Eidgenössische Technische Hochschule Zürich
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Distributed Computing

Accurate Weather Forecast

Bachelor Thesis

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Abstract

This thesis is analyzing the accuracy of forecasts from nine global and five local weather services. We investigate the forecasts for 81 locations in Switzerland. Weather forecasts are requested from the services in a time interval of 30 minutes and over a period of approximately three months. These forecasts contain temperature, rainfall, wind and air pressure values. The goal is to find differences in the accuracy of the forecasts. The results of this investigation shall help to determine the best available forecast for any place and day in Switzerland.
The ground truth is received from IDAweb, which is a portal for researchers, operated by MeteoSwiss, providing archive data for many weather stations across Switzerland.
The analysis of the accuracy of temperature forecasts is the main part of this work. On the one hand this thesis analyzes the accuracy depending on how many days in advance a service predicts the temperature. On the other hand we analyze it depending on the location. We also list a ranking for all services, to determine whether a service is better than another. As expected, temperature forecasts depend on location and time. Also the ranking is mixed and not only one service appears on top of it.
In addition, the accuracy of rainfall, wind and air pressure forecasts is examined. The results for these parameters are not as significant as for temperatures.
Based on the results a prototype of a weather application was developed. This application allows the user to request the best available weather forecast for a specific location.

Contents

Chapter 1

Introduction

In this work weather forecasts for Switzerland are being examined. With help of crawlers we obtain forecast data from 14 different services and up to 81 locations. We also get ground truth for all 81 locations from MeteoSwiss. The goal is to find out, which weather services provide better forecasts than others. The analysis of the accuracy depends on different dimensions. On the one hand we are interested in the accuracy depending on the time and on the other hand we want to investigate if the location influences the accuracy.
This thesis offers analysis for mainly four different parameters, which are provided by the forecast services. These are temperature, rainfall, wind and air pressure. Since each of the 14 weather services forecast at least temperatures, the focus of this work lies on the analysis of temperature forecast accuracy. Nevertheless this thesis also inspects differences in accuracy for the other three parameters.

1.1 Motivation

The amount of online weather services has grown in the last few years. As users of these services we do not really know which services are more accurate than others. In this work we analyze the services over a timespan of roughly three months. With help of the obtained data we want to find differences and similarities between the services. The goal is not only to find out which one of the 14 services is the best, but also to find general inferences like for example whether Swiss services perform generally better than global services or not. We also analyze the influence of geography on the forecasts. For example, if mountainous areas, like the Alps, make it more difficult to forecast weather precisely.
There are different types of weather forecast services. Some predict the weather for a whole day, whereas others forecast in more fine-grained time intervals. Here the question of how accurate it is to forecast weather for a certain time interval can be raised. For example, predicting the weather between 11:00 and 12:00, five days in advance is generally more difficult as to provide a weather forecast for the whole day.

1.2 Related Work

In the blog of Randal S. Olson[1] and [1], also temperature forecast analysis has been done. They confirmed that temperature forecasts from weather services are more accurate than forecasting the temperature for tomorrow to be the same as today. However, if predictions are made for more than ten days in advance, historical averages are generally more accurate to predict the temperature. This means, historical averages should rather be used than forecasts from weather services, if there is need for a prediction of temperatures for more than ten days in advance. In contrast to this work, this thesis also analyzes rain, wind and air pressure and asks the same questions on this data. Furthermore, in this work accuracy of forecasts depending on the location is taken into account too.

[1] Blog Article: http://www.randalolson.com/2014/06/21/we-can-only-forecast-the-weather-a-few-days-into-the-future

Chapter 2

Data and Model

We crawl 14 different weather services. Nine of them are international services and five are local services (with Swiss top-level domains.) The services provide their forecasts for a certain time interval: Some of them forecast the weather for the whole day and give minimal and maximal temperatures whereas others forecast in intervals of one or three hours. The *size of the time intervals* is called Δt. Furthermore, the terms daily-, 1-hourly- and 3-hourly forecasts are being used for the different types. The size of the time intervals for each service is available in Table 2.1.

2.1 Forecast Values

In this work, several *forecast values* are inspected. The index d states, how many *days in advance* a forecast value was generated. The forecast values with their corresponding abbreviations and units are: Average temperature $T_{\mathrm{avg},d}$, minimum temperature $T_{\mathrm{min},d}$ and maximum temperature $T_{\mathrm{max},d}$ in °C. Average wind speed $W_{\mathrm{avg},d}$ in km/h. Minimum rainfall $R_{\mathrm{min},d}$ and maximum rainfall $R_{\mathrm{max},d}$ in mm. Average air pressure $P_{\mathrm{avg},d}$ in hPa.
Not all services provide each of the mentioned values. In fact, the temperature values are actually mutually exclusive: There are services, forecasting an average temperature for a given time interval, while others provide a minimum and a maximum temperature for the whole day. None of the services provide both. Table 2.1 lists the values each service provides.
To mark ground truth values, the same abbreviations with an asterisk attached to it (e.g. T^*_{avg}) are being used. For the measured rainfall there is R^*_{tot}, i.e. the total amount of rain, fallen in a given time interval. Note that there is no need for a day index for ground truth.

2.2 Locations

This thesis investigates 81 locations, which are distributed over Switzerland. The choice of these locations was mainly influenced by the distribution of the weather stations that are operated by MeteoSwiss. This way, it is possible to directly compare the data of the forecasts to the ground truth values. Figure 2.1 shows all weather stations on the map of Switzerland. As it can be seen, some locations are very close to each other. These are pairs of locations, where one weather station is in the valley and the other on the mountain (e.g. Davos and Weissfluhjoch). With these pairs there is the possibility to analyze the differences of forecast accuracy depending on the altitude of a location.
The number of locations each service supports can be found in Table 2.1. The average number of locations supported is 58. The Swiss services cover an average of 72 stations, whereas the international ones cover only an average of 50.
It might be surprising that MeteoSwiss has the lowest number of locations (62) in the local services category, although it operates the weather stations we use to analyze the data. This comes from the design choice of the MeteoSwiss website, which allows users to search for forecasts of locations with postal codes only. However, some of the locations, which have been investigated are located on mountains and therefore have no postal code. So consequently MeteoSwiss does not provide forecasts for these locations.
BBC, CNN and NY Times only provide forecasts for the most popular locations of the 81 under investigation. A list of which locations are supported by the services is available in Appendix A.2

2.3 Data Storage

The data from the different services is stored in a MySQL database in four relations. Namely the service, location, forecast and ground truth relation. Additional explanations will be provided within the next sections.

Service Relation The service relation is a list of all weather services, which also provides the translation of service names to service ids (sid).

Location Relation The services give different names to locations, which are actually the same. As an example some services write 'Sankt Gallen' whereas others name the location 'St. Gallen'. Therefore this table maps these locations to the same location id (lid). Furthermore, the GPS coordinates of the weather station is stored.

	Service name	D	Δt	L	T_{avg}	$T_{\text{min/max}}$	W_{avg}	$R_{\text{min/max}}$	P_{avg}
Global	Wetter.com	2	1	77	✓	–	✓	✓	✓
	WWOnline	6	1	55	✓	–	✓	✓	✓
	Accuweather	3	1	58	✓	–	✓	–	–
	Wetter.net	5	3	56	✓	–	✓	–	✓
	Woeurope	7	24	62	–	✓	✓	–	–
	CNN	9	24	24	–	✓	–	–	–
	NY Times	4	24	30	–	✓	–	–	–
	Google	3	24	74	–	✓	–	–	–
	BBC	4	24	11	–	✓	✓	–	–
Local	Meteonews	5	1	79	✓	–	✓	✓	✓
	MeteoSwiss	5	1	62	✓	–	–	✓	–
	Meteocentrale	4	3	76	✓	–	✓	✓	✓
	SRF Meteo	5	3	76	✓	–	✓	✓	–
	Wetter.ch	4	24	69	–	✓	–	–	–

Table 2.1: List of all services divided into categories local and global. The parameter D is the maximum number of days in advance d of the service, Δt is the time interval and L is the number of the investigated locations it supports. The further columns state whether a forecast value is available. A list of the URLs as well as the number of forecasts, stored in the database is available in Appendix A.1.

Forecast Relation The forecast relation contains all forecasts received by the crawlers. A forecast is defined through a service id, a location, and the receive time, i.e. the time when the forecast was obtained by the crawler. The start time and the duration define the time interval of the forecast. For example, for the forecast for February 22 between 15:00 and 16:00, the start time would be '2015-02-22 15:00' and the duration would be 1(hours). The rest of the relation are the values of the forecast provided by the service.

Ground Truth Relation The ground truth relation is very similar to the forecast relation. The main difference is that the ground truth instead of forecasts is stored. Since ground truth is available in ten minute intervals, the duration in minutes is also stored.

2.4 Obtaining the Data

For extracting the data from the websites, the python based framework Scrapy[1] is being used. Using the Scrapy framework there is a spider for each weather forecast service which is crawled. In the spiders we handle the reception of

[1] Scrapy: http://scrapy.org/

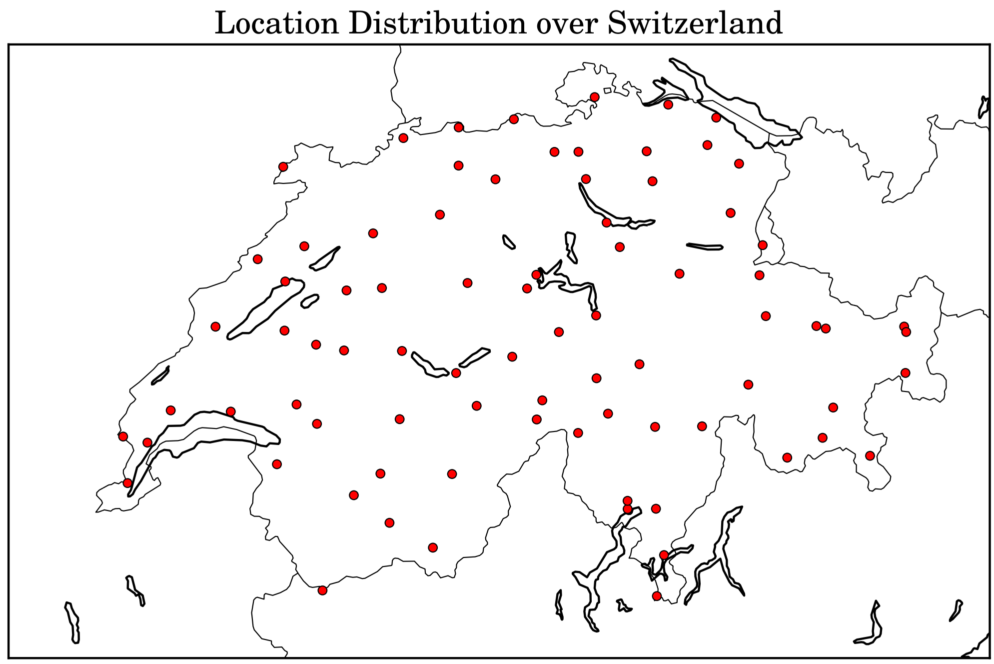


Figure 2.1: The locations investigated by this work. Coordinates correspond to the positions of the weather stations operated by MeteoSwiss.

the data from the website as well as the insertion of the received data into the database. To handle the connection between the crawlers and the database SQLalchemy is used, which is an object-relational mapping framework that eases the communication with the database.[2] In the following sections the differences in receiving forecast data and ground truth is discussed.

2.4.1 Crawling Forecasts

For crawling the forecasts the spiders get fed with a list of all URLs it has to send its requests to. So it was necessary to collect those URLs by searching for all locations on the websites and thereby find out whether a location is supported by a service. When a spider gets a HTTP response it parses the values. The parse function then also handles the insertion into the database. To keep the size of the database to a minimum, only forecasts are inserted, which have changed compared to the last one for the same location and time. The crawlers are running continuously and request data in 30 minute intervals. We obtain weather forecasts for the period from 19th December 2014 until 11th March 2015. The number of forecast records for each service is available in Appendix A.1.

[2]SQLalchemy: http://www.sqlalchemy.org/

2.4.2 Obtaining Ground Truth

We get our ground truth data from IDAweb[3], which is a data portal operated by MeteoSwiss where researchers can access the data archive of weather monitoring stations across Switzerland. The data is measured all ten minutes by the weather stations. The portal provides the data for the locations as CSV files. To insert the data into the database these files are parsed with a python script.

[3] IDAweb: https://gate.meteoswiss.ch/idaweb/more.do

Chapter 3

Data Analysis

3.1 Evaluation Method

To visualize the data the python library matplotlib is used, which provides functions to generate different kinds of plots.[1] We also want to investigate differences of forecast accuracy depending on the locations. For this, we use maps generated with the Basemap toolkit for matplotlib.[2]

3.1.1 Comparison of Temperatures

When comparing the accuracy of the temperature forecasts, there are essentially two different categories of services. On the one hand there are the services forecasting the average temperature $T_{\text{avg},d}$ in 1 and 3 hour intervals and on the other hand there are services, which forecast $T_{\text{min},d}$ and $T_{\text{max},d}$ for the entire day. For the first category of services we just compare the predicted temperature to the measured average temperature in this time interval. For the other category, the predicted interval $\Delta T := [T_{\text{min},d}, T_{\text{max},d}]$ is compared with the ground truth interval $\Delta T^* := [T^*_{\text{min}}, T^*_{\text{max}}]$. To quantify the accuracy of a minimal/maximal temperature forecast, the values u and v are introduced as follows (also see Figure 3.1).

Definition of u and v

Let $|I|$ be the length of the interval I. We first define the auxiliary intervals $A := \Delta T \cap \Delta T^*$ and $B := \Delta T \setminus \Delta T^*$ according to Figure 3.1. Intuitively, the value u states how much of ΔT^* is covered by ΔT. Formally this leads to the following definition:

$$u := \frac{|A|}{|\Delta T^*|} \in [0, 1] \tag{3.1}$$

[1] Matplotlib: http://matplotlib.org/

[2] Basemap: http://matplotlib.org/basemap/

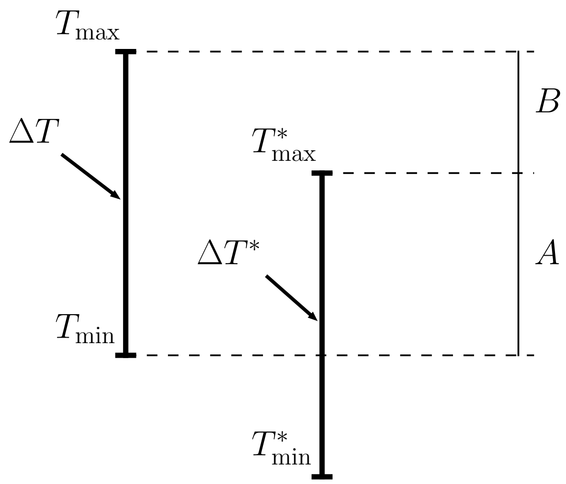


Figure 3.1: Illustration of intervals, used to derive u and v with the predicted and measured intervals ΔT and ΔT^* respectively.

With just the parameter u defined, forecasts predicting for example $T_{\text{min},d} = -100°\text{C}$ and $T_{\text{max},d} = 100°\text{C}$ always have $u = 1$ and therefore the best possible value. Obviously, such a forecast is far from a good one. To solve this problem, we define the additional parameter v. Intuitively, this parameter corresponds to how much of ΔT is *not* covered by ΔT^*. We can also see v as a measurement of how much margin a weather service gives to its forecasts. Formally:

$$v := \frac{|B|}{|\Delta T|} \in [0, 1] \tag{3.2}$$

In summary it can be said: A good forecast maximizes u and minimizes v. For comparison of two forecasts the value $u \cdot (1 - v)$ is used. In this case a value closer to 1 represents a good forecast and a value closer to 0 represents an inaccurate one.

