Radar-guided control and interpolation of rain gauge precipitation data over France

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1 SUMMARY

2 INTRODUCTION

3 THE RAIN GAUGES AND RADAR ESTIMATION PRECIPITATION DATA

3.1 THE RAIN GAUGES PRECIPITATION DATA
3.1.1 THE METEO-FRANCE RAIN GAUGE NETWORK
3.1.2 UNCERTAINTIES, "PERFORMANCE CLASSIFICATION" AND CONTROL OF RAIN GAUGE PRECIPITATION MEASUREMENT

3.2 THE RADAR ESTIMATE OF PRECIPITATION DATA
3.2.1 THE METEO-FRANCE RADAR NETWORK
3.2.2 UNCERTAINTIES AND CALIBRATION OF THE RAIN ACCUMULATIONS PRODUCT

3.3 THE FRENCH RADAR QUANTITATIVE PRECIPITATION ESTIMATION (QPE) RE-ANALYSIS PROJECT (COMEPHORE)

4 DATA PREPARATION AND FEASIBILITY STUDY

4.1 DAILY RADAR QPE WITH LOCAL RECALIBRATION BY PIXEL
4.2 DIAGNOSTIC OF FEASIBILITY OF USING RADAR ESTIMATE TO CONTROL RAIN GAUGE PRECIPITATIONS
4.2.1 THE TEMPORAL CORRELATION BETWEEN RAIN GAUGES AND RADAR ESTIMATES PRECIPITATION DATA
4.2.2 STATISTICAL SIGNIFICANCE OF THE LINK BETWEEN RAIN GAUGES AND RADAR ESTIMATES FOLLOWING RAINFALL INTENSITY RANGES

5 METHODOLOGY

5.1 METHODOLOGY OVERVIEW
5.2 THE RAINFALL SPATIALISATION TECHNIQUES
5.2.1 NEURAL NETWORKS
5.2.2 OPTIMAL INTERPOLATION
5.2.3 THIN PLATE SPLINE (TPS) IN A 3-DIMENSIONAL SPACE.
5.2.4 KRIGING OF THE RAIN GAUGES WITH RADAR ORIENTED EXTERNAL DRIFT

5.3 THE PERFORMANCE TESTS OF THE SPATIALISATION METHODS
5.3.1 THE DIFFERENT SCORES
5.3.2 CROSS-METHOD COMPARISON FOR THE TWO BEST SPATIALISATION TECHNIQUES
5.4 THE CONTROL METHOD OF DAILY PRECIPITATION USING RADAR DATA

6 RESULTS
6.1 GENERAL RESULTS
6.1.1 KRIGING OF THE RAIN GAUGES WITH RADAR ORIENTED EXTERNAL DRIFT
6.1.2 THIN PLATE SPLINES (TPS) IN A 3-DIMENSIONAL SPACE
6.1.3 CROSS-METHOD COMPARISON FOR THE TWO BEST SPATIALISATION TECHNIQUES
6.2 RESULTS FOLLOWING THE OROGRAPHY, RAIN INTENSITY, RADAR TYPE & RADAR QUALITY CODE
6.3 SEASONAL RESULTS
6.4 RESULTS FOLLOWING THE RAIN TYPE
6.4.1 THE INSTANTANEOUS CAPE FROM ALADIN MODEL
6.4.2 ANTILlope CONVECTIVE INDEX
6.5 RESULT OF CONTROL METHOD OF DAILY PRECIPITATION USING RADAR DATA

7 CONCLUSIONS

8 ACKNOWLEDGEMENTS

9 REFERENCE
1 Summary

In the framework of the EURO4M project, the DCLIM\(^1\) department of Meteo-France intends to provide the following contribution:

- Development and test of methods to control observations of rain gauges using for each rain gauge an independent estimate of known uncertainty. The independent estimate use rain gauges neighbors and radar data.
- Provide to other EURO4M members, on selected periods, series of observational data with a fine network density resolution and a mastered quality as well as a method of control of precipitation relevant to other countries in the project.

Meteo-France DCLIM is engaged in improving its quality system and a preliminary step was the analysis of defects that could compromise the quality of data by parameter or sensor type and in a historical perspective. Under the project EURO4M, Meteo-France DCLIM develops methods for monitoring precipitation on a daily base using the radar data. In order to fulfill this task, the potential use of various radar products for control purpose was analyzed while checking also to what extent those products are independent of these controlled rainfall data. The performance of the estimation of rainfall by radar has been evaluated in different situations to have an appropriate monitoring interval.

To test the control methods, a specific database, exempt from control, was carried out. It uses 1500-1800 operational Meteo-France rain gauges and 2800, which are supported by volunteers. Regarding weather radar, Meteo-France currently operates 24 operational radars for mainland France. As part of our project, data from individual radars of the 2007-2010 period have benefitted from a local calibration based on rain gauges observations. This local calibration was performed by separating observations into two lots to ensure independence between an inspected one and the other used to produce the reference estimate of the control.

Then, four different types of method for precipitation estimate via radar data spatialisation have been explored (Neural networks, Optimal interpolation, Kriging of the rain gauges with radar oriented external drift, Thin Plates Spline (TPS) in a 3-dimensional space) using, for each controlled rain gauge, the independent recalibrated radar data and the rain gauge in the vicinity from the two lots except the one controlled. Optimal interpolation, also called Objective Analysis, is used there like in a NWPM assimilation but with radar data as background. 3-dimensional TPS is based on geographical coordinates as first and second dimensions and on radar data as third dimension. The four methods produce independent estimate of precipitation for every rain gauges controlled using all available rain gauges in the vicinity. The computation over the period 2007-2010 allows us to have a statistic of error for every rain gauge controlled.

The two last methods have been retained as they did present the best score results (RMSE, bias or correlation).

Some further statistical tests have been conducted to assist in the construction of “best practice selection instructions - BPSI”. In this process, the hypothesis tested is that both methodologies are equivalent in quality in the estimate they produce for rain gauges. This hypothesis has been also decomposed following the intensity (quantile per station), the radar quality code, the orography, the season and the type of rain (convective or stratiform) using additional information from models to discriminate convective and non-convective situations. Some orientations for the BPSI arise clearly from these analyses. Indeed, the scores results in winters tend to favor the use of TPS while those of summer the use of kriging. The type of rain could explain these results, as scores results for convective rain favor kriging while those of non-convective prefer TPS.

A radar re-analysis effort is in progress at Meteo-France; while finished it will allow to have series as homogeneous as possible for the period 1996 to present time. The control method developed will be applied over that period. The potential adaptation of this method to other EURO4M countries will be the next challenge but it will request an important preliminary work of analysis on their rain gauges and weather radars networks, in terms of sensitivity as well as geographical and temporal density.

\(^1\) DCLIM: Direction de la Climatologie
2 Introduction

In the framework of the EURO4M project, the DCLIM department of Meteo-France intend to provide the following contribution:

- Development and test of methods to control the rain gauges recorded rainfall using the radar data.
- Provide to other EURO4M members, on selected periods, series of observational data with a fine network density resolution and a mastered quality as well as a method of control of precipitation relevant to other countries in the project.

