Estimating hill country rainfall without full data sets for the Manawatu River Catchment

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Abstract

Nowadays, people anticipate floods using flood warning systems, and building stop banks and flood ways in place that use flood models generated with hydrological information in their design. Nevertheless, various regions in the world are still hit by floods with catastrophic effects to urban areas, because of a lack of local hydrological knowledge, especially of upstream areas in their catchments. This lack of hydrological knowledge is a result of difficult accessible highly elevated upstream areas, which makes monitoring of hydrological variables difficult or impossible.

This thesis examines models for determining montane rainfall using spatial estimation methods and data sets. The distribution and quantity of montane rainfall were assessed by applying five appropriated spatial estimation methods, data of historical and current rain gauges, and a performance measurement.

The methodology applied to gain more knowledge about montane rainfall was established with the results of a literature analysis of 40 articles about montane rainfall. This literature analysis revealed that *ordinary kriging* is the most frequently applied spatial estimation method for montane rainfall, with *regression* and *regression kriging* completing the top three of the most applied methods. Also, two other spatial estimation methods, *empirical Bayesian kriging* and *geostatistical simulation*, performed well with rainfall data. The same literature analysis disclosed that the root mean square error was predominantly used as a performance measure of spatial estimation methods.

The literature analysis revealed a number of data gap-filling techniques, with *the inverse distance weighting* method and the *coefficient of correlation weighting* method as the two most suitable techniques. These techniques were applied to complete historical rainfall data sets and their performance was compared within this research. The result showed that the *coefficient of correlation weighting* method outperformed the *inverse distance weighting* method in 74% of all data gap estimations, and the *coefficient of correlation weighting* method was 22% more accurate (based on the overall performance) than the *inverse distance weighting* method. The most accurate data gap-filling technique, the *coefficient of correlation weighting* method, was used to complete the historical rain gauges data.

The overall ranking of the spatial estimation methods revealed that *Gaussian geostatistical simulation* performed the best. *Regression kriging* was the second best spatial estimation method, but there was no significant difference with *Gaussian geostatistical simulation*. At the same time, the results showed that the best performance of the spatial estimations was accomplished without the maximum number of rain gauges. However, better visual

representation of the distinct pattern of rainfall was generated with the historical rain gauges in the second and third experiment of the spatial estimations.

Finally, this research discussed the factors that can impact the performance of the spatial estimations. Two of these factors were the removal of “bad data” and the the strategic placing of rain gauges. The results of this research clearly defined that the removal of “bad data” increased the accuracy of estimation, while a more even and strategic distribution of rain gauges was suggested to increase the accuracy of the spatial estimation of rainfall.

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Chapter 1: Montane Rain Quantity

1.1 Context

On 16 February, 2004, the Manawatu-Wanganui region was hit by a significant storm event. The resulting flood was caused by a weather front slamming into the Ruahine Ranges. Stopbanks failed and hundreds of people in Feilding and other areas were evacuated. Several places, including Tangimoana and Scott’s Ferry, were inundated by flood waters. There was also a massive slip in the Manawatu Gorge. After the rainfall event, it was determined that Palmerston North had experienced a 1-in-100-year flood and other parts of the Manawatu had experienced a 1-in-250-year flood (Matthews, 2010).

Four years later, on 15 April, 2008, seven people from the Elim Christian College died during a flash flood in the Tongariro National Park. Six students and a teacher were a part of a group of 12 that were canyoning down the Mangatepopo Stream. According a spokesperson for the Edmund Hillary Outdoor Pursuits Centre, which ran the canyoning activity, there was no warning of heavy rain (Ritchie, 2008).

The recent events in New Zealand as traumatic they were, were not unique. Unfortunately, similar events happen in other parts of the world. Fast forward to January 2010, when heavy rainfall in Peru caused flooding and prompted landslides that killed 20 people, five people were missing and 3,500 visitors were trapped in the area of world famous tourist site of Machu Picchu, located in the Andes mountain range. Helicopters were used to evacuate the trapped tourists. The railway that transported 90 percent of the people that visit Machu Picchu each day was damaged in the floods and Peru Rail warned that repairs could take up to two months (ABC News, 2010).

The catastrophes stress a lack of hydrological knowledge of upstream areas of river catchments that are inaccessible, which makes monitoring of hydrological variables, such as rainfall, impossible in these highly elevated areas. Importantly, this knowledge gap causes inadequate flooding prediction of lower areas in the catchment. Considering the universal occurrence of similar events, and insufficient knowledge of montane rainfall and international research in algorithms to estimate rainfall, the need for the means to predict flooding has wider applications beyond New Zealand.

The literature revealed worldwide comparative research in algorithms to estimate the spatial distribution of rainfall. For example, Buytaert, Celleri, Willems, Bièvre, and Wyseure (2006) compared two algorithms to estimate montane rainfall of the Ecuadorian Andes, while Goovaerts (2000) compared three spatial estimation methods (SEMs) (see glossary) applied to hill country rainfall data of a Southern region in Portugal. However, there is no particular technique to estimate rainfall, especially montane rainfall, still some of the findings of international research are used to develop applications that incorporates spatial estimation of rainfall.

For example, NIWA (the National Institute of Water and Atmospheric Research) developed HIRDS (High Intensity Rainfall Design System), which is a New Zealand web based program that estimates rainfall frequency for each location (include mountainous regions) in New Zealand, while Giambelluca et al. (2011) developed an online interactive set of maps showing the spatial patterns of the mean monthly and annual rainfall for major Hawaiian Islands. Both applications make rainfall quantity data easily accessible, although questions can be raised about their accuracy, and especially in inaccessible geographical areas such as mountains.

