Doctoral Thesis

The alpine precipitation climate evaluation of a high-resolution analysis scheme using comprehensive rain-gauge data

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THE ALPINE PRECIPITATION CLIMATE
EVALUATION OF A HIGH-RESOLUTION ANALYSIS SCHEME USING
COMPREHENSIVE RAIN-GAUGE DATA

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Abstract

Spatially high-resolution precipitation data are essential for numerous tasks in civil engineering, for validation of climate and weather forecasting models as well as in hydrology. In this context a climatology of mean annual and mean monthly precipitation for the years 1971-1990 for a greater region of the European Alps (2°E-18°E / 42.75°N-48°N) is presented. For analyzing precipitation, the interpolation scheme PRISM (Parameter-elevation Regression on Independent Slope Model) has been modified, parameterized and applied on a grid of 1.25 minutes (~2 km) mesh width, using a uniquely comprehensive dataset of 6090 stations.

Particular emphasis was given to make best possible use of rain gauge series, even if they did not cover the full time period 1971-1990. These partial time series were extended to the full time period, and the mean values were augmented to achieve bias-free extended time series using a statistical optimal method. Validation showed very accurate reconstructed means, justifying these augmentation procedures.

The prediction intervals of the PRISM regression analyses showed distinct dependencies between network density and prediction interval. Regions with a sparse network revealed larger prediction intervals than regions with a dense network. In sparsely gauged regions, an improvement in the certainty of PRISM’s regression calculation could be achieved by adding additional stations. This finding is especially true for some high mountain areas as the Jungfrau Massif as well as for the Piemonte region in Italy.

The crossvalidation of PRISM for the tuning domain 7°E-10°E / 45°N-48°N yields a bias of -1.2 mm/a, a MAE (mean absolute error) value of 132 mm/a and a RMSE (root mean square error) value of 214 mm/a. The respective relative measures are 1.6% for MRE (mean relative error), 10% for MARE (mean absolute relative error) and 15.6% for RMSRE (root mean squared relative error). Relative to the MAD (mean absolute deviation of the mean) value of 333 mm/a of the data set, the MAE value is at 40%. Therefore, most of the precipitation variability resolved by the station network can be explained by the interpolated precipitation field.

Comparisons of PRISM to a detrended kriging interpolation and a detrended quadrant method, both using an uniform, optimized height gradient of 0.4 (mm/a)/m, were performed. Analyses separated for different height zones showed for the entire height range better results of PRISM and detrended kriging than the detrended quadrant method. PRISM displayed very small bias values for all but the topmost height zone compared to detrended kriging, which is important for model validations and water balance calculations. For a height range 250-1000 m the detrended kriging interpolation exhibited slightly better MAE values than PRISM, but at higher altitudes PRISM performed best. PRISM seems to produce more extreme outliers than kriging which yields rather mediocre RMSE values. Looking at the results of the subdomain validations, PRISM showed better results in regions with a relatively sparse station network than the other methods.
In regions with a very comprehensive station network and large horizontal as well as vertical gradients, PRISM did not perform as well. PRISM showed its power especially in regions which are difficult to model because the influence of topography on precipitation was only partly represented in station data. For these situations PRISM performed considerably better than a detrended kriging interpolation.

Water balance investigations did not lead to unambiguous performance differences between interpolation methods, as the uncertainty in determining the water balance seemed to be bigger than the differences between different interpolation schemes. When applying correction values for gauge biases to precipitation as cited in literature, there was a general tendency to get more areal mean precipitation than the sum of runoff and evapotranspiration, leading to unbalanced water balances.

Experiments with progressively thinned station networks showed distinct differences between PRISM, detrended and non-detrended kriging. Two sets of experiments were conducted, one set with unchanged settings as derived for the full data set; for the second set all considered methods were tuned for a much sparser station network. In these experiments PRISM and detrended kriging showed comparable performance at the various thinning levels provided the parameters of the methods were adapted to the respective station densities. For both experiments, the non-detrended kriging variant performed much worse than PRISM and detrended kriging, which indicates that the good performance of the detrended kriging is only an effect of the unchanged detrending scheme. In the second experiment, a much more robust parameterization could be achieved for PRISM compared to the original setting which tries to smooth noisy data and to achieve stable regression lines. Compared to the real density variations in the Alpine station network which is infrequently sparser than at a thinning of 5 grid cells, the flexibility of PRISM is satisfactory.

Spatially high-resolution precipitation analyses were produced using a very comprehensive dataset. These gridded precipitation fields, spanning national boundaries, can be used for comparing precipitation regimes across the whole Alpine range, calculating water balances and validating numerical climate and weather forecasting models.
Zusammenfassung


Ein spezieller Schwerpunkt wurde auf eine bestmögliche Verwendung der Niederschlagsdaten gelegt, die vielfach nicht die ganze Periode 1971-1990 abdecken. Diese partiellen Zeitreihen wurden auf die volle Referenzperiode verlängert und die Mittelwerte wurden mittels einer statistisch optimalen Methode erwartungstreu gemacht. Die Validierung zeigte präzis rekonstruierte Mittelwerte, was diese Mittelwert-Anpassung rechtfertigt.

Die Vorhersage-Intervalle der PRISM-Regressionsanalysen zeigten deutliche Abhängigkeiten zwischen der Dichte des Stationsnetzes und dem Vorhersage-Intervall. Regionen mit dünnem Stationsnetz zeigten grössere Vorhersage-Intervalle als Regionen mit einem dichten Stationsnetz. In dünnen Stationsnetzen kann demnach durch die Hinzunahme von zusätzlichen Daten eine Verbesserung der Regressionsberechnung von PRISM erwartet werden, was sich vorallem für gewisse Hochgebirgsregionen wie das Jungfraumassif oder für das Piemont auswirken würde.

Die Kreuzvalidierung von PRISM für das Eichungsgebiet 7°E-10°E / 45°N-48°N zeigt einen mittleren Fehler von -1.2 mm/a, einen MAE (Mittlerer absoluter Fehler) Wert von 132 mm/a und einen RMSE (Wurzel des mittleren quadrierten Fehlers) Wert von 214 mm/a. Die entsprechenden relativen Fehlermasse sind 1.6% für MRE (mittlerer relativer Fehler), 10% für MARE (mittlerer absoluter relativer Fehler) und 15.6% für RMSRE (Wurzel des mittleren quadrierten relativen Fehlers). Relativ zum MAD (mittlere absolute Abweichung vom Mittel) der Stationswerte von 333 mm/a ist der MAE-Wert nur 40%. Somit kann der grösste Teil der Variabilität der Stationsdaten durch das interpolierte Niederschlagsfeld erklärt werden.

Vergleiche wurden durchgeführt zwischen PRISM und einer detrended Kriging-Interpolation sowie einer detrended Quadrant-Interpolation, welche beide einen uniformen, optimierten Höhengradienten von 0.4 (mm/a)/m verwenden. In verschiedene Höhenzonen aufgeteilte Analysen zeigten für den gesamten Höhenbereich bessere Resultate für PRISM und für die detrended Kriging-Interpolation als für die detrended Quadranten Methode. PRISM wies sehr kleine mittlere Fehlerwerte auf verglichen mit der detrended Kriging-Interpolation, ausgenommen für die oberste Höhenzone, was wichtig für Modell-Validierungen und Wasserbilanzberechnungen ist. Für den Höhenbereich 250-
1000 m zeigte die detrended Kriging-Interpolation leicht bessere Resultate, jedoch für größere Höhenstufen wies PRISM die besten Resultate auf. PRISM scheint mehr extreme Ausreisser zu produzieren, was zu eher mittelmässigen RMSE-Werten führte. In der Validierung in einzelnen Untergebieten zeigte PRISM in Gebieten mit relativ dünnem Stationsnetz bessere Resultate als die anderen Methoden. Für Regionen mit sehr dichtem Stationsnetz und grossen horizontalen wie auch vertikalen Gradienten waren die Resultate von PRISM nicht ganz so gut. PRISM zeigte seine Stärke vor allem in Gebieten, die deswegen schwierig zu modellierenden sind, weil der Topographie-Einfluss nur teilweise in den Stationsdaten abgebildet ist. In solchen Situationen wies PRISM deutlich bessere Resultate auf als die detrended Kriging-Interpolation.

Wasserbilanz-Untersuchungen führten nicht zu eindeutigen Unterschieden in den Resultaten der einzelnen Interpolationsmethoden, weil die vermutete Unsicherheit in der Bestimmung der Wasserbilanz grösser war als die Unterschiede zwischen den Methoden. Wenn man Niederschlagskorrekturren anwendete wie sie in der Literatur beschrieben sind, war der mittlere Gebietsniederschlag im allgemeinen grösser als die Summe von Abfluss und Evapotranspiration, was zu unausgeglichenen Wasserbilanzen führte.

Experimente mit zunehmend ausgedünnten Stationsnetzen zeigten ausgeprägte Unterschiede zwischen PRISM, detrended Kriging-Interpolation und non-detrended Kriging-Interpolation (Kriging ohne detrending). Zwei Experiment-Reihen wurden durchgeführt, die eine mit unveränderter, aus dem vollem Datensatz abgeleiteter Parametrisierung; für das andere Experiment wurden die verglichenen Methoden für ein stark ausgedünntes Stationsnetz optimiert. In beiden Experimenten schiften PRISM und detrended Kriging für die einzelnen Ausdünnungsstufen ähnlich gut ab, sofern ihre Parameter an die jeweilige Stationsdichte angepasst waren. Die non-detrended Kriging-Interpolation zeigte in beiden Experimenten viel schlechtere Resultate, was darauf hinweist, dass das gute Abschneiden der detrended Kriging-Interpolation nur dem detrending Schema zu verdanken ist. Im zweiten Experiment konnte für PRISM eine deutlich robustere Parametrisierung erreicht werden verglichen zur originalen Parametrisierung, welche versucht, die Daten zu glätten und stabile Regressionsgeraden zu garantieren. Verglichen mit realen Variationen der Stationsdichte im Alpenraum, welche nur selten dünner als für die Ausdünnungsstufe von 5 Gitterzellen ist, ist die Flexibilität von PRISM befriedigend.

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1 Introduction

1.1 Motivation and outline

Monitoring and analysis of precipitation have always been central to mountain meteorology and climatology. Mountain ranges serve not only as important freshwater providers for a wide area that often includes surrounding flatland, but also many natural hazards in mountainous regions are caused or influenced by precipitation. As far back as the 19th century, researchers were interested in the spatial distribution of precipitation of the Alps. The first precipitation map for Switzerland was created in 1870 already (Benteli, 1870), using data from the period 1864-1869 (Fig. 1.1). Since then, ongoing and many-fold research efforts were performed to analyze and understand the Alpine precipitation climate (e.g. Raulin, 1879; Knoch und Reichel, 1930; Ekhart, 1948; Kubat, 1972; Fliri, 1984; Frei and Schär, 1998).

For a variety of planning tasks in civil engineering, agriculture and forestry, accurate knowledge of the spatial distribution and seasonal variation of precipitation is essential. In mountainous regions spatial and temporal variability of precipitation is markedly enhanced, as topography strongly influences precipitation mechanisms (see Chap. 1.2). Therefore sophisticated analyses are required in mountainous regions to provide adequate information. Additionally, geographical information systems (GIS) offer for these planning tasks a new and promising dimension by combining different digitally available
data, increasing the need of digital high-resolution precipitation data. Up to now high-resolution precipitation data for the whole Alpine region was available in digital form only on a 25km-grid provided by Frei and Schär (1998, see also Chap. 2), and there is an urgent need for higher-resolution data sets.

The problem of global climate change (see e.g. IPCC, 1990, 1996; Cebon et al., 1998) has prompted the investigation of climate not only globally, but also for individual regions. Downscaling of global climate change estimates (von Storch et al., 1993) or the detection of climate trends (Frei and Schär, 2001; Widmann and Schär, 1997) need high-resolution, high-quality precipitation data. Recently regional climate models have become increasingly important for global climate change research: Regional process studies investigating changes in hydrological cycle (Heck, 1999) and heavy precipitation processes in an altered global climate (Frei et al., 1998) crucially depend on accurate and thoroughly validated models.

To adequately validate these models, spatially high-resolution, high-quality precipitation data are needed: Validation of precipitation is especially important, because precipitation is probably the most important diagnostic of climate model performance (Hulme and New, 1997). Current regional climate models have spatial resolutions up to about 14 kilometers mesh width, about equal or even finer than the resolution of conventional observational networks in Europe. An appropriate interpolation or analysis scheme should estimate therefore also fine-scale precipitation structures only partly represented in the measured data. These structures are to some extent random due to the complex, feedbacked mechanism of precipitation formation. But the local terrain effects upon precipitation are mostly deterministic and should be considered in the interpolation.

Furthermore the validation of numerical weather prediction models created an enhanced necessity for high-resolution precipitation data, as current operational models reach resolutions of only a few kilometers mesh width. For example, the operational weather prediction model LM (Doms and Schättler, 1999) of the Deutscher Wetterdienst (DWD) has currently a resolution of 7 km, which is planned to be enhanced to 2.8 km soon. Although such models operate on a meteorological time scale, the inspection of their monthly means is important for validation and tuning.

The need for taking topographic dependencies into account when interpolating precipitation data is further increased due to biased networks. There is a significantly biased distribution of precipitation gauges in mountainous regions as most stations are located in valley bottoms or in adjacent forelands. If the vertical distribution of the network differs from the distribution of elevation, and if the measured quantity varies with elevation, any areal statistics based on data from the network will be systematically biased (Briggs and Cogley, 1996). The reason of this biased distribution is obvious: Rain gauges need support throughout the year in order to get reliable measurements, so most stations are placed where people live. High mountainous locations are seldom inhabited the whole year, and are often inaccessible in wintertime because of closed roads or avalanche dan-
ger. Additionally the number of qualified gauge sites in high mountain regions is quite restricted (Wolfensberger, 1994).

For the Alps in particular, the station density at higher altitudes is strongly reduced. In Figure 1.2 the normalized number of stations per height zone is indicated for a typical inner Alpine region. In the left panel the height distribution of the conventional network is shown, on the right totalizers are included. Totalizers are storage gauges usually read once or twice a year (see Chap. 2.2). Above 2000 m virtually no conventional rain gauges can be found, but about 40% of topography is higher than 2000 m in this region. This mismatch is only partly resolved when including totalizer data. Therefore, interpolation methods which do not account for this bias will produce biased areal means in most cases.

Reduced station density in high mountain regions combined with enhanced spatial variability for high altitudes (see Chap. 6.2) become especially important when performing spatial high-resolution analyses. When mapping precipitation climate fields at spatial resolutions close to or finer than the resolution of the observational network, the analysis method should represent local terrain effects upon precipitation. In the present study an analysis method that explicitly considers topographic information is therefore used (see Chap. 1.4 and 3).

In this thesis, a precipitation climatology based on monthly values is presented for the reference period 1971-1990. The analyses are performed for the domain 42.75°N/2°E - 49°N/18°E using a comprehensive network of 6090 stations. In Chapter 1 a motivation and some information related to precipitation and interpolation is given. In Chapter 2 the study domain and the employed data set is presented. Chapter 3 describes PRISM, the used analysis method. Chapter 4 presents some statistical measures as used in this study. In Chapters 5 and 6, the implementation, calibration as well as the validation of PRISM are discussed. Comparisons to other interpolation schemes are presented in Chapter 7. Results for the annual, seasonal and monthly mean precipitation distributions are discussed in Chapter 8, and some conclusions are presented in Chapter 9.
1.2 Topographic influence on precipitation

Mountain ranges such as the Alps act as a strong and permanent modifier of atmospheric circulations on a wide variety of scales (Binder and Schär, 1996). It is therefore evident, that the geographical distribution of climate zones and, in particular, the distribution of precipitation amounts, are highly linked to topography. These links are manifested from the microscale and mesoscale to the planetary scale (for definitions see Orlanski, 1975). Topography induces precipitation variability by means of aerodynamic effects, influences precipitation mechanisms, acts on synoptic systems and plays a major role in steering general circulation. Detailed descriptions of the influence of topography on precipitation can be found for example in Smith (1979), Blumen (1986), Houze (1993), Binder and Schär (1996) and Barry and Chorley (1998).

Here further consideration is given to topographic precipitation mechanisms. Houze (1993) and Smith (1979) state the following mechanisms:

Even very small hills are reported to significantly enhance precipitation due to seeder-feeder effects (Bergeron, 1965; see Fig. 1.3a). By this mechanism, precipitation from the upper cloud is falling through the lower cloud built at the hill location because of upslope airstreams. This falling precipitation can rime small droplets out of the lower cloud. Although the low-level cloud might not precipitate by its own, it can enhance already existing precipitation in an effective way.

![Mechanisms of orographic precipitation](image)

Figure 1.3: Mechanisms of orographic precipitation. (a) Seeder-feeder mechanism; (b) upslope condensation; (c) upslope triggering of convection; (d) upstream triggering of convection; (e) thermal triggering of convection; (f) lee-side triggering of convection; (g) lee-side enhancement of convection. From Houze (1993).

When stable airmasses are forced to rise due of topography, the lifted air expands and thus cools adiabatically. If the air is sufficiently moist, condensation may occur leading
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to precipitation. This upslope rain mechanism (Fig. 1.3b) exhibits highly variable precipitation efficiencies due to its sensitivity to the atmospheric stability and microphysics. It has been shown, that convective enhancements may occur for stable airmasses in such rising air (Browning et al., 1974; Browning, 1980). This means that numerous transitions exist between advective precipitation in stable airmasses and convective precipitation in unstable airmasses.

Topography can trigger convection by various mechanisms (see Fig. 1.3c-g). Some of the rainiest areas of the world, as in monsoonal areas, are dominated by such orographic convection. When potentially unstable airmasses are forced to rise, the initial lifting can start convection (Fig. 1.3c). Because of the self-enhancing mechanisms in convective clouds, small effects can lead to the development of mature convective cells producing large precipitation amounts. Convection can also be triggered upstream of mountains by stretching of the air column when airmasses flow over (Fig. 1.3d). This stretching generates a destabilization of the air column which can trigger convection. It is mostly caused by partial blocking of airmasses by topography. Differential heating in mountainous regions leads to diurnal circulations which may trigger convection, e.g. at the top of mountains (Fig. 1.3e). Convection can also be triggered to the lee of mountains by converging low level flows (Fig. 1.3f). Additionally lee waves induced by flow over a mountain can enhance already existing convective systems (Fig. 1.3g).

1.3 Observed precipitation - topography relationships

Mapping precipitation is still a challenge, despite of all the research and knowledge accumulated in the past. A major reason for this is the small spatial representativity of precipitation point measurements. Small scale experiments show precipitation variations of more than 40% on a distance of 200 m for storm totals (Arazi et al., 1997; Goodrich et al., 1995) due to modification of the windfield by local topography. Although the present study deals with climatological time scales and not in the time scale of single precipitation events, one can not expect that this tremendous variability disappears by fully averaging out (Gutermann, 1974). Some small scale variability will therefore remain also in climatological fields which can not be resolved directly by the station network.

It is thus evident that most analysis algorithms try to use additional information about dependencies of precipitation on topographic parameters to partly resolve these shortcomings. In high mountain regions of the Alps the spatial representativity is even smaller than in flatland (Chap. 6.2), so this demand is augmented. The biased height distribution of rain gauges in the Alps (see Chap. 1.1) requires assumptions to be made about precipitation - height relationships, and in many cases analysis schemes need to extrapolate to altitudes above the highest stations. In this context the analysis of the precipitation - topography relationships is central for precipitation analysis.

Measured precipitation amounts are not only a function of altitude. A lot of other parameters such as station orientation, distance from the mountain crest and meteorological
parameters are reported to correlate notably with precipitation (e.g. Prudhomme and Reed, 1998; Konrad, 1996; Frei and Schar, 1998). Velocity and stability of airmasses and in particular the precipitation mechanisms are of major importance for forming precipitation gradients. For larger precipitation intensities vertical precipitation gradients get generally smaller, and for smaller time periods the correlation of precipitation to these topographic parameters tends to become weaker (Freydank, 1986; Lang, 1985). In situations with pure convection, decreasing altitude gradients are found (Havlik, 1969) due to the preferred location of the convection centres in valleys and flatland and due to the decrease in precipitable water content with altitude. Nevertheless, altitude correlates best with precipitation for most mountainous regions of the world (e.g. Prudhomme and Reed, 1998; Konrad, 1996; Basist et al., 1994; Schermerhorn, 1967).

![Diagram of precipitation gradients](image)

**Figure 1.4:** Typical dependencies of annual precipitation (x-axis) with altitude (y-axis) in Switzerland (Schüpp et al., 1978). Three regions are shown: Northern rim of the Alps (curve “NE-Schweiz”), central parts of the Alps (curve “Wallis”) and southern part of the Alps (curve “Tessin”).

In the Alps regionally different vertical precipitation gradients can be found. As a generalized depiction, typical dependencies of annual precipitation with altitude in Switzerland are shown in Figure 1.4. The northern border of the Alps displays large gradients at low altitudes becoming smaller with height (curve “NE-Schweiz” in Fig. 1.4). The central parts of the Alps exhibit weak gradients in lower altitudes, which increase at high altitudes (curve “Wallis” in Fig. 1.4 as an example). These increasing gradients are due to shadowing: low level air masses have already lost a substantial part of their moisture when passing the first mountain ridges and descending into the central valleys, and only the highest mountains can condense moisture out of the air stream. The southern part of the Alps shows small or partially even slightly negative gradients (curve “Tessin” in Fig. 1.4) due to often convectively dominated precipitation formation and low level jets dur-
Precipitation gradients with height can be misleading sometimes. When comparing precipitation values, the stations do not only have different heights, but they also have different locations. This means that one can not properly distinguish between horizontal and vertical precipitation gradients. The resulting gradient will therefore differ with different station selection, as shown in Chapter 1.6. This effect has also to be considered when interpreting Figure 1.4. For these curves the horizontal distances between the used stations are quite large (typically ~50 km), but nevertheless the qualitative information is in agreement with Lauscher (1976) and gradients as analyzed by PRISM in the present study (Chap. 8.1).

A long-standing controversy is the question of the height zone of maximum precipitation in the Alps (Schlagintweit und Schlagintweit, 1854; Erk, 1887). This altitude depicts the topmost altitude from where precipitation always decreases with height. From a theoretical point of view, there has to exist such a maximum of precipitation because of the exponentially decreasing water vapour pressure (Havlik, 1969). In the Alps this zone seems to be considerably higher than in other parts of the world (Lauscher, 1976), but the verification is hard because of the lack of precipitation measurements above 3000 m. The consensus is to guess this zone at the topmost mountain crests, at a level of about 3500 m (Blumer, 1994; Fliri, 1975; Havlik, 1969).

1.4 Interpolation and analysis methods

For transforming point measurements to areal information and for calculating point estimates at any desired ungauged points, a range of different interpolation and analysis methods are used.