As regard to data control system, exchanges that intend to cooperate them already exist between the different European climate services. Many countries have a control system whose general structure into 4 modules is quite similar to that proposed by the project NORDKLIM with: first lowest level controls in almost real time (range, temporal controls and of inter-parameter coherence), then spatial controls in a subsequent step with a system based on the automatic detection of suspicious values and on human expertise, and finally other time-deferred controls (slow drift of sensors, homogenization). Meteo-France DCLIM is engaged in improving its quality system and a preliminary step was the analysis of defects that could compromise the quality of data by parameter or sensor type and in a historical perspective. Under the project EURO4M, Meteo-France DCLIM develops methods for monitoring precipitation using the radar data. In order to fulfill this task, the potential use of various radar products for control purpose was analyzed while checking also to what extend those products are independent of these controlled rainfall data. The performance of the estimation of rainfall by radar has been evaluated in different situations to have an appropriate monitoring interval. Additional information, which may come from models, have been tested to discriminate between situations and to refine the control interval (temperatures to discriminate between solid and liquid precipitation, atmospheric vertical instability index). The radar information were also used by itself to discriminate convective and non-convective situations.

After a description of the rain gauges and radar estimation data with their respective networks and uncertainties, details on the data preparation as well as on the feasibility of such a study will be given. The next report section will be dedicated to the methodology with first a general overview, then details on the four rainfall spatialisation techniques employed to obtain rainfall estimates, followed by details on the performance tests applied on the estimates results; and finally the applied control method of daily observed precipitation using radar data will be described. The final section will present and discuss the results.
3 The rain gauges and radar estimation precipitation data

3.1 The rain gauges precipitation data

3.1.1 The Meteo-France rain gauge network

The rainfall observation network of Meteo-France consists of a set of measuring stations (automatic and manual).

Figure 1 - The Meteo-France rain gauges network with in red and blue the “real-time” network and in green the “deferred” ones.
The solid or liquid precipitation amounts are measured using two main types of rain gauges: those that request a manual reading (limited to daily measurements) and the transducers ones associated with acquisition systems and that provide access to many time steps automatic measurement options. The automatic also called “real-time” ones could be decomposed in a half available at t+10 minutes and another every 1 to 3 hours. They uses the principle of counting the number of tipping buckets that represents a small amount of water (0.2 or 0.5 mm).

As described in Champeaux et al. (2011) the rainfall measurement network could be classified following the problematic they target. The transducers ones are used operationally in the Meteo-France products such as the Operational PANTHERE\textsuperscript{2} ones, they represent only about 1500-1800 stations. The manual network is dedicated for climate studies and composed of around 2800 stations. This network is operated by volunteers and is also called “deferred” as observations are available delayed by one month at the Meteo-France Laboratory.

The geographical distribution of both networks is represented Figure 1. The south of France presents a better coverage, but, in average, it represents a rain gauge density of 1 for 120 to 125 km\textsuperscript{2} for the full network over mainland France.

### 3.1.2 Uncertainties, “performance classification” and control of rain gauge precipitation measurement

Rain gauge data measuring solid or liquid precipitations are subject to intrinsic uncertainties of different types (Leroy, 2000) that are summarized in this section. The sources of errors are multiple; some are common to the two types of instrument:

- The main ones come from the effect of the wind. Indeed during windy days the capture efficiency for solid or liquid precipitation could be incorrect due to aerodynamic turbulence caused by the shape of rain. This could creates a lack of uptake of up to +5 / -10 % for a wind of 5 m/s and even -10 / -60 % for wind of above 10 m/s.

- Associated to the wind impact comes the influence of the instrument position as well as the design quality with respect to the obstacles around it such as: buildings in the neighborhood, trees, effect of shelter created by a small local relief…

- The need of a regular verification of the horizontality of the instrument is also an essential factor to ensure adequate measurements as it could influence significantly the capture efficiency (as an example an horizontal bias of 10° decrease by 2% the horizontal surface of the instrument).

\textsuperscript{2} PANTHERE for Projet Aramis Nouvelles Technologies en Hydrométéorologie Extension et REnouvellement
• The wetting properties of the instrument could lead to water retention and so creates uncertainty evaluated, by default, to 0.1 mm.

• Furthermore, during intense precipitation events, the instrument could be subject to overflow. Then, when a record indicates a value equivalent to the maximum capacity of the instrument (200mm for the manual reading type and 500 mm within an hour for the transducer type), the user should use this record with caution.

• Finally, under certain winter conditions, an automatic heating system may be requested. Its absence, unknown presence or unknown activation could be an important source of error, which is difficult to evaluate. The user should keep that in mind while interpreting results in winter season.

For instrument with manuals reading another obvious sources of error could come from the observer itself reading incorrectly the rain record. If this type of error could not be inputted to the transducer types those ones have also their specific problems such as an undetected clogged instrument.

All these uncertainties are shared, at different levels, with any network operators. To exchange data between producers, it is necessary to have rules in the way these data are produced. However, in practice it is not always possible to follow these recommendations. Furthermore, for measurement uncertainties and their representation related to the measurement site, the WMO recommendations are often very demanding. Also, in accordance with the recommendations issued by WMO (OMM, 1996) but with some adaptations, Meteo-France has lately defined rules for rain gauges environment and has designed a “performance classification” (Champeaux et al., 2001). In Table 1 is presented this classification (from Leroy 2000) and its link with WMO classes. A site of class 1 is considered as a reference ones with no influence of the surrounding environment, while a site of class 5 has nearby obstacles that create an unsuitable environment for meteorological measurement. Different levels of maintenance are also linked to this classification from frequent for MF class 1-2 to moderate for class 3 and no real maintenance organization for the other ones. Note that the better the site is graded, the more the measurement will be representative of a wide area.

After expert controls that take into account the uncertainties listed previously as well as the site class or the sensor type, the data could be rejected, set as doubtful or directly validated.

Table 1 – WMO and Meteo-France (MF) performance classification of measurement sites with the number of MF rain gauges per class in January 2010.

<table>
<thead>
<tr>
<th>WMO</th>
<th>WMO</th>
<th>Nb of MF</th>
<th>Meteo-France version</th>
<th>Meteo-France version</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


Another distinction than this performance classification exists and has been previously cited; when rain gauges were separated following two networks "automatic" and "volunteer". Within these networks subdivisions exist, they could be summarized as in Table 2.

Table 2 - The types of station within the two main networks "automatic" and "volunteers".

<table>
<thead>
<tr>
<th>Network type</th>
<th>Number of station 2007-2010</th>
<th>The terms of each type</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td>Synoptic station, automatic or with Meteo-France staff [real-time distribution and expertise]</td>
</tr>
<tr>
<td>1 &quot;automatic&quot;</td>
<td>1250 to 1300</td>
<td>Synoptic station with staff not from Meteo-France [real-time distribution and expertise]</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>Automatic station [real time distribution and expertise]</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>Automatic station [expertise delayed]</td>
</tr>
<tr>
<td>4 &quot;volunteer&quot;</td>
<td>2800 to 2500</td>
<td>Climate station (volunteer) [expertise delayed]</td>
</tr>
<tr>
<td>5 &quot;automatic&quot;</td>
<td>220 to 500</td>
<td>Automatic station or position questioned occasionally [data with no expertise]</td>
</tr>
</tbody>
</table>

As presented in Table 2, a part of the automatic network is not managed by Meteo-France but by partner such as CEA, EDF...this part of the network don't always benefit from complete information on the equipment and its maintenance. Also the site classification is, to date, not yet realized for the full network. In the construction of the method of control only stations receiving this filing have been used.

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3.2 The radar estimate of precipitation data

3.2.1 The Meteo-France radar network

The Meteo-France radar network called ARAMIS (Application RAdar à la Météorologie Infra-Synoptique) consists of 24 weather radars on mainland France and allows producing images on a national scale of precipitation with a very high spatial resolution (1 km² by pixel on a 512 by 512 pixels domain for each radar) and a fine temporal resolution (every 5 minutes). This network is represented Figure 2.