There is a large body of research in rainfall estimation and its incorporation in diverse applications worldwide, but at the same time there is still insufficient knowledge of montane rainfall because these areas are inaccessible and therefore the existence of sparse data. This gap of knowledge in montane rainfall created the need to determine an accurate estimation method for montane rainfall for gaining more understanding of rainfall in mountainous areas. This gap led to the following research question: How can hill country rainfall be estimated in absence of full data sets?

This research aims to develop a method to confidently predict hill country rainfall from sparse data for gaining more knowledge of montane rainfall. The research objectives to accomplish this aim are:

- Evaluate recent contributions to the literature about geostatistics (see glossary)
- Examine recent applications of geostatistics
- Identify a range of spatial estimation techniques, data filling gaps, and performance measure methods to exploit
- Determine criteria for assessing the relative efficacy of estimation methods for montane rainfall
- Clarify the selection of the region by illustrating its geography and climatic characteristics
- Apply the developed criteria (for assessing the relative efficacy of estimation methods) against standard SEMs to identify the most appropriate spatial estimation method (SEM) for montane rainfall.

1.2 Scope and limitations

This project aims to develop a reliable method to estimate hill country rainfall from sparse data. In order to remain feasible and timely, only the most common settings of the applied SEMs are examined. Secondly, the evaluation of SEMs rely heavily on available data from a various organisations. Data availability relies on the temporal extent and the spatial extent of the rain gauges. Additionally, these organisations apply different standards for rainfall monitoring, which has implications on the data quality. Data availability and data quality can have implications on the accuracy of the applied SEM on montane rainfall.

1.3 Overview of the study

To achieve the project's aim, Chapter 2 outlines recent contributions to the literature, identifies a range of spatial estimation techniques, and finally identifies common SEMs. Chapter 3 develops a new method for assessing the relative efficacy of estimation methods for montane rainfall, while Chapter 4 describes the geography and rainfall characteristics of the selected mountain region that experiences montane rainfall.

Chapter 5 reports the findings of the relative efficacy of estimation methods for montane rainfall applied to the rainfall data of the selected mountain region. Chapter 6 discusses the findings with the results and compared them with other studies, while Chapter 7 draws conclusions regarding the reliability of the SEMs for montane rainfall and the implications of limited knowledge of rainfall in upper catchment areas.

Chapter 2: Literature Review

2.1 Introduction

Practitioners and researchers require the establishment of comprehensive criteria to select appropriate SEMs; however, comprehensive criteria for choosing SEMs remain absent despite their growing interest and widespread application. Accordingly, practitioners and researchers require the establishment of comprehensive criteria to select appropriate SEMs. One way to establish a criteria set is to examine recent applications of geostatistics. This chapter firstly outlines recent contributions to the SEM literature, identifies a range of spatial estimation techniques, and finally identifies common methods.

2.2 Recent reviews

Three recent reviews (Hengl, Minasny, & Gould, 2009b; Li & Heap, 2008; Zhou, Guo, Ho, & Wu, 2007) explored the literature focussed on geostatistics. Two of them (Hengl et al., 2009b; Zhou et al., 2007) applied bibliometric analyses to determine influential authors in the field of geostatistics, while the third (Li & Heap, 2008) analysed the application of SEMs in various disciplines of environmental science. Further, the literature introduces guidelines (Burrough & McDonnell, 1998; Lark & Ferguson, 2004) and decision trees (Hengl, 2009a; Li & Heap, 2008; Pebesma, 2004) for selecting SEMs.

2.2.1 Bibliometric analyses

Bibliometric analyses identifies the number of communications and the impact of a set of researchers in a particular research field. Zhou, et al. (2007) and Hengl, et al. (2009b) investigated the impact of researchers and their articles in the field of geostatistics with bibliometric analyses. Zhou, et al. (2007) found 2866 publications in the Science Citation Index database focussed on geostatistics research. According to Hengl, et al. (2009b) the field of geostatistics deserved a more informative analysis than that provided by Zhou, et al.. To provide a more accurate picture of that field, they used more search engines (such as Web of Science (4000 publications), Scopus (2000 publications) and Google Scholar (4724 publications)) to select publications focussed on individual library items and influential authors, and established geostatistics hotspots in the world.

Zhou, et al. (2007) performed hierarchical cluster analyses and discriminant analyses as bibliometric analyses. Hierarchical cluster analyses were applied to the 2866 publications to identify the similarities among the different authors, countries, institutes, and journals. Some of the applied parameters for determining trends were the impact factor, the mean impact factor and annual citations per publication. Lastly, discriminant analyses with statistical tests were used to confirm the cluster analyses results.

Taking a different approach, Hengl, et al. (2009b) applied the citation rate and h-index (see glossary) for each database as the two indices in their bibliometric analyses. The two indices were used to distinguish influential authors who publish multiple publications. Further, statistical analyses were applied to observe summary and temporal trends. Also, geostatistical analyses were used to detect spatial pattern and map areas of scientific excellence. Finally, the citation rate and h-index were correlated with the global socio-economic maps to investigate whether certain indices can be explained by local socio-economic conditions.