One of the first important studies in this field originated with Meinardus (1900), who developed the concept of introducing pseudo stations on a regular grid, for which he subjectively estimated values. Drawing isolines and calculating areal means then becomes simple.

Another important concept was introduced by Thiessen (1911), who assigns weights to the individual stations depending on their representativity when calculating areal means. However he did not provide an objective algorithm for determining these weights, which was later done by Horton (1923). For point estimates the method of Horton (1923) corresponds to the simple nearest neighbor method.

The concept to use anomaly fields for interpolation probably appeared with Peck and Brown (1962). By eliminating the nonlinear dependencies between precipitation and topography for each station, they obtained new station values with smaller overall variability than for the original values. By drawing isolines by hand, these modified values could be then interpolated with higher accuracy. Thereupon, the precipitation-topography relationship was added again to the interpolated field. This method is often also
called “detrending” or “residual interpolation”.

All modern, state-of-the-art interpolation methods include all or most of these three above-mentioned concepts. The interpolation to a regular grid became very popular because of its simplicity when using computers. The estimation of the station weights to compute point and areal estimates became sophisticated and led to numerous different methods. The method of interpolating anomaly fields is frequently used, too. This method generally yields better results when calculating cross validation statistics than a normal two dimensional analysis (Odeh et al., 1995; Chua and Bras, 1982), often because of biased station distribution (see Chap. 1.1). To apply domain-wide relationships for the calculation of the anomaly field, it should be carefully ensured that this relationship shows good agreement in all parts of the domain. Application of this method to regions showing weak or systematically different relations between precipitation and topography can lead to erroneous results. Evidently for biased networks, different height gradients lead to systematic differences in areal means of the resulting interpolation.

For analysis in global or large-scale networks, a modified version of the interpolation method SYMAP (Shepard, 1968) is often used. SYMAP is based on a inverse distance algorithm: Surrounding stations are weighted according to their inverse distance to the interpolated point. Additionally a directional weighting is applied, so clustered stations get reduced weights. Willmott et al. (1985) extended this method for explicitly taking into account the spherical shape of the earth. Applications can be found in Frei and Schär (1998), Legates and Willmott (1990) or Rudolf et al. (1992).

Nowadays, Kriging is probably one of the most popular methods for the interpolation of climate fields. It minimizes the squared differences between the smooth surface of the expected value of the interpolated field and the station values by applying a weighted least square technique. The weights are assigned by a generalization of the covariance structure of the data, which describes the inter-station correlation as a function of distance. For this generalization usually a function with mostly 2 parameters is fitted to the covariance data. This method was developed originally for mining purposes by Krige (1966) and further developed by Matheron (1971), for a detailed description see Delfiner and Delhomme (1975) or Bastin et al. (1984). Some applications can be found in Freydank (1986), Creutin and Obled (1982), de Montmollin et al. (1980) or Kirchhofer und Sevruk (1992a; 1992b). A variety of different variants of kriging are known. This is primarily due of different statistical assumptions or properties: e.g. ordinary kriging, simple kriging, universal kriging or block kriging. As an alternative to applying kriging to height-detrended fields, a multivariate extension of kriging known as cokriging can be used. This method takes into account additional fields correlated to the precipitation field (see e.g. Phillips et al., 1992).

Thin plate smoothing splines (Wahba and Wendelberger, 1980) is formally similar to kriging (Hutchinson, 1998). A spline surface is interpolated by minimizing the squared residuals as well as the local curvature of the surface at the station locations. This method
therefore tries to fit a maximally smooth surface to the measured data. Its main advantage is, that just one parameter, the smoothing parameter, has to be estimated instead of analyzing the whole covariance structure as in case of kriging. This parameter has no physical meaning though and is usually determined by minimizing the generalized crossvalidation. A limitation is the possibility of exact interpolation at the station locations. The interpolated field then looses its smoothing quality and shows a wavy, physically meaningless surface exactly matching all station values. The only possibility to correct this seems to be to successively remove stations until this effect disappears (Hutchinson, 1998). Applications can be found in New et al. (1999) or Hutchinson (1998).

A very interesting method is AURELHY (Analysis Using RELief for HYdrometeorology; Benichou et Le Breton, 1987; Benichou, 1994). The basic idea of this method is to take into account the possible relationships between the field to analyze and the regional topography. Topography is analyzed by means of principal component analysis (PCA) of 11 by 11 neighboring gridpoints (50 km by 50 km) for the whole domain. Then, for a greater subdomain a multilinear regression of precipitation against the significant principal components is calculated. This relationship is used for detrending the station values. Finally, the residuals are interpolated with kriging. This method has the advantage that the principal components are uncorrelated and that there are thus no statistical restrictions for calculating multilinear regressions. AURELHY has been extensively used for mapping of climate parameters (Reklip, 1995; Klein, 1994; Direction de la Météorologie Nationale, 1988).

The analysis procedure being considered in this study is the regression-based model PRISM (Parameter-elevation Regression on Independent Slope Model), specifically developed for climate mapping over complex topography (Daly et al., 1994). The model applies weighted linear regressions with elevation as a predictor to localized regions, considering local topographic attributes. PRISM is a combined statistical-geographical approach to mapping climate. By setting numerous specific parameters, the user can feed in his knowledge of the local climate. It strictly works in localized regions and is therefore flexible in dealing with spatially variable precipitation properties. It models precipitation shadows and sharp transitions in a reasonable way by giving high weights to stations with similar topographic properties as the modeled grid cell. A more detailed description of PRISM can be found in Chapter 3.

All the above mentioned methods, except AURELHY and PRISM, have the potential drawback of relying directly on the measured data for representing spatial variability. When the station network is not representative for the actual precipitation field, the resulting field may be biased (Daly et al., 1994). AURELHY assumes constant relationships between precipitation and topography for a larger subdomain. Most interpolation methods using detrending make domain-wide assumptions about precipitation - height relationships. PRISM in contrast analyses the relationships between precipitation and topography in a strictly local way.
1.5 Existing precipitation maps of the Alps

Although the need for Alpine-wide precipitation maps is apparent, only very few maps exist. Most existing high-resolution precipitation maps are focused on national boundaries, small regions or river catchments. Some recent local high-resolution maps are listed in Table 1.1.

At the European scale, Steinhauser (1970) presents mean monthly and mean annual precipitation maps on a scale of 1:10'000'000 and 1:5'000'000 for the time period 1931-1960. These maps give a good overview of the European precipitation distribution, but are too generalized for detailed studies of individual European regions.

Table 1.1: Recent local high-resolution maps for different regions of the Alps.

<table>
<thead>
<tr>
<th>Region / Country</th>
<th>Reference</th>
<th>Stations, Period, Scale, Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>Steinhauser (1954)</td>
<td>1415, 1901-1950</td>
</tr>
<tr>
<td>France</td>
<td>Direction de la Météorologie Nationale (1988)</td>
<td>ca. 1500, 1951-1980, 1:1'800'000, AURELHY method</td>
</tr>
<tr>
<td></td>
<td>Direction de la Météorologie Nationale (1969)</td>
<td>1921-1950, 1:2'500'000</td>
</tr>
<tr>
<td>Germany</td>
<td>Schirmer (1978)</td>
<td>ca. 4000, 1931-1960, 1:2'000'000</td>
</tr>
<tr>
<td>Italy</td>
<td>Mori (1969)</td>
<td>ca. 2400, 1921-1950, 1:2'500'000</td>
</tr>
<tr>
<td>Switzerland</td>
<td>Uttinger (1967)</td>
<td>820, 1901-1940/1931-1960, 1'800'000</td>
</tr>
<tr>
<td></td>
<td>Kirchhofer und Sevruk (1992a)</td>
<td>ca. 400, 1951-1980, 1:500'000, bias corrected data, elevation detrended kriging, uniform height gradient</td>
</tr>
<tr>
<td>Slovenia, Croatia, Dinaric Ridge</td>
<td>Rankovic (1980)</td>
<td>1931-1960, 1:1'000'000</td>
</tr>
<tr>
<td>Rhein catchment</td>
<td>KHR (1977)</td>
<td>ca. 1800, 1931-1960, 1:2'150'000</td>
</tr>
<tr>
<td>Danube catchment</td>
<td>Stancik et al. (1988)</td>
<td>1931-1970, 1:2'000'000</td>
</tr>
<tr>
<td>Tirol</td>
<td>Fliri (1969)</td>
<td>1931-1960, 1:600'000</td>
</tr>
</tbody>
</table>

Baumgartner et al. (1983) produced the only high-resolution climatic maps of the entire Alpine region. They created a map of mean annual precipitation for the time period 1931-1960 on a scale of 1:500'000 by assembling existing local precipitation maps (Uttinger, 1967; Direction de la Météorologie Nationale, 1969; Kern, 1971; Steinhauser,
1954; Mori, 1969; Frosini, 1961; Rankovic, 1980; Fliri, 1969). The transitions between
the individual local maps were adapted by adjusting the differences in mean precipitation
caused by the different reference periods and by applying the same vertical gradients at
the border regions of the adjacent maps. Finally the mean precipitation of individual
regions was adjusted to satisfy the water balance, which implies some indirect correc¬
tions of the gauge biases (Chap. 2.5). Because of this assembling, the local qualities of
this precipitation map depend on the individual maps used for mapping. In Chapter 8.2
some comparisons of the present study to the map of Baumgartner et al. (1983) will be
made.

In general the map of Baumgartner et al. (1983) displays large vertical gradients and very
high precipitation amounts at high altitudes. Based on the map of Uttinger (1967), the
map of Baumgartner et al. (1983) depicts precipitation amounts of more than 3200 mm
for the mountain crest between Valais and the Aosta Valley. Mori (1969) finds for this
crest peak values below 2000 mm. In the Carnic and Julian Alps Baumgartner et al.
(1983) present values of more than 4000 mm. The corresponding maps of Rankovic
(1980) and Mori (1969) only exhibit maximum values of about 3500 mm and 3000 mm,
respectively. Stancik et al. (1988) even estimates maximum values of little more than
2500 mm in this region, and Kolbezen (1998) draws it’s highest isoline at 3200 mm.
These remarkable differences in the Carnic and Julian Alps exist although the maps of
Kolbezen (1998) and Stancik et al. (1988) are adjusted to balance the water balance as
well. Likewise at the Western Alps, Baumgartner et al. (1983) exhibits considerably
more precipitation than the corresponding local maps (Mori, 1969; Direction de la
Météorologie Nationale, 1969 and 1988) at high altitudes.

For the rest of the Alpine region and for low altitudes, the differences are smaller, as all
local high-resolution maps correspond well with the map of Baumgartner et al. (1983).

In contrast to the shortcoming of Alpine-wide precipitation maps, comprehensive clima¬
tological precipitation analyses exist for the Alps, describing seasonality, variability and
dependencies to different weather situations for individual Alpine regions. In a succes¬
sion of long-standing research on the Alpine precipitation climate, important contribu¬
tions were made by Fliri (1974, 1984) and recently by Frei and Schär (1998).

1.6 Horizontal vs. vertical precipitation gradients

When analyzing precipitation fields, a multitude of systematic trends and dependencies
at local and regional scales can be noticed. It is useful therefore, to try to use these
dependencies for improving interpolation algorithms. And as altitude often correlates
best of all topographic parameters with precipitation, many interpolation algorithms
exploit this dependency. But it is quite decisive for the resulting interpolation fields in
which manner these dependencies of precipitation to altitude are analyzed and used for
the interpolation algorithm. In this section the sensitivity of the estimated height gradi¬
ents is investigated with respect to the selection of the used stations. It will provide a
motivation for a local regression approach with careful consideration of station representativity.

From a statistical point of view, only by topography resolved and unresolved precipitation variability can be distinguished. Topography can resolve topographically induced precipitation variability when the topographic variability is represented in the station network. Therefore the relation of the network density to the mesh width of the analysis is decisive: When the station network is dense enough for the chosen grid cell resolution of the interpolation, and the station network is unbiased, the variations of precipitation caused by topography are represented such that the analysis value at the grid cell is representative for the mean of the grid cell. Then most of the precipitation-altitude dependency is resolved. But if the grid cell size is much smaller than the mean inter-station distance, or if the network is strongly biased, some unresolved variability caused by local topography remains.

From a climatological point of view, one can distinguish between regional (meso-beta-scale, 20-200 km) and local (meso-gamma-scale, 2-20 km) gradients and the gradients can be addressed consequently as a scale issue. On a regional scale, correlations can be found to a distance to the coast or to a mountain ridge, or gradients are referred to transitions of climatic regimes. On a local scale, gradients are related to processes of precipitation generation and precipitation deposition and to local shadowing effects.

When considering gradients to improve analysis algorithms, the concept of horizontal and vertical gradients is typically used because of its simple implementation and conceptual simplicity. The horizontal and vertical gradients can not be separated in a non-ambiguous way, however: The stations used for determining these gradients have horizontal distances as well as vertical height differences from each other. When analyzing horizontal gradients, stations at different altitudes can bias these gradients. But the opposite case is much more important: Vertical gradients are very much dependent on the horizontal distribution of the stations used for analysis. Thus, this ambiguity of separating horizontal from vertical gradients is a fundamental problem, which is especially important when extrapolating to very high or low altitudes, or when horizontally extrapolating to ungauged areas. In these cases, a precise knowledge of the separation of the gradients is essential.

To illustrate the sensitivity of the determination of vertical gradients to the station selection, a simple experiment was performed: In a region of relatively simple topographic structure, analyses with varying numbers of stations per regression are conducted, and the resulting areal means of vertical gradients as well as the mean correlation coefficients of the regression are compared.
Figure 1.5: Chosen domain 11°E-13°E / 46.85°N-49°N for the sensitivity experiment. The right panel is a zoom of the domain marked with the black frame in the left panel. Crosses mark conventional rain gauges, diamonds mark totalizers.

Figure 1.6: Mean annual precipitation 1971-1990 [mm], as analyzed by PRISM. The chosen domain 11°E-13°E / 46.85°N-49°N is located in the westerly part of Austria and in the south-eastern part of Germany (see Fig. 1.5). The northern ridge of the Alps shows here an east-west orientation and no low mountain ranges are located to the north of the main Alpine ridge. The precipitation distribution (Fig. 1.6) presents mainly east-west oriented structures as well. The southern border of the domain lies in the inner
Alpine dry zone.

In this domain, narrow, west-east oriented strips are chosen, within which vertical precipitation gradients are calculated. By varying the width of these strips, the number of stations that enter the regression calculation changes. Figure 1.7 shows the vertical precipitation gradients as a function of latitude. The gradients of curve 1 are calculated using a strip width of 0.25°, for the gradients of curve 2 a strip width of 1° was used. This corresponds to a mean number of stations per regression calculation of 42 and 160 stations, respectively. The resulting curves are vastly different. Curve 1 shows two maximum values of 0.85 (mm/a)/m and 0.96 (mm/a)/m at 47.9° and 49° latitude and a minimum value of -0.43 (mm/a)/m at 48.75°. In contrast curve 2 has a minimum of -0.13 (mm/a)/m at 47.25° and a maximum value of 1.64 (mm/a)/m at 48.2° latitude. It is obvious therefore that these extremely different gradients will lead to huge differences in precipitation estimation when applying these regressions to extrapolate to very high or very low altitudes.

The largest differences in vertical gradients occur for the zone 48° to 48.75° latitude at the northern slope of the Alps. Here the two sets of gradients differ by more than 0.7 (mm/a)/m. Further analyses reveal a very systematic dependency: For the whole zone, regression calculations using more stations lead to larger gradients.

An explanation for these huge and systematic differences in the determination of the vertical gradients is as follows: This domain shows a strong regional precipitation gradient in north-south direction. The northern part is relatively dry with precipitation values of about 700 mm/a. To the south precipitation is increasing and reaches its maximum of
about 2000 mm/a at the northern rim of the Alps. In a regression calculation for a single strip, this north-south gradient loses its spatial information and is interpreted as a vertical gradient. The resulting vertical gradient is enhanced or reduced depending on the sign of the correlation between larger-scale precipitation and larger-scale altitude. When increasing the width of these strips, the influence of this horizontal gradient on the regression calculation will augment, leading to these systematic dependencies.

Following this argument, it is preferable to choose the stations used in the regression calculation in a region as small as possible. The larger the radius of influence, the more pronounced the possible influence of these horizontal gradients. Of course, the individual regression calculation will become more random when considering just a few stations per regression, and the variability of the vertical gradients from strip to strip is enhanced. The solution for this could be a spatial smoothing of the obtained gradients before doing any further processing rather than considering more stations per regression.

Figure 1.8: South-north cross-section of mean precipitation, derived from regression values at DEM (digital elevation model) heights using the two vertical precipitation gradients of Figure 1.7. The line without markers indicates the mean height of the topography (right y-axis).

These differences in gradients have also influences on analyzed precipitation values. In Figure 1.8, mean precipitation is calculated by taking the regression line value at the mean height of a digital elevation model (DEM) of 1.25 minutes mesh width. This is performed for the two sets of gradients determined in Figure 1.7. The two resulting cross-sections show large differences in mean precipitation amounts by up to 300 mm/a. Note that the precipitation values reveal a varying sensitivity to the variation of the vertical gradients. Although the gradients of the two sets show vast differences on the northern slope of the Alps, the resulting precipitation differences are rather small. In contrast, the zone 47.5° to 48° depicts small differences between the two sets of gradients, yet the cor-
responding precipitation estimates are vastly different. This is since not only the gradient, but also the intercept value of the regression line are influencing the resulting precipitation estimate.

The experiments performed in this section are not at all suitable for determining the correct vertical precipitation gradients nor can these findings be generalized in a quantitative way. Nevertheless also other domains show strong dependencies of a similar kind can be found leading to the conclusion that an appropriate choice of the stations for regression calculation is of major importance and that this choice not only influences the local precipitation distribution, but can also systematically affect estimates of areal mean of precipitation.
2 Study domain and precipitation data

2.1 Study domain

Figure 2.1 shows a physiographic map of the domain under consideration (2°E-18°E / 42.75°N-49°N). It encompasses the whole Alpine massif and some of the surrounding forelands and low mountain ranges. The Alps are the most dominant mountain range in Europe, involving 9 different countries (France, Switzerland, Liechtenstein, Germany, Austria, Slovenia, Croatia, Italy, Monaco). The Alpine ridge is arc-shaped with a west-east extension of about 800 km and a typical width of about 200 km. It shows a mean height of 2500 m, with mountain peaks going up to 4800 m. Several low mountain ranges (primarily Schwarzwald, Vosges, Jura, Massif Central and Appennino) surround the Alps with typical heights of 1000-1500 m. Some locations of major geographic features are shown in Figure 2.2.
2.2 Data set description

Conventional rain gauge data

Collecting measured data in Europe is a difficult job and requires a great amount of time (see Hulme, 1994). Nevertheless Frei and Schär (1998) gathered 9546 stations with daily precipitation data for the Alpine region. The present study is primarily based on this data set. Data are mainly provided by national weather and hydrological services (see Tab. 2.1), and covers the time period 1971-1990 (see Frei and Schär, 1998, for a detailed description).

The data set exhibits numerous stations having incomplete time series, mainly for the countries of Italy, Croatia and Slovenia. Less than 3000 stations show time series without any missing daily values for the entire period 1971-1990. It was decided therefore to apply a data gap filling procedure as described in Chapter 2.3. As a result 5831 stations can be used over the whole period, forming a extremely comprehensive data set with a mean station density of about 1 station per 100 km$^2$, or 10 km as a mean inter-station distance. The resulting station network of conventional rain gauges is shown in Figure 2.3. Compared to other mountainous regions of the world, this is a uniquely dense station network.

As shown in Figure 2.3, the northern and western part of the domain has an extremely dense station network. To the south of the Alps some regions show sparse coverage, especially in the central and western Po Valley. Slovenia and Croatia show quite a homogeneous station density, but here the density is much lower compared to the northern side.
Study domain and precipitation data

of the Alps.

Table 2.1: Listing of data sets, providers and quality status. Datasets indicated with "totalizers" are monthly or annual data, the other datasets are daily data.

<table>
<thead>
<tr>
<th>Data sets: Region</th>
<th>Number of stations</th>
<th>Quality status</th>
<th>Data sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>1006</td>
<td>tested (status 1/95)</td>
<td>Hydrogr. Zentralbüro Wien, ZAMG, Wien</td>
</tr>
<tr>
<td>Switzerland</td>
<td>549</td>
<td>tested</td>
<td>MeteoSchweiz, Zürich</td>
</tr>
<tr>
<td>Germany, south of 49 N</td>
<td>930</td>
<td>tested spatial consistency</td>
<td>Deutscher Wetterdienst, Offenbach a. M.</td>
</tr>
<tr>
<td>France, south of 49 N, east of 2 E.</td>
<td>2492</td>
<td>tested, after 1972</td>
<td>Météo-France, Toulouse</td>
</tr>
<tr>
<td>Northern Italy, north of 43.5 N</td>
<td>508</td>
<td>partly tested</td>
<td>Servizio Idrografico e Mareografico Nazionale, Venezia, Parma, Roma</td>
</tr>
<tr>
<td>Northern Italy</td>
<td>66</td>
<td>range test only</td>
<td>Ufficio Centrale Ecologia Agraria, Roma</td>
</tr>
<tr>
<td>Northern Italy and Bosnia</td>
<td>52</td>
<td>not tested (SYNOP data)</td>
<td>Seewetteramt, Hamburg</td>
</tr>
<tr>
<td>Croatia</td>
<td>162</td>
<td>partly tested</td>
<td>Meteorol. and Hydrol. Service, Zagreb</td>
</tr>
<tr>
<td>Slovenia</td>
<td>66</td>
<td>partly tested</td>
<td>Hydrometeorological Institute, Ljubljana</td>
</tr>
<tr>
<td>Switzerland (totalizers)</td>
<td>144</td>
<td>tested</td>
<td>MeteoSchweiz, Zürich, METEODAT GmbH, Zürich</td>
</tr>
<tr>
<td>Austria (totalizers)</td>
<td>115</td>
<td>tested</td>
<td>Hydrogr. Zentralbüro Wien, ZAMG, Wien</td>
</tr>
<tr>
<td>Total: Pluviometers</td>
<td>5831</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total: Totalizers</td>
<td>259</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For Italian and SYNOP data (data that is regularly exchanged among the national weather services), location information was sometimes found to be doubtful, and some systematic checks were conducted: Comparisons to an alternate meta-data set provided by the project DAQUAMAP (Data Quality Monitoring in MAP [Mesoscale Alpine Program]: C. Häberli, 1999, pers. comm.), automatic comparisons to meta-data from the GEOnet Names Server (http://164.214.2.59/gns/html/index.html) and height comparisons between digital terrain data and the station height. This resulted in several corrections of station coordinates and altitudes.

In addition to the quality tests run by the data providers (see Tab. 2.1), the original daily precipitation data were checked by Frei and Schär (1998) with range and spatial consistency tests. These led to the exclusion (but not the correction) of suspicious data. Only about 1 per 10‘000 daily values where excluded by these tests. The resulting data gaps
are addressed in the data gap filling procedure described below.