![Figure 2 - The Meteo-France ARAMIS radar network.](image)

It produces since mid-2006, the new rain accumulation estimation of the PANTHERE project that includes treatments to correct a number of potential uncertainties:

- via treatment of the standard deviation of the signal, the ground clutters are processed dynamically.
- the urban and orographic masks are corrected.
- the anomalous propagation (ground and sea echoes) using satellite products to estimate the probability of rain / no rain.
• The radar takes 5 minutes to explore all the atmosphere. The information of each pixel is instantaneous. A temporal interpolation processing is requested to produce continuity within the rainfall accumulation. It is the treatment of advection.

• the real-time estimation of the Vertical Profile of Reflectivity (VPR) is used to correct the effects related to the elevation of the radar beam.

• the model Iso 0° of the forecast model ARPEGE is employed to determine and correct the bright bands.

• the reflectivity is deduced from a weighted linear combination of measures at the different elevation angles available for each radar.

• and, finally, a quality factor map of values going from 0 for very bad and 100 excellent and depending the elevation of the beam and rate of mask comes with each of the rain accumulation maps. The Figure 3 presents the case of the 31 December 2010 as an example. As can be seen in this example the range of the radar is on average a crown of 20 to 100 km.

![Figure 3 - Map of the pixel quality code for the 31 December 2010 situation.](image-url)
As can be noticed in Figure 3, some areas are not covered by radar. Indeed, about 80% of mainland France is covered by the network. The Massif Central has a decent enough radar coverage as opposed to the Alps where it is a very poor one. In areas not covered, obviously, no rain gauge control could be done using radar data.

A mosaic of rainfall accumulation is then drawn from the individual rainfall accumulations. The compositing technique is based on a weighted linear combination of the different available estimates at each point, with the weights being precisely the quality codes mentioned above. These new products have been available since summer 2006 and archived with spatial resolutions of 1 km and a temporal ones of 5 minutes. Unfortunately, as will be explained later, this particularly practical product couldn’t be employed in our study. Note that within this process, the attenuation by precipitation is not corrected as well as the problem linked to the precipitation type. Moreover, precipitation detected by radar may evaporate before reaching the ground thus not be detected by the rain gauges. Conversely, the lowest layer of clouds that are carrying rain may fall below the radar beam (especially in certain situations with snow in winter). These precipitation are then not detected by radar but are by ground rain gauges.

3.2.2 Uncertainties and calibration of the rain accumulations product

The measurement of rainfall estimate by radar includes intrinsic inaccuracies. Some are linked to the radar technology itself: such as inaccuracies due to a lack of radar calibration that could introduce under or over-estimation of rainfall in the image; a lack of accuracy in the radar view angle in terms of the azimuth and of the radar site angle; or even due to the impact of the non-uniformity of the vertical structure of the rain. Although most of the radar echoes arising from the intersection of the radar beam with the ground are removed by the Meteo-France processing, it is possible that some spurious echoes still remains: caused by the anomalous beam propagation conditions, freezing or frozen precipitation, low topped convection, bright banding, or the radar’s effective coverage (e.g., physical obstructions such as mountains).

Moreover, the difference between the rainfall measured by radar and the one measured by rain gauges could sometimes be temporarily important for reasons that can be linked to an electronic drift or for physical reasons such as a simplification of the Marshall Palmer law. Indeed, another significant sources of inaccuracies come from the signal processing, as the
accuracy of the reflectivity conversion to rainfall estimate depends from a conversion formula. The one used is the Marshall Palmer Law (1948) and could be written as following:

\[
Z = 200 \cdot R^{1.6}
\]

with \(Z\) the reflectivity in mm\(^6\).m\(^{-3}\) and \(R\) the precipitation intensity in mm.h\(^{-1}\)

The two coefficients present in this formula are normally dependant on the precipitation type but in the one used at Meteo-France for radar data processing they are constant and are more adapted to mid latitude stratiform precipitation. This simplification has consequences on the representation of convective precipitation radar estimate.

No improvements have been integrated concerning that matter in the PANTHERE product. However, to partially reduce this potential bias, the PANTHERE rain accumulation product benefits from a real-time control through a real-time calibration using rain gauge data. Indeed, to take into account heavy convective precipitation events that could be underestimated by radar estimation, a real-time calibration using rain gauges is made by multiplying the rain accumulation map of the current hour by the ratio rain gauge / radar estimate of the previous hours. Indeed, at the end of each hour, a unique adjustment factor is calculated for each radar with the data of the previous hours. Then, these factors are applied to all 5 minutes rainfall accumulations until the end of the hour when they are updated. This adjustment is operational on 24 radar network ARAMIS since March 29, 2007.

In the analyses proposed in this report we will use rain accumulation product without this calibration but with a special local recalibration methodology that is detailed section 4.1.

### 3.3 The French radar Quantitative Precipitation Estimation (QPE) re-analysis project (COMEPHORE)

The next Meteo-France challenge in improving the precipitation estimate is detailed through the French radar Quantitative Precipitation Estimate (QPE) re-analysis project. This project has been designed in close relationship with French hydrometeorology labs and entitles to produce a 10-year reference database of QPE over the French metropolitan territory using all available sources of data (radars, rain gauges, satellites …) with its associated estimate of uncertainty. The period it covers is 1997 to 2006 and the resolution it targets is 1 km\(^2\) spatially and the hour temporally.
This QPE reanalysis includes an important pre-processing of the radar data (Moulin et al., 2009; Champeaux et al., 2011; Tabary et al., 2011). Indeed, this project deals with old radar data that didn't benefit from the latter evolutions in terms of verifications and corrections. After a pre-processing phase of the radar data that includes specifically developed new algorithms and new verifications, corrections (of ground clutter, bright band…) and calibration techniques, the radar data are combined with hourly and daily available rain gauge data. Best 24h rain accumulation estimates are obtained using Kriging with external drift and then downscaled to provide hourly rain accumulation.

This project is in progress; it concerns our project as it enables to obtain pre-processed radar data (before calibration with rain gauges) for the period prior to the one considered in this report. Moreover, the techniques that have been selected in our project are, as will be detailed later, close in some aspect to the ones of the QPE re-analysis project.

4 Data preparation and feasibility study

4.1 Daily radar QPE with local recalibration by pixel

To answer to the problematic this study is concerned with, a special recalibration methodology has been developed and is applied radar per radar. To ensure the independence of the precipitation estimates, on a daily basis rain gauges are separated into two roughly equal lots by carrying out a totally random draw. Using these two sets independently, for each pixel of the radar data two calibration coefficients have been calculated as the median of the ratio of radar / rain gauge couples available. Then two sets of independent recalibrated radar are obtained for each radar by multiplying calibration coefficients to the non-calibrated radar data. Notice that certain requirements on radar / rainfall couples used are imposed such as: a minimum of 84 in the radar pixel quality code; a minimum of 0.6 mm and 0.1 mm for respectively the rain gauge and the radar pixel rainfall value. Moreover, the employed rain gauges have been selected with also a good quality code and finally a minimum of 3 couples has to be archived for the calculation to be done on each concerned pixel (the mean number of couples for each pixel is about 10). This calibration is abandoned if the coefficient is outside the interval 0.2-8. The search of available rain gauges in the calibration process has been done in a 30 km circle for each pixel. As an average, the recalibrated radar fields have a geographical extension of around a 100 km circle around the radar as, almost no pixels are associated with a good enough quality code further away from this radius. For pixels where

4 This value is a common Météo-France radars quality threshold, that is not used only for this project.
the calibration coefficient were not calculated (because of a lack of rain gauges), the average of surrounding pixel’s calibration coefficients were employed. This process was done if a minimum of 5000 valid (following the previously details constrains) pixels were available, otherwise the pixel was set to invalid. This local radar recalibration by pixel is inspired from the radar re-analysis project. The main advantage of this recalibration comes from the use of daily rain gauges with a high spatial density while the PANTHERE operational calibration is based on a sparser network and on past data.