3.1.2 Comparison of Wind, Rainfall and Pressure

To investigate the accuracy of wind and pressure forecasts $W_{\text{avg},d}$ and $P_{\text{avg},d}$, we compare the predicted value with the average of the ground truth in the time interval. Since rainfall is cumulative, we compare the mean value of $R_{\text{min},d}$ and $R_{\text{max},d}$ to the *sum* of the total rainfalls R^*_{tot} in a given time interval.

3.1.3 BBC Data Flaw

The weather service BBC only provides the average temperature for the remaining current day. When crawling forecasts from BBC this average temperature is stored in the database as minimal and maximal temperature and therefore the size of the forecast interval is $|\Delta T| = 0$. In the analysis this leads to bad u and v values for $d = 0$. Taking this into consideration, the evaluation of BBC is limited to forecasts with $d \geq 1$.
This flaw also appears in the analysis of wind forecasts. Lets for example assume that a day with a windy morning and a windless afternoon is inspected. A forecast from the afternoon, predicting no wind, gets then compared with the measured average wind of the whole day and therefore differs more.

3.2 Average Temperature Evaluation

In the following sections we analyze the accuracy of the average temperature forecasts for different services. We want to know, if the accuracy of a forecast depends on the number of days d, it predicts the weather in advance and also on the location. We analyze the forecast services in the two categories 1- and 3-hourly. In the last part we provide rankings of the services.

3.2.1 Accuracy Depending on Time

We want to know, if the temperature forecasts get more accurate, the closer to the actual day they are. Figure 3.2 shows the absolute difference between the measured and predicted temperatures depending on d for the service Meteocentrale as a boxplot. We see that the median difference decreases, if the date is closer to the day the forecast is generated. Also the boxes shrink with decreasing d. The other services show similar results for this too. We can therefore confirm, average temperature forecasts are generally better, the closer the day in question is. Boxplots for other services are available in Appendix B.1.

3.2.2 Accuracy Depending on the Location

Another interesting question is, if weather forecasts depend on the location. Here the expectation is that the weather is easier to predict in flat areas like the Mittelland and harder to predict in mountainous areas like the Alps and the Jura mountains. We display the median temperature differences on heat maps. The differences at the locations for a given d are the known fixed points. To generate the values between the fixed points we use linear barycentric interpolation. A description of this method can be found in Appendix A.3. Dark colors indicate big differences, whereas bright colors indicate small ones. All values above 10°C

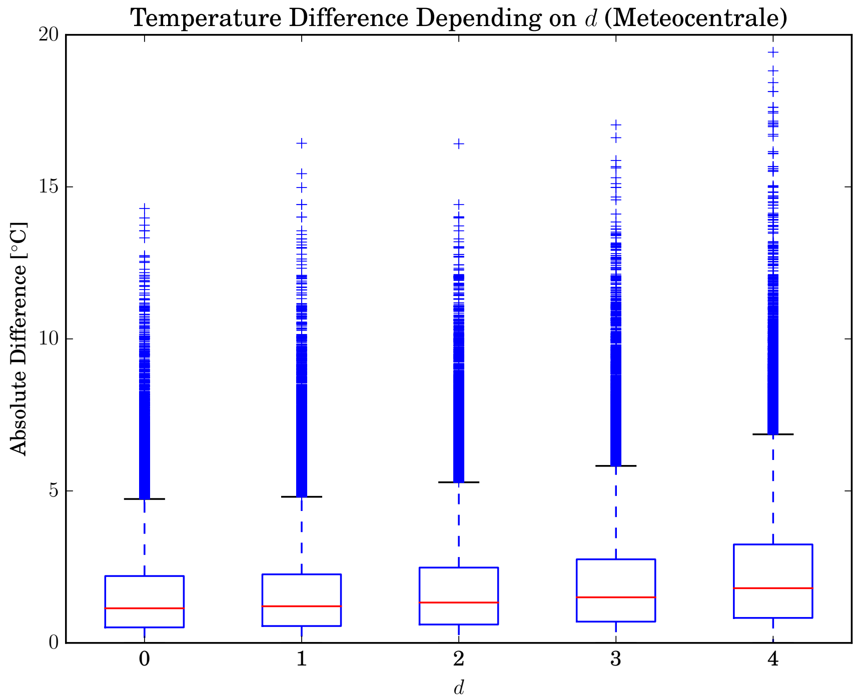


Figure 3.2: Boxplots of average temperature difference between predicted and measured values depending on d. Median values and box sizes decrease with less days in advance d.

get colored the same. Figure 3.3 shows an example for such a heat map.
In Figure 3.4 one can see a matrix of heat maps including all services with time intervals $\Delta t = 1\text{h}$. The purpose of this figure is to show the improvement of the forecast accuracy with decreasing d and also the differences between the services on the same day. As we can see the heat maps are generally brighter, if d is smaller. World Weather Online on the one hand provides highly inaccurate forecasts for the Alps, but can on the other hand keep up with the other services in the Mittelland. In general, the Swiss weather services achieve better results concerning the accuracy of their forecast in the mountainous areas. This leads to the assumption that global services do not consider differences in geography as good as local ones do. In addition, it has to be said that MeteoSwiss is keenly imprecise for both their forecasts for the mountains of Pilatus and Jungfraujoch, compared to the rest of the location it provides. These locations can be recognized by the two dark spots on the heat maps for every d.
In Figure 3.5 the same matrix of heat maps for the services with intervals $\Delta t = 3\text{h}$ is shown. In this matrix the Swiss services perform outstanding in contrast to Wetter.net.
As a consequence, at least for alpine regions one should rather use local services to get an accurate temperature forecast. Again it can be seen that global services do not take geography into account as much as local ones do. Most likely

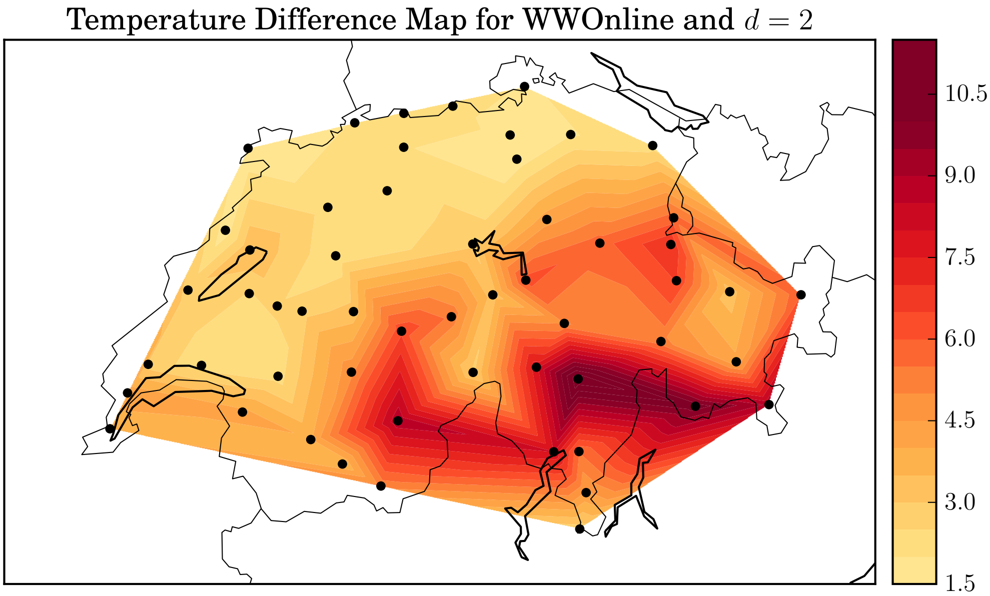


Figure 3.3: Map of interpolated temperature differences for World Weather Online and $d = 2$. Black dots are the available locations for World Weather Online. Colors represent temperature differences in °C.

local services have access to more weather stations. There is also the possibility that they have models, which are better adapted to the geographical conditions. Therefore these services are able to predict temperatures more accurately.

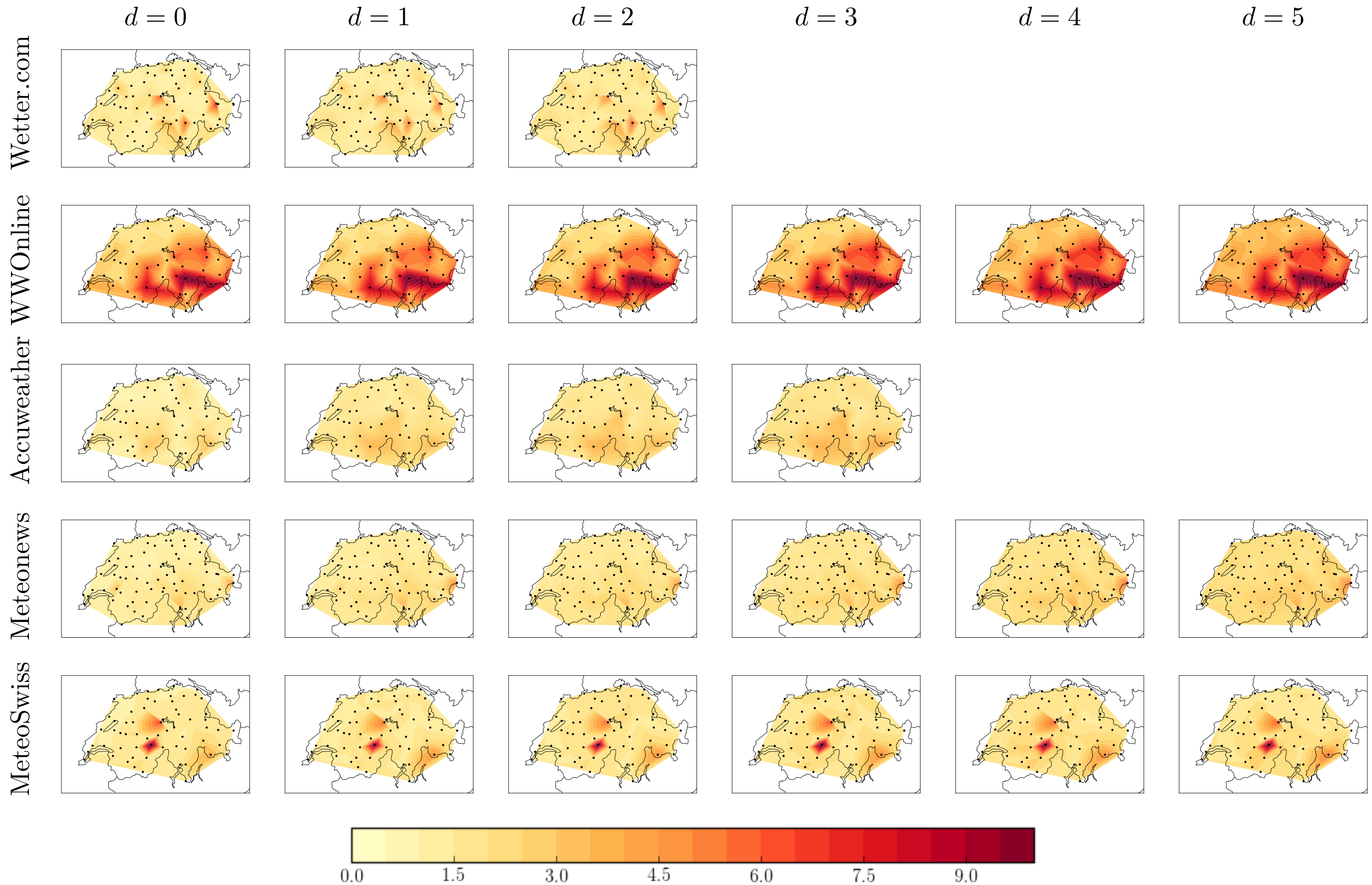


Figure 3.4: Temperature difference heat map matrix of services with $\Delta t = 1\text{h}$. Increasing day in advance d from left to right. Heat map $d = 6$ for WWOnline is omitted.

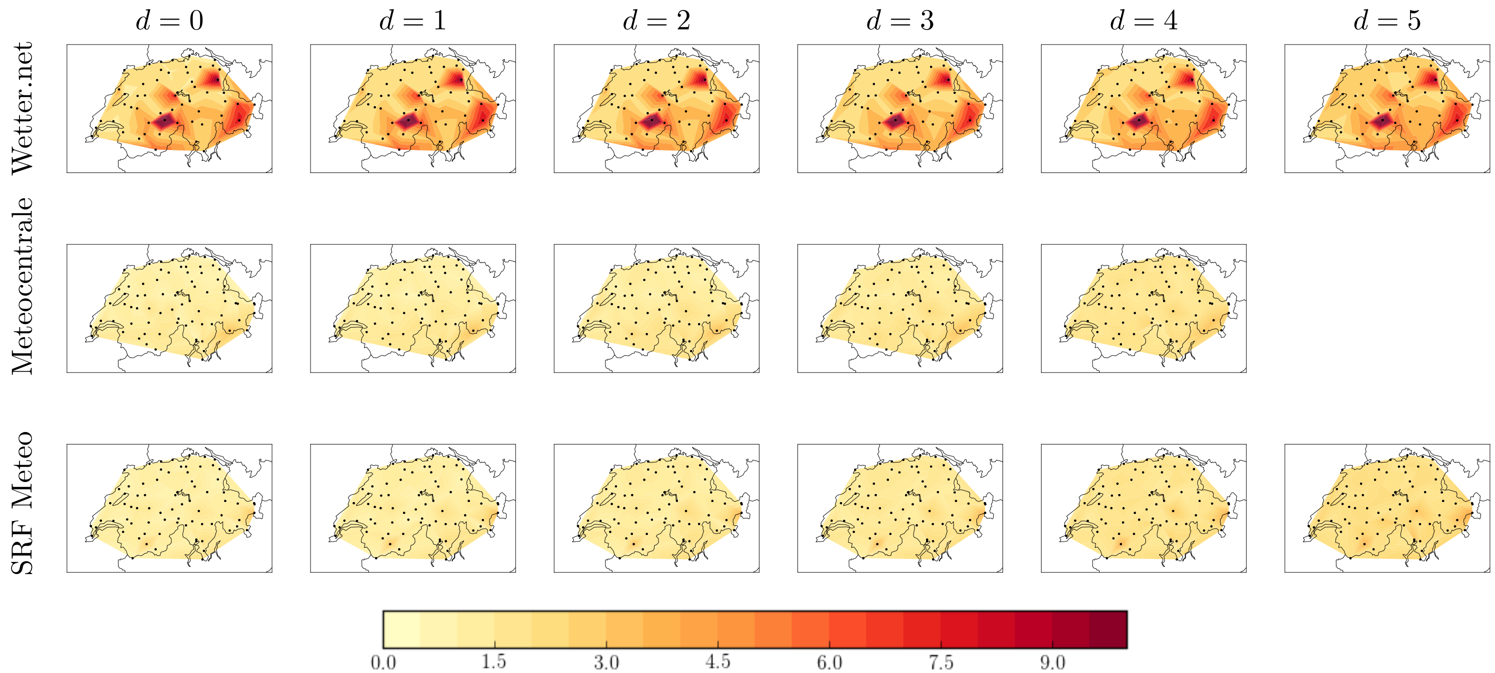


Figure 3.5: Temperature difference heat map matrix of services with $\Delta t = 3\text{h}$. Increasing day in advance d from left to right.