In the Alpine region several types of rain-gauges are utilized. In Austria, Germany and Switzerland various types of the Hellmann rain-gauge (gauge orifice of 200 cm$^2$) are widely in use, and in France the SPIEA rain-gauge (gauge orifice of 400 cm$^2$) is very common. In general, no allocation of rain-gauge types to a individual rain-gauge station is known.

**Totalizer data**

Despite the comprehensive size of the conventional data set, there is not enough information at high altitudes, as there are hardly any conventional stations above 2000 m (see Fig. 1.2). To partially compensate this lack of measurements at high altitudes, totalizer data were also included. Totalizers are storage gauges designed for remote and high mountain areas and are read normally once or twice a year, sometimes also monthly. Their data quality is less certain, but nevertheless they can give good indications of the expected precipitation amounts in regions where no other information is available (see also Chap. 2.5).

For this study Swiss and Austrian totalizer data is utilized (see Tab. 2.1). Most of the Austrian totalizer data has been digitized manually from printed yearbooks. A total of 259 totalizers are used, whereof 85 Austrian stations provide monthly values. The remaining totalizers only measure annual totals. The locations of the totalizers are highly clustered (see Fig. 2.4), because they are mostly installed by hydroelectric power companies for water management purposes. These totalizers are mostly placed in remote, high-mountain areas: The mean height of the totalizers is about 2200 m, and the highest totalizer (Mönchsgrat) exhibits an altitude of 3810 m (see Fig. 2.5).
While creating precipitation maps with PRISM, special attention was given to the quality of totalizer data. Spatial plausibility in combination with information about possible errors from Wolfensberger (1994) led to some corrections in observed precipitation amounts.

### 2.3 Data gap filling and augmentation

Although the station database was very comprehensive in general, some regions exhibited many stations that do not cover the full period 1971-1990, mainly in Italy. Excluding all stations with incomplete time series would result in poor station density for these
regions. In this case less than 3000 stations could have been used, and more than 3000 stations had to be dropped.

Using partially available station records as representative for the mean precipitation may lead to shifts in the mean values, questioning the use of these data. Some global precipitation analyses used station records with only vague restrictions to a common measurement period (e.g. Legates and Willmott, 1990), valuing spatial density higher than temporal comparability, whereas others are strictly using a common time period (e.g. New et al., 1999). The decision whether to prefer spatial density over temporal comparability is dependent on the considered region: Europe shows little interdecadal variability in precipitation at a regional scale and therefore spatial resolution is of major importance here (Hulme and New, 1997).

Additionally the effect of spatial aliasing can become important in sparse climatological networks (Robeson and Janis, 1998). Like the well known temporal aliasing in time series analysis, spatial aliasing can sophisticate the interpolation process by transferring unresolved small-scale information to the larger scale of the station network (see Fig. 2.6).

![Figure 2.6: Hypothetical example of aliasing in a spatial cross-section. Dashed line: true variation. Solid line: aliased interpolation using the provided stations (dots). From Robeson and Janis (1998).](image)

From these points of view, it is important to consider as many stations as possible without changing the areal means too drastically. In this study, data gaps were thus filled on a monthly basis and incomplete time series were extended to the full period using nearby stations.

The basic idea of the applied reconstructions is that neighboring stations show similar temporal variations of the precipitation values as the target station, although they may have different mean values. The best correlating neighboring station is chosen to supply the temporal variations for the data gaps. Then the mean values of these temporal variations are adapted to fit into the time series of the target station. For this adjustment an augmentation procedure according to Vogel and Stedinger (1985) is used, which provides an optimal, unbiased maximum likelihood estimator for the mean value of the full
time period of the reconstructed time series.

This augmentation of the reconstructed monthly values \( y_i \) has the following scheme:

\[
y_i = \frac{\mu_y}{\bar{x}_3} \cdot x_i
\]

with:

- \( y \): time series to be extended
- \( x \): time series used for extension = reference record
- \( \mu_y \): estimation of the mean value of the full record to be extended
- \( \bar{x}_3 \): mean value of the full reference record
- \( \bar{y}_1, \bar{y}_2 \): mean values of the common period, for the reference and extended record
- \( \bar{x}_2 \): mean value of the non-common values of the time series used for extension
- \( n_1 \): number of values of the common period
- \( n_2 \): number of missing values in the time series to be extended
- \( \rho \): correlation between the two time series \( x \) and \( y \) for the common time period
- \( \beta \): regression coefficient of the equation \( y = \bar{y} + \beta(x - \bar{x}) \)

and:

\[
\mu_y = \bar{y}_1 + \Theta \cdot \frac{n_2}{n_1 + n_2} \cdot \beta \cdot (\bar{x}_2 - \bar{x}_1)
\]

\[
\Theta = \frac{(n_1 - 3) \cdot \rho^2}{(n_1 - 4) \cdot \rho^2 + 1}
\]

\[
\rho = \frac{\sum_{i=1}^{n_1} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n_1} (x_i - \bar{x})^2 \cdot \sum_{i=1}^{n_1} (y_i - \bar{y})^2}}
\]

\[
\beta = \rho \cdot \frac{\sum_{i=1}^{n_1} (y_i - \bar{y})^2}{\sum_{i=1}^{n_1} (x_i - \bar{x})^2}
\]

When the correlation of the reference record to any of the neighbor stations is poor, an alternate method is used: For interpolating a missing data value, a simple inverse distance interpolation is applied, adapting the means as described below in point 7. This alternate method was chosen in about 8% of all months where data gap filling was necessary.

In detail, the following procedure has been applied to stations with incomplete time series:

1) Only stations with time series of at least 4 years out of 20 years are considered for extension. Shorter time series are disregarded.
2) The gap filling procedure is applied on a monthly basis. For each monthly value to be filled, time series of the 3 directly surrounding months are built for the target station itself, as well as for all nearby stations in a radius of 0.6 degrees. E.g. when calculating a fill value for a February, time series consisting of the months January, February and March are constructed.

3) For all these nearby stations, correlations to the target time series are calculated.

4) If the best correlation is better than 0.75, this best correlating station is taken as a reference for the extended time series.

5) For adapting the mean of the common partial time series, an unbiased maximum likelihood estimator of the new mean value \( \mu_n \) is used (see Eq. (2)), as described in Vogel and Stedinger (1985). The interpolated value \( y_i \) is given then following Equation (1).

6) When \( n_1 < 10 \) or \( n_2 < 6 \), the following simple adaptation of the mean is applied, because of robustness reasons. Only the common time period is used for adjusting the time series:

\[
y_i = \frac{\bar{y}}{\bar{x}} \cdot x_i
\]  

7) If the best correlation coefficient is less than or equal 0.75, each missing monthly value is reconstructed by applying an inverse distance interpolation to the relative anomalies \( x_i / \bar{x}_1 \). For this inverse distance interpolation a quadrant interpolation with 8 stations and an exponent of 1.5 was chosen. This quadrant method selects in each quadrant of the compass the 2 closest stations and uses them for interpolation. For details see Chapter 7.1.

### 2.4 Validation of the data gap filling procedure

In each box of 0.5x0.5 degrees of the whole domain a station with a complete time series was chosen for validation, resulting in 79 considered stations. For these stations the accuracy of the used data gap filling method was investigated. The second 10 years of each time series were reconstructed just using the first 10 years and the surrounding station network. The used statistical measures are explained in Chapter 4.

The achieved results are promising: Although the individual months sometimes show large discrepancies between original and reconstructed time series, the reconstructed mean and standard deviation of the time series show good agreement with the original values.

In Figure 2.7, the validation for the mean of all 79 stations is presented. The reconstructed monthly mean shows a marginal deviation from the true monthly mean of only -0.52 mm. Compared to the difference between the 2 decades of 6.3 mm, this error is small. Also the individual mean months are well reconstructed, which show errors typically smaller than 5 mm. The mean absolute error (MAE) for this mean monthly reconstruction is only 2.2 mm. So the data gap filling procedure seems to preserve the overall areal mean very well. But also the individual stations show in nearly all cases better esti-
mates of the mean as would result from just taking the mean of the first 10 years. In Figure 2.8 an example of an individual station is shown. It exhibits some months with poor reconstruction, but the estimated mean is very accurate (difference of -1.3 mm/month) and the mean shift of 15.5 mm/month between the two decades is well represented.

Figure 2.7: Comparison of the true (solid) and the reconstructed (dotted) mean monthly time series of 79 stations. The second half of the time series is reconstructed from the first half using the surrounding stations. In the lower panel, the differences between the two time series are shown.

Figure 2.8: As Figure 2.7, but for a single station: Bourg-de-Sirod.

In Figure 2.9 a scatterplot of the true and reconstructed differences between the mean values of the first half ($\mu_1$) and the second half ($\mu_2$) of the time series is displayed for all 79 stations. The error in reconstruction ($\mu_{2,\text{rec}} - \mu_{2,\text{obs}}$) for the individual stations can be
seen in the difference between the y-values and the diagonal. It displays an bias of -0.52 mm/month and an MAE value of 4.4 mm/month. The values are grouped quite close to the diagonal and no systematic dependencies can be found.

![Figure 2.9:](image)

Figure 2.9: Differences of the mean of the second half of the time series (\(\mu_2\)) minus the mean of the first half of the time series (\(\mu_1\)), both for true (x-axis) and reconstructed (y-axis) time series. Values are in mm/month.

![Figure 2.10:](image)

Figure 2.10: Differences of the mean of the whole time series (\(\mu_3\)) minus the mean of the first half of the time series (\(\mu_1\)), both for true and reconstructed time series, in mm/month. On the left for reconstruction after Vogel and Stedinger (1985), on the right for reconstruction using an inverse distance interpolation.

Next we test the performance of the simplified scheme as described in Chapter 2.3, step 7, as 2 of the 79 stations in the above experiment are partly reconstructed using the inverse distance interpolation. To this end, the performance of the augmentation after Vogel and Stedinger (1985) and the augmentation using inverse distance interpolation are analyzed separately (Fig. 2.10). The augmentation is the difference of the mean value
of the whole period ($\mu_3$) to the mean value of the existing period ($\mu_1$), which is thus for this experiment exactly half as large as the values in Figure 2.9. The method after Vogel and Stedinger (1985) ($\text{Bias} = -0.3 \text{ mm/month}, \text{MAE} = 2.2 \text{ mm/month}$) performs slightly better than the quadrant method ($\text{Bias} = -0.5 \text{ mm/month}, \text{MAE} = 2.5 \text{ mm/month}$).

### 2.5 Precipitation gauge errors

Point precipitation measurements are afflicted with a variety of potential measurement errors. Wind induced errors, wetting losses, evaporation out of the gauge, splashing losses and snowdrift can markedly influence precipitation measurements (Sevruk, 1982). Mainly two sources can lead to large systematic errors: deformation of the wind field and snowdrift. A precipitation gauge influences the local wind field and the hydrometeors are deflected in such a way, that less of these particles are falling into the gauge (Nespor, 1995; Nespor and Sevruk, 1999). This yields an undercatch of up to several 10%, depending on wind speed, drop-size distribution and fall velocity of the hydrometeors. Large undercatches occur for high wind speed, small droplets and for snowflakes (Sevruk, 1985). Moreover comparisons to snow measurements are indicating large gauge errors in wintertime (Steinegger, 1997).

![Figure 2.11: Height dependency of gauge correction estimates [%] in Switzerland for summer and winter season. Big points indicate exposed gauge sites, small points indicate sheltered gauge sites. From Sevruk (1985).](image)

Snowdrift can be very important as an error source in high mountain regions. Here snow is falling mostly at temperatures well below zero degrees in wintertime. The specific weight of fresh snow is very low, typically below 100 kg/m$^3$ (Rohrer, 1992). This can
yield to large wind induced undercatches. On the other hand, fresh snow is very mobile and may easily be raised again from the ground into the atmosphere, whereupon is may be caught by the precipitation gauge. When temperatures stay below freezing, snow may remain mobile for days and weeks. For instance Førland (1996) reported 190 mm “precipitation” in 3 days due to snowdrift. In the Alps some totalizers are assumed to be affected by snowdrift, a few probably even overestimating precipitation (Steinegger, 1997; Müller-Lemans et al., 1993; Wolfensberger, 1994).

For wind-induced undercatch, detailed correction schemes were developed (e.g., Sevruk, 1982; Førland, 1996). Correction is mainly dependent on site exposure, mean wind speed, gauge type and percentage of snowfall. This information is often unknown. Only in rare occasions, also wind speed is measured at the same location. For the data set used in this study, neither site exposures, nor wind informations, nor gauge types are known in general. For Switzerland, Sevruk (1985) has determined correction estimates for 64 stations (Fig. 2.11). They show a general increase with altitude, but have great variability, especially at higher altitudes. As a general guideline, Sevruk and Zahlavova (1992) have provided generalized correction estimates for wind induced gauge losses (see Tab. 2.2). It is obvious therefore that correction schemes based on altitude alone are not appropriate, and that a treatment using detailed station meta-data is required.

<table>
<thead>
<tr>
<th>Region</th>
<th>Exposure class</th>
<th>1*</th>
<th>2*</th>
<th>3*</th>
<th>4*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>less windy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lowlands</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summer</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Winter</td>
<td>8</td>
<td>18</td>
<td>6</td>
<td>14</td>
<td>5</td>
</tr>
<tr>
<td>Mountains</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summer</td>
<td>11</td>
<td>25</td>
<td>8</td>
<td>19</td>
<td>6</td>
</tr>
<tr>
<td>Winter</td>
<td>27</td>
<td>59</td>
<td>22</td>
<td>50</td>
<td>16</td>
</tr>
</tbody>
</table>

For errors caused by snowdrift, very little quantitative information is available. For daily read precipitation gauges, some plausibility checks using weather information can be conducted. But for totalizers read once or twice a year no correction procedure seems to be feasible. As indirect measures of the plausibility of such gauges, only water balance investigations can be conducted (see Chap. 7.5). An appropriate choice of gauge sites is of primary importance therefore. In high-mountain regions, the number of qualified sites is quite restricted, however (Wolfensberger, 1994).

In summary, large negative as well as positive gauge errors from a variety of sources are possible. These can be partially corrected provided appropriate meta-data are available. For the present study, no useful meta-data were disponible and therefore no corrections were applied.
3 PRISM

3.1 Introduction

PRISM (Parameter-elevation Regression on Independent Slope Model) is an analytical model developed for producing climate maps. It interpolates irregularly distributed station values to a regular fine mesh grid. This grid then can be easily plotted by an external tool.

PRISM applies weighted linear regressions with height at each grid point. The main focus of the routines is to choose the representative stations and their appropriate influence on the regression line. Validation shows that the selection of stations with similar topographic characteristics is of major importance (see Chap. 5) for having good performance. Additionally, selecting unsuitable sets of stations can lead to systematic errors in calculating precipitation gradients and therefore to different area means of precipitation (see Chap. 1.6).

By applying regressions with height, PRISM explicitly takes into account topography and is therefore especially suitable for mountainous regions such as the Alps. All interpolation is done locally, so PRISM is very flexible concerning spatially variable precipitation properties. PRISM performs therefore much better than two dimensional interpolation schemes (see Chap. 7).

PRISM was originally developed for producing precipitation climate maps (Daly and Neilson, 1992). Since then, it was generalized and can be applied now to virtually any climate parameters (Daly et al., 1994). It has been used extensively to map precipitation, temperature, maximum and minimum temperature, dew point, freeze-free season length, growing degree days and other parameters over the United States, Canada and other countries (e.g. Huffman et al., 1997; see also the PRISM-homepage http://www.ocs.orst.edu/prism). A current project is to produce peer-reviewed, “official” precipitation maps for all 50 states of the United States (Bishop and Church, 1995; Daly et al., 2000).

The sequence of calculation as implemented in PRISM is as follows: Appropriate stations are selected for calculation of the regression line. Weights for each of these stations are determined, and the regression line is calculated by minimizing the weighted squared residuals. Then, the regression line value at the grid cell height is taken as the raw interpolation value. Finally, a postprocessing is applied, which removes too large height gradients between neighbor cells.

PRISM itself includes no plotting routines, but produces data files which can be easily imported into plotting tools such as GIS programs. One of the specialities of PRISM is a graphical user interface (GUI), which makes the mapping procedure very transparent and yields to a better tuning of the parameters. Beyond that, PRISM serves also as an excel-
lent tool to observe and understand different climate regimes and helps a lot in finding erroneous data points.

The objective of this section is to give a short overview of PRISM and its governing equations. Chapter 3.2 describes the mechanism of selecting stations for use in the interpolation scheme, Chapter 3.3 explains the regression weights, Chapter 3.4 presents some examples of the weighting scheme, Chapter 3.5 gives an overview of the different programs of PRISM, Chapter 3.6 describes the postprocessing and Chapter 3.7 describes the GUI.

### 3.2 Station selection and topographic facets

For almost any mountain ridge, relationships between the climatic fields and the topographic features can be found (see also Chap. 1.3). PRISM uses this basic rule and selects the representative stations for the target grid cell (cell for which interpolation is done) by their topographic similarity. For this purpose, the concept of topographic facets is used. Facets are defined as single connected domains with the same topographic orientation. These facets are calculated for 6 different smoothing levels of the topography. With a sophisticated algorithm, the grid cells are grouped to domains of equal orientation. PRISM distinguishes 8 points of the compass and a flat class (see Fig. 3.1). For choosing the appropriate stations, PRISM starts at the facet set with the weakest smoothing level and collects the stations which are on the same facet as the target grid cell.

![Facet orientations for the Alpine region at a medium smoothing level (low pass filtering at a wavelength of ca. 20 km).](image)

As long as the minimum number of stations for the calculation of the regression line is not reached, the smoothing level is increased when collecting stations. If the minimum number of stations isn't reached even at the highest smoothing level, the closest stations regardless of the facet orientation are additionally chosen. These stations obtain weak weights for the regression calculation, however. Three parameters can be set for adjust-
ing the selection process: maximum and minimum number of stations and a minimum search radius. Within this minimum search radius, all stations are selected regardless of the topographic orientation.

3.3 Weighted linear regressions

PRISM uses a weighted linear regression as the core function of the interpolation scheme. The data points get weights according to the representativeness of their topographic regime compared to the modeled grid point. With these weights, the regression line is calculated, and the resulting regression line value at the grid point height serves as the raw interpolation value.

The resulting gradient can be limited by upper and lower limits. This avoids unreasonable gradients in situations with weak correlations. Too large or too small gradients are set then to a default gradient.

In PRISM, a linear regression function is chosen, although often nonlinear dependencies are showing the best fits when analyzing local precipitation height relationships. As shown in Chapter 1.3, different nonlinear precipitation gradients occur in different regions of the Alps. But sometimes these dependencies with height are quite weak and therefore the calculation of nonlinear regressions with variable shapes can lead to very unstable results, especially for extrapolations to very high or low altitudes. The reason is, that there is at least 1 more free parameter which has to be determined for nonlinear regressions which makes the result less stable.

But PRISM is also capable to deal with nonlinear dependencies by applying piecewise linear regression lines. This is done by enhancing the weights of stations horizontally and vertically close to the target grid cell. The regression line will therefore be dominated by those stations, which leads to height gradients appropriate to the localized region of the target grid cell.

At first glance, multilinear regressions seem to be very promising, because they are capable of explaining more of the variability of the data than simple regressions. But in case of horizontal or vertical extrapolation, they fail completely. The regression parameters are not independent and hence multiple solutions of the equation are possible. In case of extrapolation, this leads to undetermined results. So when applying gradients with height, the only reasonable choice seems to be linear regressions.

The resulting weight $W$ for a given station is given as a function of weights due to factors contributing to the representativity of a station for the interpolation point:

$$W = \sqrt{F_d W_d^2 + F_z W_z^2} \cdot W_l \cdot W_f \cdot W_p$$

(7)
with:

\[
\begin{align*}
W_d & \quad \text{horizontal distance weight} \\
W_z & \quad \text{elevation difference weight} \\
W_c & \quad \text{cluster weight} \\
W_l & \quad \text{layer weight} \\
W_f & \quad \text{facet weight} \\
W_p & \quad \text{proximity weight} \\
F_d, F_z & \quad \text{importance factors}
\end{align*}
\]

Most of these factors are normalized individually over all stations, so the weighting is not heavily dependent upon scaling units. Finally the resulting weights are again normalized. The importance factors control the importance of horizontal distances in relation to vertical distances. Values for the parameters used in this study can be seen in Table 5.1 in Chapter 5.

### 3.3.1 Distance weighting

Stations close to the target grid cell are more meaningful and therefore receive a higher weight than remote stations.

The distance weights \( W_d \) are given as follows:

\[
W_d = \begin{cases} 
1000 &; d \leq 0.001 \\
1/d^a &; d > 0.001 
\end{cases}
\]

where \( d \) is the distance between the station and the target grid cell in cell units, and \( a \) is the distance weighting exponent. The weights are then normalized to sum 1.

### 3.3.2 Elevation difference weighting

Stations at a similar altitude as the target grid cell receive more weight than others. This allows to calculate appropriate regressions even when nonlinear precipitation gradients with height occur by emphasizing the relevant height zone.

The elevation difference weighting \( W_z \) is given as follows:

\[
W_z = \begin{cases} 
1/\Delta z_m^b &; \Delta z \leq \Delta z_m \\
1/\Delta z^b &; \Delta z > \Delta z_m 
\end{cases}
\]

\( \Delta z \) is the absolute elevation difference between the DEM elevation of the station and the target grid cell. \( b \) is the elevation difference weighting exponent and \( \Delta z_m \) is the minimum elevation difference. The weights are then normalized to sum 1.
3.3.3 Cluster weighting

When stations are unevenly distributed in space, the clustered stations possess redundant information and therefore one should reduce their weight. The threshold distance for being recognized as clustered is chosen as a function of the distance to the target grid cell and also as a function of the elevation difference between the possibly clustered stations. The cluster weight \( W_c \) for station \( i \) is calculated as:

\[
W_c = \frac{1}{1 + \sum_{j \neq i} \max\left(\frac{R^2 - d_{ij}^2}{R^2}, 0\right) \cdot \max\left(\frac{\Delta z_p - |\Delta z_{ij}|}{\Delta z_p}, 0\right)}
\]

\( \Delta z_p \) is the minimum elevation difference (in meter) for clustering and \( \Delta z_{ij} \) the height difference between two stations. \( R = r_c r_x \) is the minimal horizontal distance for clustering (in grid cells) with \( r_c = 0.2 \) and \( r_x \) the maximum distance of all chosen stations to the target grid cell, and \( d_{ij} \) is the distance between two stations.