Zhou, et al. (2007) and Hengl, et al. (2009b) applied different analyses, although the results of both studies showed similarities such as the most productive authors in geostatistics. Zhou, et al. (2007) showed that Dowd and Stein were the most productive authors and Goovaerts' publications had the most impact. Stein, Goovaerts and Atkinson were identified by Hengl, et al. (2009b) as some of the most productive geostatistics authors.

The geostatistical analyses applied in the bibliometric analyses by Hengl, et al. (2009b) demonstrated a world map of the density of publications with hotspots in Europe and the US. The correlations revealed that the year of publication was correlated with the economic growth, indicating that these developing countries are publishing more.

In summary, the studies by Zhou, et al. (2007) and Hengl, et al. (2009b) revealed similar trends in publications in the scientific field of geostatistics. More importantly, both studies draw a concise picture of the literature in the field of geostatistics with bibliometric analyses, which provide this research valuable information for searching literature for the literature analysis. To provide a more detailed picture of SEMs 'in action', the following section focusses on a research by Li and Heap (2008, 2011) that compared the performance of SEMs in various disciplines.

2.2.2 Applications of spatial estimation methods

The first stage of Li and Heap's research (2008, 2011) revealed that the performance of SEMs is irregular, however they attempted to determine an accurate common SEM by investigating a number of publications involving SEMs applied in various disciplines of environmental science. In comparison to the bibliometric analyses by Zhou, et al. (2007) and Hengl, et al. (2009b), Li and Heap did not specify the selection procedure of their selected literature. They used 53 studies for their first stage of the research, which established the most common SEMs by the frequency of each individual applied SEM. Importantly, this first stage revealed that *ordinary kriging*[1] was the most applied SEM.

[1] All spatial estimation methods and data gap-filling techniques are in italics.

The second stage of their research examined the performance of the SEMs. Only 18 of 53 studies were selected because only these contained information about the performance of the applied SEMs. The examination of the 18 studies revealed that *kriging* methods perform better than other SEMs. Furthermore, the same review of the performance of SEMs showed that *ordinary cokriging* and *regression* appeared to be more accurate than the other SEMs based on the relative mean absolute error.

The third stage established factors affecting the performance of the SEMs applied in the 18 studies. Li and Heap concluded that sampling density, coefficient of variation, and sampling design affected the performance of SEMs. However, there is some scepticism about these findings because Li and Heap's literature review reveals inconsistent performance of the SEMs in various circumstances (for example low and high sample density).

Lastly, Li and Heap developed a decision tree for selecting an appropriate SEM according to the nature of the data and the expected estimation in combination with the features of each SEM (Appendix 5). Furthermore, their study highlighted that the availability of software is an important consideration in the selection of SEMs, which were not incorporated in their decision tree. More details about this decision tree and others, and SEMs overviews introduced in the literature, are outlined in the following section.

2.2.2.1 Spatial estimation methods overviews and decision trees

Besides Li and Heap's decision tree, the literature revealed other examples of decision trees that are outlined in this section. Also, the literature introduced a SEMs overview, which is another support for selecting an appropriate SEM, and examples of this tool are also outlined in this section.

SEMs overviews reveal properties (such as modelling time, benefits, and limitations) of a number of SEMs, whereas decision trees show questions about the supplied data and guide the user to an appropriated SEM. Both have the purpose of making the selection of SEMs for a particular purpose easier. The literature shows some decision trees and SEMs overviews developed by several authors including Burrough and McDonnell (1998), Lark and Ferguson (2004), and Pebesma (2004).

Burrough and McDonnell (1998) were among the first authors that published an overview showing a comparison of SEMs with their characteristics, disadvantages, advantages, computer processing time, and output types (Appendix 1). Independently, Johnston, et al. (2001) generated a very similar overview displaying a comparison of SEMs that are only available in ArcGIS software (Appendix 2). Compared to these two overviews by Burrough and McDonnell (1998) and Johnston, et al. (2001), Basistha, et al. (2008) developed an overview containing limitations and advantages based on practical experiences of applying SEMs from other studies

(Appendix 3). However, all three overviews have the purpose of making the selection of a SEM easier.

Lark and Ferguson (2004), and Pebesma (2004) were also among the first authors that developed and introduced their own decision tree for selecting a suitable SEM before using it in an application.

Pebesma's (2004) decision tree (Figure 2-1) was incorporated in gstat, an open source computer code for multivariable geostatistical modelling, prediction, and simulation. Based on the information that the gstat user puts in the command file, gstat decides what to do: semivariogram (see glossary) modelling, prediction or simulation, and, in the case of prediction, which prediction method to use.

