 97350, 99710, 99760, 99790,
99840)

for (i in 1:30) {

  print(paste("Stnr =", stnr[i]))

  # Reads TAM, RR and SAM values from the Climate Data Wear House (KDVH)
  obs.TAM <- KDVH4DS(StNr=stnr[i], fom="01.01.1850", param="TAM")
  obs.RR <- KDVH4DS(StNr=stnr[i], fom="01.01.1850", param="RR")
  obs.SAM <- KDVH4DS(StNr=stnr[i], fom="01.01.1850", param="SAM")

  # Replaces negative SAM values with NA
  SAM.error <- obs.SAM$val < 0
  obs.SAM$val[SAM.error] <- NA

  # Calculates dimension of the matrix
  a <- dim(obs.SAM$val)

  # Calculates number of elements in the matrix
  le <- length(obs.SAM$val)

  # Creates a vector of obs.RR$val (obs.RR.v)
  obs.RR.v <- t(obs.RR$val)
  obs.RR.v <- obs.RR.v[1:le]

  # Creates a vector of obs.TAM$val(obs.TAM.v)
  obs.TAM.v <- t(obs.TAM$val)
  obs.TAM.v <- obs.TAM.v[1:le]

  # Creates a vector of obs.SAM$val(obs.SAM.v)
  obs.SAM.v <- t(obs.SAM$val)
  obs.SAM.v <- obs.SAM.v[1:le]

  # Calculates monthly change in SAM
  SAM.change <- rep(0,le)
  SAM.ok <- is.finite(obs.SAM.v)
```

```

nr1 <- (1:le)[SAM.ok][1] # første element med obs for SAM
SAM.change[1:nr1] <- NA
for (i in (nr1+1):le) {
  SAM.change[i] <- obs.SAM.v[i] - obs.SAM.v[i-1]
}

for (i in 1:5) {

print(paste("t=", i))

# Creates constraints on the TAM values
t <- i
cold <- obs.TAM.v < -t
mid <- (obs.TAM.v >= -t) & (obs.TAM.v < t)
warm <- obs.TAM.v >= t
SAM.change.not.zero <- (SAM.change != 0)
data.ok <- is.finite(obs.TAM.v) & is.finite(obs.RR.v) & is.finite(obs.SAM.v) & is.finite(SAM.change) &
obs.SAM.v >= 0
predictor.data.ok <- is.finite(obs.TAM.v) & is.finite(obs.RR.v)

# Creates data frames for predictor og predictand
cal.cold <- data.frame(y = SAM.change[cold & data.ok], x1 = obs.RR.v[cold & data.ok], x2 = obs.RR.v[cold &
data.ok] * obs.TAM.v[cold & data.ok])

cal.mid <- data.frame(y = SAM.change[mid & data.ok & SAM.change.not.zero], x1 = obs.RR.v[mid & data.ok
& SAM.change.not.zero], x2 = obs.RR.v[mid & data.ok & SAM.change.not.zero] * obs.TAM.v[mid & data.ok
& SAM.change.not.zero], x3= obs.TAM.v[mid & data.ok & SAM.change.not.zero])

cal.warm <- data.frame(y = SAM.change[warm & data.ok & SAM.change.not.zero], x1 = obs.TAM.v[warm &
data.ok & SAM.change.not.zero])

# Creates a linear model for the different temperature intervals
lm.cold <- lm(y ~ x1 + x2, data = cal.cold)
lm.mid <- lm(y ~ x1 + x2 + x3, data = cal.mid)
lm.warm <- lm(y ~ x1, data = cal.warm)

for (i in 5:25) {

c3 <- -i # c3 is the melt-rate coefficient

print(paste("c3 =",i))

# Estimates change in SAM
est.SAM.change <- rep(NA,le)
est.SAM.change[cold & predictor.data.ok] <- predict(lm.cold, new.data = cal.cold)
est.SAM.change[mid & predictor.data.ok] <- predict(lm.mid, new.data = cal.mid)
#est.SAM.change[warm & predictor.data.ok] <- predict(lm.warm, new.data = cal.warm)
est.SAM.change[warm & predictor.data.ok] <- c3*obs.TAM.v[warm & predictor.data.ok]

# Finds the first August month with both observations of TAM and RR
predictor.data.aug.ok <- is.finite(obs.TAM$val[,8]) & is.finite(obs.RR$val[,8])
nr2 <- (1:le)[predictor.data.aug.ok][1]
nr2 <- -4+(nr2*12)

```

```

# Estimates SAM
est.SAM <- rep(NA,le)
est.SAM[1:(nr2-1)] <- NA
est.SAM[nr2] <- 0
for (i in (nr2+1):le) {
  not.ok1 <- (est.SAM.change[i] < -est.SAM[i-1]) & !is.na(est.SAM.change[i]) & !is.na(est.SAM[i-1])
  not.ok2 <- is.na(est.SAM.change[i])
  not.ok3 <- is.na(est.SAM[i-1])
  aug <- c(8+(12*(0:a)))
  aug.ok <- is.element(i,aug)
  if(not.ok1) {est.SAM[i] <- 0} else
  if(not.ok2 & !aug.ok) {est.SAM[i] <- NA} else
  if(not.ok2 & aug.ok) {est.SAM[i] <- 0} else
  if(not.ok3 & !aug.ok) {est.SAM[i] <- NA} else
  if(not.ok3 & aug.ok) {est.SAM[i] <- 0} else
  {est.SAM[i] <- est.SAM[i-1] + est.SAM.change[i] }
}

# Plots measured vs estimated SAM
plot(obs.SAM.v,est.SAM, main = paste(obs.SAM$station, obs.SAM$location), xlab="Observed SD (cm)",
ylab="Modelled SD (cm)", col = "blue")

# Adds linear regression line to the plot
cal.SAM <- data.frame(y=est.SAM, x=obs.SAM.v)
lm.SAM <- lm(y ~ x, data=cal.SAM)
abline(a=lm.SAM$coefficients[1], b=lm.SAM$coefficients[2])

# Adds multiple R2 and the sample number
obs.mod.ok <- is.finite(obs.SAM.v) & is.finite(est.SAM)
n1 <- length(obs.SAM.v[obs.mod.ok])
mtext(paste("R2 =",round(summary(lm.SAM)$r.squared,3)," n =", n1))

# Makes matrix of est.SAM (est.SAM.m)
est.SAM.m <- matrix(est.SAM, nrow = a[2], ncol = a[1])
est.SAM.m <- t(est.SAM.m)

# Creates time series of measured and estimated annual mean SAM
an.mean.SAM.ts <- ts(data.frame(obs.SAM = an.mean.SAM, est.SAM =
an.mean.est.SAM), start = obs.SAM$yy[1], end = obs.SAM$yy[1] + a[1] - 1)

# Plots time series of measured and estimated annual mean SAM
plot.ts(an.mean.SAM.ts, plot.type = c("single"), main = paste("Annual mean snow depth,",
obs.SAM$station,obs.SAM$location), ylab="Snow depth (cm)", col =c("blue", "red"), type="o", lwd =1,
pch=19, lty=1:2)
mtext(paste("R2 = ",round(summary(lm.an.mean.SAM)$r.squared,3), " n =", n2))
legend("topleft", legend=c("Observed", "Modelled"), lty=1:2, col = c("blue", "red"), pch=19)

print(paste("R2 =", round(summary(lm.SAM)$r.squared,3), "n =", n1))

}}
sink()

```