3.3.4 Layer weighting

In PRISM, there is a possibility of setting two layers for calculation of gradients, for example for regions with a low altitude of maximum precipitation as on Hawaii or for interpolation of temperature fields with temperature inversions in the valleys. In these two layers, the gradients are calculated independently, just keeping the connection of the two regression lines. Some crosstalk between the two layers is allowed by applying the following layer weights:

\[
W_l = \begin{cases} 
1 & \text{if } \Delta l = 0 \\
\frac{1}{\max((\max(|\Delta z| - \Delta z_m, 0))^y, 1)} & \text{otherwise}
\end{cases}
\]

\( \Delta l \) is the layer difference (0 for the same layer, 1 when in a different layer), \( \Delta z \) is the elevation difference in meter between the station and the target grid cell, \( \Delta z_m \) is the minimum elevation difference for layer weighting, and \( y \) is the layer weighting exponent. There is an option allowing PRISM to reduce \( y \) itself when including stations from the other layer does not lead to a too large increase in the MAD (mean absolute deviation; see Chap. 4) of the regression line. This allows a varying amount of crosstalk according to the local differences of the properties of the two layers. The algorithm of reducing the exponent is explained in Chapter 3.3.5. In this study, layer weighting is not used (see Chap. 5).

3.3.5 Facet weighting

As already mentioned in Chapter 1.4, PRISM uses the concept of facets to choose which stations to consider for calculating the regression lines. Stations on the same facet receive full weight, stations on other facets get reduced weights. Additionally, barriers on
the straight line between the station and the target grid cell are considered. The facet weights $W_f$ are defined as follows:

$$W_f = \begin{cases} 1 & : B \leq B_x \text{ and } |\Delta f| \leq 1 \\ \frac{1}{\max(|\Delta f| + B, 2)^c} & : \text{else} \end{cases}$$

(12)

$\Delta f$ is the orientation difference between the station and the target grid cell in units of numbers of sectors of the compass, $B$ is the number of barriers (cells with orientation other than the target cell) on the straight line between the station and the target grid cell, $c$ is the facet weighting exponent, and $B_x$ is the maximum number of allowed barrier cells. This formula is dependent on the mesh width of the grid, so tuning is necessary when changing the resolution. Like the layer weighting, it’s also possible to allow PRISM to reduce the exponent $c$, when the inclusion of stations not on the same facet as the target cell is not enlarging the MAD of the regression residuals by more than a factor of 2. This implies a recursive approach: Using first guesses for the weights and calculating the regression lines for two cases: with all stations and just with stations on the same facet as the target grid cell. Then, the two resulting MAD’s of the regression lines are compared. If $\text{MAD}_{\text{all}} \leq 2 \times \text{MAD}_{\text{facet}}$ then the facet exponent is set to a fraction of the original value:

$$c_{\text{new}} = c \cdot \max\left(1 - \frac{\text{MAD}_{\text{facet}}}{\text{MAD}_{\text{all}}}, 2, 0\right)$$

(13)

This facet weighting accommodates sharp transitions between different precipitation regimes. As an example, a discussion of regressions for two different locations are shown in Chapter 3.4.

### 3.3.6 Proximity weighting

In ungauged or sparse gauged regions, there is often a problem in portraying the knowledge of the climatic behavior into the interpolation procedure. This knowledge can be a horizontal precipitation gradient such as the proximity to a mountain ridge, to the coast or to the border of the interpolation domain. For these situations, a proximity weight allows to the user to indicate which pixels are considered to have similar values. For this purpose, a user defined proximity field can be set up, which indicates the level of similarity. This field is used then for selecting stations as well as for calculating proximity weights $W_p$:

$$W_p = \frac{1}{\max(|\Delta p|^v, 1)}$$

(14)

$\Delta p$ is the difference of the proximity field values of the station and the target grid cell and $v$ is the proximity weighting exponent. The weights are then normalized to sum 1. In this study, no proximity weighting is used.
3.4 Examples of the weighting scheme

The mechanism of the weights in the regression calculation is illustrated in the Figures 3.2 and 3.3. Two regression lines are calculated for two interpolation sites on either sides of a mountain ridge. Figure 3.2 shows a sample regression line on the north side of the ridge. There are clearly two different sets of stations, quite a few wet stations and 6 dryer stations. These 6 stations are the ones on the southern side of the ridge. Because they are on the wrong side of the mountain crest, a lot of barrier cells are between these stations and the target grid cell. Additionally, their facet orientation is completely opposite the target grid cell. They therefore get very small weights and have virtually no influence on the regression line. If these two sets of stations would be treated equally, the regression line would become much steeper.

![Figure 3.2: Example of a regression calculation on the northern slope of the mountain ridge at the location of the black cross (arrow). The white crosses localize the used stations. In the lower part a visualization of the regression calculation is shown. The size of the dots corresponds to their overall weight for the regression.](image)

Just a few kilometers to the south, on the other side of the mountain crest, the situation is completely reversed (see Fig. 3.3). The 7 wet stations on the northern side of the ridge obtain very small weights, whereas the stations in the valley bottom and on the southern
flank dominate the regression line. The two dry high-altitude stations located to the very south of the domain receive likewise small weights because of their reversed orientation.

Figure 3.3: Example of a regression calculation on the southern slope of the mountain ridge at the location of the black cross (arrow), a few kilometers to the south of the location of Figure 3.2.

3.5 The model suite PRISM

PRISM is actually a suite of programs (see Fig. 3.4). The program LATTICE filters the topography to the desired resolution and selects the desired region. FACET builds the topographic facets for 6 different smoothing levels of the topography. ASSAY is a cross-validation tool which helps in determining the best input parameters for PRISM. PRISM is the actual core of the model and calculates the weighted linear regressions and resulting predictions. POLISH does some postprocessing, and GISLINK and MIRROR produce output files in desired formats.
3.6 Postprocessing

The regressions are calculated completely independently for each grid cell. Therefore some inconsistencies with the original PRISM parameter setting can occur. In a postprocessing routine, these interpolated values are then adapted. When the normalized precipitation gradients between neighbor cells are falling outside specified thresholds, their precipitation values are centered recursively as long as there are slopes outside of these thresholds. This results in a slight smoothing in zones with large horizontal gradients and removes singular peaks in the interpolated field. Since two adjacent grid cells are linearly adjusted to fit the thresholds, the areal mean values are not changed. Additionally, some smoothing is applied in flatlands so spotty values can be removed which have no relation to topography. In regions which are not completely flat, no additional smoothing is applied.
3.7 Graphical User Interface

PRISM has a sophisticated Graphical User Interface (GUI) based on Tcl/Tk. It can run the model chain and the setting of parameters in an interactive way. But the main advantage is its cell mode, which allows calculation of single selected grid cells. For these calculations, the regression line with its involved stations is plotted, and the station properties as well as the regression properties are displayed in great detail. In Figure 3.5 a screenshot of the zoom window with its integrated regression line plot is shown. In the upper part, a zoomed area of the computational region is shown with topography as background. The black cross is the location of the target grid cell, the white crosses are the selected stations. In the lower part, the regression line is shown. The radius of the dots corresponds to their weight for the regression calculation. The point which is surrounded with a square is the interpolated value of the regression line at the height of the target grid cell.

Figure 3.5: Screenshot of the zoom window of the PRISM graphical user interface (GUI) with zoomed area and a regression line plot.
A station monitor shows all the information about the used stations (see Fig. 3.6). The name, height and coordinates as well as their facet orientation and the number of barrier cells between the station and the target grid cell are indicated.

In the messages window (see Fig. 3.7) all relevant information about the interpolation process are given. The different weights are listed for every station, as well as the regression statistics and details concerning the station selection procedure.
4 Validation statistics

For validation purposes, several statistical measures are used in the present study. In Chapter 4.1 these measures are briefly listed and explained. In Chapter 4.2 a description of the procedure of crossvalidation is given, which is used in the present study for tuning and validation purposes.

4.1 Statistical measures

In the present study, 2 types of measures are used, deviation measures and error measures. For their descriptions, the following definitions are used:

\[ n \] Number of validation stations
\[ \bar{x} \] Mean value of the considered true values
\[ x_i \] True value at station \( i \)
\[ \hat{x}_i \] Estimated or interpolated value at station \( i \)

4.1.1 Deviation measures

Deviation measures describe the data variability of a single dataset. When compared to error measures, these can be used for their normalization.

MAD

The mean absolute deviation (MAD) describes the first order deviation from the mean. It is a commonly used measure to describe precipitation data. Extreme values are not amplified so strongly as with the standard deviation (SDV) measure and therefore individual extreme values are not dominating the statistics.

\[ \text{MAD} = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}| \] (15)

SDV

The standard deviation (SDV) is a common measure in statistics. It is defined as the second order deviation from the mean. It is more strongly influenced by extreme values than the MAD measure.

\[ \text{SDV} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2} \] (16)

Quantiles

Quantiles are a robust description of the data variability of a dataset in the sense that outliers have only marginal influence on the measure. The \( q\% \)-quantile is defined as the value for which \( q\% \) of all values in the dataset are smaller. In an upward sorted array this
corresponds to the \((q\%*n)\)-tieth value. If this index is not matching a whole number, then generally a linear interpolation between the values of the indices above and below is applied. In the present study quartiles and deciles are used. The lower quartile corresponds to the 25%-quantile, thus it denotes the value which is smaller than 75% of all values and larger than 25% of all values, the upper quartile vice-versa. Accordingly, the first decile is defined as the 10%-quantile, and the ninth decile as the 90%-quantile.

4.1.2 Error measures

Error measures describe the differences between two different datasets. In crossvalidations (see Chap. 4.2), they are used to compare the true, measured dataset to the estimated or interpolated dataset. In this study absolute as well as relative error measures are used. The latter are defined to isolate the main sources of error, as they downweight differences of stations with large true values compared to stations showing small values.

**Bias**

The bias indicates the difference between the mean values of an interpolated and a true dataset, and hence it describes the systematic error of interpolation.

\[
\text{bias} = \frac{1}{n} \sum_{i=1}^{n} (\hat{x}_i - x_i)
\]  

(17)

**MAE**

The mean absolute error (MAE) is a first order error measure. It is commonly used to describe the errors of an interpolated precipitation dataset. Extreme values are not amplified so strongly as with the root mean squared error (RMSE) measure and therefore few extreme errors are not dominating the statistics.

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\hat{x}_i - x_i|
\]  

(18)

**RMSE**

The root mean squared error (RMSE) as a second order error measure is more strongly influenced by extreme differences than the MAE measure.

\[
\text{RMSE} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\hat{x}_i - x_i)^2}
\]  

(19)

**MRE**

The mean relative error (MRE) is the relative variant of the bias measure. As large precipitation values generally show larger errors than small values, the MRE measure partially compensates this dependency and downweights large values in respect to small values.
MRE = \frac{1}{n} \sum_{i=1}^{n} \frac{\hat{x}_i - x_i}{x_i}

MARE

The mean absolute relative error (MARE) is the relative counterpart to the MAE measure. It is given as follows:

MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{x}_i - x_i}{x_i} \right|

RMSRE

The root mean squared relative error (RMSRE) is the relative variant of the RMSE measure. It is defined as follows:

RMSRE = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{\hat{x}_i - x_i}{x_i} \right)^2}

4.2 Crossvalidation

Crossvalidation is a common way to validate interpolated fields. The concept of this validation is an interpolation at the location of a station without using the station value itself. This is done for many or all stations, so the differences between original and interpolated station values can be statistically analyzed, for example by applying the error measures of Chapter 4.1.2.

In this study two versions of crossvalidation are used: Crossvalidation without replacement and jackknife crossvalidation. Crossvalidation without replacement performs an interpolation with a reduced set of stations used for interpolation. The stations that are not used for interpolation are validated using error measures. This concept is used for the experiments with thinned station networks (Chap. 7.6). The jackknife crossvalidation method in contrast removes only one station out of the dataset and calculates an interpolation value at the station location. For subsequent interpolation steps, the station is put back into the set of stations used for interpolation. This validation is done for all stations, so for each station an interpolation value can be provided using for interpolation an almost original set of stations. Then, the differences to the true values are analyzed using error measures. The jackknife crossvalidation procedure is used in Chapter 5.1 to tune PRISM and in Chapter 5.3, 6.3 and 7 to assess the performance of PRISM.
5 PRISM-specific implementation and calibration

5.1 PRISM parameters

In this chapter the application of PRISM to the Alpine region is shown, and the PRISM settings used and their sensitivity are documented. The used statistical measures are described in Chapter 4.

As described in Chapter 2, precipitation data for a wide area of the Alps was used for analysis. In this domain a range of different precipitation regimes occur, showing very localized features. Because of the uniquely comprehensive dataset and the observed small scale precipitation features, it was decided to apply PRISM on a 1.25 minutes grid (ca. 2 km) instead of a 2.5 minutes grid as usually used by PRISM. PRISM was mainly designed using a 2.5 minutes grid and some parameters are not independent of the grid size. For this smaller grid much less experience in tuning of the parameters is available and therefore a systematic investigation of the parameter settings had to be performed.

Table 5.1: Most important PRISM settings as used for the Alpine region. The symbols in brackets are given as used in Chapter 3.3.

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
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<tr>
<td>iprecision</td>
<td>25 m</td>
<td>Station elevation precision</td>
</tr>
<tr>
<td>ibuf_elev (\Delta z_m)</td>
<td>50 m</td>
<td>Buffer for maximum elevation weighting</td>
</tr>
<tr>
<td>levsta</td>
<td>400 m</td>
<td>Max. DEM-station elevation difference</td>
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<td>default slope, normalized</td>
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<td>blmina</td>
<td>-10%/km</td>
<td>Minimum slope, normalized</td>
</tr>
<tr>
<td>bimaxa</td>
<td>200%/km</td>
<td>Maximum slope, normalized</td>
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<td>0 cells</td>
<td>Maximum facet barrier cells treated as no barrier</td>
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<td>Distance weighting exponent</td>
</tr>
<tr>
<td>exp_lev (b)</td>
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<td>Elevation weighting exponent</td>
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<tr>
<td>exp_fac (c)</td>
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<td>b_lev (F_g)</td>
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<td>Elevation weighting importance factor (b_lev=1-a_dis)</td>
</tr>
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<td>c_fac</td>
<td>0.05</td>
<td>Max. relative facet parameter variability</td>
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<td>Radius of influence</td>
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<td>minsta</td>
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</tr>
<tr>
<td>isubfac_pr</td>
<td>20</td>
<td>Minimum number of stations in regression</td>
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</table>

In Table 5.1 the most important parameters and their settings as used in this study are
listed. For each of these parameters, sensitivity plots were produced: With the program ASSAY, jackknife-crossvalidation calculations were performed. For each station of the regarded domain, an interpolation to its location is accomplished without the use of the respective station. The resulting differences at each station location are then statistically validated. These analyses were performed for different parameter settings, yielding sensitivity information for the particular parameter.

The jackknife crossvalidations are performed for the domain 7°E-10°E/45°N-48°N. This tuning domain covers most of Switzerland and some surrounding foreland to the north and the south, including 852 stations (see Fig. 5.1). It is considered to contain most precipitation features of the whole domain, but emphasizing the characteristics of the central Alps. In this tuning domain also the higher zones of the Alps are sufficiently represented, in terms of number of rain gauges as well as in terms of number of grid cells of topography (Fig. 5.2). When tuning PRISM using the entire domain, the flatland stations would be clearly over-represented, and therefore regions easy to analyze would dominate validation. On the respective sensitivity plots, normalized values of the mean absolute error (MAE) as well as of the root mean squared error (RMSE) are shown. Normalization was achieved by dividing by a default value. Below the parameters listed in Table 5.1 are further explained.

![Figure 5.1: Domain 7°E-10°E / 45°N-48°N with underlying topography as used for tuning.](image)

The parameters used by PRISM are not independent from each other and therefore tuning can not be done in straight forward way. Starting from a default setting, the parameters were changed iteratively unless good performance as well as climatologically meaningful precipitation distributions were achieved. For checking the meaningfulness particular regions were regularly compared with existing precipitation maps and individual regression lines were inspected using the PRISM GUI.
Station elevation precision (iprecision):

This parameter indicates the expected uncertainty of the provided station heights. Station height differences smaller than this value are considered as null. Large values of this parameter help taming of the regression line when very small height differences produce large precipitation gradients. In the used domain there were no such problems and iprecision was kept small and set to 25 m. Figure 5.3 shows a moderate increase of the MAE and RMSE statistics for larger iprecision values.

Buffer for maximum elevation weighting (ibuf_elev, \( \Delta z_m \)):

Stations with height differences to the target grid cell larger than this buffer get reduced weights in the regression calculation. Keeping this parameter small enables PRISM to
adapt easily to nonlinear precipitation gradients. But as Figure 5.4 shows, performance is considerably better for higher values. Nevertheless it was decided to choose a small value for ibuf_elev, because several cases were found were stations at high altitudes were receiving insufficient weights because of the biased vertical station distribution. Especially at the mountain crest between the Valais and the Aosta Valley, dry stations at medium altitudes were over-represented and dominated the regression lines. Single, mostly wet stations at high altitude were not able to influence adequately the regression line.

![Sensitivity plot for the parameter ibuf_elev. Plotted is the relative change in performance of MAE and RMSE, normalized for ibuf_elev=50.](image)

**Maximum DEM-station elevation difference (levsta):**

PRISM generally uses DEM elevations at the location of the stations as input for the regression line. When this height differs too much from the actual station height, the difference will be limited to the value of levsta. This has been changed (see Chap. 5.2 for details): In the original version the used height is set to the station height when the difference exceeds the value of levsta, because then the DEM elevation is considered as being not representative.
In Figure 5.5 the improvement of using DEM heights instead of stations heights can be clearly seen. When setting levsta to 0, always station heights are used, and the performance is much worse than for large levsta values. For levsta values larger than 400 m, the performance becomes nearly constant. Some particular examples show however an improvement when limiting this height difference. Some totalizers located in mountain valleys with DEM heights much higher than the actual station heights exhibited low precipitation amounts due to shadowing and fitted much better in the overall regression line when the used heights approached the actual station heights.

**Normalized default gradient for the regression line (db1a):**

When a regression line is out of the allowed thresholds, a default gradient is used instead. As a change to the original version of PRISM, two different default gradients are used (see Chap. 5.2 for details), one at the middle of the minimum threshold and the default gradient, and the other at the middle of the maximum threshold and the default gradient. This yields some tuning problems because the two default gradients are depending on the default gradient db1a as well as on the maximum and minimum thresholds. PRISM uses normalized gradient parameters because of its reduced variability. To get the absolute gradient values, they have to be multiplied by the mean precipitation of the stations used for regression calculation. The sensitivity plot in Figure 5.6 was produced using -10%/km as minimum threshold and 200%/km as maximum threshold. The differences in performance seem to be rather small, but it has to be considered that only about 5% of all regression calculations are using a default gradient, and 95% of the jackknife-crossvalidated stations are unaffected by the change of the default gradients. The default gradient db1a seems to have its optimum in the range of 20%/km to 50%/km and is set to 30%/km in this study.
Figure 5.6: Sensitivity plot for the parameter db1a. Plotted is the relative change in performance of MAE and RMSE, normalized for db1a=0.3 (± 30%/km). Changing the upper and lower thresholds also influences the default gradient, see text.

**Normalized minimum gradient for the regression line (b1mina):**

Precipitation gradients lower than this minimum threshold are considered erroneous and are set to a default gradient of (b1mina+db1a)/2. The performance as shown in Figure 5.7 is extremely sensitive to the choice of this minimum gradient, but it has to be considered that for high values of b1mina much more grid cells are set to a default gradient than for low values. Therefore the sensitivity is increased for high values by more grid cells being involved.

Figure 5.7: Sensitivity plot for the parameter b1mina. Plotted is the relative change in performance of MAE and RMSE, normalized for b1mina=0.1 (± 10%/km). Changing this parameter influences also the default gradient, see text.
Normalized maximum gradient for the regression line ($b_1 \text{max}_a$):

Precipitation gradients higher than this maximum threshold are considered erroneous and are set to a default gradient of $\frac{(b_1 \text{max}_a + \text{db}1_a)}{2}$. In contrast to the minimum boundary, the maximum gradient seems to be insensitive (see Fig. 5.8).

![Figure 5.8](image)

**Figure 5.8:** Sensitivity plot for the parameter $b_1 \text{max}_a$. Plotted is the relative change in performance of MAE and RMSE, normalized for $b_1 \text{max}_a = 2.0$ ($\approx 200\%$/km). Changing this parameter influences also the default gradient, see text.

Maximum facet barrier cells treated as no barrier ($\text{maxbar, } B_x$):

![Figure 5.9](image)

**Figure 5.9:** Sensitivity plot for the parameter $\text{maxbar}$. Plotted is the relative change in performance of MAE and RMSE, normalized for $\text{maxbar} = 0$.

When checking for stations on the same facet as the target grid cell, up to $\text{maxbar}$ cells of
other facets are allowed to be on the direct line from the target grid cell to the station. Otherwise the station receive a reduced facet weight. This parameter controls for facets being twisted, e.g. when running from one valley into another. The performance of MAE gets a little worse with increasing maxbar value (see Fig. 5.9). On the contrary, the RMSE values get slightly better with increasing maxbar. In this study a maxbar value of 0 was chosen.

**Distance weighting exponent (exp\_dis, a):**

The selected stations get weights according to their distance to the target grid cell using a weighting exponent, as described in Chapter 3.3. This distance weighting exponent can not be directly compared to values obtained by some inverse distance interpolation schemes. In PRISM other weighting parameters have also some distance weighting effect as e.g. the facet weighting scheme or the clustering scheme. Therefore this parameter can be expected to be smaller than the exponent of inverse distance interpolation algorithms. In Figure 5.10, a sensitivity plot of this distance weighting exponent is shown. Best performance is encountered for MAE values in a range of about 0.9 to 1.2, for RMSE even at slightly smaller values. A value of 1.0 was used for this study.

![Figure 5.10: Sensitivity plot for the parameter exp\_dis. Plotted is the relative change in performance of MAE and RMSE, normalized for exp\_dis=1.0.](image)

**Elevation weighting exponent (exp\_lev, b):**

Stations with large elevation differences with the target grid cell get a smaller weight in the regression calculation than stations on a similar height. This can be tuned by the elevation weighting exponent (see Chap. 3.3). The performance (Fig. 5.11) remains constant for increasing exp\_lev up to a value of 1.1 and gets slightly worse afterwards, but the sensitivity stays moderate.
PRISM-specific implementation and calibration

Figure 5.11: Sensitivity plot for the parameter exp_lev. Plotted is the relative change in performance of MAE and RMSE, normalized for exp_lev=1.0.

Facet weighting exponent (exp_fac, c):

The facet weighting exponent controls the influence of stations not lying on the same facet as the target grid cell or having intervening barrier cells. Surprisingly the performance changes little when varying the facet exponent in Figure 5.12. But this is probably a problem in the crossvalidation procedure: When leaving out a station, the selection of the facet level may change, and perhaps not in a favorable way. Additionally, the stations on the same facet as the target grid cell are not influenced by this exponent because they get always full weights. This facet weighting takes effect only when there have not been found enough stations on the same facet even on the highest facet level.