$d = 0$		$d = 1$		$d = 2$	
Service	Diff.	Service	Diff.	Service	Diff.
Accuweather	1.36	Meteonews	1.67	Meteonews	1.81
Meteonews	1.37	Wetter.com	1.73	Wetter.com	1.85
Wetter.com	1.67	MeteoSwiss	1.84	MeteoSwiss	1.95
MeteoSwiss	1.73	Accuweather	1.94	Accuweather	2.01
WWOnline	3.91	WWOnline	3.99	WWOnline	4.18

$d = 3$		$d = 4$		$d = 5$	
Service	Diff.	Service	Diff.	Service	Diff.
Meteonews	1.97	Meteonews	2.17	MeteoSwiss	2.13
MeteoSwiss	2.10	MeteoSwiss	2.19	Meteonews	2.39
Accuweather	2.23	WWOnline	4.90	WWOnline	5.02
WWOnline	4.52	–	–	–	–
–	–	–	–	–	–

Table 3.1: Temperature rankings for $d = 1$ to $d = 5$ and services with time intervals $\Delta t = 1\text{h}$. The Diff. columns contain the average difference between $T_{\text{avg},d}$ and T^*_{avg} in °C. The table with $d = 6$ is omitted, since it only contains the service World Weather Online (Difference = 5.11°C).

3.2.3 Ranking of Services

In this section, rankings of services for $T_{\text{avg},d}$ are set up. The purpose of this is to determine if some services are generally better than others. We analyze the *average difference* for each service and d. This average value is built from the median differences of each location (The fix points of our heat maps). With this value, it can be seen, which service is best for how many days in advance d.
Table 3.1 shows the rankings for the services with time intervals $\Delta t = 1\text{h}$. There one can see that not only the local services (MeteoSwiss and Meteonews) perform well but also some global ones. Surprisingly, Accuweather provides the best value for $d = 1$, but performs bad for the rest of the days. World Weather Online performs the worst in every daily ranking, like it was already shown at the heat maps.

Table 3.2 shows the rankings for the services with time intervals $\Delta t = 3\text{h}$. Here, the local services (SRF Meteo and Meteocentrale) dominate the global service (Wetter.net). As seen in Figure 3.6, both local 3-hourly services perform better than all 1-hourly services. It is suspected that forecasting an average temperature for a 3h interval is easier than forecasting an average temperature for a 1h interval. World Weather Online and Wetter.net provide worse forecasts for all days than the rest of the services. Whereas the rest of the services have in average at most a difference of 1.75°C for $d = 0$. For $d = 5$ the worst average value for these services is 2.39°C. SRF Meteo and Meteocentrale perform similarly well for each day they appear together. This might be indicating that

$d=0$		$d=1$		$d=2$	
Service	Diff.	Service	Diff.	Service	Diff.
SRF Meteo	1.20	Meteocentrale	1.31	SRF Meteo	1.43
Meteocentrale	1.22	SRF Meteo	1.32	Meteocentrale	1.43
Wetter.net	3.09	Wetter.net	3.16	Wetter.net	3.20

$d=3$		$d=4$		$d=5$	
Service	Diff.	Service	Diff.	Service	Diff.
Meteocentrale	1.59	SRF Meteo	1.84	SRF Meteo	2.17
SRF Meteo	1.60	Meteocentrale	2.85	Wetter.net	3.52
Wetter.net	3.23	Wetter.net	3.36	–	–

Table 3.2: Temperature rankings for $d = 1$ to $d = 5$ and services with time intervals $\Delta t = 3$h. The Diff. columns contain the average differences between $T_{\text{avg},d}$ and T^*_{avg} in °C.

they use similar methods to determine the weather forecasts.
In only one case the average value increases with decreasing d (MeteoSwiss from $d = 5$ to $d = 4$). In all other cases the values get either better or stay equal.

3.2.4 Summary

As expected average temperature forecasts of any type improve the closer the days is, they predict. However differences depending on the location are mainly evident for global services in the 1-hourly and 3-hourly category. It seems that global services do not take geography as much into account as the local services, whereas local services perform similarly well for every supported location. Exceptions are Accuweather and Wetter.com that can keep up with the local services. The local services however perform better, although they support more of the investigated locations on average. This even emphasizes the good result of the local services. Therefore, a local service should also be preferred over a global one for at least the alpine regions.
For the 3-hourly local services, smaller differences than for the 1-hourly local services can be seen. Also the 3-hourly global service Wetter.net performs better than the 1-hourly global service World Weather Online. In contrast to the 3-hourly forecasts, the 1-hourly forecast ranking is much more mixed. For the 3-hourly forecasts one can clearly see that SRF Meteo and Meteocentrale perform similarly good and the global service Wetter.net ranks always worse. Such an evident pattern is not visible for the 1-hourly forecasts.

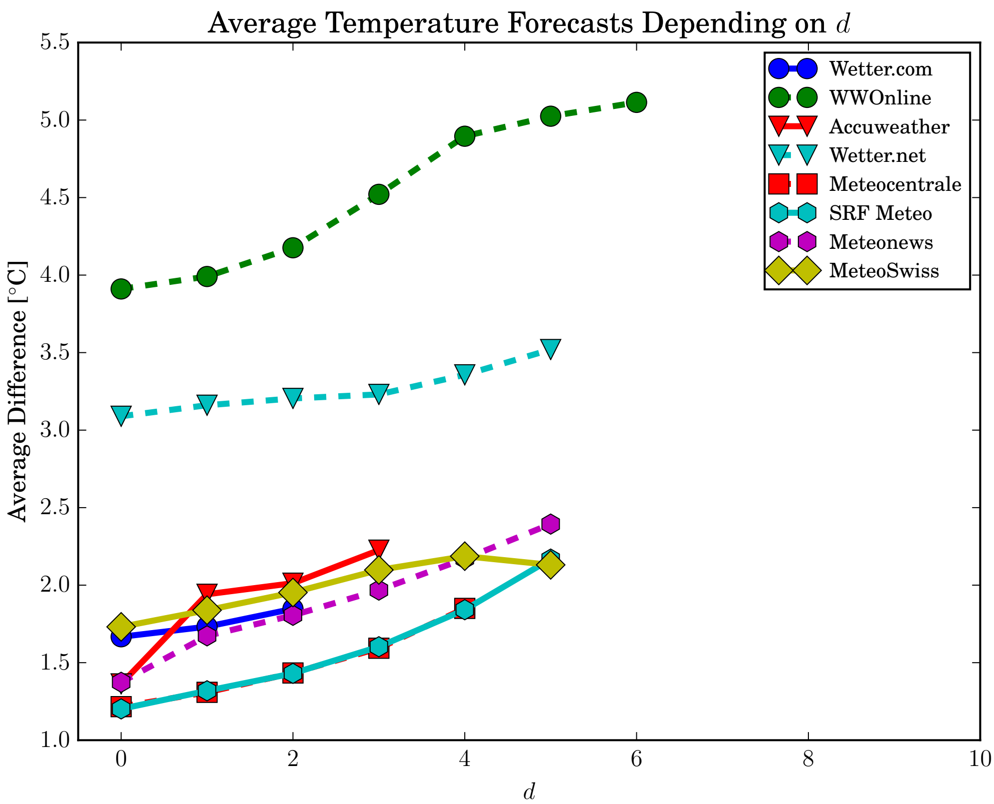


Figure 3.6: Development of the average difference between measured and predicted average temperature values in °C, depending on days in advance d.

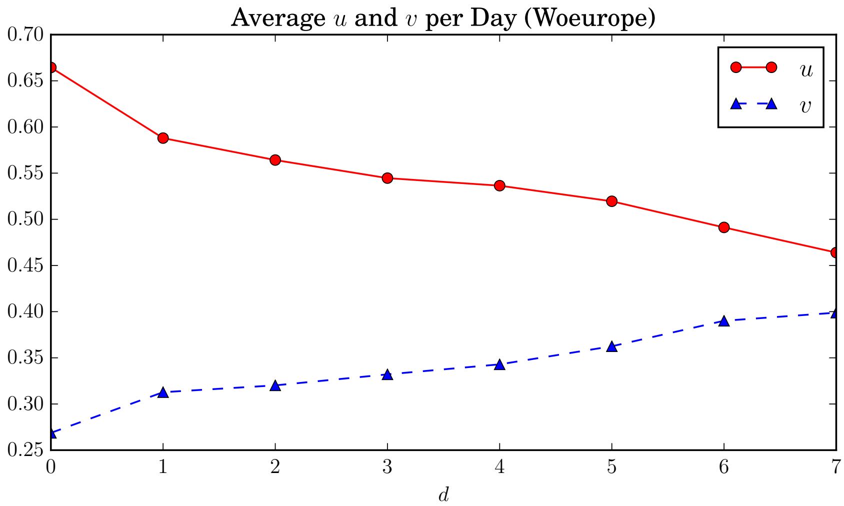


Figure 3.7: As expected, u heads to the upper left corner and v to the lower left with decreasing days in advance d for the service Woeurope.

3.3 Minimal and Maximal Temperature Evaluation

In this section the accuracy of minimal and maximal temperature forecast is analyzed. We also use heat maps and rankings. In contrast to the analysis of average temperatures, we use the u-v-values to compare the accuracies of different forecasts.

3.3.1 Accuracy Depending on Time

The services, which forecast $T_{\text{min},d}$ and $T_{\text{max},d}$ cannot be compared with the same method as for average temperatures. Therefore u and v (defined in Section 3.1.1) are used to state whether a forecast is more accurate or not. For a good service an increasing u and decreasing v is expected, the smaller d is. In Figure 3.7 one can see the expected behavior of u and v using the example of Woeurope. However, in this category there are also services, which do not show the expected results. In Figure 3.8 (the same diagram for BBC) one can see the values u and v converge with decreasing d. This behavior is a consequence from the data flaw described in Section 3.1.3. Another way to illustrate the forecasts is to plot a point for each forecast in the u-v domain $[0,1] \times [0,1]$ as depicted in Figure 3.9 for Woeurope and $d = 0$. It can be seen that many forecast points are located either on the line $u = 1$ or $v = 0$. Remember that the point $(1,0)$ represents a perfect forecast, whereas the point $(0,1)$ is indicating a highly inaccurate forecast. The red *mass point* is the average u-v coordinate. We see that the forecast points build lines for some v value. These points lie on the lines

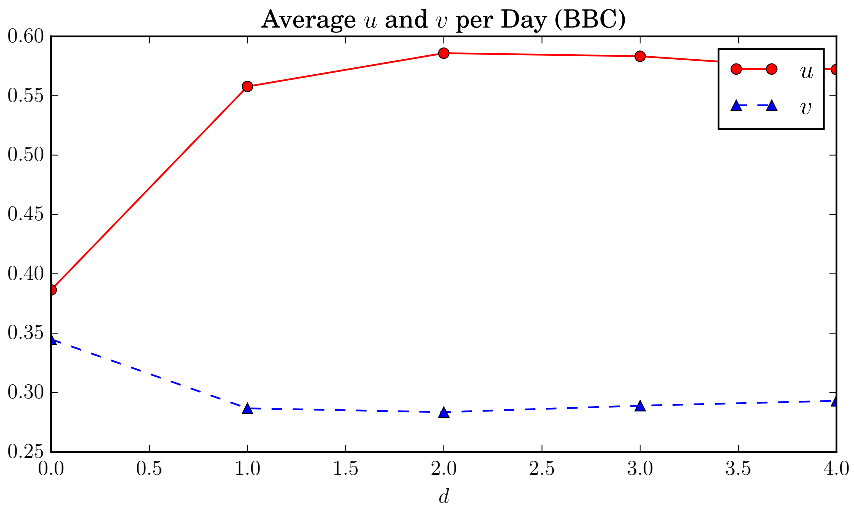


Figure 3.8: As an exception, BBC provides only average temperatures for $d = 0$ and normal minimal/maximal temperature forecasts for the other days. Therefore, values for $d = 0$ are not relevant. Also see Section 3.1.3.

$v = \frac{i}{10}, i \in [0, \ldots, 10]$. For this, recall the definition of v. The denominator in the definition is the forecast interval ΔT. Since the weather services use integers for their minimal and maximal temperatures, this interval will also always be an integer. Considering this fact, values tend to accumulate on lines if it happens that the numerator is also an integer. This is not the case in the definition of u, since ground truth temperatures are more precise.
Subsequently, only the position of the mass point for different d's is analyzed. In Figure 3.10 a mass point diagram for the service Woeurope can be seen. The mass points for the different d's head to the lower right corner with decreasing d. This implies that the forecast intervals get more precise for lower d's. Therefore, daily forecasts get more accurate when forecasting weather for fewer days in advance. The mass point diagrams for the other services are available in Appendix B.2.

3.3.2 Accuracy Depending on the Location

Again, the same type of heat maps are used to illustrate the accuracy of the services as for average temperatures. Instead of the difference between the ground truth and forecasts, the parameter $u \cdot (1 - v)$ is displayed. This means that in contrast to the maps of average temperatures, greater values are good and small values are bad. Since values are rarely greater than 0.7, a lower bound of 0 (dark color) and an upper bound of 0.7 (bright color) is used for the points on the heat maps. Everything above 0.7 gets the same color as a point with value 0.7. This way, the differences are more evident. Figure 3.11 is an example for such a

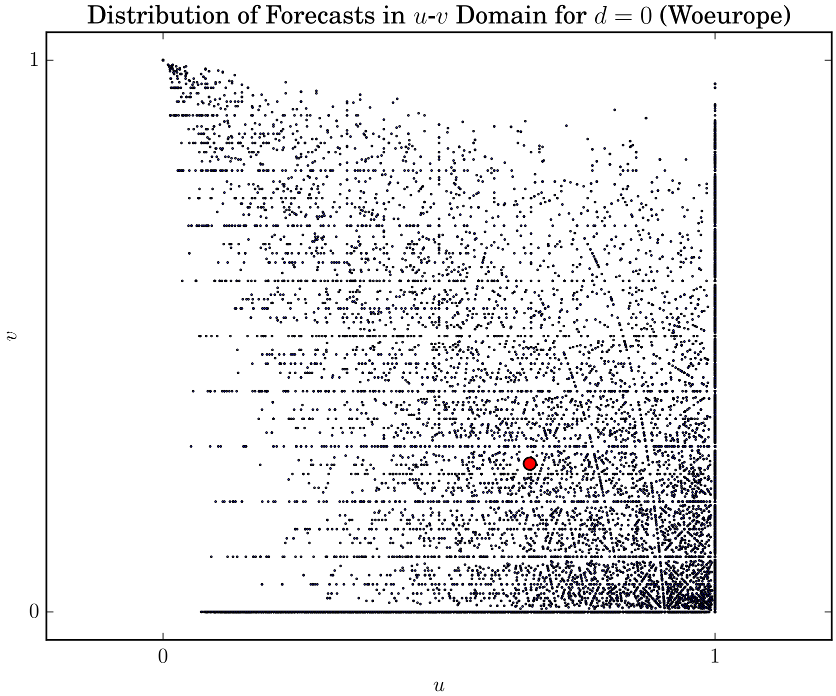


Figure 3.9: This figure shows the u-v coordinates of daily forecasts for service Woeurope and $d = 0$. The red point is the mass point, defined as the average

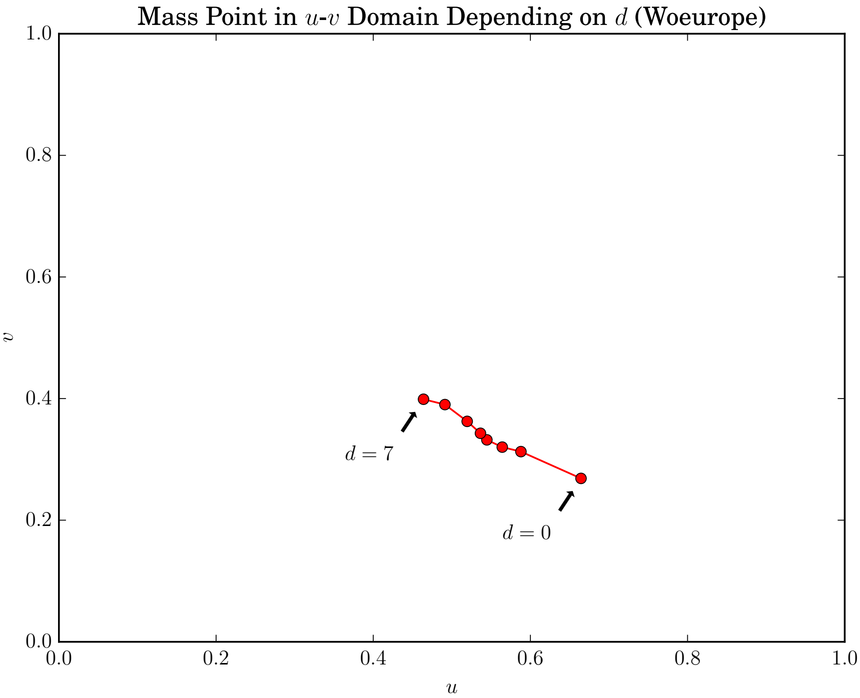


Figure 3.10: Mass point diagram for service Woeurope. This diagram shows the position of the mass point for the different days in advance d.