In cases where only a few pixels of a radar and rain gauges have values indicating precipitation, the situation was described as “a state of non-rain”. These cases are treated, with respect to the recalibration, in a manner different from that described previously. To avoid losing information, a recalibration factor of 1 was used.

4.2 Diagnostic of feasibility of using radar estimate to control rain gauge precipitations

In this section, attention will be focused on the usage of radar precipitation estimates to control rain gauges ones. The feasibility and the relevance of such a scheme are viewed in terms of correlation between the two types of data and through the significance of a link between them following precipitation intensity. To do so, analyses will be performed with daily data for the period starting beginning of 2007 and finishing end of 2010. To avoid introducing spurious uncertainties linked to rain gauge instrument type only data above 0.6 mm will be taken into account for rain gauge precipitations. The rain gauges have been separated following two categories: Automatic that includes synoptic and automatic stations and the Volunteers ones. Concerning the radar precipitation estimates, only the data associated to a good quality factor $\geq 84$ are employed and they have been used without or with the PANTHERE operational calibration.

4.2.1 The temporal correlation between rain gauges and radar estimates precipitation data

For statistical purpose only samples with a minimum of 100 radar/rain gauge couples of data per station are employed. The Table 3 presents the annual and seasonal averages values of station based correlation between the two types of rain gauges and of radar estimates. In blue are represented the lowest correlations and in red the highest. This table highlights a weak variability between the season results, not important enough to be significant. The
The lowest temporal correlation is in winter between the volunteer’s rain gauges and the non-calibrated radar data.

Table 3 - Annual and seasonal averages of station based correlation rain gauge / radar rainfall data over France for two types of rain gauge data (automatic & volunteer) and of radar data (not calibrated & calibrated).

<table>
<thead>
<tr>
<th>Year</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not</td>
<td>0.81</td>
<td>0.79</td>
<td>0.81</td>
<td><strong>0.78</strong></td>
</tr>
<tr>
<td>calibrated</td>
<td>0.88</td>
<td>0.86</td>
<td>0.88</td>
<td>0.86</td>
</tr>
</tbody>
</table>

While comparing average temporal correlation with the radar data without or with the PANTHERE operational calibration, it is obvious that the calibration improves results. If this is logical while looking at correlation with automatic rain gauges (as most of them are used in the calibration), it is not the case with volunteers ones. The importance of this statistic becomes even more obvious when one considers that it implies that even if the calibration is based on a simple mathematical process, it has positive effects on the all rain accumulation representation for small and large-scale events.

In Figure 4, the individual station year correlation values between the two types of rain gauges and the non-calibrated radar data are represented. The two maps highlights the density difference between the automatic and the volunteer’s rain gauges networks, as well as the area not covered in both case by the radar network such as the Alps (see figure 2). The usage of the volunteers network of rain gauge takes even more sense while looking at the density difference between these two maps. But, it shows also that most of the correlation values taken individually are good (above 0.7). The lower correlation values could be found close to mountains area.
Figure 4- Annual correlation between (left) automatic (right) volunteers rain gauge and non calibrated radar data by station over France.

This is also the case while looking at the map of the other results (not shown here) indicating that values averaged over France could be considered as representative of the individual values.

4.2.2 Statistical significance of the link between rain gauges and radar estimates following rainfall intensity ranges

The correlation between the variables being demonstrated, it is now necessary to quantify their connection. The Tschuprow test (Tschuprow, 1923) is retained in this matter. It measures, at the root square accuracy, the ratio between the theoretical and the maximum Chi2 values if the variables were independent. This coefficient can be translated as a percentage of information explained by the link (equivalent to the coefficient of determination with variables quantitative). The Tschuprow coefficient, if above 0.35, implies a strong link between rain gauge and radar rainfall data and the stronger the value the stronger the link is. Prior to the calculation of this coefficient, the two types of data have been separated following equiprobable classes (from 2 to 8 classes) of precipitation intensity quantiles.
Table 4 - Station based (average over France) Tschuprow coefficient between (A) automatic (V) volunteer rain gauge and not calibrated or calibrated radar rainfall data. Note that rainfall data have been separated using quantiles in a number of 2 to 8 equiprobable classes of rainfall intensity before the calculation of the coefficient.

<table>
<thead>
<tr>
<th>Nb of equiprobable classes</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>V</td>
<td>A</td>
<td>V</td>
<td>A</td>
<td>V</td>
<td>A</td>
<td>V</td>
</tr>
<tr>
<td>Not calibrated</td>
<td>0.66</td>
<td>0.63</td>
<td>0.58</td>
<td>0.55</td>
<td>0.52</td>
<td>0.50</td>
<td>0.49</td>
</tr>
<tr>
<td>calibrated</td>
<td>0.71</td>
<td>0.68</td>
<td>0.64</td>
<td>0.61</td>
<td>0.58</td>
<td>0.55</td>
<td>0.54</td>
</tr>
</tbody>
</table>

The Table 4 is organized as Table 3, it gives the Tschuprow coefficient averaged over France between rain gauge for (A) Automatic or (V) volunteer ones and radar estimates without or with PANTERE operational calibration. The top of the table gives the number of classes the data have been decomposed in before calculation. This table indicates that up to 8 equiprobable classes of precipitation, the two sources of data are significantly linked. As for correlation, the link is always stronger with automatic rain gauges than with volunteer ones and with calibrated radar estimates than for non-calibrated ones.

Figure 5 - Tschuprow coefficient between (left) automatic (right) volunteers rain gauge and non calibrated radar data by station over France while rainfall has been previously separated using quantiles in 5 equiprobable classes of rainfall intensity.
Focus is now given, in Figure 5, to individual station Tschuprow coefficient value while data are decomposed using 5 equiprobable classes of precipitation intensity quantiles and while radar estimates with PANTHERE operational calibration are employed.

These two maps highlight, with the color “cluster” structure, a decrease of the value of the Tschuprow coefficient while going further away from each of the radar position and up to each radar extension. The correlation weighted by the inverse on the rain gauge/radar position distance didn’t present a significant difference from the results without the weighting shown in Figure 5. However, as far as this statistical test is concerned, this distance should not be neglected.

The area with a steep orography presents also a slightly lower value, pointing out the importance of taking it into account.

## 5 Methodology

The target of this project is to develop and test a method to control observations of rain gauges using for each rain gauge an independent estimate of known uncertainty with the help of radar data and using a spatialisation methodology.

The literature contains a lot of review comparing the different spatialisation methodologies such as Hofstra et al., 2008, Jin & Heap, 2008 or Mestre, 2005. Also the use of radar data in the process of rain gauges spatialisation has been already experimented by Schuurmans (et al., 2007) and DeGaetano (et al., 2009).