Figure 5.12: Sensitivity plot for the parameter exp_fac. Plotted is the relative change in performance of MAE and RMSE, normalized for exp_fac=1.0.
**Distance and elevation weighting importance factors (a\_dis (F_d) and b\_lev (F_z)):**

With these parameters the relative importance of horizontal versus vertical distances can be tuned. They will always be normalized to sum 1. The sensitivity plot (Fig. 5.13) shows a strong dependency on the choice of these parameters. Good performance can be achieved with \(a\_\text{dis}=0.8\) and \(b\_\text{lev}=0.2\).

![Sensitivity plot for the parameter a\_dis. Plotted is the relative change in performance of MAE and RMSE, normalized for a\_dis=0.8. Changing a\_dis changes also b\_lev, because a\_dis+b\_lev=1.](image)

**Maximum facet parameter variability (c\_fac):**

When the variability of the precipitation values around the regression line exceeds the relative value \(c\_\text{fac}\) of the mean precipitation, PRISM tries to reduce the variability by moving stations off-facet, until the variability is small enough or until the minimum number of stations on facet is reached. The choice of \(c\_\text{fac}\) (Fig. 5.14) seems to influence only the RMSE value, the MAE stays constant. For \(c\_\text{fac}\) values larger than 0.8 the RMSE jumps to a higher level. So setting \(c\_\text{fac}\) to a small value helps to correct a few erroneous regression lines producing large error values, but this shows up only when looking at the higher order regression statistics.
PRISM-specific implementation and calibration

Parameters for choosing the number of stations on regression:

The three parameters maxrad (minimum search radius), minsta (minimum number of station on facet) and isubfac_pr (minimum number of stations in regressions) are used to determine how many stations are used per regression calculation (see also Chap. 3.2) and are the most important parameters of PRISM. The sensitivity functions of these three parameters are very much depending on each other however, which makes tuning difficult. For this reason no systematic sensitivity analyses were possible. The program ASSAY is designed for this tuning purpose. It runs a series of jackknife crossvalidations with different settings of these three parameters. The resulting listing (Tab. 5.2) can be used then to set these parameters to some appropriate values which show good performance for all measures. However, it is suggested that not only these jackknife crossvalidation results, but also the resulting precipitation fields should be investigated to choose the definitive settings. Crossvalidation can only tell the performance at the station sites. But in most cases the interesting parts of a precipitation field are not at the location of the stations, but in some remote ungauged areas. Because of the biased station distribution for the Alps, it is of major importance to choose settings which provide robust and meaningful extrapolations to higher altitudes. Running PRISM in single cell mode and inspecting regression lines using PRISM's GUI is helpful for this purpose.
Table 5.2: List of ASSAY output used for tuning maxrad, minsta, and isubfac_pr.

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<th>MAE</th>
<th>RMSE</th>
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5.2 Code changes

While tuning PRISM, attempts were made to improve some particular behaviors of PRISM by changing the programming code. Additionally, more diagnostics were implemented for tuning and postprocessing. In the following sections the most important changes were documented.

Two default gradients

Using the GUI of PRISM, individual regression lines can easily be inspected. When applying PRISM to the Alpine region, it was realized that in cases where the gradient was out of bounds some systematic behavior could be detected nevertheless. When the gradient was too small, nearly all surrounding gridpoints with valid gradients showed rather small gradients, and vice versa. This led to the conclusion that although the resulting gradient was definitely not correct, the sign of the deviation was systematic. It was decided though to implement two different default gradients, one for cases with gradients too small and one for cases with too large gradients. As modifications of the graphical interface for setting the parameters are quite complicated, these two defaults were set to the middle of the lower threshold and the default gradient, respectively to the middle of...
the upper threshold and the default gradient. Hence no changes to the GUI were necessary. This change resulted in a better jackknife crossvalidation performance and in a more homogenous distribution of the precipitation gradients.

**Changed treatment of maximum DEM-station elevation difference**

When the difference between DEM elevation and station height exceeds the value levsta, the height used in regression is set to the station height instead of the DEM height. In the Alps many steep slopes occur and therefore this height difference is often large. But the DEM heights nevertheless represent the mean height of the grid cell and are meaningful in terms of the influence of the terrain on the air streams. It was therefore decided only to limit the height difference instead of switching to the station height. As an example, for a station height of 1000 m and a corresponding DEM height of 2000 m, a levsta value of 400 m will result in a height of 1600 m used for the regression line. It is still possible to use the station elevation or the DEM elevation for individual stations by setting flags in the input station file. This change slightly improved the crossvalidation performance. Additionally the resulting fields became more stable and changed more gradually with changing levsta.

**Changed distance weighting algorithm**

When creating precipitation climate maps, an interpolated value at a grid cell should be representative for the whole grid cell rather than being an exact interpolation at the location of the center of the grid cell. It was decided therefore to limit the distance from a station to the target grid cell to a minimum of half a grid cell. With this setting stations located very close to the center of the grid cell are pushed out to the border of the grid cell. In the present study this is about the precision of the station coordinates, which are indicated to a precision of 1/100 degrees or about 1 kilometer. This change improved the performance of the jackknife crossvalidation about 1% in MAE and RMSE.

**Changed clustering weighting scheme**

As described in Chapter 3.3.3, the maximum distance of all chosen stations $r_c$ is used as a normalizing factor in this weighting scheme. There are 2 disadvantages using this parameter: First, when adding or omitting a remote station, the whole clustering weights change completely, although this remote station may have no influence at all on the regression line due to downweighting by the distance weighting scheme. Second, having a lot of stations nearby the target grid cell is punished, because they will be downweighted, especially when including one station with a large distance. In this case the nearby stations will be downweighted almost equally because the interstation distances are negligible compared to $r_c$. This was changed by using the distance of the considered station $i$ to the target grid cell instead of $r_c$. Stations close to the target grid cell have to be grouped much closer now than remote stations for being considered as clustered. Additionally there will be much more pronounced differences in clustering for stations nearby to the grid cell. Consequently, the second parameter $r_i$ has to be changed, too. The mean
distance for normalizing is about half of the original parameter $r_x$, and therefore $r_c$ was set to 0.4 instead of 0.2. This change improved the performance of MAE about 1%.

**Changed facet weighting scheme**

The number of barrier cells is a parameter used for the facet weighting scheme (see Chap. 3.3.5). When enhancing the grid resolution, there will be more grid cells at the same distance, and the barrier cells will become more influential compared to the parameter for the orientation difference. The underlying algorithm was originally developed for a grid size of 2.5 minutes, and therefore a normalization of the number of barrier cells to this grid size was introduced. This modification did not change the performance per se, but it can help in comparing the parameter settings to parameters used in other investigations.

**Faster algorithm for searching neighbor stations**

When profiling the PRISM program, it was recognized that more than 60% of the CPU time is used for searching neighbor stations. An analysis of the code showed some improvements: Jumping out of a loop when a station is far away improved the speed significantly. Additionally some IF statements could be avoided. The resulting performance of this routine is now about as twice as fast as before.

**Resolved endless loop in POLISH**

Because of a precision issue, the postprocessing routine POLISH failed to stop running unless the maximum number of allowed loops was reached. The results were always correct nevertheless. By testing the difference of the raw minus the postprocessed values against a threshold, the routine now correctly indicates whether the raw values have been changed. This results in faster execution and in correct indication of the number of changed grid cells.

**Modifications in ASSAY**

Some additional output has been implemented in ASSAY, which helps tuning PRISM and allows additional processing of the crossvalidation results. Firstly, as additional statistical parameter, the RMSE and the relative RMSE value are calculated and printed. Secondly, decile values of the residuals are printed into a file, allowing the statistical distribution of the residuals to be checked, which can be used to isolate the main contributions to the crossvalidation error as well as for tuning.

For some experiments with reduced station network, an algorithm for selecting subsets of stations is implemented, limiting station selection to some subdomains or height zones or thinning the station network in a regular way by setting a minimum interstation distance. For comparisons with kriging, an option to select only stations with unique coordinates was implemented.
5.3 Sensitivity of POLISH

As described in Chapter 3.6, the PRISM suite has a postprocessing program named POLISH which eliminates discrepancies between neighbor cells. Because the regression lines for every grid cell are calculated independently, occasionally large gradients between neighbor cells can occur, and therefore POLISH is used to limit these gradients. In this study the thresholds are set to 300%/km and -50%/km (relative gradients, see Chap. 5.1), thus slightly larger than the corresponding thresholds for individual grid cells (see Tab. 5.1). It is the purpose of this section to show quantitatively the effect of POLISH on crossvalidation results given in Chapter 6 and 7, as these analyses are performed with ASSAY, without any postprocessing by POLISH. Calculating jackknife crossvalidations using POLISH is virtually not feasible, because each calculation of a station value in the crossvalidation procedure would require to run PRISM and POLISH for the entire domain.

In Figure 5.15 the relative differences between polished and raw fields of mean annual precipitation are separated into different classes. About 50% of all grid cells are affected by the postprocessing, but most of them only get minor corrections. The percentage of grid cells per class is shown for grid cells with relative precipitation differences before and after POLISH greater than 1%. Only 8.6% of all grid cells show relative differences greater than 2%, and about 7.5% of all grid cells exhibit differences between 1% and 2%. Therefore POLISH will have only small influences in general.

![Figure 5.15: Percentage of grid cells per class of relative differences between polished minus raw mean annual precipitation. Absolute numbers of grid cells are indicated on top of the bars. Differences smaller than 1% are not displayed. The total number of grid cells is 231469.](image)

To quantitatively estimate the possible influences of POLISH on crossvalidation results made with ASSAY, statistics for the differences between polished and raw mean annual precipitation are shown in Table 5.3. Assuming that all single corrections applied by POLISH to the individual grid cells are improving the overall performance of PRISM,
performance as shown for instance in Table 6.1 would be improved by about 5% for MAE: For the bias and MAE values the improvement is approximately given by simple subtraction of the mean of the differences between polished minus raw precipitation, and of the mean absolute deviation of these differences (MAD) respectively, as shown in Table 5.3. The mean difference of 0.1 mm/a caused by POLISH is very small, as by design POLISH tries to not affect the domain mean values (see Chap. 3.6). Therefore the expected changes to the bias values of crossvalidation results made with ASSAY are marginal.

But it can not be expected that all of the changes applied by POLISH are amending the resulting fields, and therefore the expected improvements will be considerably smaller. Consequently, the improvement caused by POLISH can be expected to be smaller than typical differences in performance between different interpolation methods as shown in Chapter 7.

Table 5.3: Statistics of the differences between polished and raw mean annual precipitation for the whole domain. MAD: mean absolute deviation; SDV: standard deviation (cf. Tab. 6.1).

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.1 mm</td>
</tr>
<tr>
<td>MAD</td>
<td>4.6 mm</td>
</tr>
<tr>
<td>SDV</td>
<td>12.5 mm</td>
</tr>
</tbody>
</table>

Separating the MAD values for different height zones (Tab. 5.4) reveals a smaller increase with height than typical MAE height distributions of crossvalidation results. Therefore it can be expected that the relative improvements effected by POLISH mainly accentuate in lower height zones.

Table 5.4: Mean absolute deviations (MAD) and mean absolute relative deviations (MARD) of the mean annual correction values applied by POLISH, separated into different height zones (cf. Fig. 7.9).

<table>
<thead>
<tr>
<th>Height zone</th>
<th>MAD</th>
<th>MARD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-250 m</td>
<td>3.26 mm</td>
<td>0.38%</td>
</tr>
<tr>
<td>250-500 m</td>
<td>4.23 mm</td>
<td>0.44%</td>
</tr>
<tr>
<td>500-750 m</td>
<td>5.04 mm</td>
<td>0.45%</td>
</tr>
<tr>
<td>750-1000 m</td>
<td>5.49 mm</td>
<td>0.44%</td>
</tr>
<tr>
<td>1000-1500 m</td>
<td>5.90 mm</td>
<td>0.43%</td>
</tr>
<tr>
<td>1500-2000 m</td>
<td>5.57 mm</td>
<td>0.41%</td>
</tr>
<tr>
<td>2000-5000 m</td>
<td>7.91 mm</td>
<td>0.62%</td>
</tr>
</tbody>
</table>

At individual locations large changes can be noticed. In Figure 5.16 the differences between the raw and polished PRISM fields of mean annual precipitation are shown. Single small, antagonistic pairs of areas are affected by this postprocessing, but most of the
domain stays unchanged. The correction values generally remain below 50 mm/a and only at a few spots larger changes are made. At locations with sparse station data and in regions with very small or very large gradients (see Fig. 8.1) slightly larger corrections are applied (western Po Valley, Appennino).

This postprocessing will smooth the resulting fields by adjusting extreme gradients and singular points not fitting into the local precipitation field. While tuning PRISM, parameter settings leading to smooth fields yielded better crossvalidation results. It can be expected therefore, without performing jackknife crossvalidation experiments, that by POLISH postprocessed fields will show more accurate results than the raw fields, especially for higher order statistics as the RMSE values (C. Daly, 2000, pers. comm.). But these improvements will be rather small and therefore meaningful qualitative comparisons between interpolation methods can be achieved by just using the raw interpolation fields provided by ASSAY, although some quantitative improvements of the performance of the full PRISM suite compared to ASSAY results will take place.
6 PRISM statistics

6.1 Prediction intervals

The purpose of this section is to validate PRISM with respect to its skill to reproduce spatial variations. A good measure to spatially show the precision of the prediction is the prediction interval. It indicates the range within which a given percentage of data points used for regression calculation lie (assuming a t-distribution of the data), and indicates therefore the probability for an additional value (e.g., a pseudo station at the target grid cell) to lie inside this band. This is in contrast to the confidence interval, which indicates the interval within the regression line lies for a given probability. The prediction interval is generally much wider than the corresponding confidence interval and provides a measure of the uncertainty of the interpolation within the stochastic model employed in PRISM and with the available data. The prediction interval can also be interpreted as an measure of how successful PRISM is in selecting a homogeneous set of stations used for a regression calculation. In contrast to crossvalidations as performed in Chapter 6.3, prediction intervals can show spatial variations of the accuracy of interpolation. The range of the prediction interval is defined as follows:

\[ 
\hat{y} \pm t_{\alpha/2, n-2} \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-2}} \sqrt{\frac{1}{n} + \frac{1}{n} \frac{(x - \bar{x})^2}{\sum (x_i - \bar{x})^2}} 
\]

with:

- \( x, \hat{y} \): x- and y-value of the considered point on the regression line
- \( t \): t-distribution
- \( n \): number of stations used for regression calculation
- \( \alpha \): two-sided prediction level

In the following, the second, additive term of the Equation (15) is addressed as “prediction interval”.

In Figure 6.1 the prediction interval for a probability of 70% is shown. To get the range for the prediction, this prediction interval has to be added to and subtracted from the precipitation value. 70% of all data points are expected to lie inside this range of the prediction interval.

The prediction interval for the northern Alpine ridge shows moderate values which rarely exceed 400 mm/a, corresponding to about 25% of the mean precipitation (see Fig. 6.2). The Jungfrau massive (about at 8°E / 46.5°N) shows huge absolute prediction interval values of up to 800 mm/a and more, but expressed as relative values this is only ca. 30%, an acceptable amount for this high mountain, sparse gauged region.
At the southern rim of the Alps, huge values of the prediction interval are found. At the entrance of the valley of Aosta, there is a large zone with prediction intervals of more than 600 mm/a, but here the mean precipitation is only 1000-1500 mm/a, so the relative values exceed 60%. Also the Toce valley to the north-north-east of this zone as well as the entire southern rim of the Alps from the east border of the Ticino region (Switzerland, at 9°E / 46.2°N) to the east of Lake of Garda (at 11°E / 45.5°N) shows much enhanced prediction intervals. The high prediction interval values in the Carnic Alps (Slovenia) are again due to high precipitation amounts of about 3000 mm per year.
At first glance it is surprising, that also the upper Po Valley shows large prediction intervals, although this is all flatland without any mountains causing additional precipitation variability. But in this region there are virtually no stations, and therefore PRISM uses distant stations with variable climatic properties, which leads to an enhanced variability of the regression residuals.

This fact is even enhanced when looking at the relative prediction intervals (Fig. 6.2). But the relative variability of precipitation is usually enhanced for low precipitation values. This explains also the high relative values in the dry inner Alpine zones as the Valais or the Venosta Valley.

There is obviously a dependency between network density and prediction interval. Regions with a sparse network show larger prediction intervals than regions with a comprehensive network. In these sparse gauged regions an improvement in the certainty of the regression calculation could be achieved by adding additional stations. The station search radius for the regression calculation will then get smaller, and the variability of the station values becomes smaller by reducing the influence of horizontal gradients on the regression (see also Chap. 1.6).

### 6.2 Dataset statistics

In this chapter, statistical descriptions of the dataset of mean annual precipitation are presented. This information is used in Chapter 6.3 for comparison purposes. For descriptions of the statistical measures see Chapter 4.

In higher regions of the Alps, variability of measured precipitation is much enhanced. This is just partly due to higher precipitation amounts, as it is well known that spatial precipitation variability is correlated to the precipitation amount. A lot of the variability originates from the more pronounced shadowing effects, which have a direct influence on the precipitation amount. Additionally an indirect influence occurs by enhanced or reduced gauge biases (see Chap. 2.5). In Figure 6.3 the mean, mean absolute deviation from the mean (MAD) and standard deviation (SDV) of the station values are plotted for different height zones for the domain 7°E-10°E / 45°N-48°N (see Fig. 5.1). The mean shows an increase up to a maximum at 1000-1500 m, staying at about 1500 mm for the upper zones. On the contrary, the MAD as well as the SDV values show a marked decrease from the lowest zone to 250-500 m. Most of the stations in the 0-250 m height zone originate from the Po Valley, which exhibits enhanced prediction intervals (see Fig. 6.1) and reduced station density (see Fig. 2.3). For heights above 500 m both MAD and SDV increase continuously. The topmost zone shows an extremely large standard deviation of about 800 mm, leading to very imprecise interpolations.

The mean absolute relative deviations (MARD) and root mean squared relative deviations (RMSRD) are shown in Figure 6.4. The decrease from the lowest height zone to the height zone 250-500 m is much enhanced compared to the non-relative measures.
(Fig. 6.3) due to the small precipitation mean of the lowest height zone. The increase from the zone 250-500 m upward is moderate; even the height zone 2000-2500 m exhibits its smaller relative measures than the lowest height zone.

![Graph showing PRISM statistics](image)

**Figure 6.3:** Mean absolute deviation (MAD), standard deviation (SDV) and mean values of all stations in the domain 7°E-10°E / 45°N-48°N, for mean annual precipitation and separated into different height zones. The left axis applies to MAD and SDV, the right one to the mean.

![Graph showing PRISM statistics](image)

**Figure 6.4:** Relative mean absolute deviation (MARD), root mean squared deviation (RMSRD) and number of stations per height zone in the domain 7°E-10°E / 45°N-48°N, for mean annual precipitation and separated into different height zones. The left axis applies to MARD and RMSRD, the right one to the number of stations.
6.3 Crossvalidation results

In this chapter, statistical results of validations for mean annual precipitation are presented. The statistics of the interpolated precipitation field as derived by PRISM are shown and some summary statistics are presented.

To validate the interpolated values, a jackknife crossvalidation was applied. This means, to remove each station individually from the station sample, and to interpolate the precipitation value at the station’s location. After interpolation, the station is then returned to the station sample. The resulting differences between the interpolated and the observed values are used as a measure of the performance of the interpolation scheme. This was done using the program ASSAY, which provides only raw interpolation values, without a postprocessing by POLISH. It can be expected that the postprocessing provides more robust interpolation values, improving performance. These improvements will be pronounced for higher order statistics as the RMSE value (C. Daly, 2000, pers. comm.). The qualitative results of the performed crossvalidations can be considered as correct nevertheless (see Chap. 5.3).

In Figure 6.5 the bias, the mean absolute error (MAE) and the root mean squared error (RMSE) of this crossvalidation are plotted for different height zones. The lower height zones up to 1500 m show almost no bias, thus giving accurate areal mean values. The region of 1500 m to 2500 m is slightly overestimated, whereas the topmost zone is strongly underestimated. This underestimation is probably due to some totalizers showing excessive values, which do not fit into the local precipitation-height dependencies and are therefore difficult to predict. All bias values are by far not statistically significant,
due to the great spatial variability of precipitation and the small station samples in the upper height zones (Fig. 6.4). The MAE and RMSE values are quite low for the height zone 250-500 m, but increase more rapidly than the corresponding MAD and SDV values in Figure 6.3. The ratio MAE/MAD rises from 0.35 to 0.7 with increasing height and the ratio RMSE/SDV increases from 0.4 to 0.8. This is probably due to the decreasing station density with height as well as the more uncertain precipitation measurements at high altitudes.

Figure 6.6 shows the mean relative error (MRE), the mean absolute relative error (MARE) and the root mean squared relative error (RMSRE). While the MARE and the RMSRE show a very similar behavior as the non-relative measures, the MRE exhibits very different properties than the bias values. Here all values are positive, so PRISM is overestimating precipitation when looking at this relative measure, yet all values are smaller than 6%. The upper height zones above 1500 m show larger positive values. Even the negative bias for the uppermost height zone does not lead to a negative MRE. Combining the information of the non-relative as well as the relative measures, PRISM seems to overestimate small precipitation values and to underestimate high precipitation values.

![Figure 6.6: Mean relative error (MRE, estimated-observed), mean absolute relative error (MARE), root mean squared relative error (RMSRE) of a jackknife crossvalidation of PRISM applied to the domain 7°E-10°E / 45°N-48°N, for mean annual precipitation and separated into different height zones. The left axis applies to MARE and RMSRE, the right one to MRE.](image)

The summarized statistical values of PRISM for this tuning domain (7°E-10°E / 45°N-48°N) and for the entire domain (2°E-18°E / 42.75°N-49°N) are listed in Table 6.1. The bias of the entire domain is very small, as it was an intention to keep the bias small while tuning. The statistics for the entire domain are mainly dominated by stations at low altitudes, and it is not surprising therefore that also the domain-wide bias with a value of 1.71 mm is very small, as PRISM shows very good estimates of the mean for low alti-
tudes (see Fig. 6.5). The ratio MAE/MAD indicates, how much of the variability of the station data can be explained by the interpolated precipitation field. For the tuning domain, this ratio shows a value of 0.4, and for the entire domain a value of 0.3 is found. Therefore, a large part of the variability can be explained by the achieved precipitation field. The MAE and RMSE measures are analyzed in more detail in Chapter 7 by comparisons to other interpolation schemes.

Table 6.1: Crossvalidation statistics of PRISM and station value statistics for the tuning domain as well as for the whole domain, for mean annual precipitation.