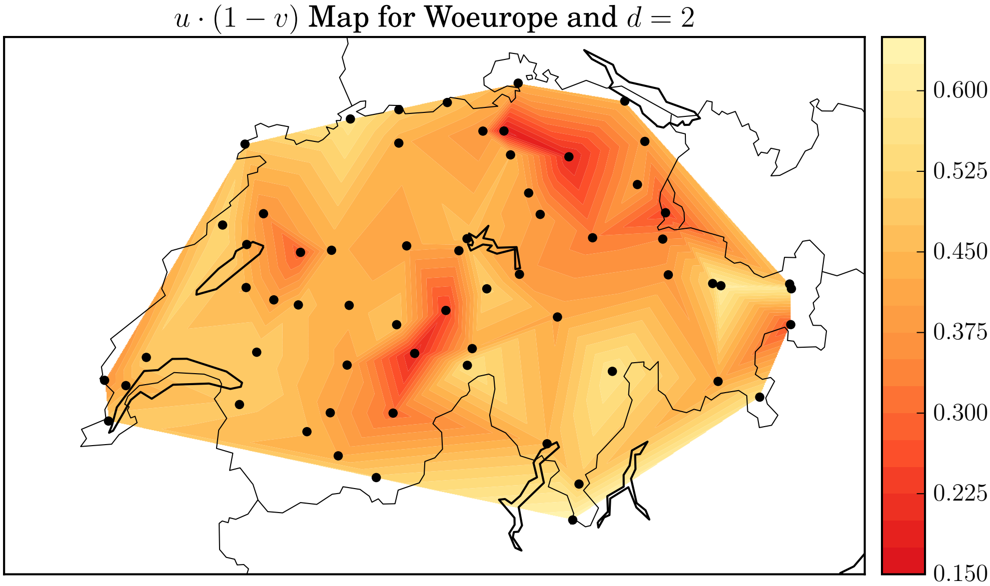


Figure 3.11: Map of interpolated $u \cdot (1 - v)$ values for Woeurope and $d = 2$. Black dots are the available locations for Woeurope. Colors represent $u \cdot (1 - v)$.

heat map. In Figures 3.12 and 3.13 one can see the matrices for daily temperature forecast services. Figure 3.12 includes the services with lower number of supported locations, whereas Figure 3.13 depicts the heat maps for the services with more locations. The colors get brighter with decreasing d in the matrices as expected. However, no such geographical differences (e.g. darker colors in mountainous areas) can be seen as the ones on the heat maps for average temperatures. The service BBC provides a too small number of locations to derive a significant result. The only local service in this category is Wetter.ch. This service provides good results for the closer days but gets worse rapidly.

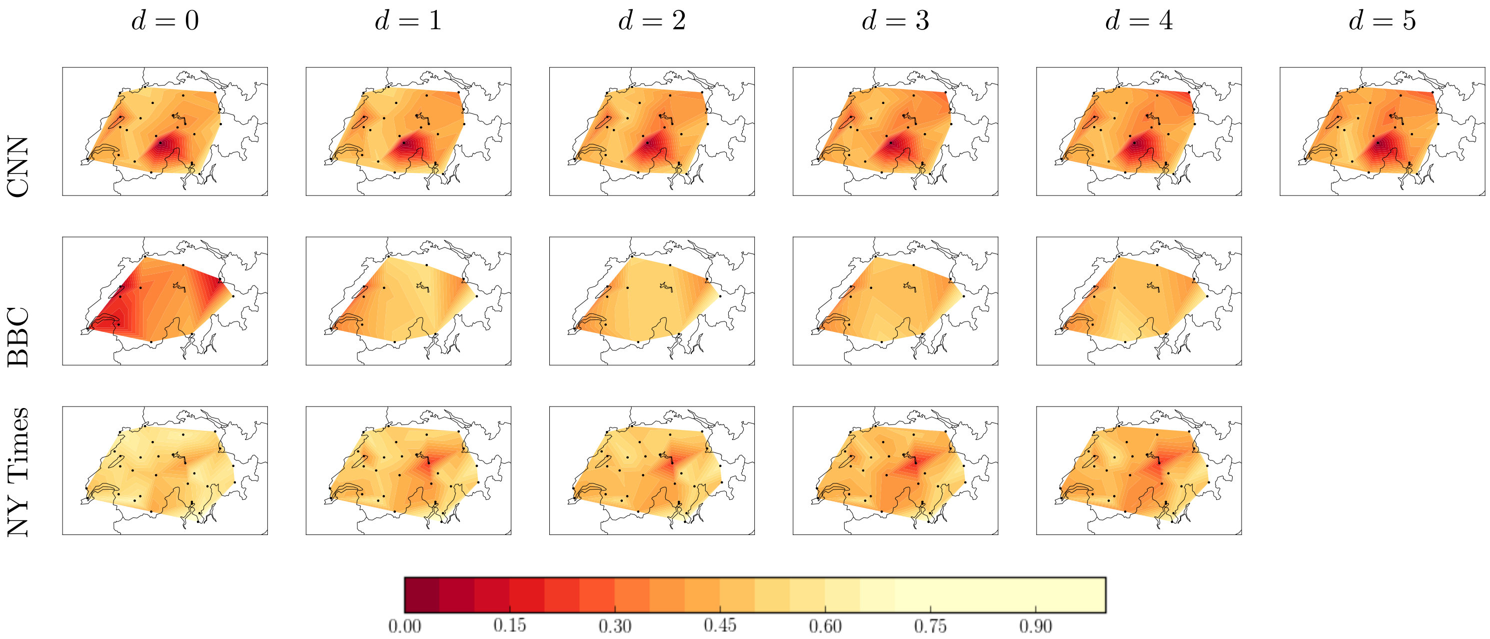


Figure 3.12: Heat map matrix for $u \cdot (1 - v)$ values of services with $\Delta t = 24\text{h}$ and *low* number of supported locations. Increasing day in advance d from left to right. Heat maps with $d \geq 6$ are omitted.

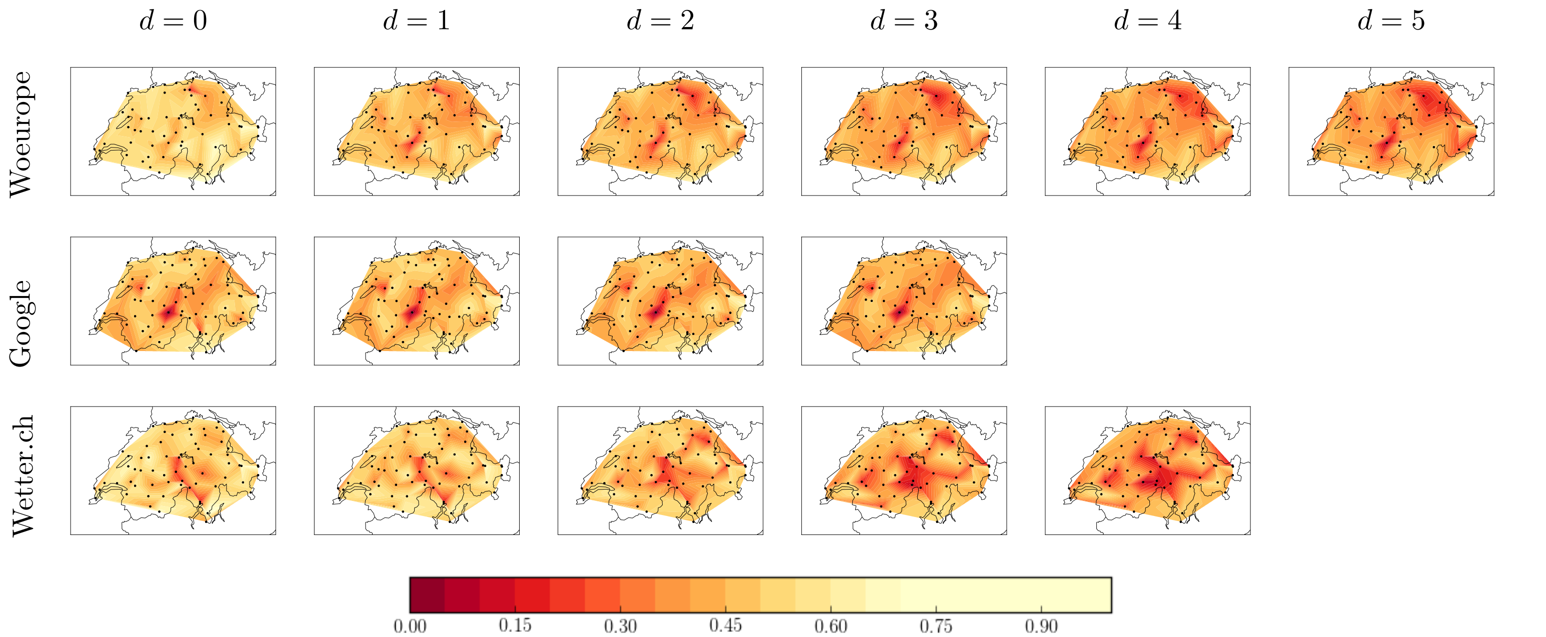


Figure 3.13: Heat map matrix for $u \cdot (1 - v)$ values of services with $\Delta t = 24\text{h}$ and *high* number of supported locations. Increasing day in advance d from left to right. Heat maps with $d \geq 6$ are omitted.

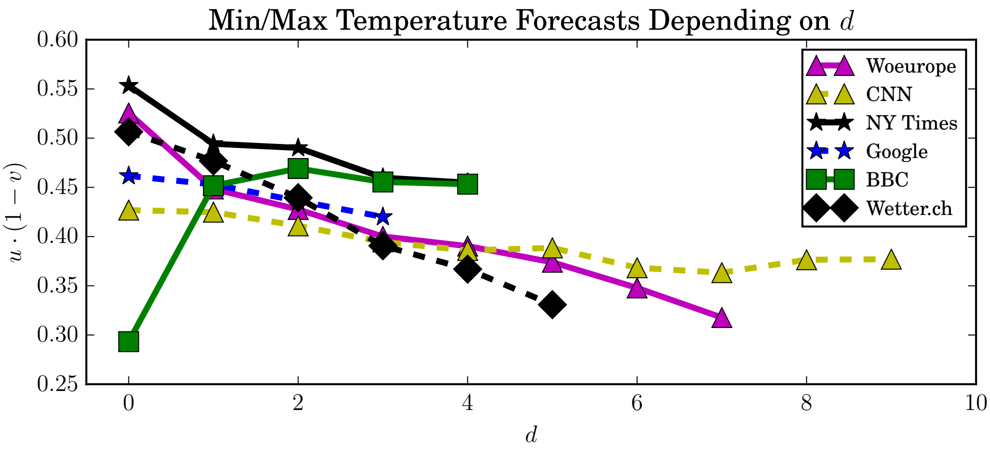


Figure 3.14: Development of $u \cdot (1-v)$ for services with $\Delta t = 24$h depending on days in advance d. The bad value for $d = 0$ and BBC is explained in Section 3.1.3.

3.3.3 Ranking of Services

Furthermore, we also ranked the services for $\Delta t = 24$h, with the same method as for average temperatures. In Table 3.3 one can see this ranking. NY Times provides the best forecasts for minimal-maximal temperatures. Actually BBC receives a good ranking for $d = 2, 3, 4$ but as shown in the heat maps the number of locations, for which they provide forecasts is too limited. It might be easier to forecast minimal and maximal temperatures for these locations, which mainly are the biggest cities in Switzerland. BBC does not provide forecasts for locations that are harder to predict accurately (e.g. mountainous regions). The same argument also applies for NY Times. CNN and Woeurope appear mostly in the lower regions of the table, except for $d = 0$, where Woeurope ranks second best. Google appears in the middle regions of every ranking.
In Figure 3.14 these facts are illustrated as a graph for each service. Wetter.ch has the steepest graph. Until $d = 2$, Wetter.ch ranks in the upper half but ranks last for the remaining days. Woeurope and CNN provide forecasts for the most days in the minimal and maximal temperature category. Woeurope is better than CNN for $d \leq 4$. For later days, CNN provides better results. Although CNN does not support many locations with their forecasts, it never appears in the upper regions of the table for small d's

3.3.4 Summary

For the services with minimal and maximal temperatures also surprising results were found. The only local service in this category ranks in the top three until

$d = 0$		$d = 1$		$d = 2$	
Service	Diff.	Service	Diff.	Service	Diff.
NY Times	0.553	NY Times	0.494	NY Times	0.490
Woeurope	0.526	Wetter.ch	0.477	BBC	0.469
Wetter.ch	0.506	Google	0.453	Wetter.ch	0.439
Google	0.462	BBC	0.452	Google	0.436
CNN	0.427	Woeurope	0.448	Woeurope	0.428
BBC	0.293	CNN	0.425	CNN	0.411

$d = 3$		$d = 4$		$d = 5$	
Service	Diff.	Service	Diff.	Service	Diff.
NY Times	0.460	NY Times	0.455	CNN	0.388
BBC	0.455	BBC	0.453	Woeurope	0.374
Google	0.420	Woeurope	0.390	Wetter.ch	0.331
Woeurope	0.400	CNN	0.386	–	–
CNN	0.395	Wetter.ch	0.367	–	–
Wetter.ch	0.390	–	–	–	–

Table 3.3: Ranking for services with $\Delta t = 24\text{h}$. The Diff. columns contain the average $u \cdot (1 - v)$ value. Tables for $d \geq 6$ are omitted. The bad value for $d = 0$ and BBC is explained in Section 3.1.3.

$d = 2$, but the ranks last for $d \geq 3$. The top services in this category provide not so many locations. In fact that means that other services are providing forecasts for exactly those hard-to-forecast-locations, which then is leading to worse results. Daily temperature forecasts are therefore a trade-off between quantity of locations and quality of forecasts. For daily services, the dependence on locations is not given as in average temperature forecasts.

3.4 Rainfall, Wind and Air Pressure Analysis

In the following the same methods used for the temperature analysis are applied to the other forecast values. This will be done in a more abbreviated way than the one for the temperatures.