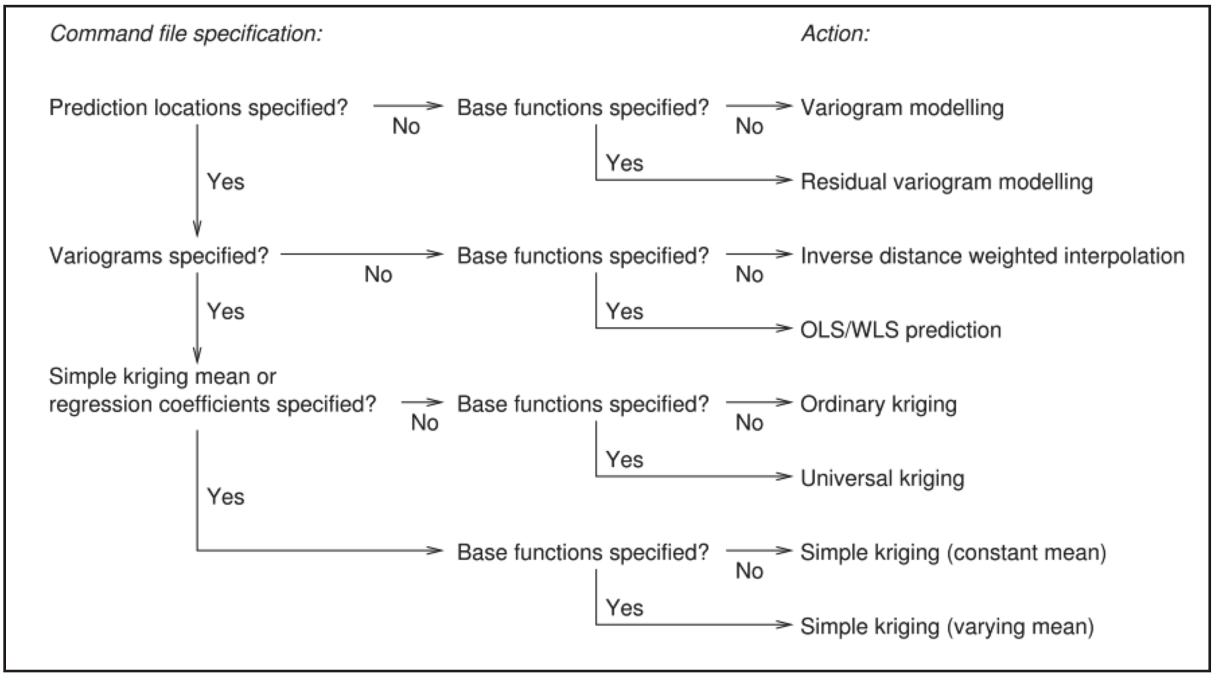

Figure 2-1: A decision tree by Pebesma (2004)

In contrast, Lark and Ferguson's (2004) decision tree was developed on the basis of their case study, which compared *Gaussian disjunctive kriging* and *indicator kriging* empirically by applying these two SEMs to phosphorus values in a large number of soil samples (Appendix 4). The two SEMs gave very similar results and it was concluded that neither of the techniques could be appropriated. To differentiate these two methods and use them in any given circumstance, practical considerations were summarized in a decision tree (Appendix 4).

In comparison with Lark and Ferguson (2004), and Pebesma (2004), Li and Heap (2008) independently introduced a more comprehensive decision tree (Appendix 5) based on findings of an extensive literature review, as described in the previous section. Additionally, the comparison overview by Burrough and McDonnell (1998) is highlighted as one of the first introduced comparison overviews, was also used in the development of this decision tree. In contrast with the other decision trees, this one contains substantially more selection options of SEMs than Lark and Ferguson's (2004) (2), and Pebesma's (2004) (7) decision trees, with 26 different SEMs in total. According to Li and Heap (2008), this decision tree should be only treated as a guideline for selecting an appropriate SEMs based on the nature and availability of the data and the expected outcomes, because there are many other factors (such as sharp changes in the data and availability of secondary data) that could influence the selection of the appropriate SEM.

The most recent decision tree (Figure 2-2) was introduced by Hengl (2009a) and it is similar to the decision tree incorporated in gstat software by Pebesma (2004) (Figure 2-1). Using this decision tree requires knowledge about the input data (such as the existence of a physical model and correlation with other data) by the user (Hengl, 2009a). Unfortunately, Hengl did not provide details about the development of this decision tree.

Interestingly, all identified decision trees and comparison overviews discussed above have not been widely applied and cited in literature, and there are still many comparative studies of SEMs applied in various fields of science. Further, it is advised that decision trees should be treated as a guideline because of other factors (such as the nature and availability of the data and the expected outcomes) (Isaaks & Srivastava, 1989; Li & Heap, 2008). Lastly, these decision trees and comparison overviews contain common SEMs (such as *ordinary kriging* and inverse distance weighting) and are not updated with new available SEMs (such as *empirical Bayesian kriging*) (Krivoruchko, 2011; Schroeder, 2013).

2.2.3 Summary

The two bibliometric analyses revealed similair results and draw a concise picture of the literature in the field of geostatistics, which provide for this research valuable information for further literature analyses. Secondly, a literature analysis that involved publications that applied SEMs in various disciplines showed that *ordinary kriging* was the most common SEM, and *ordinary cokriging* and *regression* appeared to be more accurate than other SEMs. Also, the same literature analysis revealed that sampling density, coefficient of variation and sampling design affected the performance of various SEMs. Lastly, this literature analysis and other studies independently developed decision trees and comparison overviews to make the selection of SEMs simple. Importantly, these overviews and trees are not up to date with new SEMs and they contain mostly common SEMs.

However, the existing literature reviews on SEMs does not specifically address particular methods for estimating montane rainfall, which is the focus of this research, but they all build some expectations around authors (productive authors), research locations (US and Europe), and common applied SEMs. Therefore, the following literature analysis investigates common SEMs specifically applied to montane rainfall for establishing an effective method for estimating montane rainfall as an outcome of this research.