<table>
<thead>
<tr>
<th></th>
<th>tuning domain</th>
<th>whole domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias</td>
<td>-1.15 mm</td>
<td>1.71 mm</td>
</tr>
<tr>
<td>MAE</td>
<td>131.76 mm</td>
<td>90.39 mm</td>
</tr>
<tr>
<td>RMSE</td>
<td>213.85 mm</td>
<td>148.80 mm</td>
</tr>
<tr>
<td>MRE</td>
<td>1.62%</td>
<td>1.25%</td>
</tr>
<tr>
<td>MARE</td>
<td>9.98%</td>
<td>7.80%</td>
</tr>
<tr>
<td>RMSRE</td>
<td>15.63%</td>
<td>11.84%</td>
</tr>
<tr>
<td>MAD</td>
<td>333.34 mm</td>
<td>304.38 mm</td>
</tr>
<tr>
<td>SDV</td>
<td>417.16 mm</td>
<td>385.51 mm</td>
</tr>
</tbody>
</table>

For evaluating the statistical distribution of the residuals, decile values (see Chap. 4) can be used (Tab. 6.2). The decile values of the residuals show a slight shift towards high values, especially when looking at the decile 6, 7 and 8. Many stations are therefore moderately overpredicted. This is more pronounced when looking at the relative residuals. In contrary to the negative overall bias, the median (decile 5) is positive, so it can be assumed that a few stations with large negative residuals have a strong influence on the mean.

Table 6.2: Decile values for the residuals of the jackknife crossvalidation of PRISM, applied to the domain 7°E-10°E/45°N-48°N. Column 2 shows decile values for the absolute residuals in mm, column 3 for the relative residuals.

<table>
<thead>
<tr>
<th>Decile</th>
<th>Absolute residuals</th>
<th>Relative residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-198.242 mm</td>
<td>-0.12625</td>
</tr>
<tr>
<td>2</td>
<td>-105.109 mm</td>
<td>-0.07436</td>
</tr>
<tr>
<td>3</td>
<td>-54.539 mm</td>
<td>-0.04498</td>
</tr>
<tr>
<td>4</td>
<td>-20.419 mm</td>
<td>-0.01659</td>
</tr>
<tr>
<td>5</td>
<td>4.960 mm</td>
<td>0.00433</td>
</tr>
<tr>
<td>6</td>
<td>30.149 mm</td>
<td>0.02421</td>
</tr>
<tr>
<td>7</td>
<td>63.728 mm</td>
<td>0.05630</td>
</tr>
<tr>
<td>8</td>
<td>111.799 mm</td>
<td>0.09413</td>
</tr>
<tr>
<td>9</td>
<td>196.588 mm</td>
<td>0.15565</td>
</tr>
</tbody>
</table>
7 Comparison against other interpolation schemes

When applying an interpolation scheme, the validation of its performance is a primary duty. However, appropriate validation is a difficult task: (i) Not all areas are of the same interest. High mountain areas are of major importance in the Alps, because precipitation variability is much enhanced and the resulting interpolated fields are more uncertain. At present, no reliable precipitation values are available for these regions as they would be needed for glacier mass balance and water balance calculations. (ii) Crossvalidation validates at the station locations only, but the performance at ungauged sites and averaged over subdomains and catchments is at least as important. (iii) Depending on the purpose of the precipitation fields, different measures have to show good performance. For validating high resolution climate models as well as for water-balance issues, good areal means are fundamental. Therefore the resulting fields should exhibit small biases.

In this section, jackknife crossvalidation measures (see Chap. 4.2) for PRISM are compared to a set of simpler climate interpolation schemes. Additionally the water balances for some catchments are inspected, and some experiments using thinned station networks are made. All jackknife crossvalidations in this section are made with the program ASSAY, and no postprocessing is made using the routine POLISH. Nevertheless, it can be expected that no qualitative effects on the achieved comparisons should occur (see Chap. 5.3).

7.1 Descriptions of used interpolation methods

In the following experiments, PRISM was compared to a detrended, ordinary kriging and to a simple, detrended variant of an inverse distance interpolation. Here, these interpolation methods are briefly explained.

Kriging was used as a first reference method. It is a statistically optimal interpolation algorithm which minimizes the squared differences between the interpolated field and the station values (see Chap. 1.4 for description and references). The properties of the interpolated field are influenced by the parameters of the semivariogram function, which is a description of the spatial covariance structure of the data. The semivariogram is often called "variogram" by convention; this terminology will be used in the following. The variogram (see Fig. 7.1) as fitted by data analysis was set to an exponential function with a range of 1.3 degrees and a nugget value of 12% of the variance. The exponential variogram as a function of the distance \(d\) is given as follows:

\[
\text{variogram}(d) = \text{nugget} + (\text{variance} - \text{nugget}) \cdot \left(1 - \frac{3 \cdot d}{\text{range}}\right) 
\]

Before doing the kriging interpolation, a detrending of the data was performed. For this a fixed overall precipitation - height gradient was subtracted. The optimal value of this gradient was 0.4 (mm/a)/m, as determined by jackknife crossvalidation. In principle the var-
Comparison against other interpolation schemes

Comparison against other interpolation schemes

Varioogram analysis should be done after detrending. In this study, this analysis was performed before detrending because of a simpler crossvalidation calculation. Tests showed that the resulting differences in the variogram are negligible compared to the uncertainties of determining the variogram function. Additionally to the standard precipitation gradient of 0.4 (mm/a)/m, two variants of this kriging method are used for comparison purposes: kriging with a detrending gradient of 0.8 (mm/a)/m for comparisons to other investigations of the water balance of Switzerland (Chap. 7.5.2) and kriging without any detrending for the experiments with thinned station networks (Chap. 7.6).

As a second interpolation method, an inverse distance interpolation known as “quadrant method”, was used (Mendel, 1977; Schädler, 1985b). In each quadrant of the compass the closest 2 stations were selected for an inverse distance interpolation using an exponent of 1.5. The interpolated precipitation value \( p_i \) for the target grid cell \( i \) is given as:

\[
p_i = \frac{\sum_{j=1}^{8} \frac{p_j}{d_j^{1.5}}}{\sum_{j=1}^{8} \frac{1}{d_j^{1.5}}}
\]

(25)

where \( p_j \) denotes the precipitation values for station \( j \) and \( d_j \) the distance to the target grid cell \( i \). To be comparable to kriging, likewise a detrending with a gradient of 0.4 (mm/a)/m was applied.

7.2 Comparison of precipitation fields

To perform spatial comparisons of the precipitation fields produced by the different interpolation methods, plots of mean annual precipitation 1971-1990 and of their difference fields were performed. In Figure 7.2 precipitation as analyzed by PRISM is depicted. To the north of the Alps, much more structure can be seen than in the Lago Maggiore region.
Comparison against other interpolation schemes  

(see Fig. 2.2) due to larger mean vertical gradients. In contrast, the kriging and quadrant methods (Fig. 7.3), with their prescribed gradients of 0.4 (mm/a)/m, show strong relationships to topography in both regions. These two interpolation methods are largely dominated by the detrending algorithm and show rather small differences to each other. This is confirmed when looking at the difference fields (Fig. 7.7).

Figure 7.2: Mean annual precipitation 1971-1990 in mm for the tuning domain 7°E-10°E / 45°N-48°N, as analyzed by PRISM. The letters indicate locations discussed in the text.

Figure 7.3: Mean annual precipitation 1971-1990 in mm for the tuning domain 7°E-10°E / 45°N-48°N, as analyzed by detrended kriging (a) and by detrended quadrant interpolation (b).
In inner Alpine regions, the PRISM map often compares better than the kriging maps to measured data and to hand drawn maps as Uttinger (1967), who has given careful consideration to local variations of the vertical precipitation gradients. For example in the southern part of the Valais (see letter “A” in Fig. 7.2), the analysis of Uttinger (1967) extends the dry zone far to the south which closely matches the structures of the PRISM analysis. In this area PRISM derives very low gradients, which are consistently about at or below 0.3 (mm/a)/m, see Figure 7.4 for a typical regression line of PRISM in this region.

![Figure 7.4: Typical regression line at location “A” of Figure 7.2 as derived by PRISM, showing a vertical gradient of 0.26 (mm/a)/m.](image)

PRISM often shows more pronounced transitions between different regimes than the other methods. At locations with a dense station network, the measured values indicate that these steep transitions are real. For example the sharp rain shadow to the south-east of the Jura (letter “B” in Fig. 7.2) is supported by several stations (see Fig. 7.5), which indicate a marked precipitation reduction to the lee-side (south-east) of the crest, even if not every single station fits in this scheme.

![Figure 7.5: Plot of the station distribution at location “B” of Figure 7.2 with indicated precipitation values (mm/a). Darker colors mean higher altitudes. This region shows a distinct rain shadow to the south-east side of the crest.](image)

At the northern crest of the Valais (letter “C” in Fig. 7.2), the effects of the conceptual differences between the used methods appear distinctly. The topmost zone of this crest is
poorly covered by stations, so the interpolation methods have to extrapolate towards high altitudes. The detrended kriging method extrapolates by its detrending mechanism using a fixed gradient of 0.4 (mm/a)/m. The regression analyses of PRISM, however, consistently indicate vertical gradients of 0.7 to 1.0 (mm/a)/m for the whole crest. Additionally, PRISM favours stations with similar altitudes as the grid cell for the regression analysis. These two factors lead to much larger precipitation values for the PRISM analysis than for the kriging analysis. The consistent gradients as well as the few high mountain stations clearly indicate the PRISM analysis being superior in this region.

In Figure 7.7a the differences between PRISM and kriging are shown. The largest differences occur at the southern border of the Alps due to a sparse station network (see Fig. 2.3). To the south-west of the Lago Maggiore as well as at the Bergamask Alps, PRISM shows much smaller precipitation values than kriging, whereas on the flat areas to the east and to the north-west of Lago Maggiore, PRISM exhibits much larger precipitation amounts. Due to the sparse dataset in Italy, there are no clear indications as to which of the analyses is more reasonable for these regions. To the north of the Alpine crest, the differences are generally smaller. In Figure 7.7, small differences below 10 mm are drawn in white. Only a part of all station locations are triggering single white spots, because both methods are not exact interpolation methods, which means that the interpolation values at the station locations are not necessarily matching the station values.
The differences between kriging and quadrant method (Fig. 7.7b) are much smaller than between these two methods and PRISM. Kriging is smoothing the precipitation field a bit more and shows therefore smaller peak values than the quadrant method, for example at the Jungfrau Massif.

### 7.3 Validation for different height zones

The station data set used in this study has a pronounced bias in height distribution towards low altitudes. Thus, stations at low altitude are overrepresented in the overall statistics. To obtain information for higher altitudes, separate statistics for different height zones were calculated for the domain 7°E-10°E / 45°N-48°N. Jackknife crossvalidations of PRISM calculations were compared to detrended kriging and quadrant interpolations. PRISM shows very low biases at low altitudes up to 1500 m (Fig. 7.8). From 1500 m to 2500 m it moderately overestimates precipitation, and for the topmost zone above 2500 m a strong underprediction occurs. Kriging shows too much precipitation at the lowest zone, then strongly underpredicts at the height zone 1000-1500 m and reveals a huge overprediction for the height zone 2000-2500 m. The topmost zone has almost no bias. Surprisingly the detrended quadrant method shows nearly no bias for all height zones. Of all bias values, only the two extreme bias values of kriging at the height zones 1000-1500 m and 2000-2500 m are statistically significant at a p-value of 0.05.
Comparison against other interpolation schemes

Regarding mean absolute errors (MAE, see Fig. 7.9), PRISM shows about the same performance as kriging up to 1000 m and is better than kriging for the zone 1000 m to 2500 m. The quadrant method shows 10% to 20% higher values for all zones.

In Figure 7.10 the mean absolute relative errors (MARE) are shown. Using this relative measure PRISM performs much better than the other interpolation schemes for the lowest height zone 0-250 m. But for the upper height zones PRISM exhibits slightly worse results compared to the MAE results. Therefore in these zones large precipitation
amounts are modeled better by PRISM than small values compared to kriging.

The RMSE values (Fig. 7.11) show about the same characteristic as the MAE values, but here PRISM performs slightly worse than kriging. In the zone 250 m to 1000 m kriging is slightly better and for higher zones the performance is almost the same. As for the MAE values, the quadrant method performs notably worse than PRISM and kriging.

Using the RMSE measure, large errors get large weights, so it can be assumed that PRISM produces more interpolation values with large errors, but for most stations above 1000 m PRISM seems to provide better interpolations than kriging.

![Graph](image_url)

**Figure 7.10:** Mean absolute relative error (MARE) of a jackknife crossvalidation of the domain 7°E-10°E / 45°N-48°N for PRISM, detrended kriging and detrended quadrant method, separated for different height zones.

![Graph](image_url)

**Figure 7.11:** RMSE of a jackknife crossvalidation of the domain 7°E-10°E / 45°N-48°N for PRISM, detrended kriging and detrended quadrant method, separated for different height zones.
In summary, PRISM and kriging show better results than the simple inverse distance method. PRISM is showing very good bias values for all but the topmost height zone compared to detrended kriging, an important issue when looking at areal means. PRISM seems to produce more extreme outliers than kriging which produces mediocre RMSE values. But when applying the PRISM postprocessing routine, slightly enhanced RMSE values can be expected (see Chap. 5.3).

7.4 Validation for different subregions

The Alpine region consists in very different climatic regimes. It is therefore interesting to validate individual regions. For this purpose 5 different regions were chosen, each of them characterizing an individual precipitation regime (see Fig. 7.12):

1) Region “Ticino”; a wet, convectively dominated region showing low gradients. 44 stations.
2) Region “France”; a flat and relatively dry region. 199 stations.
3) Region “Vosges / Schwarzwald”; showing large precipitation gradients and marked rain shadows. Very comprehensive station network. 337 stations.
4) Region “Tirol”; high mountain, dry inner Alpine zone with irregular station network. 161 stations.
5) Region “West Austria”; a region typical of the northern rim of the Alps showing a markedly horizontal precipitation gradient. Very comprehensive station network. 243 stations.

For these regions a jackknife crossvalidation was performed using PRISM, detrended kriging and detrended quadrant interpolation.

The bias results (Fig. 7.13) are quite difficult to interpret. For the “Ticino” region PRISM
overestimates precipitation about 10 mm/a and kriging underpredicts by about 6 mm/a. As relative measures, though, these values correspond to only 5.7% and 3.5% in this wet region. Another reason of these comparatively large biases is the small data base of just 44 stations for this experiment. The other 4 regions show very low biases. Although the detrended quadrant method has shown very low biases for the whole tuning domain (Fig. 7.8), for the subdomains used for this comparison this method exhibits mostly the worst bias results.

![Image of a graph showing bias (mm/a) of a jackknife crossvalidation for 5 subdomains.](image)

**Figure 7.13:** Bias [mm/a] (estimated-observed) of a jackknife crossvalidation for 5 subdomains.

![Image of a graph showing MAE (mm/a) of a jackknife crossvalidation for 5 subdomains.](image)

**Figure 7.14:** MAE of a jackknife crossvalidation for 5 subdomains.

When looking at the MAE values (Fig. 7.14), all methods show rather similar performance. PRISM displays good performance for the "Ticino" and the "Tirol" region. Both zones have small vertical precipitation gradients and a relatively sparse station network. Kriging as well as the quadrant interpolation seem to have problems to cope with their fixed detrending being too large, because the station network is not dense enough to resolve the gradients. Due to the very small gradients, omitting the detrending procedure improves the performance for both methods. However, PRISM shows better performance than these undetrended analysis variants.
In two regions detrended kriging shows better results than PRISM, for the “Vosges / Schwarzwald” region and for the “West Austria” region. Both regions show quite large precipitation gradients, and one might think these are the situations at which PRISM excels. But both regions show an extremely comprehensive station network and so most of the precipitation gradients are resolved by the network. Additionally, the whole range of altitudes is covered by rain gauges, so no extrapolation is necessary.

When looking at individual regression lines using PRISM’s GUI, it seems that sometimes PRISM gets confused by horizontal precipitation gradients, interpreting them as vertical gradients, which can result in incorrect gradients (see also Chap. 1.6). Additionally the horizontal gradients lead to an enhanced variability of the regression residuals. An example of this phenomenon is presented in Figure 7.15. Here a strong north-south gradient is prevailing, so dry stations tend to be located to the north of the target grid cell. For the same height zone the stations are spread over a large range of precipitation values, which leads to a vague and unstable determination of the regression lines. For this example the regression line looks ok, but only minor changes in the station weights could markedly alter the regression line. In these regions, statistically optimal methods as kriging focus mainly on spatial interpolation with prescribed vertical gradients, and are doing a better job.

![Figure 7.15: Instable regression calculation as an influence of horizontal precipitation gradients. For this example located at the northern slope of the Alps in West Austria, dry stations tend to have larger distances to the Alpine crest.](image-url)
Especially for the “West Austria” region kriging as well as quadrant interpolation are profiting a lot from the fixed detrending scheme. Without this detrending both methods are showing much worse MAE values than PRISM.

The “France” region shows very low MAE values for all interpolation methods. Surprisingly PRISM shows even slightly better values than kriging, although PRISM was designed for mountainous regions, and kriging should be the optimal method for this trend free, flat region.

Very instructive is the inspection of the ratio MAE/MAD as a measure of how much of the observed variability can be explained by the interpolation schemes. The “Ticino” and the “Tirol” region both show ratios of about 0.6, whereas the other regions exhibit values below 0.35. The “Vosges / Schwarzwald” region even has a very low ratio of 0.27. So the performance of PRISM compared to the other methods is strongly correlated to the ratio MAE/MAD: in regions with large ratios PRISM performs better than the other interpolation methods, and in regions where a lot of the variability can be explained by the interpolation schemes PRISM performs slightly worse, but comparable.

The RMSE values (not shown here) show behavior similar to that of the MAE values; therefore a detailed discussion is omitted.

Looking at the results of these subdomain validations, PRISM shows good results in regions with low gradients and relatively sparse station data. PRISM does not do as well in regions with very comprehensive station networks and large horizontal as well as vertical gradients. Here a good spatial interpolation is of primary importance because most gradients are resolved by the station network. PRISM shows its power especially in regions which are difficult to model because the influence of topography on precipitation is only partly represented in station data. For all regions the quadrant method is only slightly worse than kriging, emphasizing the difficulty of improving interpolation schemes.

7.5 Water balance

7.5.1 Water balance of selected catchments

A complementary method to validate high-resolution precipitation fields is the inspection of the water balance. Runoff plus evapotranspiration (R+E) of a catchment should be equal to the mean areal precipitation including the gauge losses, when no storage changes occur. For a detailed discussion of water balance investigations in Switzerland see Schmidler (1985a). Especially for sparse gauged regions this is often the only possibility to validate the areal mean of precipitation.

The calculation of the water balance bears some uncertainties, because the values for all terms of the balance may be inaccurate. Evapotranspiration can be measured directly only by weighable lysimeters. These are containers filled with soil and natural vegetation. The
measured weight differences correspond to the effective evapotranspiration in rain-free periods. As equipment and installation are expensive, only very few exist in the Alpine region. To determine areal information therefore, evapotranspiration can not be interpolated from measurements, but has to be calculated using the energy budget or using some empirical formulas, see Brutsaert (1982) for a good overview. The uncertainties in calculating evapotranspiration originate from the assumptions and simplifications made by the methods used as well as from measurement and interpolation errors of their input data. The quantification of the possible errors will thus strongly depend on the methods used.

The runoff of a river, in contrast, is quite simple to determine. Generally the height of the water table is measured and transformed by calibrated functions into volumetric runoff. These functions are usually well known for normal runoff conditions. But for high water the height-runoff functions are often uncertain and changes in the river bed can occur during such events, changing these runoff relations abruptly. Additionally runoff in subsoil can hardly be detected and quantified. These subsoil runoffs are reported to be small for big Swiss catchments of several thousands km² (Schädler, 1985a), but can probably be important for some small catchments.

Precipitation shows several well documented error sources (e.g. Sevruk, 1982, 1985). Most of these errors lead to undercatch. But snowdrift can increase measured precipitation dramatically in special conditions (see Chap. 2.5). In general these errors can not be quantified due to lack of data.

Additionally, high mountain areas are often glacierized, which complicates the derivation of the water balance. Glaciers in the Alps mostly have a markedly negative mass balance (Gletscherkommission, 1983-1993) resulting in storage changes of the water bal-

![Figure 7.16: Used catchments for water balance comparisons. Coordinates are given in Swiss kilometer coordinates.](image-url)
Comparison against other interpolation schemes

ance which can not be neglected. But usually glaciologists determine the mass balance of a glacier by using the water balance, presuming an areal mean of precipitation. So this is a vicious circle which can not be resolved. In this study therefore, catchments with very low percentages of glaciers are chosen.

For 5 catchments in Switzerland (see Fig. 7.16), the water balance for the period 1971-1990 is investigated, both using PRISM and kriging interpolation for determining mean areal precipitation. The catchments are selected to have reliable runoff measurements as reported by Schädler und Weingartner (1992) and M. Rohmann (1999, pers. comm.). The catchments Simme, Aare, Plessur and Verzasca have percentage glacierized areas of less than 4%. The catchment of Massa includes most of the Jungfrau massive and is glacierized by 66.6%. This high Alpine area was selected despite its difficulty from glaciation due to the potential role of the precipitation interpolation methods for area mean precipitation. The size of these catchments is about 17000 km² for the Aare catchment and 200-350 km² for the other catchments.

Figure 7.17: Water balance for the time period 1971-1990 in mm/a for different catchments in Switzerland. R+E, the sum of runoff and evapotranspiration, is compared against precipitation analyses made by PRISM and by a detrended kriging. Numerical values in mm for R and E are given in the R+E bars.

Figure 7.18: As Figure 7.17, but for corrected precipitation.
Runoff data and catchment areas for all catchments except Verzasca were taken out of hydrological yearbooks (LHG, 1971-1990). Data for Verzasca originated from the hydroelectric power plant Verzasca SA. Evapotranspiration was taken from the evapotranspiration map of Switzerland (Menzel et al., 1999). For these evapotranspiration values no error assessment was available.

In Figure 7.17 the water balance for the time period 1971-1990 is shown for the five catchments Simme, Plessur, Massa, Aare and Verzasca, both using PRISM and a detrended kriging with a precipitation gradient of 0.4 (mm/a)/m. The interpolated precipitation values are not corrected for gauge undercatch (see Chap. 2.5), so actually these values should be less than the sum of runoff plus evapotranspiration. In Figure 7.18 the estimated areal mean of the gauge undercatch is added to the interpolated precipitation values according to Sevruk (1985) and Kirchhofer und Sevruk (1992b).

For the Simme catchment PRISM and kriging show more precipitation than runoff plus evapotranspiration without any gauge loss correction. Adding a gauge correction of 13% (Fig. 7.18), the resulting precipitation values are much too high. Possible explanations are the existence of some undetected subsoil runoffs out of the catchment, unrepresentative rain-gauge sampling and uncertainties in evapotranspiration. As evapotranspiration is a small component of the water balance, errors in evapotranspiration are unlikely to be responsible for a major part of the total errors.