3.4.1 Rainfall Analysis

For rainfall the development of the differences between the average of the predicted values $R_{\min,d}$ and $R_{\max,d}$ and the measured values R^*_{tot} is investigated. In the given measurement period, rainy days were rare. From the 969'354 ground truth entries in the database, only 77'005 entries (ca. 8%) contain a rain value greater than 0 mm. Therefore the average difference is very close to zero if all

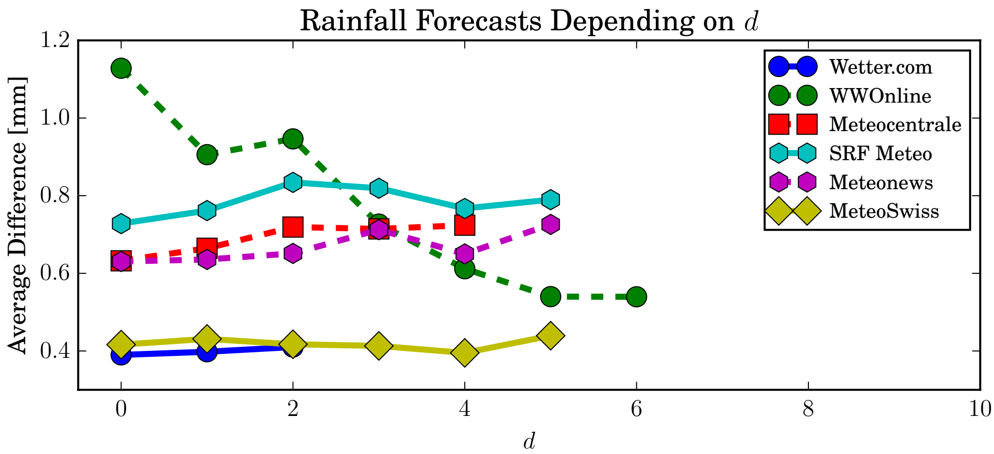


Figure 3.15: Development of the average difference between measured and predicted rainfall, depending on days in advance d.

available forecasts are taken into account. We decided to only analyze differences, if $R^*_{\text{tot}} > 0$. The assumption here is that it is easier to forecast no rain accurately than predicting the exact amount of rain, when it actually does rain. In Figure 3.15 we see the development of the rainfall differences. World Weather Online has a curve, heading in the wrong direction. For the other services we mostly see slight improvements for decreasing d's.

3.4.2 Wind Analysis

Figure 3.16 shows the development of the absolute difference between $W_{\text{avg},d}$ and W^*_{avg}. Wind is measured by the stations as the average wind of the last ten minutes. Most services get better, the smaller d is. Wetter.net shows inexplicable behavior between $d = 1$ and $d = 5$. Meteocentrale ranks best for the 3-hourly services. Accuweather is the best 1-hourly service and BBC is the best daily service predicting wind (the bad value for $d = 0$ and BBC is explained in Section 3.1.3). The good results of BBC might be influenced by the fact that this service does not support locations on mountains. However, the most extreme wind speeds were measured on mountains (e.g. 127 km/h on Chasseral or 111.6 km/h on Säntis). Due to this, we assume it is easier to predict wind speed for non-mountainous locations. The fastest measured wind speed for such a location was 66 km/h at the weather station in Plaffeien.

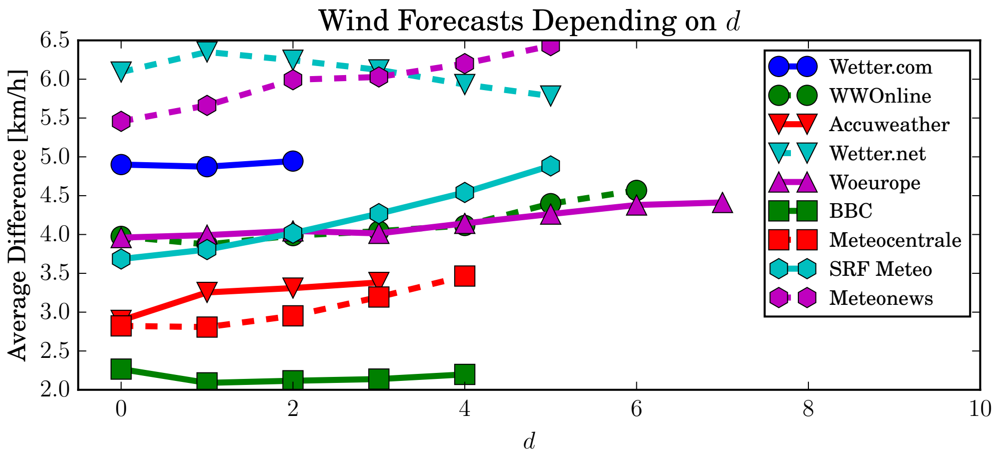


Figure 3.16: Development of the average difference between measured and predicted wind, depending on days in advance d. The bad value for $d = 0$ and BBC is explained in Section 3.1.3

3.4.3 Air Pressure Analysis

Figure 3.17 is indicating the absolute difference between measured and predicted pressure values. Obviously these kinds of forecasts do not depend on how many days in advance a service predicts the value. This means that once a pressure forecast has been published, a weather service does rarely change it afterwards. It is also evident that pressure forecasts tend to be very inaccurate for some services. Assuming an average value for pressures is 1000 hPa, a difference of about 115 hPa is more than ten percent. Among the forecast services which were investigated, one should only use Meteocentrale to get the best pressure forecast. In addition, this service also supports many locations.
One reason for the never changing pressure forecasts could be that pressure is an input parameter for the weather models of the services and not a result of the model.

3.4.4 Location Dependent Analysis

We also analyzed the heat maps for the parameters rainfall, wind and air pressure. Due to the limited significance of the results, it was decided to omit them in the main part of the work. However, the heat map matrices can be found in Appendix B.3

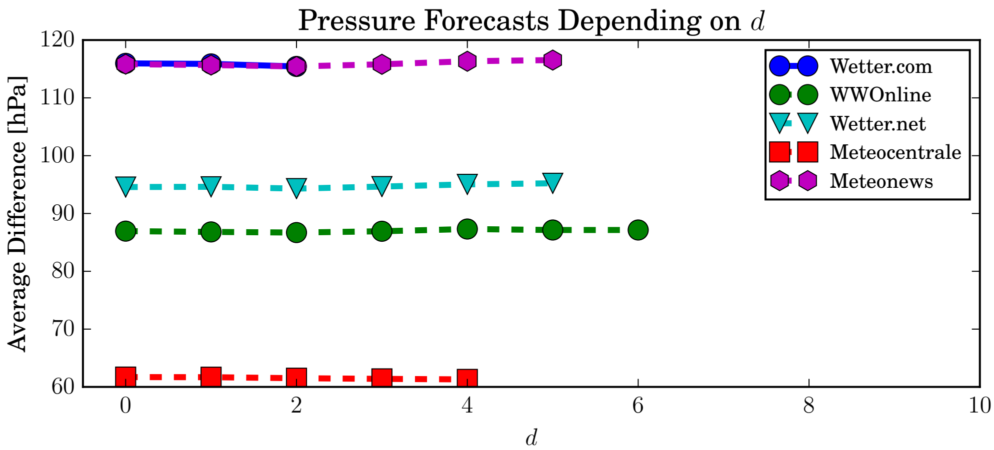


Figure 3.17: Development of the average difference between measured and predicted pressure, depending on days in advance d.

3.5 Conclusions and Future Work

It can be seen in this work, that *average temperature forecasts* get better, the closer the day is, they predict. These results apply for both, global and local services. When analyzing location dependence, global services tend to treat every location the same and do not take geographical differences into account. This leads to bad forecast accuracy for locations in extraordinary areas like the Alps. In contrast, most local services provide accurate forecasts for these locations too. We can therefore suppose that local services apply models, which are adapted more to the local geographical conditions. Also global services sacrifice accuracy on specific locations to the benefit of providing forecasts for many locations spread over the world.
In the rankings it can be seen, 1-hourly local services rank always worse than 3-hourly local services. Consequently, it must be easier to predict average temperatures for greater time intervals than for small ones. However this does not mean one should always prefer 3-hourly over 1-hourly services. An average temperature forecast for 3-hour intervals has the disadvantage that the forecasts differ more at the beginning and the end of the interval. If there is need for a forecast for a small time interval, 1-hourly forecasts can therefore be even better.
Daily temperature forecasts do also improve for less days in advance. However with our methods we are not able to prove a location dependence as for the 1-hourly and 3-hourly services. Therefore it is possibly easier to forecast minimal and maximal temperatures also for specific locations.
The analysis of the additional parameters rainfall, wind and pressure does not provide results as significant as for temperatures. Nevertheless an improvement of forecast accuracy depending on days in advance d can be observed at least

for rainfall and wind. The results of the air pressure forecast analysis lead to the assumption that air pressure is rather an input parameter for the weather models than an output parameter. This would be an explanation for the barley changing average values depending on days in advance.

3.6 Limitations of Results

Since the data was only received between December 2014 and March 2015 this thesis can obviously only make statements for the quality of the services in this limited time span. To get more accurate results, it would be necessary to crawl the data for at least a year or even longer. With this, all four seasons could be included. It might be possible that some weather services produce better forecasts in summer than in winter. For further analysis there is also need for more services and forecasts, which can be evaluated.

Chapter 4

Weather Application

Based on the results from the data evaluation it is possible to implement a prototype of a distributed weather application. The main idea of this application is to display the statistically best available forecast to the user.

4.1 Design

We developed a web application using Java. To get the forecasts, locations and services, the same MySQL database was used. To determine which service is the best for a given location and day JSON files, which store the average difference of temperatures, rainfalls, winds and pressures per day for each service were used. The user can choose among the locations to get a weather forecast. He can also choose the desired time interval of the forecasts (1, 3 and 24 hours). Given these settings, the application finds the best forecast service for each day and forecast value. It then displays the forecasts for all available days. For each day and forecast value the user can check the average difference and the source service, where the data comes from. So far, the application is implemented for 1-hourly forecasts.

4.2 Possible Enhancements

By now users can only query forecasts for the locations of the weather stations. There are different possibilities to enhance the weather application such that querying for more locations is possible. To solve this problem there is the need to crawl for many more locations on the different websites. Since there are no ground truth values for the additional locations yet, there would also be the need to find a method to determine, which service is the best one.
As a heuristic the service, which is best for the nearest weather station can also be used for the location in question. However a problem with this approach would be, that the nearest weather station may not represent the location appropriately.

(e.g. location on a mountain and weather station in the valley)
As a second approach the interpolated values from the heat maps could be used to generate a matrix, which for each coordinate stores the best available service. For the services outside of the interpolated area the firstly proposed heuristic could come into action.

Bibliography

[1] Silver, N.: The Signal and the Noise: Why So Many Predictions Fail–but Some Don't. Penguin Books (February 2015)

Appendix A

Additional Information

A.1 Weather Forecast Services

A list of all weather forecast services is available in Table A.1

A.2 Locations

A list of the locations and which service supports them is available in Tables A.2 and A.3

A.3 Barycentric Interpolation

With the help of barycentric interpolation one can find interpolated values of points inside a triangle. In Figure A.1[1] one can see such a triangle. Let $A = A_1 + A_2 + A_3$. The value at x is now defined as follows:

$$x = \frac{A_1 p_1 + A_2 p_2 + A_3 p_3}{A} \tag{A.1}$$

Intuitively this means the following: The closer the interpolation point x is to one of the corners, the bigger is the corresponding area and therefore the influence of the corners value to the value of x.

[1]Source: http://www.voronoi.com/wiki/index.php?title=Image:Barycentric.png

Service Name	URL	#FC	End Date
Global			
Wetter.com	http://www.Wetter.com	205297	2015-01-21
WWOnline	http://www.worldweatheronline.com	736011	2015-03-11
Accuweather	http://www.Accuweather.com	542915	2015-03-11
Wetter.net	http://www.Wetter.net	488607	2015-03-11
Woeurope	http://www.Woeurope.eu	177902	2015-03-11
CNN	http://weather.cnn.com	79171	2015-03-11
NY Times	http://www.nytimes.com/weather	24470	2015-03-11
Google	http://www.google.com	94747	2015-03-11
BBC	http://www.bbc.com/weather	24282	2015-03-11
Local			
Meteocentrale	http://www.Meteocentrale.ch	574452	2015-03-11
SRF Meteo	http://www.srf.ch/meteo	562061	2015-03-11
Meteonews	http://Meteonews.ch	496079	2015-03-11
MeteoSwiss	http://www.meteoschweiz.admin.ch	4298688	2015-01-18
Wetter.ch	http://www.Wetter.ch	43764	2015-03-11

Table A.1: List of all Services and their URLs. The column #FC contains the number of forecasts we crawled for each service. End date is the date we stopped crawling. The Crawlers for Wetter.com and MeteoSwiss stopped earlier because of banning by the owners of the websites. The start date for all services is: 2014-12-19.

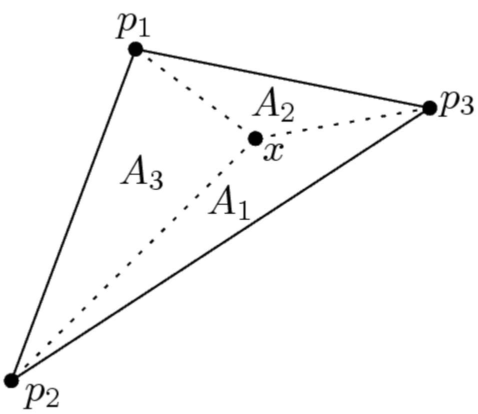


Figure A.1: Triangle divided in Areas A_1, A_2 and A_3 through point x (interpolation point).

	Wetter.com	WWOnline	Accuweather	Wetter.net	Woeurope	CNN	NY Times	Google	BBC	Meteocentrale	SRF Meteo	Meteonews	MeteoSwiss	Wetter.ch
Schaffhausen	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Salen-Reutenen	✓	–	–	–	–	–	–	–	–	✓	✓	✓	–	–
Leibstadt	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Basel	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Möhlin	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Güttingen	✓	–	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Fahy	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	–
Lägern	✓	–	–	–	✓	–	–	✓	–	✓	✓	✓	–	–
Bischofszell	✓	–	–	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Rünenberg	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Kloten	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Aadorf	✓	✓	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Buchs/Aarau	✓	–	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Zürich	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hörnli	✓	–	–	–	✓	–	–	✓	–	✓	–	✓	–	✓
St. Gallen	✓	✓	–	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Grenchen	✓	✓	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Wynau	✓	✓	✓	✓	–	✓	✓	✓	–	✓	✓	✓	✓	✓
Säntis	✓	–	–	✓	✓	–	–	–	–	✓	✓	✓	–	✓
La Chaux-de-Fonds	✓	✓	✓	✓	✓	–	✓	✓	–	✓	✓	✓	✓	✓
Chasseral	✓	–	–	–	✓	–	–	✓	–	✓	✓	✓	–	–
Wädenswil	✓	–	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Neuchâtel	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mühleberg	✓	–	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Bern	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Napf	✓	–	–	–	✓	–	✓	✓	–	✓	–	✓	–	✓
Pilatus Kulm	✓	–	–	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Luzern	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Einsiedeln	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Vaduz	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	–	✓	✓	✓
Bullet	✓	✓	✓	–	–	–	–	–	–	✓	✓	✓	✓	–
Payerne	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓	✓
Fribourg	✓	✓	✓	✓	✓	✓	–	✓	–	✓	✓	✓	✓	✓
Plaffeien	✓	✓	✓	✓	✓	–	✓	✓	–	✓	✓	✓	✓	✓
Thun	✓	✓	✓	–	✓	–	–	✓	–	✓	✓	✓	✓	✓
Interlaken	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Meiringen	–	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Engelberg	✓	✓	–	✓	✓	✓	–	✓	–	✓	✓	✓	✓	✓
Altdorf UR	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Glarus	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Bad Ragaz	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓

Table A.2: Listing of the locations (Part 1).