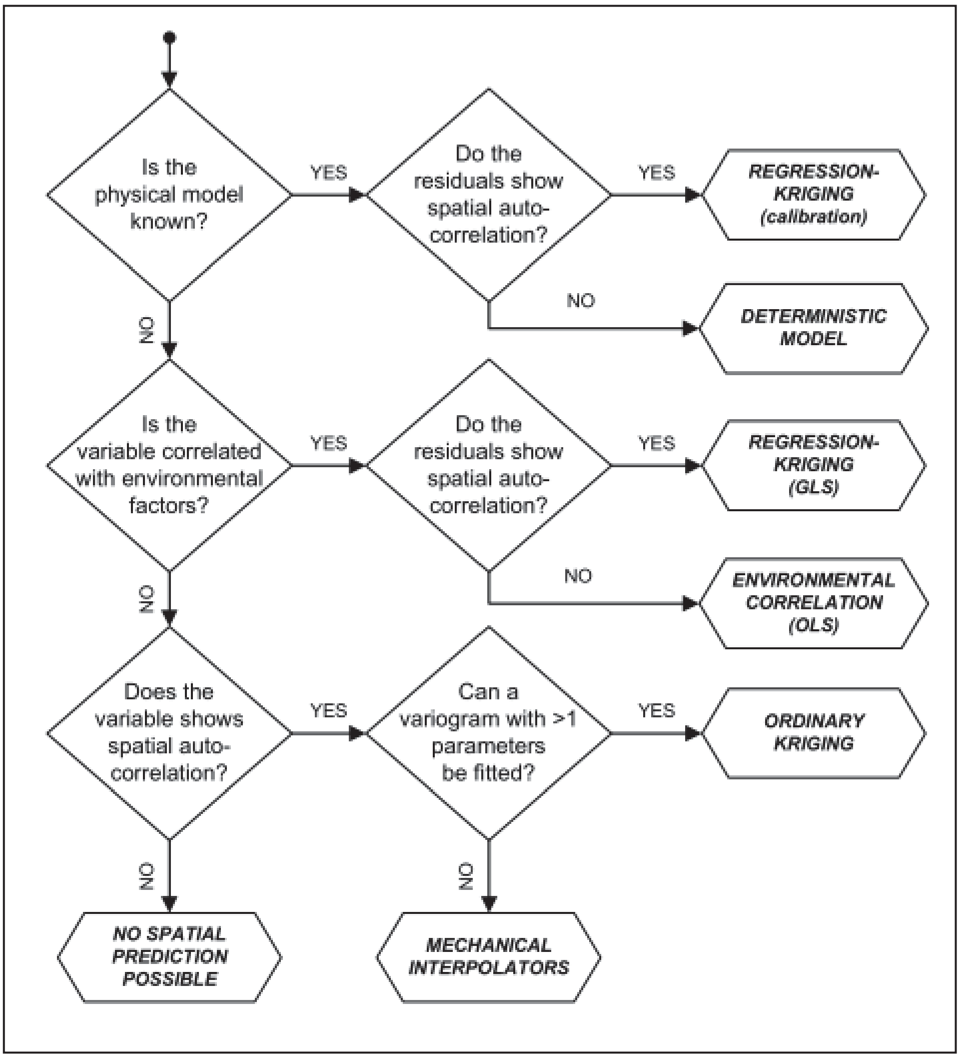

Figure 2-2: A decision tree by Hengl (2009a)

2.3 Montane rainfall estimation

The absence of a specific method for estimating montane rainfall forces an analysis of publications about estimating rainfall to determine common applied methods. The identification of common methods to estimate montane rainfall requires a selection procedure of the literature and comparison details as described in this section. Finally, the challenges of the examination of literature and the results of the literature analysis are outlined.

2.3.1 Selection of journal articles

In conducting this analysis, journal articles were selected from GeoRef, Google Scholar and Web of Science databases. The keywords “interpolation”, “rainfall”, and “orographic” were applied to search for recent (not older than 30 years) journal articles that cover SEMs applied to montane rainfall. Additional criteria were that the publications had to specify the area of interest, the applied SEMs, the incorporated data sets, the applied validation (see glossary) method and the performance of the SEMs.

Applying the keywords in all three databases identified a range of publications (Appendix 7). For example, Google Scholar identified 10,358 publications between 1983 and 2013. In comparison, the Web of Science (33 publications) and Georef (17 publications) databases identified far fewer publications. Google Scholar contains more publication formats (for instance books and conference papers), explaining the large differences in the numbers of identified publications between databases. The number of identified publications in Google Scholar has increased in the last two years and the number of identified publications in the two other databases is variable across the years (Appendix 7).

Compared to Li and Heap's (2008, 2011) selection of 53 articles for their literature analysis, this study selected 40 articles that met the above criteria. The selection covered a time period of 24 years with the oldest publication from 1988 by Dingman et al. (1988) and the most recent publications from 2012 by Wagner et al. (2012), and Yavuz and Erdoğan (2012). Thirty-three of the 40 articles were published after 2000. Figure 2-3 shows the geographical locations of the 40 selected articles and Appendix 8 provides more background information about them. The criteria of the literature analysis with their challenges to examine these 40 studies for determining a reliable SEM for montane rainfall are discussed in the following section.