In our case, mainly, four different types of method for precipitation estimate via radar data spatialisation have been explored. These techniques use recalibrated radar data (as described in section 4.1) and are the following:

- Neural networks (Deterministic).
- Optimal interpolation (Stochastic).
- Kriging of the rain gauges with radar oriented external drift. (Stochastic & geostatistical & multivariable mode)
- Thin Plates Spline (TPS) in a 3-dimensional space. (Deterministic & non-geostatistical & multivariable mode)

In brackets next to the method type is given some further information about the statistical family they are associated to. Such as deterministic when no assessment of errors with the resulting predicted value is producible as opposed to stochastic that includes randomness and as such could gives an estimate and its associated error. Or non-geostatistical when only the distribution of a set of sample data is examined as opposed to geostatistical that takes into account the statistical as well as the spatial distribution.
From these spatialisation products, a range of uncertainties around estimates are obtained and enables to call as doubtful a rain gauge data beyond it.

After a methodology overview, a broad review of these different spatialisation techniques is given. Moreover the different score (RMSE, MAE, bias and correlation) employed to discriminate the performance of the different methodologies as well as the cross-method comparison done for the two best methods will be also detailed in this section. Finally, the control method of daily precipitation using radar data will be presented.

5.1 Methodology overview

The input data are, on the one hand the daily rainfall accumulation data of each of the 24 radars without calibration and on the other hand daily rain gauge records (automatic network and volunteers).

Observations from rain gauges are divided into two roughly equal lots by carrying out a totally random draw. The calibration of radar data by local calibration method is done twice, each time using one of the lots of rainfall observations to produce a set of radar recalibrated fields. So, the first recalibrated radar field is fully independent from the second rain gauges lot and vice versa. Then data fusion techniques (kriging with external drift, thin plate splines in 3D, optimal interpolation, neural networks) are employed to produce for each rain gauge of a controlled lot an independent estimate of the rain that uses: the radar recalibrated data independent from the controlled rain gauge and surrounding rain gauges observation. Rain gauges are selected from the neighborhood as much in Lot I and Lot II, with the exception of the controlled rain gauge. This treatment is applied to long series (four years from 2007 to 2010 in our test version). The result obtained is a series of independent estimates for each controlled rain gauge and the statistical error of estimation can then be calculated.

At that stage the procedure for automatic control of rain gauges is carried out. It qualifies to doubtful an observation when the difference between this observation and the independent calculated estimate is too high to be plausible in the light of the known statistical error of estimation.

The developed control technique relies heavily on producing an estimate of rainfall using both radar data and rain gauges ones. For this reason, a detailed study on the pre-cited spatialisation techniques has been performed. The choices that were made are very inspired by those who were retained in the re-analysis radar under construction at Meteo-France over the period 1997-2006. In particular, the use of a local recalibration technique followed by a fusion of radar-rain gauge (Tabary et al., 2011).

However, two main differences are worth noting with respect to the re-analysis. First, the goal of having an independent estimate of the rain has required to realize the local
recalibration in two lots. Furthermore, estimates have been produced only for the geographical position of the controlled rain gauges while the re-analysis requested to produce them for all points of the treated area. Although the techniques are rigorously the same as spatialisation, this greatly reduces the computational load.

Figure 6 - Methodology flow chart.
Other considerations must be taken into account. The radar mosaics couldn’t be employed as it is not possible to have the data before calibration and as a consequence these data are not independent from rain gauges. Therefore individual radar fields have been the only possible option, while they do not necessarily have a spatial continuity (a significant proportion of the pixels is invalid). Moreover, the quality of valid radar pixels is good on a crown of about 100 km around the radar but weak beyond. Each controlled rain gauge has been linked to the nearest radar, as a consequence a significant proportion of rain gauges have been excluded from monitoring because of the too low radar data quality code or the association to an invalid radar pixel.

5.2 The rainfall spatialisation techniques

Our study has mostly been devoted to performances of spatialisation methods, the control method for the precipitation has been addressed but are yet to be explored more thoroughly.

5.2.1 Neural networks

The neural network technique is usually used for discriminant analysis or classification. The scheme employed while implementing neural network for the purpose of our study is based mainly on Matsoukas et al. (1999) and on Hongping He et al. (2001) and Tapiador et al. (2004).

The developed neural network is of type back-propagation Multi-Layer Perceptron (MLP) with a sigmoid activation function for all neurons (hidden layer and output layer), 6 input neurons and a hidden layer with 25 neurons. Before use in any step of this neural network, rain radar and rain gauges data are transformed into log (rr+1) and normalized between 0.1 and 0.9. Using the two independent sets of radar data as input, different structure of neural networks have been set up and tested. However, none of them did give satisfactory results. The major difference with Matsoukas et al. paper comes from the spatial resolution. Their analysis use 46 rain gauges for radar data of resolution 50x50 (no more details on the size of each pixel or quality). The basis of our study consists of radar images 512 x 512 and about 200 rain gauges “usable”.

A case study on Trappes radar (Mounier, 2011) as well as an experiment over France for year 2010 has emphasized that the technique of a neural network using the radar is able to reproduce the radar imagery, but does not have the same ability to reproduce a network such as the sparse rain gauge ones. This technique developed as an adaptation of the one described in the article Matsoukas et al. certainly shows the limitations associated with the small number of rain gauges available. The excessive necessary computing power, the
complexity of the methodology as well as the poor quality of the obtained results has for logical consequence to not pursue the use of neural network in our study.

5.2.2 Optimal interpolation

The optimal interpolation method was first suggested by Eliassen in 1954 but has been developed for meteorology by Gandin in 1963 while kriging was developed in the geosciences field. This method is close to Kriging to the difference that it assumes the meteorological background field as a prior knowledge. This methodology, in the context of this study, produces a rainfall estimate through the radar field as first guess meteorological background field corrected by a linear combination of the difference between this first guess and the rain gauge data. The coefficients associated to the linear difference are the statistical result of the minimization of the expected square error of the data and are expressed as covariance matrices of observed and radar data. The target of the interpolation (the rainfall estimates) is calculated under mathematical BLUE (Best Linear Unbiased Estimation) version of the optimal interpolation as described in Figure 7.

![Figure 7 - Schematic representation of the optimal interpolation.](image)

This analysis minimizes the error variance analysis. Such a methodology has been already employed for similar study such as in Lussana (et al., 2009). It has given quite good results in their case and in the case of our study. However, this method has not been retained (and
these results will not be shown) as compared to the kriging and TPS method, it provides results of lower quality.

5.2.3 Thin Plate Spline (TPS) in a 3-dimensional space.

The thin plate spline interpolation methodology is formally known as “laplacian smoothing splines” and is a deterministic non-geostatistical surface-fitting method (by a polynomial which is most often of degree 3) that entitles to adjust a set a function that interpolate observations while minimizing the smoothness term. This smoothness term $E$ represents a compromise between the curvature of the surface and the distance with observations and is calculated by iteratively minimizing the generalized cross validation function. For the purpose of this study, the methodology has been used in a multivariable mode as it has been generalized in an area greater than two with a third dimension that use the radar data (daily data with local recalibration - see section 4.1).

Given a set of source points $(p_1,..,p_n)$ and target points $(q_1,...,q_n)$, the formulation minimizing the smoothness term $E$ could be written as following:

\[
E = E_f + wE_d
\]

Equation 5-1

with $E_f$ the fitting term, $E_d$ the distortion term and $w$ the weight.

The fitting term measures the proximity of the source with respect to the deformed target. It could be written as a formulation that minimize the sum of squared distance between $(p)$ and $(q)$ points:

\[
E_f = \sum_{i=1}^{n} \| f(p_i) - q_i \|^2
\]

Equation 5-2

with $f(p)$ the spatial deformation function for every point $(p)$ in the volume.