	Wetter.com	WWOnline	Accuweather	Wetter.net	Woeurope	CNN	NY Times	Google	BBC	Meteocentrale	SRF Meteo	Meteonews	MeteoSwiss	Wetter.ch
Chur	✓	✓	✓	✓	✓	✓	–	✓	–	✓	✓	✓	✓	✓
Weissfluhjoch	✓	–	–	–	✓	–	–	✓	–	✓	–	✓	–	✓
Davos	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓
Naluns-Schlivera	✓	–	–	–	✓	–	–	✓	–	✓	✓	–	–	✓
Scuol	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Bière	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Pully	✓	✓	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Le Moléson	–	–	–	–	✓	–	–	–	–	–	✓	✓	–	✓
Château-d'Oex	✓	✓	✓	–	–	–	–	✓	–	✓	✓	✓	✓	✓
Adelboden	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Jungfraujoch	✓	–	–	✓	✓	✓	–	✓	–	–	✓	✓	✓	✓
Ulrichen	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Grimsel Hospiz	✓	–	–	–	✓	–	–	✓	–	✓	✓	✓	–	✓
Gütsch	–	–	–	–	–	–	–	–	–	–	–	✓	–	–
Sedrun	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Andeer	✓	✓	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	✓
Samedan	✓	✓	✓	✓	–	–	✓	✓	–	✓	✓	✓	✓	✓
Buffalora	–	–	–	–	✓	–	–	✓	–	✓	✓	✓	–	✓
La Dole	✓	–	–	–	✓	–	✓	–	–	✓	✓	✓	–	✓
Nyon	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Aigle	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sion	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	–
Montana	✓	–	✓	✓	✓	–	✓	✓	–	✓	✓	✓	✓	✓
Visp	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Robiei	✓	–	–	–	–	–	–	✓	–	✓	✓	–	–	✓
Piotta	✓	✓	✓	✓	–	–	✓	✓	–	✓	✓	✓	✓	✓
Comprovasco	✓	✓	✓	✓	–	–	–	✓	–	✓	✓	✓	✓	–
San Bernardino	✓	–	–	–	✓	–	✓	✓	–	✓	✓	✓	–	✓
Vicosoprano	✓	✓	✓	–	–	–	–	✓	–	✓	✓	✓	✓	–
Piz Corvatsch	✓	–	–	–	✓	–	–	✓	–	–	✓	✓	–	–
Poschiavo	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	✓	✓	✓
Genf	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grand St. Bernard	✓	–	–	–	–	–	–	✓	–	–	✓	✓	–	–
Evolène	✓	✓	✓	–	✓	–	–	✓	–	✓	✓	✓	✓	✓
Zermatt	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Locarno	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
Cimetta	✓	–	–	–	–	✓	✓	✓	–	✓	✓	✓	–	✓
Magadino	✓	✓	✓	–	–	–	–	✓	–	✓	✓	✓	✓	–
Lugano	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	✓
Stabio	✓	✓	✓	–	✓	–	✓	✓	–	✓	✓	✓	✓	✓

Table A.3: Listing of the locations (Part 2).

Appendix B

Plots

B.1 Temperature Difference Boxplots

The Figures B.1 to B.7 show the average temperature boxplots that are not included in the main part of the work.

B.2 Mass Point Plots

In Figure B.8 one can see the mass point diagrams for the daily services. Since all points lie in the sub domain $[0.35,0.8]\times[0,0.45]$, only this part of the domain is depicted for each service.

B.3 Rainfall, Wind and Pressure Heat Maps

In Figures B.9 and B.10 one can see the rainfall heat map matrices for the global and local services respectively.
In Figures B.11 one can see the wind heat map matrix for the global 1-hourly and 3-hourly services. In Figure B.12 one can see the wind heat map matrix for the daily global and all local services.
In Figures B.13 and B.14 one can see the pressure heat map matrices for the global and local services respectively.

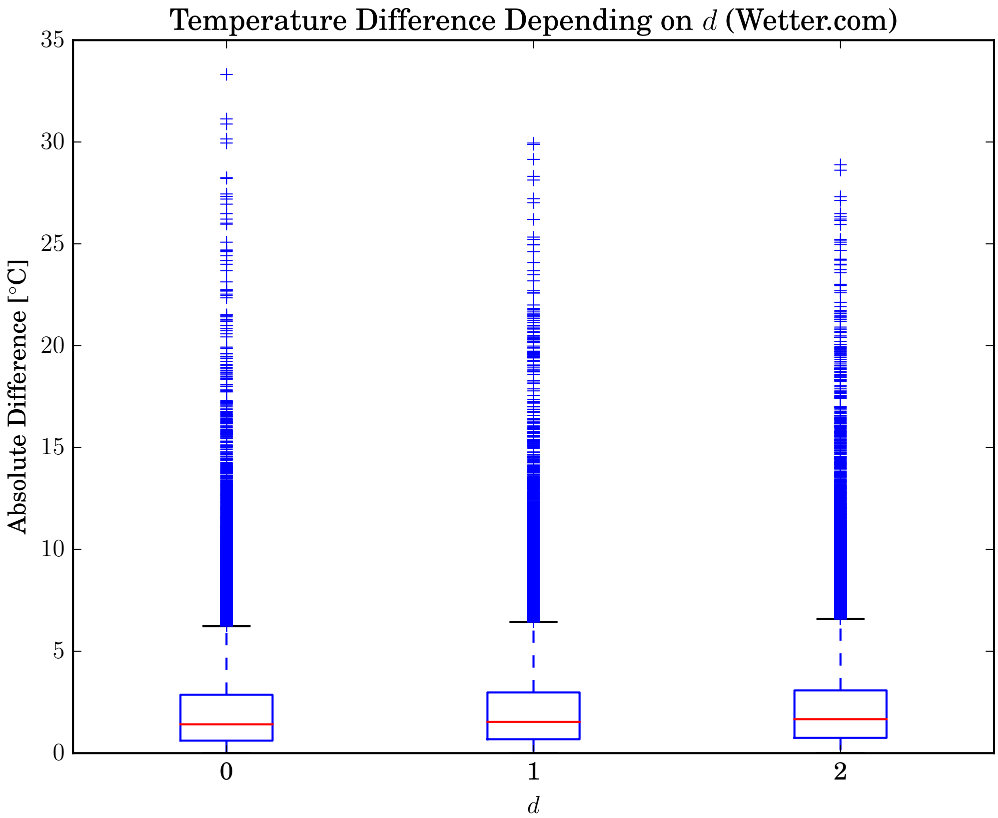


Figure B.1: Absolute temperature differences for service Wetter.com depending on days in advance d.

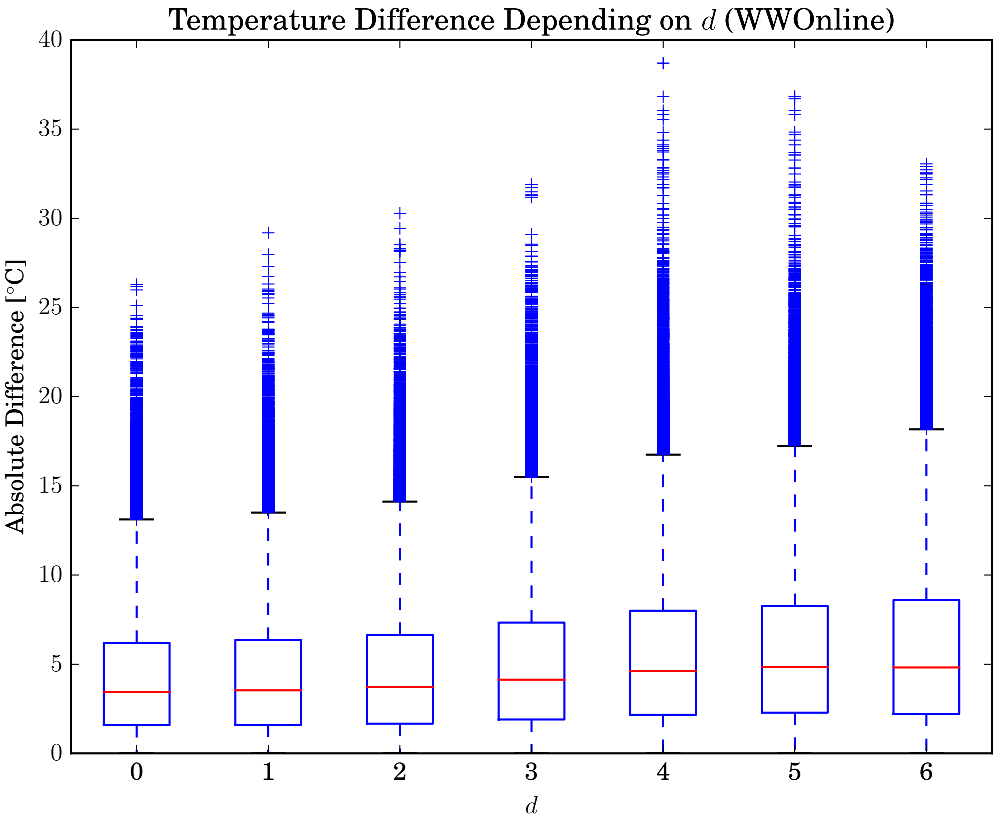


Figure B.2: Absolute temperature differences for service World Weather Online depending on days in advance d.

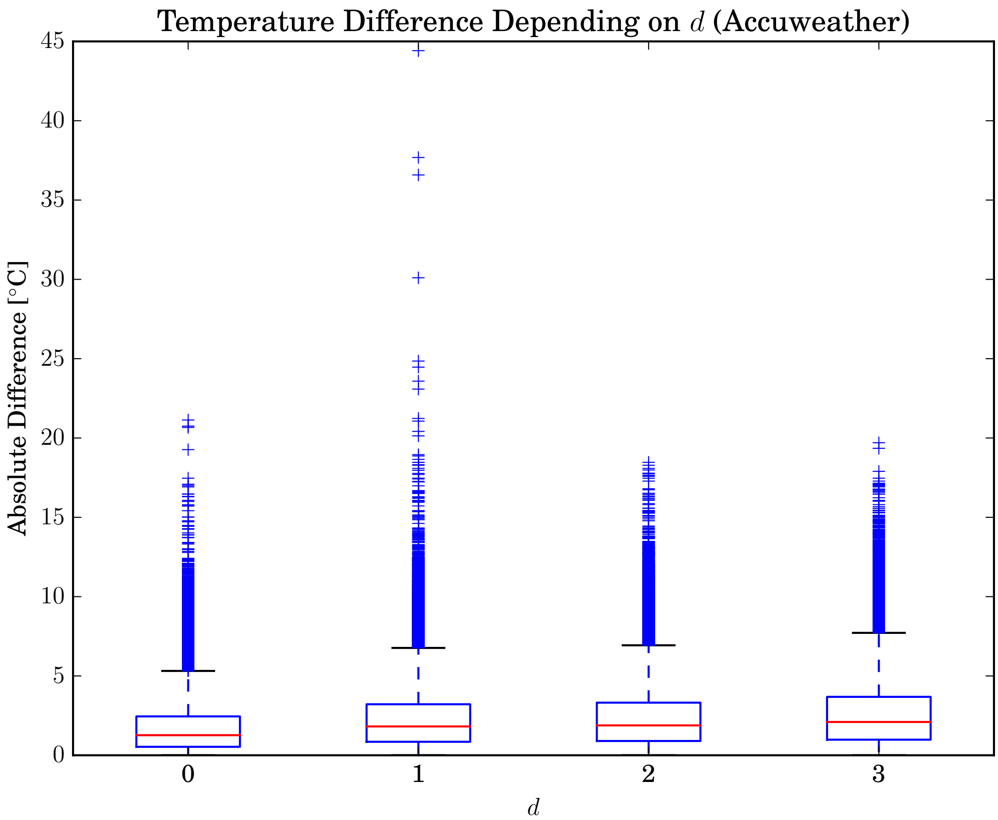


Figure B.3: Absolute temperature differences for service Accuweather depending on days in advance d. Big outlier at arround 45 °C for $d = 1$ is a corrupt value that was crawled from the website. Accuweather predicted 35 °C at Leibstadt for 24th of December.

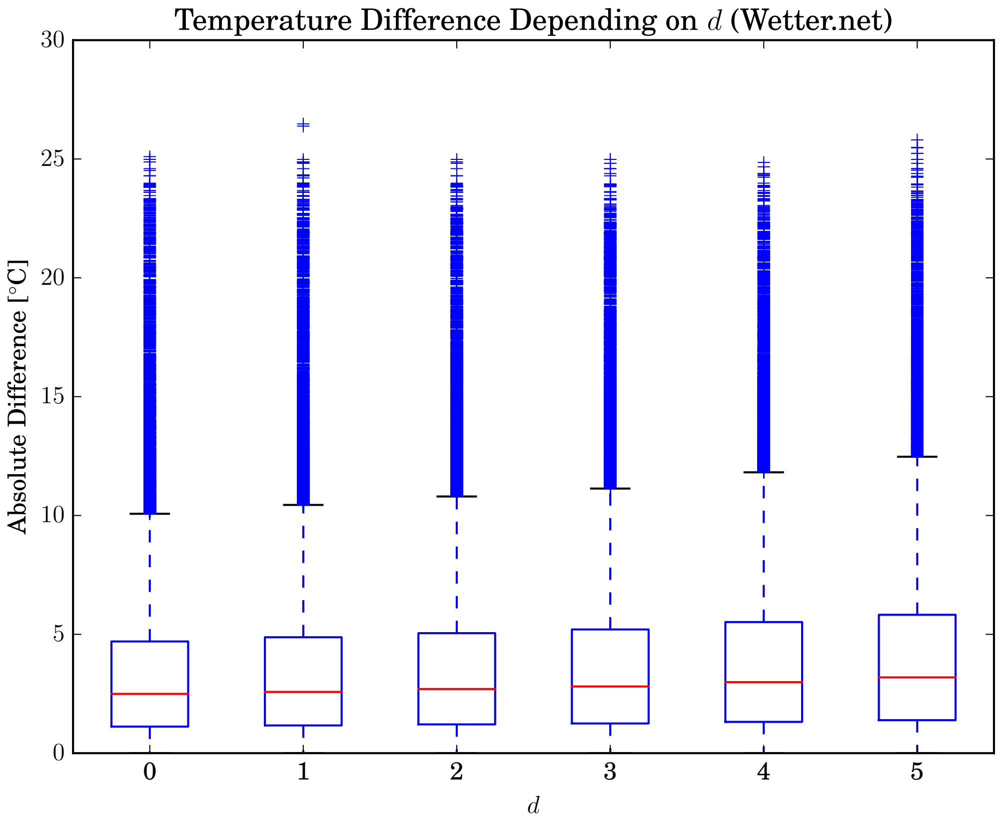


Figure B.4: Absolute temperature differences for service Wetter.net depending on days in advance d.