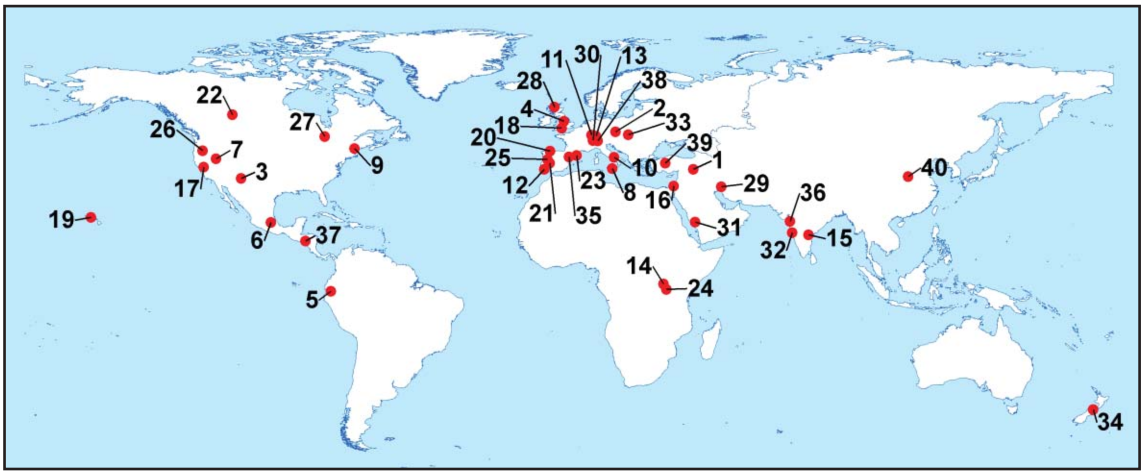

Figure 2-3: The geographical locations of the 40 studies applied in the literature analyses

Note: The numbers on the map correspond with the numbers of a table with the 40 journal articles applied in the literature analyses in Appendix 6.

2.3.2 Comparison of 40 studies

Information such as the applied SEM, the performance of the SEM, motivations of applying certain SEMs, temporal rainfall data, auxiliary data sets, methods to determine the estimation error, diagnostic statistics (see glossary) and applied software are important in establishing an effective method for estimating montane rainfall. However, these details are often unavailable or not clearly stated in publications. In this review, this kind of information is provided whenever it is available in the 40 studies (Appendix 6), and information on methods to determine the estimation error, diagnostic statistics and applied software is also provided. Additionally, the frequency of each SEM in combination with the number of times that these SEMs performed the best were used to determine the effectiveness of the top five most frequently used SEMs. The results of this review were taken into account in the research design.

2.3.3 Challenges in reviewing the 40 studies

There were some challenges in applying the above criteria in the analysis of the literature because such information is often not clearly stated or is unavailable in articles. Occasionally the same SEM was presented with different names. For example, *nearest neighbour* estimation method can also be named as *Thiessen polygon* method (used by Buytaert et al., 2006). Another example is the *inverse distance squared* method (used by Nalder & Wein, 1998) while it is the same as the commonly used *inverse distance weighted* method with a power setting of two.

The 40 studies illustrated that the most common reason to apply a specific SEM was based on experiences of other studies (literature review). In some cases (for example Vicente-Serrano, Saz-Sanchez, & Cuadrat, 2003) the publication did not specify it, but there was enough support in the form of background information of other studies to assume that their selection of a specific SEM was based on fellow scientists' experience.

A number of studies applied more properties of a data set as an auxiliary data set in the spatial estimation. For example, Drogue, Humbert, Deraisme, Mahr, and Freslon (2002) used directional morpho-topographic properties of a digital elevation model as an auxiliary data set. In that case, only elevation was noted as an auxiliary data set for simplicity in this analysis.

Lastly, in some cases it was difficult to define the applied method for determining the spatial estimation error because of the unavailability of the description of the applied method (for example Bankanza, 2011). In the absence of this information, the applied method for determining the spatial estimation error was established by the tables, figures and maps in the article.

2.3.4 Results

The 40 reviewed studies applied a total of 134 SEMs consisting of 24 different SEMs. The frequency of all applied SEMs was recorded as a percentage of the total (134) SEMs. *Ordinary kriging* was the most applied SEM with 19%, while *inverse distance weighting* was the second most applied SEM with 12%. Figure 2.4 reveals each applied SEM's frequency of the 40 studies.