For the Plessur catchment the differences in interpolation are quite large. This region shows small precipitation gradients of about 0.21 mm/m as derived by PRISM, and therefore the detrended kriging with a fixed gradient of 0.4 mm/m produces larger precipitation values when extrapolating to high, ungauged areas. The uncorrected mean areal precipitation of PRISM is 85% of R+E, which is much more reasonable than kriging with a value of 96% (Fig. 7.17). In this mountainous catchment with an average height of 1800 m, gauge losses of about 13% can be expected (Fig. 7.18), leading to good matching of the water balance for PRISM.

The Massa catchment lies in the wettest region of Switzerland. Some totalizers show annual mean values of more than 3500 mm. It is a high mountain catchment with a mean height of about 3000 m, 66.6% of the area being covered by glaciers. The mass balance of the glaciers is therefore of major importance. For uncorrected precipitation values, kriging shows a balanced water balance and PRISM exhibits considerably more precipitation than runoff plus evapotranspiration. Sevruk (1985, 1992b) expects about 25% gauge losses as a mean value for this region. When adding this correction (Fig. 7.18), the precipitation values become much higher than the sum of runoff and evapotranspiration. There are several possibilities to explain this discrepancy. A pronounced positive mass balance may exist for this period. But glaciologists expect to have about a balanced mass balance for this time period 1971-1990 (Gletscherkommission, 1983-1993) as derived from a simple water balance. Further, some high mountain totalizers could get too much input because of snowdrift and therefore the appropriate gauge loss
correction could be small or even negative (see Chap. 2.5). The precipitation values calculated by PRISM are much higher than the analyses made by kriging owing to different height gradients. As expected, the interpolated areal means of precipitation for PRISM and for kriging differ markedly. PRISM shows large mean gradients of about 0.9 (mm/a)/m leading to large extrapolated values for high altitudes. Kriging in contrast has lower peak values due to the nugget parameter which leads to a smoothing effect.

The Aare catchment covers almost half of Switzerland. For this big catchment the water balance looks good: the interpolated uncorrected areal mean precipitations amount to 96% of R+E for both PRISM and kriging. Considering some uncertainty in determining evapotranspiration, the balance agrees well with the expected gauge losses of about 8% (see Fig. 7.18). But for validating interpolation methods this catchment is not meaningful, because both interpolation schemes show exactly the same mean areal precipitation. The water balance for such a large area seems to be less sensitive concerning the applied interpolation method.

The Verzasca catchment is situated to the south of the main crest of the Alps and the precipitation regime is different than on the north side. Precipitation is dominated by convection often causing heavy rainfalls. Therefore the precipitation gradients quite are small (see Chap. 1.3 and 8.1): PRISM derives an average precipitation gradient of 0.14 (mm/a)/m. The differences of the interpolated values made by PRISM and kriging are rather small although they used completely different precipitation gradients. The uncorrected precipitation values are 87% and 90% of R+E, slightly too small (Fig. 7.17), because the expected gauge losses are only about 7% (see Fig. 7.18). But this correction value is quite uncertain because in this region only stations at low altitudes were used for determining the correction terms (Sevruk, 1985, 1992b). In this catchment also the total area can be slightly wrong because no official area values were available and the catchment area was determined by hand.

As a result it can be noticed that the uncertainty of determining the water balance seems to be larger than the differences between different interpolation schemes. Distinct differences between PRISM and detrended kriging can be observed only for two catchments. For the Plessur catchment PRISM shows a much more reasonable result. For the Massa catchment it can not be decided which interpolation method is more appropriate, because the mass balance of the glaciers as well as the amount of gauge losses is virtually unknown. When applying reasonable correction values for gauge biases to precipitation, there is a general tendency to get more areal mean precipitation than the sum of runoff and evapotranspiration, leading to unbalanced water balances.

7.5.2 Water balance of Switzerland

As an additional comparison, the water balance of the whole of Switzerland is calculated using PRISM and a detrended kriging interpolation. Kriging was applied both with a gradient of 0.4 (mm/a)/m as determined by crossvalidation, and with a gradient of
0.8 (mm/a)/m as it is used by Kirchhofer und Sevruk (1992a; 1992b).

For this investigation, the water balance of Switzerland 1901-1980 (see Fig. 7.19) as determined by Schädler (1985a) were adapted for the time period 1971-1990 as follows: Runoff as well as storage changes are quite difficult to determine for Switzerland (see Schädler, 1985a) and therefore the values of the new period 1971-1990 were calculated by simple regressions. The runoff of Swiss origin as calculated by Schädler (1985a) is correlated against the sum of the runoff of major rivers of Switzerland for the time period 1920-1980. Applying this relationship, the runoff of Swiss origin for the time period 1971-1990 was determined to be 971.5 mm/a. Likewise the storage changes as calculated by Schädler (1985a) are correlated against the mass balance of the Aletsch glacier (M. Hoelzle, 1999, pers. comm.; Gletscherkommission, 1983-1993), the largest glacier in Switzerland. Using this correlation function, the storage changes for the time period 1971-1990 were estimated to be +5.5 mm/a. Mean evapotranspiration was set to 484 mm/a as indicated by Menzel et al. (1999) for the period 1973-1992. The sum of runoff, evapotranspiration and storage change (R+E+S) therefore amounts to 1461 mm/a.

Possible errors of the determination of runoff and storage change were discussed in detail by Schädler (1985a) and amount to about 2% for runoff and to 10% for storage change. The adaptation of this water balance to the period 1971-1990 leads to additional uncertainty of the balance. But as both regression calculations showed very small residuals, these uncertainties should be small.
Comparison against other interpolation schemes

PRISM and the detrended kriging with a gradient of 0.4 (mm/a)/m show very similar results (Fig. 7.20). The mean annual precipitation for Switzerland results to 1378 mm for PRISM and 1388 mm for the detrended kriging with a gradient of 0.4 (mm/a)/m. The respective ratios to R+E+S are 94.3% and 95%. Using a detrended kriging with a gradient of 0.8 mm/m, mean annual precipitation amounts to 1457 mm, which is almost as much (99.7%) as R+E+S.

When applying an overall gauge correction of 10% as derived from Sevruk (1985, 1992b), all values for mean annual precipitation are larger than R+E+S. But PRISM and kriging with a detrending of 0.4 (mm/a)/m are much closer to R+E+S than kriging with a detrending of 0.8 (mm/a)/m. The latter value seems to be very high and the difference from R+E+S probably can not be explained by random errors of runoff, evapotranspiration or storage changes. The advantage of PRISM is an implicit estimate of the precipitation gradients, as these gradients seem to have a notable influence on areal mean precipitation and water balance.

7.6 Validation with thinned station networks

Station networks often entail regions with high and low network densities. To test the robustness of PRISM concerning variations in network density and to evaluate the possible performance in other regions with coarser networks, experiments with successive thinning of the station network were performed for the domain 7°E-10°E / 45°N-48°N, using mean annual precipitation. All stations within a given minimum distance to a neighbor station are excluded from the interpolation, but are considered as stations to validate. The station selection is done by a recursive filtering of stations along the input station list of PRISM, starting at the beginning of the list. This procedure results in a reduced set of
Comparison against other interpolation schemes

stations that exhibit distances to their neighbors that exceed the chosen thinning radius. The remaining stations are used for validation. For each thinning level a crossvalidation without replacement (see Chap. 4.2) was performed using the full PRISM suite, a detrended kriging interpolation as well as a non-detrended kriging. The non-detrended kriging was calculated to evaluate the effect of the detrending scheme itself. For all schemes, the station selection and the analyses were done for the whole PRISM domain, but the validations were restricted to the domain 7°E-10°E / 45°N-48°N, and therefore no border effects have to be considered.

Two different experiments were conducted: a first one using the unchanged settings for the full dataset, and a second one using settings which are tuned for a thinning radius of 20 grid cells.

Any crossvalidation-based calibration of a mapping procedure is likely to be representative for subdomains with high network density. An application of this setting to areas with lower density may be less optimal, however. The purpose of experiment 1 is to examine the flexibility of the considered analysis techniques in a situation of variable network density. The setting of the analysis schemes is kept at values optimized for the full network and applied to successively thinned networks. In this experiment, results will be interpreted until thinning level 10, as this range reflects typical conditions in the Alpine region.

On the other hand, experiment 2 examines the flexibility of the analysis procedures when applied to an area of low station density (e.g. in another, less instrumented mountain region), but carefully recalibrated to that particular situation. In this experiment the compared models are tuned for a thinning radius of 20 grid cells. This allows on the one hand to evaluate the performance of the interpolation schemes in such a sparse dataset, and on the other hand it indicates the robustness of the schemes against variations of the station density as in the first experiment, but for a much sparser dataset.

**Thinning experiment 1**

In a first experiment, both PRISM and kriging were run with unchanged settings as determined for the full data set. Therefore the performance of either method for application with coarse resolution data will be somewhat biased. The results are shown as functions of the thinning radius, so that the performance changes as a function of the network density can be tracked.

In Figure 7.21 the bias of this crossvalidation experiment is displayed. Up to a thinning radius of 5 grid cells or 10 km, PRISM generally shows better biases than detrended kriging. But for larger thinning radii, PRISM exhibits large negative biases whereas the detrended kriging shows very small biases. The non-detrended kriging shows for small thinning radii about the same biases as PRISM, but for radii larger than 2 grid cells this method exhibits markedly larger negative biases than PRISM.
Inspections of the thinned datasets reveal, that the systematic increase of the negative biases with increasing thinning radius is mainly due to a non-representative thinning of the station network. Stations at high altitudes are likely to get lost in the thinning procedure because of their under-representation. For PRISM, these stations are essential to determine correct precipitation gradients. The detrended kriging in contrast profits from its fixed gradient of 0.4 (mm/a)/m, as can be noticed by comparing the two kriging variants. In a thinned network, precipitation gradients are not properly resolved anymore; thus detrending with a uniform gradient (accurately estimated from the entire station collective) improves the performance substantially. Additionally, PRISM has a fixed number of used stations per regression calculation. With increasing thinning radius, it will therefore enlarge the search radius unless a sufficient number of stations is found. This can affect vertical gradients in the regression calculation (see Chap. 1.6). Again the detrended kriging uses fixed vertical gradients and is not affected by this problem.

When comparing relative biases (Fig. 7.22), PRISM and the non-detrended kriging show very small biases and perform much better than the detrended kriging. This indicates that primarily stations with high precipitation values are causing the negative biases in Figure 7.21. Separating the analysis into different height zones (not shown here) exhibits very large negative biases for thinning radii larger than 5 grid cells and stations at altitudes of 2000 m and more, especially for PRISM and non-detrended kriging.
Comparison against other interpolation schemes

Figure 7.22: Relative bias ((estimated-observed)/observed) of a crossvalidation for PRISM (solid), for a detrended kriging (dotted) and a non-detrended kriging interpolation (kriging 2d; dot-dashed), using a successively sparser station network. The thinning radius is indicated in grid cells (about 2 km). On the right-hand y-scale the number of crossvalidated stations (out of 852) is given.

The MAE and RMSE values (Figs. 7.23 and 7.24) of this crossvalidation show a strong decrease in performance for increasing thinning radius. Up to a thinning radius of 5 grid cells, the performance of PRISM and kriging are similar and for larger radii detrended kriging performs much better, whereas the non-detrended kriging generally shows the largest MAE and RMSE values. But looking at the large difference in bias between PRISM and detrended kriging of about -40 mm in the thinning range of 6 to 18 grid cells (see Fig. 7.21), the differences in MAE are rather small. Therefore, these differences might be largely an effect of the systematic errors (bias) and not due to random errors.

Figure 7.23: MAE of a crossvalidation for PRISM (solid), for a detrended kriging (dotted) and for a non-detrended kriging interpolation (kriging 2d; dot-dashed), using a successively sparser station network. The thinning radius is indicated in grid cells (about 2 km). On the right-hand y-scale the number of crossvalidated stations (out of 852) is given.
Comparison against other interpolation schemes

Figure 7.24: RMSE of a crossvalidation for PRISM (solid), for a detrended kriging (dotted) and for a non-detrended kriging interpolation (kriging 2d; dot-dashed), using a successively sparser station network. The thinning radius is indicated in grid cells (about 2 km). On the right-hand y-scale the number of crossvalidated stations (out of 852) is given.

The quartiles of the error values (Fig. 7.25) support these findings: For the upper quartiles PRISM performs almost always better than kriging, but the differences between the different interpolation methods are small. The upper quartiles stay stable up to the largest thinning radius. Therefore most of the increase in MAE and RMSE seems to originate from negative residuals. For the lower quartiles the detrended kriging shows much better results than PRISM up to the thinning radius 20. The non-detrended kriging exhibits the smallest lower quartile values. The detrending mainly influences the negative errors therefore and can partly compensate the underestimation issuing from the strongly biased network.

Figure 7.25: quartiles of a crossvalidation for PRISM (solid), for a detrended kriging (dotted) and a non-detrended kriging interpolation (kriging 2d; dot-dashed), using a successively sparser station network. The thinning radius is indicated in grid cells (about 2 km). On the right-hand y-scale the number of crossvalidated stations (out of 852) is given.
In summary, at thinning levels larger than 5 grid cells, PRISM has a tendency to infer too low precipitation gradients when the station networks are coarse and elevation biased. The individual regression lines in the Alps are often pulled down towards high and dry inner-Alpine stations which receive too much weight. In the current setting of PRISM for the full dataset, some weighting parameters are set in a liberal way, allowing also remote stations to have decent influence. This permits PRISM to produce more stable regression lines and to better smooth noisy data. In a comprehensive network, the search radius is quite small and the involved stations all lie in similar precipitation regimes. For a sparse dataset the search radius will become larger and therefore nearby stations should be favored more strongly by the PRISM settings. For the actual range of network densities in the Alpine region (i.e. up to a thinning level of 5 grid cells or 10 km), PRISM and detrended kriging perform similarly and therefore the flexibility of PRISM can be considered as satisfactory for Alpine applications.

**Thinning experiment 2**

A second experiment is conducted for which the used models were tuned for a thinning radius of 20 grid cells. This thinning level was chosen because it represents the network density of a typical SYNOP station network, which, for some regions of the world, is the main dataset available in climatological analyses. For this experiment therefore, only 32 out of 852 stations in the validation area were used for interpolation. This roughly corresponds to the actual number of SYNOP stations in this area.

The modified PRISM settings were mainly determined by inspection of individual regions using the graphical interface of PRISM, and no jackknife crossvalidation for parameter tuning was performed. The resulting parameter setting was considerably different from the original setting. As main changes, the range of allowed vertical gradients was restricted to 20%/km as minimum and 150%/km as maximum value, the distance weighting exponent was increased from 1.0 to 2.0 and the number of used stations per regression analysis was drastically reduced from 20 to 6. For details of the parameterization see Table 7.1.

The new, retuned setting for the kriging analysis turned out to be not very different from the original setting. The range of the variogram was decreased from 1.3 to 0.9 degrees and the nugget value was reduced from 12% to 5%. However, the type of the theoretical variogram had to be changed from an exponential variogram to a cubical variogram, so that the range parameter has a somewhat different meaning for the shape of the variogram. As there are no shorter distances than 20 grid cells by design, the determination of the variogram settings for shorter distances was difficult. In the range of reasonable parameterizations, the setting was chosen to be not too different from the original, and hence kriging was not punished for the poor estimation of the variogram. The detrending gradient was determined by crossvalidation as in the case of the full dataset. It was set to 0.3 (mm/a)/m and therefore only slightly smaller than the original value. Tests have shown, however, that the optimal value was very much dependent on the exact variogram parameters.
Comparison against other interpolation schemes

Table 7.1: Changed PRISM settings as tuned for a sparser dataset, using a thinning radius of 20 grid cells (see text). The symbols in brackets are given as used in Chapter 3.3. For comparison purposes the original values from Table 5.1 are listed again.

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Value</th>
<th>Orig. Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>b1min</td>
<td>20% km</td>
<td>-10% km</td>
<td>Minimum slope, normalized</td>
</tr>
<tr>
<td>b1max</td>
<td>150% km</td>
<td>200% km</td>
<td>Maximum slope, normalized</td>
</tr>
<tr>
<td>exp_dis (a)</td>
<td>2.0</td>
<td>1.0</td>
<td>Distance weighting exponent</td>
</tr>
<tr>
<td>exp_fac (c)</td>
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<td>1.8</td>
<td>Facet weighting exponent</td>
</tr>
<tr>
<td>minsta</td>
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<td>14</td>
<td>Minimum number of stations on facet</td>
</tr>
<tr>
<td>isubfac_pr</td>
<td>6</td>
<td>20</td>
<td>Minimum number of stations in regression</td>
</tr>
</tbody>
</table>

![Figure 7.26](image)

In Figure 7.26 the bias values of this retuned experiment are shown. For a larger range around the thinning radius used for tuning, the bias values for PRISM and detrended kriging are very similar. Only for thinning radii smaller than 13 grid cells, for away from the station density used for calibration, kriging slightly excels. The non-detrended kriging shows more negative values for the whole range. Above a thinning radius of 25 grid cells, all interpolation methods reveal a dramatic increase of the negative biases.

The MAE values (Fig. 7.27) are again very similar for both PRISM and detrended kriging, except for thinning radii larger than 22, where PRISM performs however slightly better. In contrast to the first experiment tuned for the full dataset, the MAE values of PRISM and kriging are now very comparable. The RMSE values are behaving very similarly to the MAE values and are thus not shown here. As for the first experiment, both MAE and RMSE reveal a strong decrease in performance for increasing thinning radius.
At the highest thinning level, the interpolation results even reach the MAD (330 mm) and SDV (420 mm) values of the stations used for interpolation. This means that the simplest interpolation approach of setting all values to the mean of the stations used for interpolation performs as well as the investigated methods. These large values are due to the large negative biases (Fig. 7.21).

Figure 7.27: MAE values as in Figure 7.23, but here the used schemes were tuned for a thinning radius of 20 grid cells (black bar).

Figure 7.28: Quartile values as in Figure 7.25, but here the used schemes were tuned for a thinning radius of 20 grid cells (black bar).

Also when looking at the quartile values (Fig. 7.28), both interpolation methods present very similar performance. For thinning radii larger than 20 grid cells PRISM exhibits slightly better values of the first quartile.
Figure 7.29: Mean annual precipitation 1971-1990 in mm for the tuning domain 7°E-10°E / 45°N-48°N, as analyzed by PRISM using the full dataset.

Figure 7.30: Mean annual precipitation 1971-1990 in mm for the tuning domain 7°E-10°E / 45°N-48°N, as analyzed by PRISM (a) and by detrended kriging (b), both models tuned and applied to a sparse dataset. The red crosses indicate the locations of the stations used for interpolation.

The information of overall crossvalidation measures on the performance of the two schemes is limited. Therefore plots of the interpolated fields were analyzed for the thinned station network as it was used for tuning. In Figure 7.29 the original analysis as derived by PRISM using the full dataset is shown again. Compared with the analyses of the thinned station network (Fig. 7.30), distinct differences can be noticed. The perfor-
mance of individual regions is strongly dependent on the representativity of nearby stations for these regions. For example, both schemes are not able to reproduce the wet conditions at the Glarner Alpen, as information in terms of station data about the wet condition at this location is missing. The wet anomaly at the Schwarzwald is reasonably well modeled by PRISM, whereas kriging drastically underestimates the precipitation values for this region. Here the good performance of PRISM is mainly due to its flexibility to use large gradients. It is able to derive an appropriate gradient of about 1 (mm/a)/m inferred from the surrounding stations, although no stations are available directly at the Schwarzwald. On the other hand, kriging performs much better at the Lago Maggiore region than PRISM, because PRISM has no stations at low altitude in this region and therefore calculates too large gradients by using distant stations in the Po Valley.

Summary

In the first experiment, PRISM performs distinctly worse than the detrended kriging, as PRISM shows a larger increase in performance loss for increasing thinning than kriging. This seems to be partly due to the chosen setting, which tries to smooth noisy data and to achieve stable regression lines. On the other hand, PRISM presents some parameters which are dependent on the station density and therefore regions with much lower or higher network density can not be expected to have optimal settings. The detrended kriging in contrast seems to profit from the fixed detrending, stabilizing the extrapolations to high altitudes. However, for small thinning radii, the performance of PRISM is comparable to detrended kriging, and the flexibility of PRISM is satisfactory for Alpine applications therefore.

The second experiment, using a much sparser station network, displayed about the same performance for PRISM and detrended kriging, both in terms of absolute performance and in terms of robustness against variations of the station network density. The interpolation fields displayed large differences for individual regions, but were not providing clear preferences for a individual method.

When comparing the two experiments, the used setting of PRISM for the full dataset does not seem to be favorable concerning strongly variable network densities. In the second experiment, a much more robust parameterization could be achieved for PRISM which yielded to good crossvalidation results. These experiments thus suggest an alternative specification of the PRISM parameter minsta and isubfac_pr (see Tab. 7.1). Ideally, these parameters should depend on station density, to make PRISM more robust with respect to varying station density. Additionally, these experiments indicate again, that in high mountainous regions such as the Alps, comprehensive, non-biased station networks are of primary importance. None of the tested methods were able to fully compensate for the biased network.
8 Results

In this chapter the vertical precipitation gradients as well as the annual, seasonal and monthly precipitation maps of the Alpine region are presented, as analyzed by PRISM. As mentioned in Chapter 1, this study is probably the first homogeneous high-resolution precipitation climatology for the Alpine region. The analyses of Frei and Schär (1998) used a similar comprehensive data set, but were restricted to a mesh width of 25 km.

8.1 Vertical precipitation gradients

PRISM calculates vertical gradients for each grid point. Although vertical precipitation gradients are actually a theoretical concept (see Chap. 1.6), these gradients are very useful for mapping issues. All interpolation schemes using the concept of height detrending require adequate informations of the vertical precipitation gradients.

Figure 8.1 shows the vertical gradients for mean annual precipitation as derived and used by PRISM. When interpreting these vertical gradients, it has to be considered that PRISM is reducing the range of allowed gradients in flatland areas. In complete flat regions without any mountains in vicinity, PRISM sets the gradient to zero. The resulting maximum and minimum values for these gradients depend on the setting chosen for PRISM. For the present analyses the relative gradients are limited to 200%/km as maximum and -10%/km as minimum gradient (see Chap. 5).

The rims of the Alps exhibit the largest gradients. In these zones relatively small height differences occur, so small differences in precipitation can lead to large gradients. This effect occurs mainly in the Po Valley. Moreover some horizontal gradients can be noticed towards the main Alpine crest. These horizontal gradients may be interpreted then as vertical gradients (see Chap. 1.6). As examples show, the regression calculations of PRISM can be affected at some locations by this issue (see Chap. 7.4).