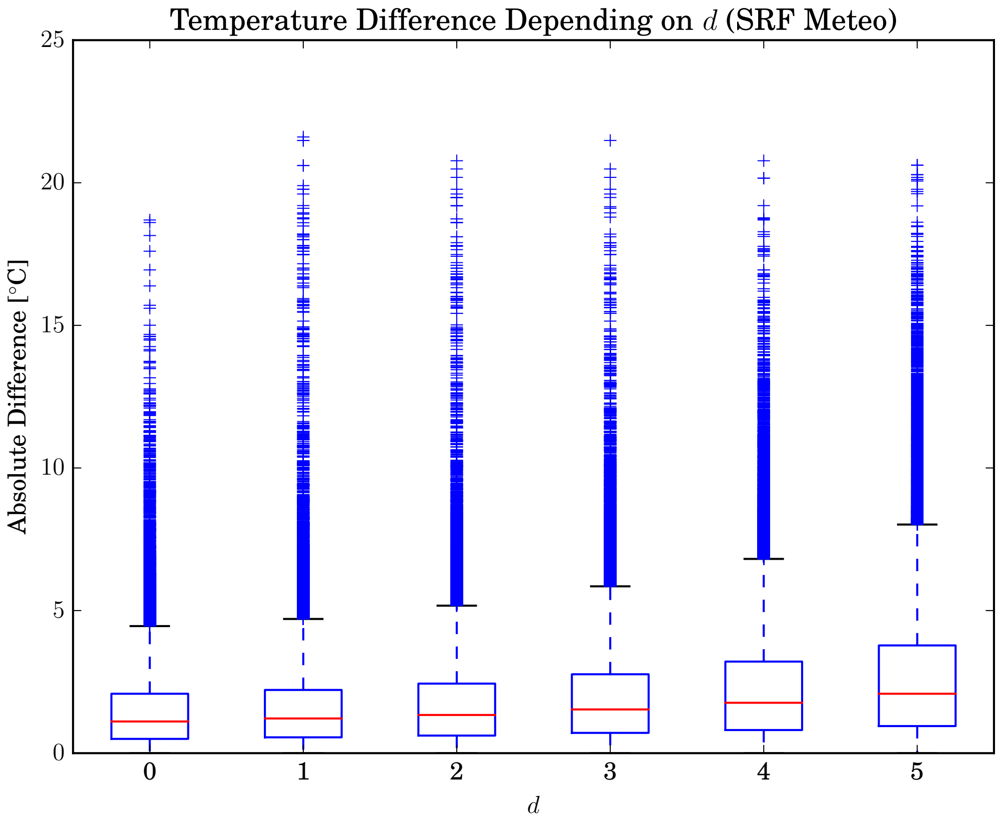


Figure B.5: Absolute temperature differences for service SRF Meteo depending on days in advance d.

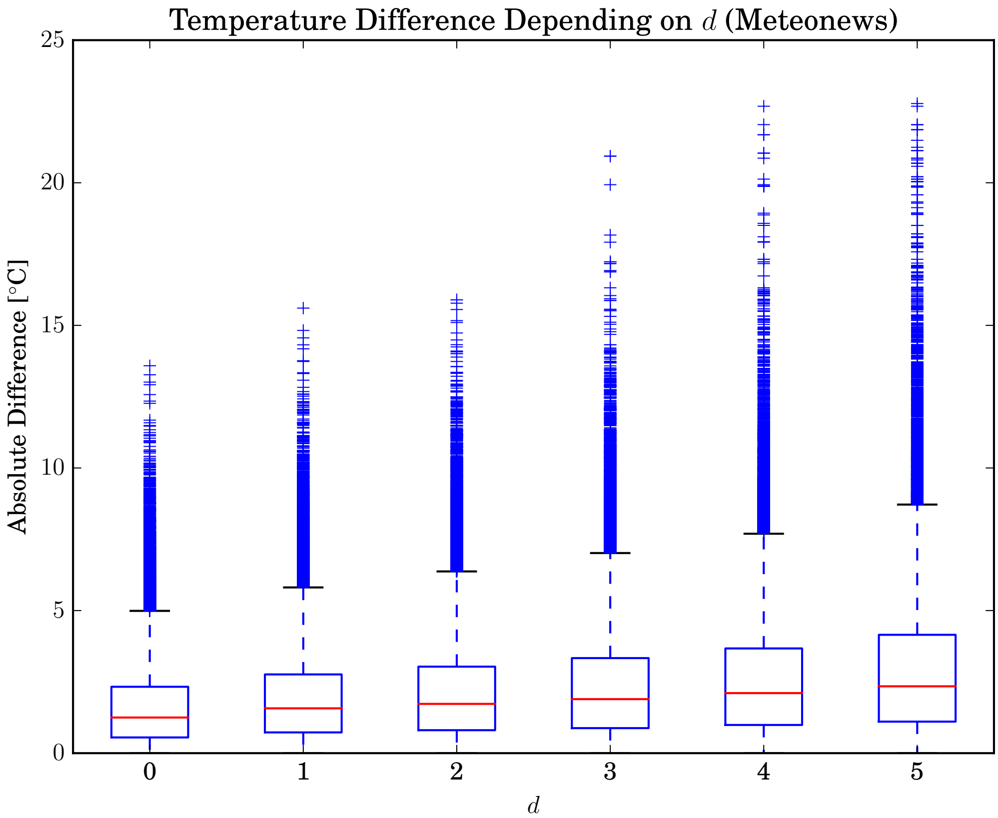


Figure B.6: Absolute temperature differences for service Meteonews depending on days in advance d.

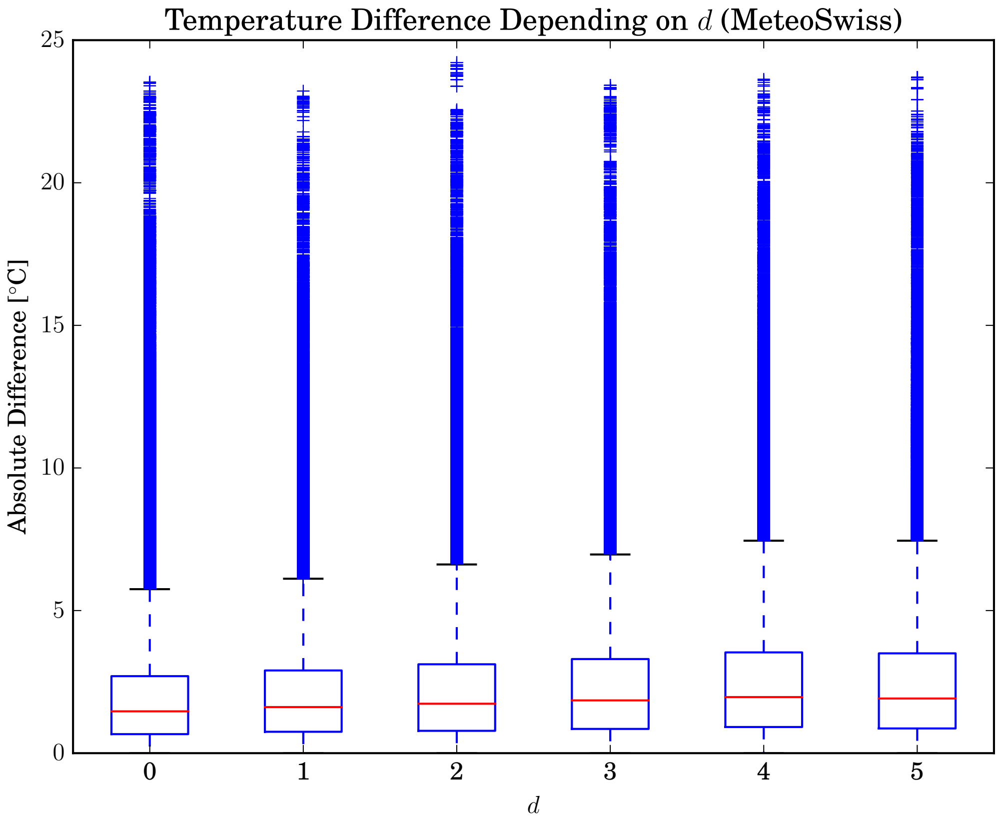
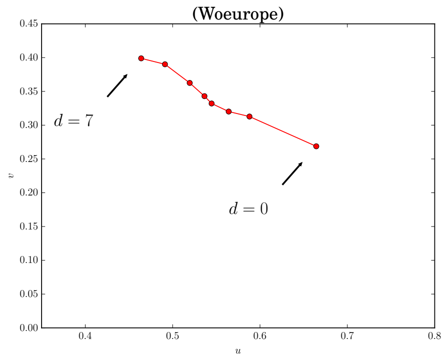
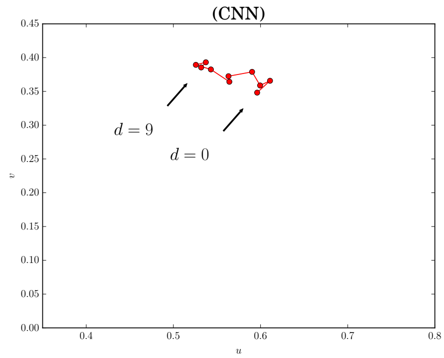


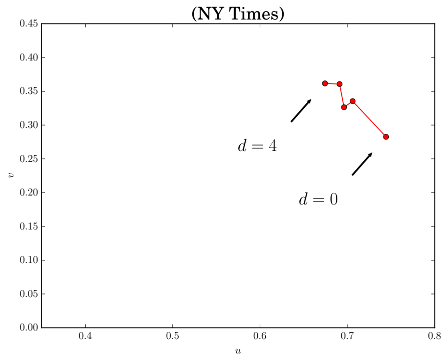
Figure B.7: Absolute temperature differences for service MeteoSwiss depending on days in advance d.



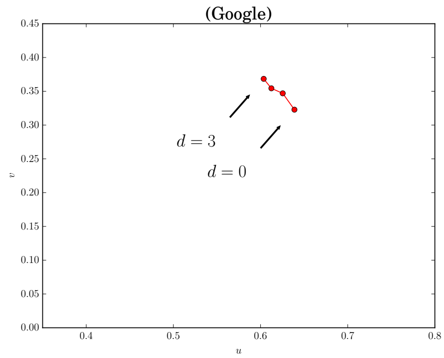
(a)



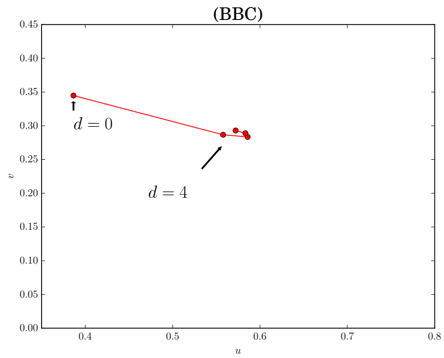
(b)



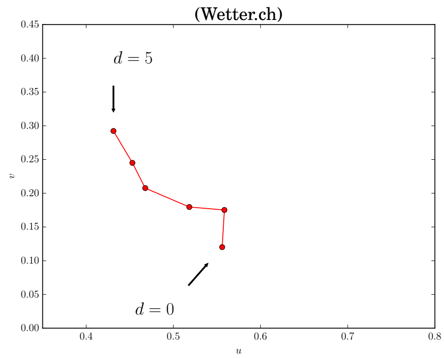
(c)



(d)



(e)



(f)

Figure B.8: The diagrams (a) to (f) show the position of the mass point in the u-v sub domain $[0.35,0.8]\times[0,0.45]$. Diagram (e) has a corrupt value for $d = 0$ according to the flaw described in Section 3.1.3.

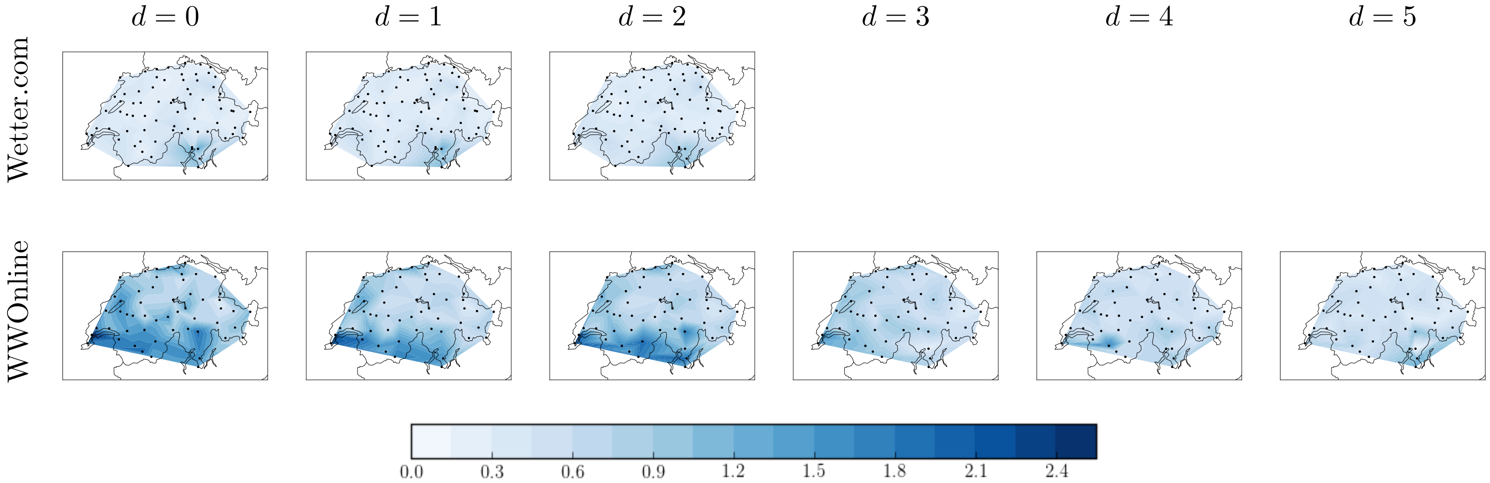


Figure B.9: Rainfall heat map matrix of global services. Increasing day in advance d from left to right. Maps for $d \geq 6$ are omitted. Unit is mm.

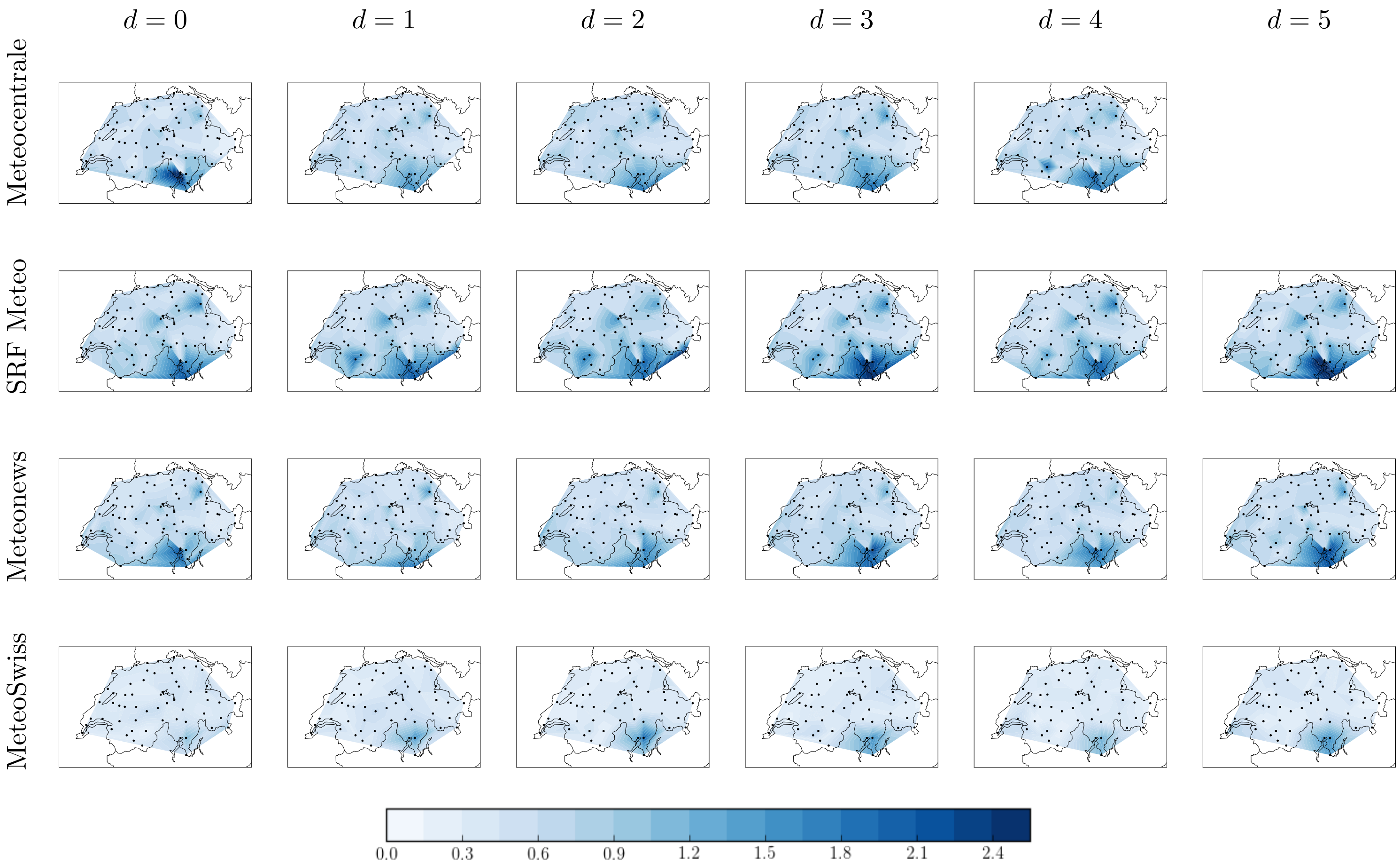


Figure B.10: Rainfall heat map matrix of local services. Increasing day in advance d from left to right. Unit is mm.