The spatial deformation function is the cornerstone of the method. It is also called the minimizer of the smoothness term and could be written as following:
\[
\mathbf{f}(p) = \mathbf{M} - p + \sum_{i=1}^{n} \mathbf{v}_i \phi\left(\|p - p_i\|\right)
\]

Equation 5-3

with \( \mathbf{M} \) an affine transformation matrix, \( \mathbf{v}_i \) deformation vector and \( \phi(d) = d^2 \log(d) \)

The other part of the smoothness term formula is the distortion term; it enables to measure the volume of the deformation and depends on the weight \( w \) that controls how much non-rigid warping is allowed.

The practical implementation has been as following: the estimate of a controlled rain gauge is calculated using the neighbors in a square of 150 km resolution and is computed with the “Tps” function of the “fields” library of R software. This “Tps” function has the advantage of automatically adjusting the smoothing factor to minimize the error (for iterations and cross-validation). Neighboring rain gauges employed for this calculation have to be of type lower than 5, with a valid quality code and have to be associated with valid radar pixel (that could be under 84) as for its quality code. Moreover, a station should have at least 5 neighboring stations for the calculation to be done.

The main advantage of this method compared to kriging, detailed in the next section, is that it doesn't request to develop a semi-variogram. However, in spite of everything it has an obvious structural disadvantages: spline is by definition smoothly varying, therefore this method could have difficulty to reproduce abrupt change. This potential structural problem should be kept in mind while looking at convective precipitation events.

5.2.4 Kriging of the rain gauges with radar oriented external drift

The Kriging with external drift (KED) method is a stationary geostatistical version of universal kriging, designed to estimate a variable sparsely distributed on a study area using another variable which is exhaustively known for this area. Therefore the kriging of the rain gauges with radar oriented external drift seems particularly adapted in this study. The Kriging method is an exact interpolator (the estimated value of a measurement point is equal to the value of the measurement point) as opposed to the TPS method previously detailed.

This technique find its sources beginning of the fifties in the mining industry. The mining engineers Krige and the statistician Sichel worked on a way to improve gold ore reserve estimation in South Africa and published their results in 1951. A decade later, the French mathematician Matheron (1969) derived the formula and the essential part of the universal kriging method that could be written as the following model for the location \( \mathbf{s} \):
As presented by this model, the variability in space of Z is modeled by this random function $Z(s) = \mu(s) + \delta(s)$, which is the sum of a smoothly varying deterministic drift component $\mu(s)$ and a more rapidly varying and spatially correlated stochastic component $\delta(s)$ also known as residual. It is the shape of the drift that determine the model:

- For the simple kriging $\mu(s)$ is a known constant.
- For the ordinary kriging $\mu(s)$ is an unknown constant.
- For the universal kriging $\mu(s)$ is a linear combination of functions of the position $\mathbf{s}$ so of coordinates $(x, y)$. The drift component is then modeled as following:

$$\mu(s) = a_0 + a_1 x + a_2 y$$

Equation 5-5

- In the case of kriging with external drift (KED), this drift part is defined externally as a linear function of the auxiliary radar data variable rather than coordinates and could be written:

$$\mu(s) = a_0 + a_1 z(s)$$

Equation 5-6

with $z$ the radar data corresponding to the point $\mathbf{s}$

Indeed, with the KED method it is the radar data secondary attribute that defines the drift part to guide the estimation of the primary rainfall variable at the rain gauge.

At first, this method looks like a sophisticated version of weighted inverse distance interpolation. The originality comes from the residual part that includes the underlying semi-variogram as will be seen later on.

The kriging explores the spatial structure of the data to see if they are autocorrelated. The main tool for this exploration is the semi-variogram which describes the evolution of the semi-variance as a function of the distance between the measurements. It could be defined as follows:
\[ \gamma(h) = 0.5 \times Var[Z(x+h) - Z(x)] \]

Equation 5-7

with \( Z(x) \) and \( Z(x+h) \) the values of the two points separated by the distance \( h \).

The accuracy of kriging estimates is driven by the use of variogram models to express autocorrelation relationships between controlled points in the data set. Therefore the adaptation of a model (also called variography) is essential. Three parameters are used to describe the variogram (see Figure 8):

- The **nugget**, which appears on the variogram as a discontinuity at the origin.
- The **sill**, which is the difference between the limiting value apparently reached by the variogram, when it becomes more or less stable, and the nugget.
- And finally, the **range**, which is the distance \( h \) at which the correlation between \( Z(x) \) and \( Z(x+h) \) disappears.

![Figure 8 - Illustration of the parameters describing the variogram](image)

One variogram model has been estimated for each radar and each day. It has been applied to derive semivariances at all locations around each radar and to solve the kriging weights (\( a \) coefficients).

The creation of variograms and covariance functions to evaluate the spatial autocorrelation represents the first stage of KED process. The second stage is the prediction of unknown values. The way it is done is by using the following estimator:
\[
\hat{Z}(s) = \sum_{i} \beta_{i} Z(s_{i})
\]

Equation 5-8

The drift is implicitly taken into account in the weighting factor \( \beta_{i} \). In this particular case, the weights must satisfy not only the conditions of ordinary kriging (estimation bias equal zero and a minimum error variance) but also the one provided by the additional external drift \( \sum_{i} \beta_{i} \mod(s_{i}) = \mod(s) \).

The practical implantation of this KED methodology has been done radar by radar and could be summarized as following. Kriging is done within an area of 150 km but only neighboring rain gauges which have a valid and good quality (superior to 84\(^{5}\)) radar pixel associated were employed. Moreover as for the type of site (see Table 2) station has to be of type less than 5 and has to have at least 5 neighboring other stations (the average is 86 stations).

The KED and TPS methods were not applied to meteorological situations with no rain.

5.3 The performance tests of the spatialisation methods

Testing of processing variables in log \((rr+1)\) have been performed, no improvement regarding the methods of spatial performances have been noticed. Therefore this type of transformation has not been retained at that stage of the process.

5.3.1 The different scores

Hereafter are presented the advantage and purpose of the different scores that were calculated for each station over the period 2007-2010 to compare the performance of the different spatialisation methods described in the previous section.

The RMSE (root mean square error) has the advantage of being very sensitive to the occasional large error as the squaring process gives disproportionate weight to very large errors. Therefore, it is a good approach to analyze where the spatialisation methodology performs badly so have a high RMSE. Moreover, it is also useful to inter-compare the different spatialisation methodology performances as the lower the RMSE the better the spatialisation methodology performed. The MARE (mean absolute relative error) is produced for purposes of reporting; it is expressed in generic percentage terms as so it highlights, clearly, area where the methodologies produce really significant errors. The absolute bias

\(^{5}\) Code internal to Meteo-France radar network.
has been calculated to evaluate if methodologies have a tendency to under or over estimate rainfall. The correlation factor has been used as a residual diagnostics somehow as a goodness-of-fit test of the meteorological process in progress. With no real consideration of under or over estimation produced by a spatialisation methodology, it enables to evaluate if they could reproduce properly in time and space meteorological structures.

5.3.2 Cross-method comparison (bootstrap + student test) for the two best spatialisation techniques

Following the results, the two best interpolation methodologies have been selected and some further statistical tests have been conducted to assist in the construction of best practice selection instructions. In this process, the hypothesis tested (called the null hypothesis, main assumption or H0) is that both methodologies are equivalent in quality in estimates they produce for rain gauges.