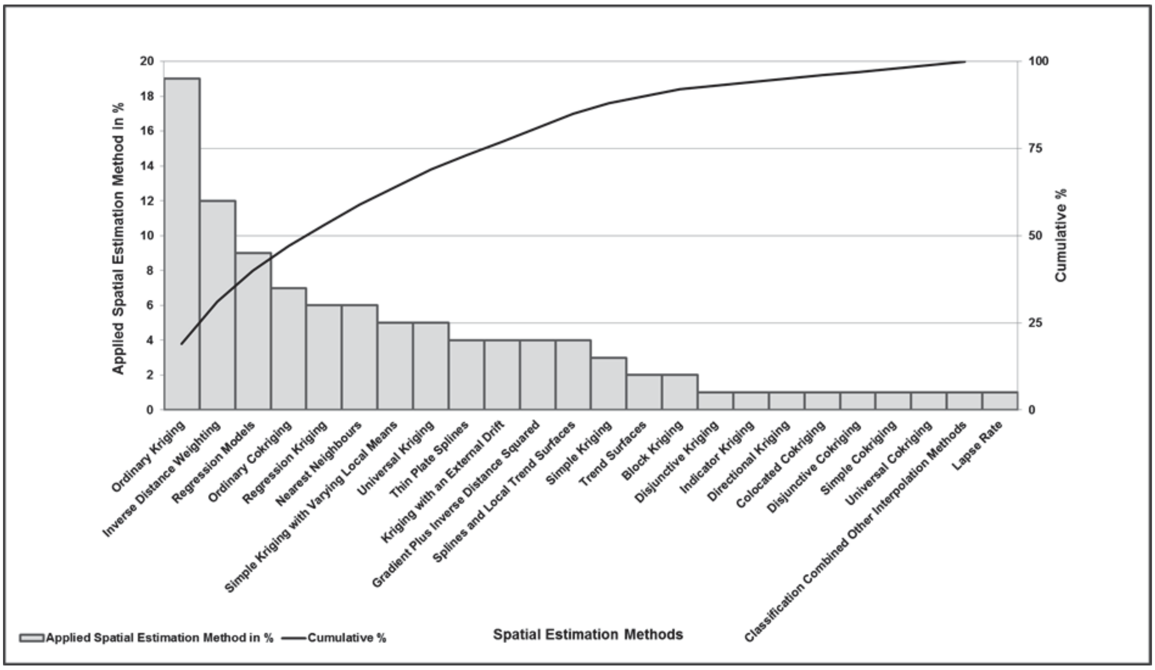

Figure 2-4: The frequency in percentage of all SEMs applied in the 40 articles

The frequency of the top five most used SEMs of the 40 studies was used to determine the effectiveness of these SEMs. The effectiveness (%), also called rate of recommendation (%) by Li and Heap (2008, 2011), was established by the number of times the spatial estimation (see glossary) performed the best (defined by the lowest estimation error) in a study divided by the frequency of use of the SEM, and multiplied by 100 (Table 2-1). Once more, *ordinary kriging* came out on top with 27%. *Regression models* and *regression kriging* were the second most effective SEMs, both with 25%.

Also, the intentions of applying certain SEMs in the 40 articles were compared. The two most common reasons for selecting and applying certain SEMs to estimate montane rainfall were based on experiences of other research (literature review) and comparing their performance. Other reasons were: filling gaps of missing data; experimenting with a new SEM; incorporating more auxiliary variables at the same time; and the simplicity of the SEM.

Table 2-1: The effectiveness of the top five of the most preferred estimation methods of the 40 studies

SEM	Times applied	Times best performed	Effectiveness (%)	Applied temporal rainfall
Ordinary kriging	26	7	27	1 x normal (30 years), 2 x annual, 4 x monthly, 2 x seasonal and 2 x daily rainfall
Regression models	12	3	25	3 x annual and 2 x monthly rainfall
Regression kriging	8	2	25	2 x annual and 1 x monthly rainfall
Ordinary cokriging	10	2	20	2 x annual and 1 x seasonal rainfall
Inverse distance weighting	16	2	13	2 x daily rainfall

Furthermore, details such as auxiliary data sets, methods to determine the estimation error, diagnostic statistics and applied software were compared. Table 2-2 provides an overview of the top three of each of the aspects that were compared in this review. All these aspects were recorded as a percentage of the total number of entries. In addition to the statistical results, these 40 studies illustrate other important information:

1. Most of the studies incorporated auxiliary data sets to minimise the impact of sparse network of rain gauges, large spatial and temporal variability of montane rainfall, and complex topography on the performance of the SEM. Elevation was by far the most preferred auxiliary data set (34 of the 40 studies).
2. Only one study by Carrera-Hernández and Gaskin (2007) incorporated visual validation as an addition of their applied method for determining estimation error. Most of these studies applied cross validation (see glossary) as their preferred method for determining estimation error because they were dealing with sparse network of rain gauges.
3. Over half of the 40 studies applied root mean square error as their diagnostics statistic to measure the performance of SEMs.

Table 2-2: The top three of each reported aspect

Reported aspects	Top 3 of each reported aspect of the literature analyses measured in %					
	1	**%**	**2**	**%**	**3**	**%**
Temporal rainfall data sets	Monthly rainfall	32	Annual rainfall	26	Daily rainfall	21
Auxiliary data sets	Elevation	47	Coordinates	15	Slope	11
Methods for determining estimation error	Cross validation	89	Validation	10	Visual validation	1
Diagnostic statistics	Root mean square error	23	Mean absolute error	14	Mean error	13
Software	ArcGIS	22	GSLIB	17	GSTAT	14

2.4 Further investigation

The overviews and decision trees introduced in the literature contain common SEMs. Also, the top five of the most applied SEMs in this research and Li and Heap's (2008, 2011) study are very similar (Table 2-3 and Appendix 9). More investigation is required to explore the performance of uncommon SEMs, such as *empirical Bayesian kriging* and *simulation*, to ensure that accurate SEMs for montane rainfall are examined. This research seeks to address this gap. Lastly, the literature analysis of this research revealed that additional SEMS were applied to fill missing data gaps, which is a common aspect of monitoring rainfall (Shaw, Beven, Chappell, & Lamb, 2010). The following section outlines uncommon SEMs and additional SEMs used for filling in gaps of missing data illustrated in the literature.