In general the northern Alps show larger gradients than the south-side of the Alps. The Swiss Middleland exhibits mostly gradients greater than 0.6 (mm/a)/m, often exceeding 1 (mm/a)/m. The southern part of Germany reveals gradients often surpassing 2 (mm/a)/m. The high mountain regions of the Alps exhibit generally smaller gradients than the northern Alpine upland. Here most gradients are in a range of 0.2 to 0.8 (mm/a)/m. The south-side of the Alps as well as the Tirol region typically show weak gradients, often being even slightly negative.
Figure 8.1: Vertical precipitation gradients [mm precipitation/m height] as derived and used by PRISM, for mean annual precipitation 1971-1990. These gradients have to be interpreted carefully, as the range of gradients is restricted. In flatland, this range is strongly reduced, see text.
The mean monthly gradients show very stable spatial patterns. The gradients as analyzed by PRISM are therefore extremely deterministic. In Figure 8.2 the two months most opposite, April and September, are displayed. To eliminate the effects of the different areal mean values of the two months, the relative gradients are shown in units of % per km height. In April the relative gradients are almost everywhere slightly larger than in September, but the general patterns are virtually identical.

The annual cycle of the vertical gradients shows distinct, but rather small variations. As an example, the annual cycle of an inner Alpine region (46.5°N/8°E - 47.5°N/10°E) is shown in Figure 8.3. This region covers the north-eastern part of Switzerland and the main Alpine crest to the south. It was selected because most gradient values are not affected by the limiting thresholds in this subdomain. The largest gradients can be found
in early spring with values of about 40% per km height. Summer and autumn reveal smaller gradients of about 30% per km height, and in winter intermediate values can be seen. This general pattern, with some variations, can be found for most subdomains of the Alpine region. Generally the largest gradients can be noticed in early spring and the smallest gradients are encountered in early autumn.

![Graph showing annual cycle of the mean vertical relative precipitation gradient (\%/km height) as analyzed by PRISM, for an inner Alpine region (46.5°N/8°E - 47.5°N/10°E).](image)

### 8.2 Mean annual precipitation

The mean annual precipitation for the period 1971-1990 as analyzed by PRISM is shown in Figure 8.4. On a mountain range scale it exhibits a wet zone along the northern rim of the Alps, two wet zones at the southern rim as well as a vast inner Alpine dry zone at the broadest part of the Alpine arc.

The wet zone at the northern rim is somewhat subdivided in singular cells due to individual mountain massifs as the Allgäuer Alpen or the Glarner Alpen. To the east as well to the west of the central parts, this wet zone along the northern rim gets slightly dryer. The area of maximum precipitation is located at the north most mountain chain. Although the mean altitude is increasing to the south, precipitation is decreasing, and so this area of maximum precipitation shows only a mean height of about 1000 m (see also Frei and Schär, 1998). Compared with the map of Baumgartner et al. (1983), a distinct shift in precipitation amounts between the eastern and western part of this wet zone can be noticed. In Baumgartner et al. (1983) with its reference period 1931-1960, the Salzburger Alpen are at least as wet as the Allgäuer Alpen, whereas in the present analysis (reference period 1971-1990) the Allgäuer Alpen are considerably wetter. This may be caused by the different reference periods.

One pronounced precipitation maximum to the south of the Alps is located in the region of Lago Maggiore. It is situated at the narrowest zone of the Alpine arc which promotes airstreams crossing the Alps. In this region with steep but moderately high mountains,
Precipitation values often exceed 2000 mm, with peak values up to 2400 mm. This wet zone reaches slightly into the adjacent foreland to the south, but this finding is poorly supported by station data (see Fig. 2.3). In Baumgartner et al. (1983) this zone shows much larger precipitation values with peak values of more than 3200 mm, but it is less extended to the south.

The other major wet zone of the southern Alps is located from the Dolomiti to the Carnic and Julian Alps. The maximum values are found at the Julian Alps with values up to 3100 mm per year. As discussed in Chapter 1.5, different precipitation maps reveal strongly different precipitation values for this region. The present analysis compares well to recent high-resolution maps of this region as Kolbezen (1998), Mori (1969) or Rankovic (1980), but Baumgartner et al. (1983) in contrast exhibits precipitation values of more than 4000 mm for the Julian Alps, which is about 30% more than for the present analysis.

The main inner Alpine dry zone is centered at the region of Tirol. It is sheltered from all directions by mountain ridges, and its central parts mostly show precipitation values attaining less 1000 mm. The Venosta Valley, which displays precipitation values of about 500 mm, is the driest location of this inner Alpine region. At low altitudes the precipitation amounts are in good agreement with Baumgartner et al. (1983), but for higher altitudes Baumgartner et al. (1983) reveals up to 50% more precipitation. At the Italian part of this dry zone, higher altitudes are poorly covered by stations, which leads to some uncertainty in interpolation. But such large differences occur also in the Austrian part, which shows good coverage with totalizers and conventional rain gauges.

To the east of this dry zone the Hohe Tauern, a mountain range with high precipitation amounts, lies between the wet zone at the northern rim and the Carnic Alps to the south. Its high precipitation values are in complete contrast to the adjacent dry zone to the west showing high mountains as well. This wet zone is mainly supported by totalizer data. When only using the network of conventional rain gauges, this wet anomaly does hardly appear. The precipitation values are in good agreement with Baumgartner et al. (1983), which shows values of 2000 mm to 2500 mm for this ridge as well. Looking at the vertical gradients in this region, the Hohe Tauern reveals quite large gradients of more than 0.8 (mm/a)/m.

Two interesting valleys, the Valais and the Aosta Valley, are situated to the west of the wet zone of Lago Maggiore. Both are directed west-east and present quite low precipitation values below 600 mm. In between, there is a small, but very high mountain range located with altitudes of more than 4000 m. It exhibits interpolated precipitation values up to 2200 mm. In this region very sharp rain shadows occur. For example, the totalizer Furgghorn shows 2830 mm precipitation at an altitude of 3360 m. Only 8 km in north-eastern direction the station Zermatt displays 725 mm precipitation at an altitude of 1640 m. The highest ranges of the crest are poorly covered with gauges and therefore most peak values at the crest are extrapolated.
Figure 8.4: Mean annual precipitation 1971-1990 [mm], as analyzed by PRISM.
The bordering flatland of the Alps is typically characterized by less than 1000 mm precipitation. The region of Wien to the east of the Alps shows very dry conditions with values of around 500 mm, which means that this region is dryer than the Mediterranean coast in France. But the surrounding low mountain ranges (Vosges, Schwarzwald, Jura, Massif Central and Appennino) exhibit remarkably high precipitation values, sometimes even higher than 2000 mm. The small mountain Monts du Morvan for example is only 900 m high and shows a peak value of 1760 mm precipitation, about the double amount of the surrounding flatland. For these smaller low mountain ranges, precipitation is centered at the top of the mountains. The Massif Central in contrast reveals a similar feature as the central Alps: The inner parts are much dryer than their borders, and the maximum precipitation is not centered at the center of the mountain range. Here mainly the northwest and the southeast rim present high precipitation amounts, whereas the central parts show typically less than 1000 mm.

The Rhein Valley between Vosges and Schwarzwald exhibits a distinct rain shadow. Although the surrounding mountains are less than 1500 m in altitude, the shadowing effect is about as large as in the Valais, which is enclosed by mountain crests higher than 4000 m.

Due to the spatially differentiated height gradients (see Fig. 8.1), topographic structures are represented very variably in the precipitation fields. In regions with large vertical gradients, as at low mountain ranges surrounding the Alps or as at the northern rim of the Alps, structures of the precipitation field with a scale smaller than the mean inter-station distance are dominated by topographic variability. For regions with weak gradients as in the Lago Maggiore region or as in Tirol, precipitation shows only reduced correlation to topography at this small scale.
8.3 Mean seasonal precipitation

The precipitation distribution in the Alpine region shows distinct seasonal variations. In spring (March, April and May; Fig. 8.5), it is mainly the southern Alps that get large amounts of precipitation due to frequent southerly winds (for seasonal frequencies of weather types see e.g. Fliri, 1984). The Lago Maggiore region as well as the Carnic and Julian Alps get typically more than 600 mm, partly even more than 800 mm precipitation. The inner Alpine regions mostly get about 200 mm or less.

In summer (June, July and August; Fig. 8.6), the main precipitation zone lies along the northern rim of the Alps, which shows increased convective activity. Here the eastern part gets more precipitation than the western part, prevalently exceeding 800 mm precipitation. The two maximum zones are located about to the south of München and at the Jungfrau massif (46.5°N/8.5°E). The Lago Maggiore region is now much drier than in spring, showing values mostly below 600 mm. The inner Alpine dry zone of Tirol is markedly wetter than in spring (it presents typically less than 250 mm of precipitation in spring, compared to typically more than 400 mm in summer), but the dry zones in the western Alps, the Valais and the Aosta Valley, do not show this property. As opposite to spring, the Aosta Valley is drier than the Valais. The flatland surrounding the Alps shows a distinct decrease of precipitation in southern direction. The southern regions are quite dry in summer due to the Mediterranean climate, as it can be noticed in France, Italy as well as in Croatia.

Autumn (September, October and November; Fig. 8.7) shows quite similar characteristics as spring. Compared to spring, in autumn the low mountain ranges are wetter. For example, the Massif Central reveals peak values of about 700 mm in autumn and about 500 mm in spring. The Appennino in particular seems to catch a lot of moisture coming from the south, so the southern rim of the Alps is somewhat drier. The Lago Maggiore region shows peak values of about 800 mm in spring and almost 700 mm in autumn. The highest precipitation amounts of about 900 mm can be found in the Kápela Mountains in Croatia, a low mountain range with typical altitudes of 1000 to 1500 m.

Winter (December, January and February; Fig. 8.8) is the driest season for the most part of the main Alpine crest. Especially the inner Alpine regions which are well sheltered to the north show very dry conditions of partly below 100 mm. In contrast, for the low mountain ranges to the north of the Alps (Vosges, Schwarzwald and Jura) winter is even the wettest season at all. The flat regions to the east of the Alps are extremely dry in wintertime, which exhibit large areas with less than 100 mm precipitation.
Figure 8.5: Mean seasonal precipitation 1971-1990 [mm], Spring (March, April and May), as analyzed by PRISM.
Figure 8.6: Mean seasonal precipitation 1971-1990 [mm], Summer (June, July and August), as analyzed by PRISM.
Figure 8.7: Mean seasonal precipitation 1971-1990 [mm], Autumn (September, October and November), as analyzed by PRISM.
Figure 8.8: Mean seasonal precipitation 1971-1990 [mm], Winter (December, January and February), as analyzed by PRISM.
8.4 Mean monthly precipitation

In Figures 8.9 to 8.12 mean monthly precipitation for the period 1971-1990 is shown. January is quite wet in the low mountain ranges surrounding the Alps. In February and March these mountains are much drier as well. For the whole Alpine region February seems to be the driest month. From March to April and to May a steady increase in precipitation on the southern side of the Alps can be found. From May to June a drastic change in precipitation distribution occurs. In June the northern rim of the Alps becomes much wetter and on the southern side precipitation decreases. Moreover the southern flatland starts to get dry. In July the southern flat parts of the domain are extremely dry, but already in August this effect vanishes. Then the wet zone at the northern rim of the Alps disappears in September. In October the southern low mountain ranges as well as the Lago Maggiore region are very wet, whereas the northern part of the Alps do not receive much precipitation. These southern wet zones suddenly disappear in November except for the region of the Carnic and Julian Alps, which shows quite wet conditions. Additionally the northern low mountain ranges Vosges, Schwarzwald and Jura start getting a lot of precipitation. December is quite similar to November, but the Carnic and Julian Alps receive less precipitation than in November.
Figure 8.9: Mean monthly precipitation 1971-1990 [mm] for January, February and March, as analyzed by PRISM.
Figure 8.10: Mean monthly precipitation 1971-1990 [mm] for April, May and June, as analyzed by PRISM.
Figure 8.11: Mean monthly precipitation 1971-1990 (mm) for July, August and September, as analyzed by PRISM.
Figure 8.12: Mean monthly precipitation 1971-1990 [mm] for October, November and December, as analyzed by PRISM.
9 Conclusions

With the present study a climatology of mean annual and mean monthly, uncorrected precipitation for a greater region of the European Alps is presented. The analyses are performed for the domain 42.75°N/2°E - 49°N/18°E and for the reference period 1971-1990, using a uniquely comprehensive network of 6090 stations. For analyzing precipitation, the interpolation scheme PRISM has been modified, parameterized and applied on a grid of 1.25 minutes (~2 km) mesh width.

The derived precipitation climatology is the first analysis at a km-scale resolution using original rain gauge data for the entire European Alps, including its surrounding low mountain ranges. These gridded precipitation fields, extending across national boundaries, can be used for comparing precipitation regimes across the entire Alpine range, calculating water balances and validating numerical climate and weather forecast models. As the present climatology has a very high resolution of only about 2 km mesh width, this precipitation data can be used for water balance calculations in small catchments. Furthermore, the comprehensive domain allows to achieve boundary crossing tasks as to derive water balances for major Alpine river catchments and to adequately validate recent highest-resolution numerical models. As a side-product, the analysis has revealed a comprehensive, spatially differentiated picture of the variability of vertical gradients. Up to now, information about spatial structures and spatial variability of these gradients was limited. For scientific use, it is planned to allow access to the digital, gridded datasets.

Using PRISM, a new approach in mapping precipitation of the European Alps has been applied and tested. In opposition to other interpolation methods which only exploit domain-wide properties of the station network and domain-wide dependencies to topography, a combined statistical-geographic approach is used strictly working in localized regions, which considers the regionally variable relationships between precipitation and topography. This method has been thoroughly validated against other analysis methods, and quantitative measures of performance are indicated.

Comparisons of PRISM to a detrended kriging interpolation and a detrended quadrant method revealed no conclusive, perspicuous preference for a particular method, as the crossvalidation differences were rather small compared to the huge spatial variability of precipitation. Compared to detrended kriging, PRISM reveals very good bias values for all but the topmost height zone, which is of major importance for validating numerical models. For a height range 250-1000 m the detrended kriging interpolation exhibits slightly better MAE values than PRISM, but at higher altitudes PRISM performs best. PRISM seems to produce more extreme outliers than kriging which yields rather mediocre RMSE values.

Looking at the results of the subdomain validations, PRISM shows its power especially in regions which are difficult to model with any analysis scheme, where the influence of
topography on precipitation is only partly represented in station data. As a measure for this difficulty, the ratio between the absolute interpolation errors (MAE) and the variability of the station data (MAD) can be used. For these situations showing a large ratio, PRISM performs considerably better than a detrended kriging interpolation. This is one of the main advantages of PRISM as found in this study.

Water balance investigations were not leading to unambiguous performance differences between interpolation methods, as the uncertainty of determining the water balance seems to be bigger than the differences between different interpolation schemes. Nevertheless these analyses were insightful and unfolded some difficulties in determining the water balance. When applying correction values for gauge biases to precipitation as cited in literature, there is a general tendency of all considered analysis methods to get more areal mean precipitation than the sum of runoff and evapotranspiration, leading to unbalanced water balances. No conclusive reasons for this mismatch could be found, but the present investigations suggest that precipitation is not the only error source. Unfortunately the lack of error estimates for runoff and evapotranspiration did not allow detailed investigations. Potential sources of errors for water balance calculations are possibly too large gauge corrections for some catchments, systematic undercatches in runoff measurements, unconsidered storage changes and errors in the determination of evapotranspiration.

Experiments with thinned station networks showed distinct differences between PRISM, detrended and non-detrended kriging. In a first thinning experiment, all analysis methods were run with unchanged settings as derived for the full data set. This experiment was chosen to test the flexibility of the schemes to deal with spatially varying network densities. Up to a thinning radius of 5 grid cells, the performance of PRISM is comparable to detrended kriging. For larger radii however, PRISM performs distinctly worse than the detrended kriging. This good performance of the detrended kriging is only an effect of the unchanged detrending for the whole experiment: The non-detrended kriging variant shows much worse results with increased thinning and performs worse than PRISM. As the station network gets more and more biased with increased thinning, PRISM has problems to determine appropriate gradients from the remaining stations. The detrended kriging in contrast can partly compensate this biased network due to its prescribed detrending gradient and choice of variogram. Compared to the real density variations in the Alpine station network which is infrequently sparser than at a thinning of 5 grid cells, the flexibility of PRISM is satisfactory.

In a second thinning experiment, the performance of the considered methods applied to a much sparser station network is tested. To this end, the schemes were tuned for a thinning radius of 20 grid cells, which corresponds to the density of a typical SYNOP station network. This experiment displayed about the same performance for PRISM and detrended kriging, both in terms of absolute performance and in terms of robustness against variations of the station network density. It seems that a much more robust parameterization could be achieved for PRISM in this sparse network compared to the
original setting which tries to smooth noisy data and to achieve stable regression lines. Although the performance expressed in statistical measures is similar, the interpolation fields show large differences for individual regions between PRISM and detrended kriging. They were not providing clear preferences for a individual method, however.

A conceptual comparison between PRISM and other interpolation methods reveals several assets and drawbacks. At first glance PRISM shows many parameters which have to be investigated and tuned, complicating its application. But most of these parameters have a rather small sensitivity. Once standard settings for different resolutions, precipitation regimes and station network densities are available, the work of tuning PRISM confines to the tuning of just a few parameters. On the other hand, the simplicity of other methods is elusive sometimes. In case of kriging, most difficulties are hidden in assumptions and suppositions which influence the choice of the appropriate kriging variant, the choice of the theoretical variogram and the decision whether a detrending procedure is admissible. As the present analyses show, a uniform gradient for detrending is not appropriate for the Alpine region. In contrast, PRISM itself estimates locally the vertical gradients, thus better exploiting the station data. Further, PRISM is not an optimal nor an objective interpolation method. Therefore different precipitation fields will result, if two scientists perform the same analyses using PRISM. But in reality also most other interpolation methods (as e.g. kriging) are neither optimal nor objective, even if they promise to satisfy these attributes. The restraints for fulfilling these criteria are mostly illusory and can not be satisfied by real data.

In the present study no corrections for gauge biases could be performed, as no adequate metadata was available for applying spatially differentiated corrections. For water balance applications and for model validation, this is a potential drawback, yet such corrections can be applied as a postprocessing in an approximative way, although the proper procedure would be to correct data before interpolation. For Switzerland such corrections are available (Kirchhofer und Sevruk, 1992b). For other regions generalized dependencies of gauge biases with height, sheltering or percentage of snowfall can be applied (see e.g. Sevruk, 1986; Sevruk and Zahlavova, 1992). Such corrected precipitation data will be closer to the true values, as the errors are mostly systematic, but the errors and uncertainties of these adjustments have to be regarded when interpreting the results.

As an outlook, three important issues should be addressed in future work:

- The present investigations reveal the necessity to collect further data. Some regions, especially in Italy, display an insufficient data basis in the present analyses to generate high-quality, high-resolution precipitation fields. Additionally, the extension of the analyses to the climatological standard period 1960-1990 would be attractive.

- PRISM still shows numerous possibilities for improvement. Some parameters depend on the grid resolution or on the network density. With an independent formulation of all
parameters, PRISM would gain further flexibility and probably better performance, too. The performance in extremely comprehensive networks has not revealed the expected superior performance compared to simpler methods. Here spatial interpolation is central, as vertical gradients are mostly resolved by the station network. Perhaps PRISM could be extended with a horizontal analysis scheme which would allow to cope well with such situations. As this study shows, the ratio MAE/MAD can be a good indicator of the ability of the network to resolve topographic dependencies. This ratio could probably be used to automatically detect such situations and to adapt the interpolation algorithm of PRISM.

- To analyze monthly and annual precipitation data, many powerful analysis schemes exist. And as these methods show quite similar performances, the possibilities for further improvements seem to be rather small. In contrast, the development of schemes to analyze precipitation on a daily time scale would be promising. Furthermore there is a pressing need for high-quality analysis schemes on this shorter time scale. Dimensioning tasks in civil engineering, validation of numerical weather prediction models as well as hydrological modelling crucially depend on accurate, high-resolution precipitation data on a daily basis. On this time scale, precipitation is not only correlated to topography, but it also shows strong relationships to meteorological parameters. On the one hand, precipitation patterns depend on the involved precipitation mechanisms. For example, the spatial scale of precipitation patterns as well as the correlation of precipitation to topography are systematically influenced by the atmospheric stability. On the other hand, wind direction and velocity strongly affect shadowing effects, displacement of hydrometeors and gauge biases. A possible approach to this task could be the combination of interpolation schemes with qualitative smallscale information obtained from precipitation radars. An other approach is the combination of analysis schemes with modelled data, as current weather prediction models are able to provide accurate estimates of the windfield.
References


Benichou, P. et Le Breton, O., 1987: Prise en compte de la topographie pour la cartographie des champs pluviométriques statistiques. La Meteorologie Série 7 no. 19, 23-34.


Bergeron, T., 1965: On the low-level redistribution of atmospheric water caused by orography. Supplement to the Proceedings of the International Conference on Cloud Physics, 96-100. IAMAP/WMO.


References


Daly, C., 2000: personal communication.


Fliri, F., 1974: Niederschlag und Lufttemperatur im Alpenraum. Wissenschaftliche Alpenvereinshefte 24, 110 S.


References


Häberli, C., 1999: Personal communication.


Hoelzle, M., 1999: Personal communication.


Kubat, O., 1972: Die Niederschlagsverteilung in den Alpen mit besonderer Berücksichtigung der jahreszeitlichen Verteilung. Veröffentlichungen der Universität Innsbruck 73, 52 S.


Meinardus, W., 1900: Eine einfache Methode zur Berechnung klimatologischer Mittelwerte von Flächen. Meteorologische Zeitschrift Jg. 17 Nr. 6, 241-275.


References


Rohmann, M., 1999: Personal communication.


Schädler, B., 1985a: Der Wasserhaushalt in der Schweiz. Mitteilung der Landeshydrologie und -geologie Nr. 6, 83 S.


Stancik, A. et al., 1988: Hydrology of the river Danube. Enclosed map "Mean annual precipitation in the Danube basin. 1:2000000".


Wolfensberger, H., 1994: Chronik der Totalisatoren. Veröffentlichungen der Schweizerischen Meteorologischen Anstalt Nr. 55, 390 S.
11 Curriculum vitae

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Education
1976 - 1982Primary school in Kriens
1982 - 1989Secondary school in Lucerne; Matura Typus C

University
1990 - 19912 semester study of physics at ETHZ, passed 1st prediploma.
    traineeship:
    5 weeks traineeship at SMA (Swiss Meteorological Agency) with J. Quiby.
    Work: Development and Implementation of an automated verification of
    the numerical weather forecast model SM with foreign Synop stations.
    Diploma thesis:
    "Witterungsanalyse anhand der Alpenwetterstatistik mit Bezug auf den
    Niederschlag". Publication in Berichte und Skripten Nr. 58, IKF ETHZ.

Dissertation
1996 - 2000Dissertation at the Institute for Climate Research ETH Zürich.
    Theme: The Alpine Precipitation Climate.

Further scientific work
1993 - 1995Auxiliary assistant at the Institute for Climate Research ETHZ. Work:
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