![Diagram](image-url)

**Figure 9 - Implementation of the two-tailed student test applied for one station for three scores (correlation, RMSE and bias) and comparing estimates of rainfall values obtain with two different methodologies**
The formulation of the alternative hypothesis $H_1$ compares the performance of the two methodologies, as such a two-tailed student test has been performed with a 5% error probability allowed. The implementation of the student test has been done per station and could be summarized as in Figure 9. For one station, the temporal evolution of the observed rainfall value is controlled with the help of the temporal evolution of the radar data around that station and using spatialisation methodologies. While the two best methodologies are selected, the performance of two times series of respectively $n$ for methodology 1 (M1) and $m$ for methodology 2 (M2) couples (observation / estimate) are compared. The number of available couples ($n$ and $m$) are close but different as the constrains associated with each of the two methodologies doesn’t always give the same daily results. The statistical process is carried on only if $n$ and $m$ are above 100. If above 100, correlation, RMSE and bias are calculated 1000 times on bootstrap sequences of respectively $n$ or $m$ couples following the methodology. Student test are then calculated for each of the three scores. This process is done for each of the station and the t-values of the student t test are spatialised per score. The t-value between $-1.96$ and $1.96$ indicates that $H_0$ can’t be rejected meaning that both methodologies could be used. By contrast, if t-value is above 1.96 it means that the first methodology has shown better performance than the second ones and opposite if under $-1.96$. The choice of +/- 1.96 comes from the use of 1000 iterations that yields to a Gauss Law distribution for the student test values.

5.4 The control method of daily precipitation using radar data

After studying the performance of spatialization methods, we turn now to the method of rain gauges control.

As described in Figure 10, for each rain gauge, to process control of the rain gauge observation (O), an independent estimate of precipitation (E) at each rain gauge point controlled for each day of the period 2007-2010 was calculated using KED or TPS methods and radar data as well as the statistical error of the estimate (RMSE and bias). From RMSE and the bias the standard deviation can be calculated. Then, an observation is qualified as doubtful when the difference with the independent estimate $|O-E|$ is greater or equal to 3 times the standard deviation.

This control has been done on transformed data $10 \times \log (rr+1)$ as under these conditions the standard deviation of error is relatively stable for low or high rainfall.
6 Results

6.1 General results

In this sub-section, correlation, RMSE, bias and MARE are presented as maps where the results per station have been interpolated on a grid to facilitate the reading. In Figure 11 is represented the geographical positioning of the rain gauges that have been used to estimate the performance of the spatialisation methods. One should remember while interpreting the data that some areas were not covered by the Meteo-France radar network (see Figure 2).
6.1.1 Kriging of the rain gauges with radar oriented external drift

The results presented in Figure 12 employs the kriging with external drift spatialisation method (see section 5.2.4). This figure displays very few problematic areas as most of the correlations are above 0.9, areas with a bias are sparse and most of RMSE and MARE are low.

![Correlation, Bias, RMSE, MARE](image)

Figure 12 – Correlation, bias, RMSE and MAE scores following spatialisation by kriging. Results were obtain by station but have been interpolated to facilitate the reading. Initial station positioning could be seen on Figure 11. Bias, RMSE and MARE are in hundredth of a millimeter.
6.1.2 Thin Plate Splines (TPS) in a 3-dimensional space

The results presented in Figure 13 employ the Thin plate splines in a 3-dimension space spatialisation method (see section 5.2.3). This figure displays results coherent with the one presented in the previous section.

Figure 13 - Correlation, bias, RMSE and MAE scores following spatialisation by 3D thin plate splines. Results were obtained by station but have been interpolated to facilitate the reading. Initial station positioning could be seen on Figure 11. Bias, RMSE and MARE are in hundredth of a millimeter.
6.1.3 Cross-method comparison (bootstrap + student test) for the two best spatialisation techniques

Figure 14 – Results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. Only value above +/-1.96 are coloured when \( H_0 \) couldn’t be rejected the maps have been set to white. The positive t-value implies that kriging performs better than thin plane splines and opposite when negative. On the right bottom corner is presented the Kernel density plots to view the distribution of the three scores (data within +/-1.96 are set to zero).

As presented in section 5.3.2 a further statistical test has been conducted to assist in the construction of “best practice selection instructions - BPSI” with regard to the spatialisation
method to be employed to construct the estimate of rainfall necessary for the control process. The results is presented in Figure 14 that maps for correlation, bias and RMSE the value of the student test while comparing estimates from KED and TPS methods. Blue (red) areas indicate that the most favorable spatialisation method choice tends to be TPS (KED) ones. The Kernal density plots in the right corner enables to evaluate which method is in average the most favorable ones when you add up all the results of mainland France. In the case of Figure 14, it indicates that while looking at all the results of the period 2007-2010 the most favorable method is, in average, KED. Indeed, the Kernal density plot structure is not symmetric, it has a stronger peak and a slower decay so a higher dispersion in the positive student values (geographically represented in red in the three associated maps).

6.2 Results following the orography, rain intensity, radar type & radar quality code

This type of statistical test has been also done while decomposing following, among others:

- **The orography**: with 3 classes low orography (0-500 meters), medium orography (500-1000 meters) and high ones above 1000 meters.
- **The rain intensity**: with 4 quantiles classes determined for each station.
- **The radar type**: as presented in Figure 2, the Meteo-France ARAMIS radar network is composed of two types of radar (band-C & band-S).
- **The radar quality code**: with 5 classes of quality codes (less than 60), (60-84), (84-90), (90-95) and (greater than 95).

No real tendency in terms of BPSI arose from these tests (results are, then, not shown in this report). However, other tests such as the one following seasonal decomposition are of interest.

6.3 Seasonal results

In this section, results of Figure 14 are presented after a seasonal decomposition. Stations results are no more interpolated but represented as circles to enable to evaluate the station number employable per season as well as the geographical distribution of the student test values for the correlation, RMSE and bias scores.

Some orientation for the BPSI arise clearly from this seasonal decomposition. Indeed, as shown in Figure 15, the scores results in winter tend to favor the use of TPS method while, as shown in Figure 16, those of summer favor the use of KED ones. Indeed, the Kernal density plot structure is not symmetric, it has in winter (summer) a stronger peak and a slower decay so a higher dispersion in the negative (positive) student values (geographically represented in blue (red) in the three associated maps).
Figure 15 - Winter season results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. Only value above +/-1.96 are not in green, when H0 couldn’t be rejected the maps have been set to white. The positive t-value implies that kriging performs better than thin plane splines and opposite when negative. On the right bottom corner is presented the Kernal density plots to view the distribution of the three scores (data within +/-1.96 are set to zero).
Figure 16: **Summer** season results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)

In spring (Figure 17) the results have a similar orientation as those of the summer but with less differentiation between the structure of the two Kernal density plot peaks.
Figure 17 – **Spring** season results of spatialised *t-value* for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)

In autumn (Figure 18) no clear BPSI arises. Indeed, the Kernal density plot structure is almost symmetric, it has equivalent peak and decay for the negative and positive student values (geographically represented in blue (red) in the three associated maps).
Figure 18 - Autumn season results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)

Following these results, an investigation on the potential causes have been conducted. The hypothesis was that this could be explained by the convective or non-convective character of the rain. Indeed, summer tends to have more convective events than the winter and spring and autumn a higher mix of the two types. Two types of data have been employed to discriminate the convective situations from the non-convective ones: the CAPE that has been extracted from Aladin model and the ANTILOPE convective index.
6.4 Results following the rain type (i.e. convective / non-convective)

6.4.1 The instantaneous CAPE from Aladin model

The employed CAPE is the instantaneous Cape (Convective Available Potential Energy) from Aladin model. An air parcel need sufficient potential energy for convection, then above a CAPE value of 20j/Kg the rain gauge is associated with a convective situation.