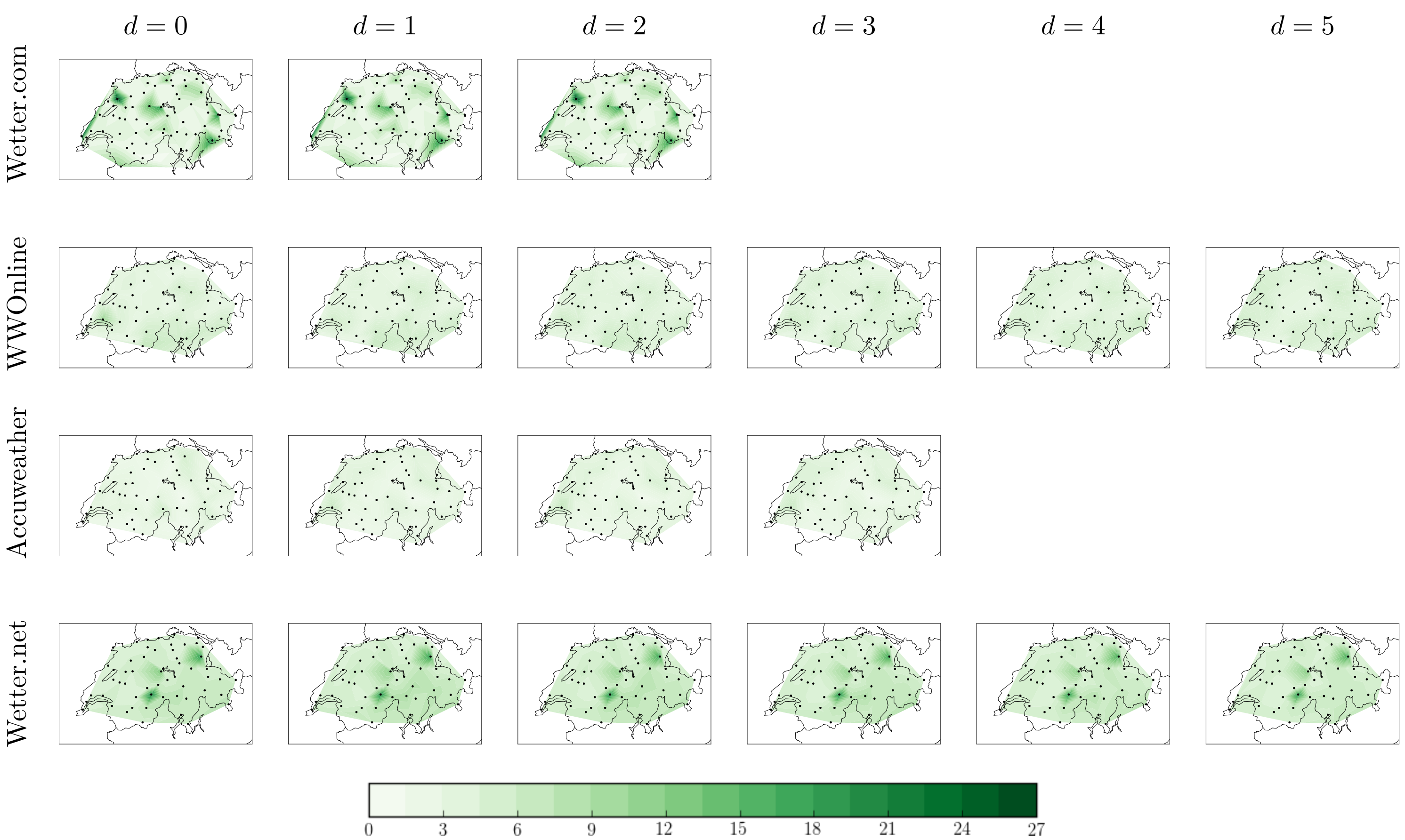


Figure B.11: Wind heat map matrix of global 1-hourly and 3-hourly services. Increasing day in advance d from left to right. Maps for $d \geq 6$ are omitted. Unit is km/h.

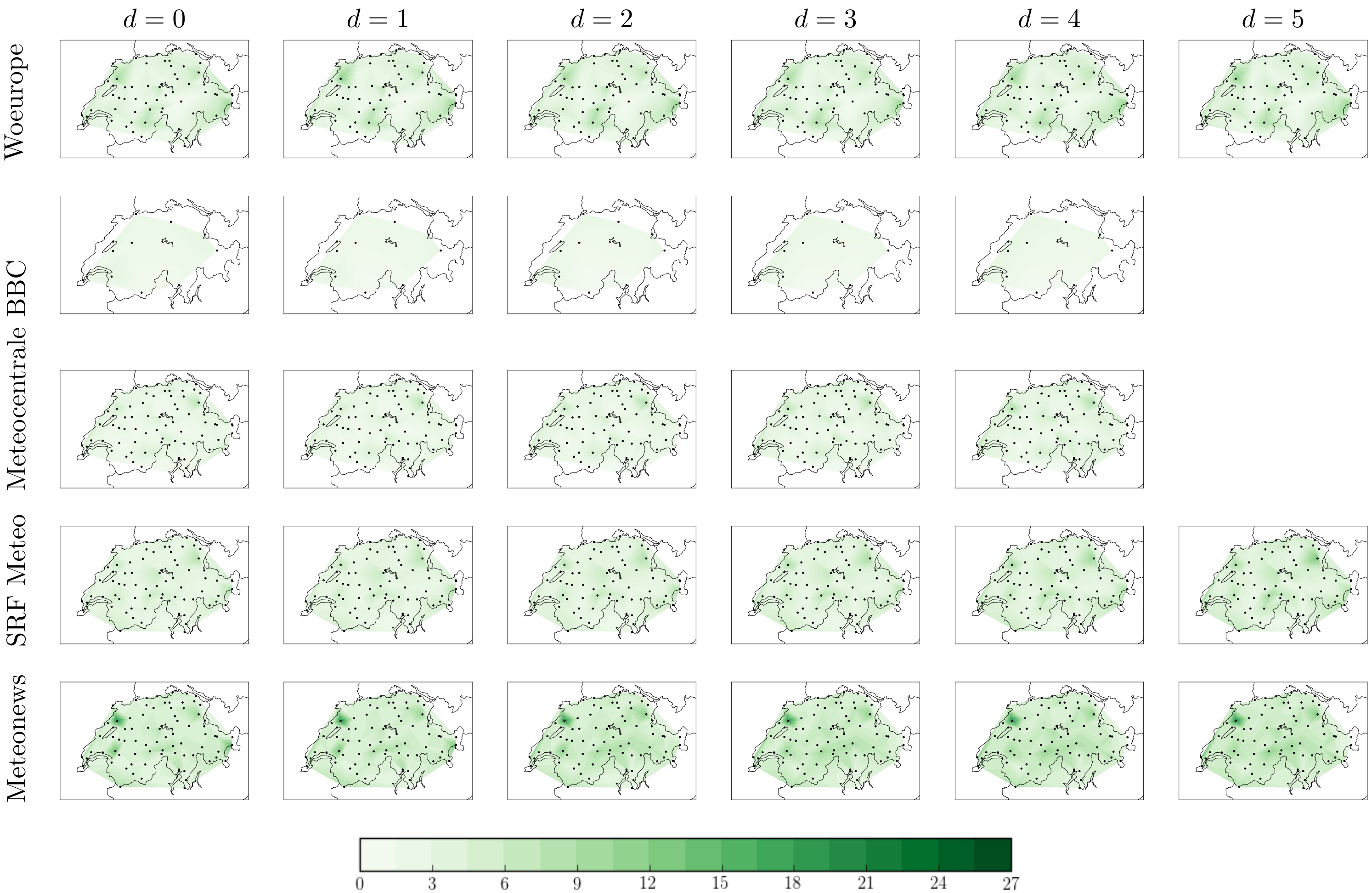


Figure B.12: Wind heat map matrix of global daily services and local services. Increasing day in advance d from left to right. Maps for $d \geq 6$ are omitted. Unit is km/h.

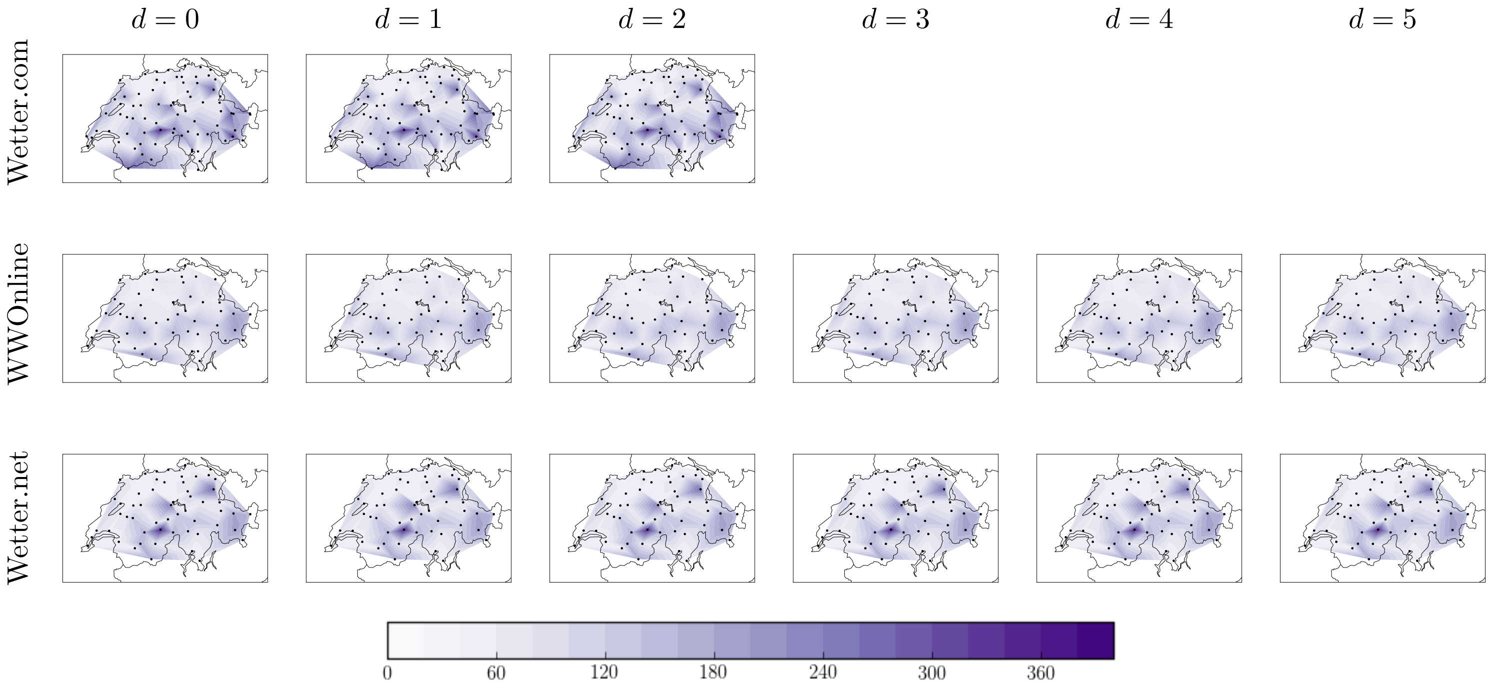


Figure B.13: Pressure heat map matrix of global services. Increasing day in advance d from left to right. Maps for $d \geq 6$ are omitted. Unit is hPa.

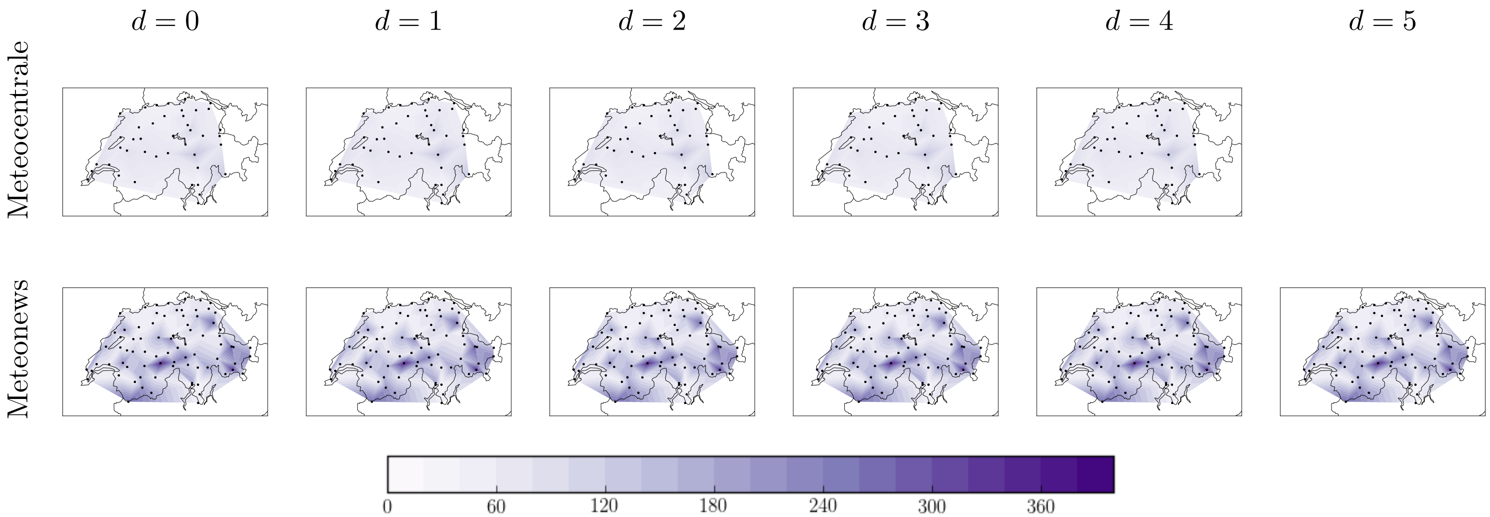


Figure B.14: Pressure heat map matrix of local services. Increasing day in advance d from left to right. Unit is hPa.