Figure 19 - Non-convective cape results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)
The BPSI tends to favor slightly TPS method during non-convective situations following the use of the instantaneous CAPE from Aladin model (Figure 19) to classify the type of rain. The Kernal density plot bimodal structure is not symmetrical for correlation results and has a wider dispersion on the negative values. This tendency is very slightly marked as opposed to the BPSI tendency in the case of convective situations which is clearly KED over mainland France as shown in Figure 20.

Figure 20 - Convective cape results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)

These results seem to validate our hypothesis explaining the difference of BPSI in winter and summer.
6.4.2 ANTILOPE convective index

To confirm these results another data source was used, the ANTILOPE convective index. Generated from the ANTILOPE radar product of Meteo-France, the convective index is based on radar reflectivity gradients in the immediate vicinity of the pixel associated with controlled rain gauge; Above a 0 value the rain gauge is associated with a convective situation and to a non-convective one if equal to 0.

Figure 21 - Non-convective ANTILOPE index results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)
The BPSI tends to favor TPS method during non-convective situations following the use of the ANTILOPE convective index (Figure 21) to classify the type of rain. Indeed, as with the CAPE, the Kernel density plot bimodal structure is not symmetrical and has a wider dispersion on the negative values. Moreover, as shown in Figure 22, the BPSI tendency in the case of convective situations is clearly KED over mainland France.

Figure 22 - Convective ANITILOPE index results of spatialised t-value for correlation, bias and RMSE comparing kriging and thin plane splines. (see previous figure for details)

These results seem to validate even more than the one of section 6.4.1 our hypothesis explaining the difference of BPSI in winter and summer.
6.5 Result of control method of daily precipitation using radar data

This was the main target of our study but we have only preliminary results available at the time of writing this report.

The control method has been presented section 5.4; the Figure 23 presents the results station by station using KED (left) and TPS (right) methods to evaluate the rain gauges observations. The colored circles indicates the stations with a percentage of doubtful values through the period 2007-2010.

Figure 23 - Percentage of doubtful values by station following the control process using KED (left) and TPS (right) method to evaluate the rainfall estimates. In blue crosses are positioned the controlled station without doubtful value. In colored circles are presented the stations with a percentage of up to 12% of doubtful values.

Details on the number of available rainfall observations during the control process for the period 2007-2010, with the number of doubtful one following the method employed to obtain the estimates and the rainfall value are given in Table 5.

We are planning to compare these results with the results of existing operational spatial controls of Meteo-France.
Table 5 - Number of rainfall observations available during the control process, with the number of doubtful ones following the method employed to obtain the estimates and the rainfall value.

<table>
<thead>
<tr>
<th>rainfall value</th>
<th>rainfall observations tested</th>
<th>doubtful using KED</th>
<th>doubtful using TPS</th>
<th>doubtful common to both methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal to 0</td>
<td>3,230,695</td>
<td>2,312</td>
<td>2,394</td>
<td>1,718</td>
</tr>
<tr>
<td>0 to 0.6mm</td>
<td>935,775</td>
<td>917</td>
<td>1,043</td>
<td>682</td>
</tr>
<tr>
<td>Greater than 0.6</td>
<td>2,190,305</td>
<td>1,637</td>
<td>2,805</td>
<td>1,079</td>
</tr>
</tbody>
</table>

Following the method employed to obtain the rainfall estimates, the stations with doubtful values are not always the same and the percentage they highlight are different.

To illustrate this, let’s focus attention on stations in the area of radar “Falaise” in the northwest of France (see Figure 2). In this area more stations present doubtful values with TPS than with KED method. Moreover, percentages of doubtful values per station are in average higher with TPS method than with the use of KED. This suggests that the choice regarding the method for obtaining rainfall estimates is essential in the control process. This choice should be indexed on the convective / non-convective character of the controlled precipitation as detailed section 6.4.

Moreover, in mountain regions, there are a large number of doubtful rain gauges. It has often been a disagreement between the rainfall estimation using radar and the rain gauge observation which is linked to a strong dependency to phenomena of very small scale in these areas.

7 Conclusions

The TPS and KED methods perform well to produce estimates of rain gauge data using radar data. TPS tends to perform better for non-convective situations while KED better for convective ones. Following the results of the control method of daily precipitation using radar, the choice of the method to obtain the rainfall estimates should be taken following the BPSI that could be summarized as in Figure 24.
This BPSI should also be taken into account in the process associated to the operational development of this part of the WP1 contribution. Moreover, one aspect that has yet to be built, is the construction of a control method for situations of rain / no-rain as well as the establishment of special treatment for the snow situations.

Moreover, further works are requested on hourly data, the treatment of hourly precipitations has already started. The applied processes are, with some adaptations, the same methods as for the treatment of daily precipitations. About 1800 rain gauges (including those who arrive in delayed time) for mainland France are available on an hourly time step base. The proportion of cases significantly different from zero at this temporal iteration is much lower than with daily time step. On average, for the same station, it is necessary to treat six times more of the hourly networks than the daily ones to get an equivalent number of observations $\geq 0.6$ mm. Therefore, the process of performance evaluation of spatial methods is linked with a mass of data much more higher.

The daily data method of local calibration per pixel (see section 4.1) has been applied to hourly radar data. However, given a density of station available three times lower, the number of couples radar / rain gauge available in a 30 km radius for each pixel is significantly lower and the quality of the recalibration is affected. Up to now, the period 2009-2010 has been treated. In Figure 25, the histograms of correlations rain gauges / radar data (with: local calibration and samples with more than 100 pairs for each station) are presented for 2009-2010 hourly (a) and 2007-2010 daily (b) data.
Statistics such as RMSE, bias and average absolute relative error were also calculated and showed also that the performance at hourly time step is much lower than at daily time step. The rainfall estimation by kriging with external drift was produced for hourly data in the same conditions as for daily data but for the period 2009-2010. Insofar, as for the local calibration, the density of neighboring stations used in the kriging is three times lower, hourly results performance is significantly lower than the daily results of kriging with external drift. This is well illustrated in Figure 26. Statistics such as RMSE, bias and average absolute relative error were calculated and, in the same way than previously, the performance for hourly estimates using kriging with external drift is significantly lower than with daily time step.

The diagrams of Figure 26 while compared to the ones of Figure 25 also show that the kriging with external drift spatialisation method gives better results than the radar data that have been subject only to the local calibration, for both hourly and daily time steps.
The spatialisation methods give results, at hourly time steps, much lower than with daily ones. This was predictable in view of, first, the much lower density of rain gauges and, secondly, because of the increased variability of hourly rainfall. The use of TPS method has not yet been tested but is planned to be and we expect results to confirm that TPS gives performances very close to KED.

A promising way to improve the performance of hourly rainfall spatialisation methods is proposed by the COMEPHORE French radar re-analysis project (see section 3.3). It is based on adjusting the hourly precipitations so that the total of the 24 data of the day for a grid cell is equal to the daily aggregate calculated independently (this daily aggregate is estimated using the entire volunteer network and its quality is then better due to the higher network density).

Finally, having less efficient methods at hourly time step should not prevent to use these results in a procedure for monitoring rain gauges. We planned to continue our treatments to determine if there are still the same hourly BPSI as for TPS method to be use during non-convective situations and KED in convective conditions.

Furthermore, the possibility to adapt the control method outside mainland France should be evaluate. This adaptation will follow the establishment of a critical study on the rain gauge network density in the other EURO4M countries as well as a good understanding of treatments related to their radar data.
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9 Reference

hourly QPE data base for hydrology and climate change studies. 34th Conference on Radar Meteorology, 5-9 October 2009, Williamsburg.