Table 2-3: The top 5 of the most applied SEMs in Li and Heap's review (2008, 2011) and this review

Review by Li and Heap (2008, 2011) – 53 articles				This review – 40 articles			
SEM	**Times applied (and in %) of the 53 articles (Column A)**	**Times best performed (Column B)**	**% Effectiveness = (B/A) * 100**	**SEM**	**Times applied (and in %) of the 40 articles (Column C)**	**Times best performed (Column D)**	**% Effectiveness = (D/C) * 100**
Ordinary kriging	**37 (70)**	**8**	22	Ordinary kriging	**26 (65)**	**7**	**27**
Inverse distance weighting	**30 (57)**	**2**	7	Inverse distance weighting	**16 (40)**	**2**	**13**
Splines and local trend surfaces	**16 (30)**	**0**	0	Regression models	**12 (30)**	**3**	**25**
Regression kriging	**15 (28)**	**4**	27	Ordinary cokriging	**10 (25)**	**2**	**20**
Ordinary cokriging	**14 (26)**	**4**	29	Regression kriging	**8 (20)**	**2**	**25**

2.4.1 Empirical Bayesian kriging

Krivoruchko (2012a, 2012b) and Schroeder (2013) applied the SEM *empirical Bayesian kriging* in their estimation of the spread of radiation around the nuclear power stations of Chernobyl and Fukushima, and rainfall of Hawaii. Krivoruchko's (2012a, 2012b) studies were more focussed on the effectiveness of the *empirical Bayesian kriging* method, while Schroeder's (2013) research compared the performance of *empirical Bayesian kriging*, *ordinary kriging* and *ordinary cokriging* applied to monthly rainfall data of Hawaii.

The studies by Krivoruchko (2012a, 2012b) identified that *empirical Bayesian kriging* provides a better understanding of possible radiation contamination levels with the estimation standard errors combined with the estimation, and they claim it is a straightforward and robust method. More importantly, Schroeder's (2013) research in estimating monthly rainfall revealed that *empirical Bayesian kriging* outperformed (based on prediction error statistics: standardized mean, root mean square error, average standard error, and standardized root mean squared error) *ordinary kriging* and *ordinary cokriging* for nine months of the year.

In summary, the three studies by Krivoruchko (2012a, 2012b) and Schroeder (2013) demonstrated that *empirical Bayesian kriging* is simple and robust, and it outperformed a very reliable method *ordinary kriging* (based on the findings of this research and Li and Heap's review (2008, 2011)), in estimating monthly rainfall.

2.4.2 Geostatistical simulation

Geostatistical simulation is, like *empirical Bayesian kriging*, an uncommon SEM. Nevertheless, some literature show good performances, which is highlighted in this section. For example, Grimes and Pardo-Igúzquiza (2010), and Mendez-Venegas, Diaz-Viera, Herrera, and Valdes-Manzanilla (2013) used *geostatistical simulation* to estimate rainfall, whereas Castrignanò, Lopez, Prudenzano, and Steduto (2002) compared the accuracy of *ordinary kriging* with *stochastic simulation* to estimate the soil texture. Grimes and Pardo-Igúzquiza (2010) reviewed *kriging* methods applied to rainfall data from Ethiopia, while Mendez-Venegas et al. (2013) examined the *geostatistical simulation* method for estimating rainfall of the Mexico City Valley with rain gauge and rain radar data.

Castrignanò et al. (2002) examined the performance of *ordinary kriging* and *stochastic simulation* for estimating the soil texture in the Apulia region in southern Italy. According to Castrignanò et al. (2002), the most suitable method would produce the smallest mean error and root mean square error, and the spatial distribution matched expert knowledge on local soil type distribution. Castrignanò et al. (2002) claimed that the *ordinary kriging* method outperformed *stochastic simulation* based on the mean error and root mean square error values. However, the estimated clay maps with *kriging* looked too smooth and failed to identify the smallest structure, while *stochastic simulation* defined more details on the maps. According Castrignanò et al. (2002) *stochastic simulation* is the preferred method for mapping to reproduce the spatial distribution of the estimated aspect.

Grimes and Pardo-Igúzquiza (2010) reviewed *ordinary kriging*, *cokriging*, *kriging with external drift*, *error-weighted merging* and *geostatistical simulation* used to estimate rainfall. According to their study, *ordinary kriging* can generate good estimations only within the local neighbourhood of each estimated point, while *cokriging* facilitates the incorporation of a secondary data set, but the results are not always accurate. Grimes and Pardo-Igúzquiza (2010) claimed that a better result may be obtained with simpler methods such as *kriging with external drift* or *error-weighted merging*. Grimes and Pardo-Igúzquiza (2010) emphasised that the use of *geostatistical simulation* generates realistic ensembles of rainfall fields conditional on a set of measured points, and this method can be used to explore sensitivity and uncertainty in the rainfall model.

Mendez-Venegas et al. (2013) selected the *sequential Gaussian simulation* method to estimate the rainfall distribution of three storm events using rain gauge data and radar data. Their study discovered that the combination of rain radar and rain gauge data generated the most precise rainfall distribution estimation. Finally, Mendez-Venegas et al. (2013) claim that the analysis of the results shows that the *sequential Gaussian simulation* method reproduces the statistical characteristics of rain well and thus it is the ideal estimation tool to model the spatial distribution of rainfall.

In summary, research experts suggested that the *stochastic simulation*, *geostatistical simulation* and *sequential Gaussian simulation* generate realistic outputs of the estimated aspect (Castrignanò et al., 2002; Grimes & Pardo-Igúzquiza, 2010).

2.4.3 Data gap-filling techniques

Problems with measuring instruments, loss of records, and lack of funds to support the maintenance of instruments can cause data gaps in full records. Missing data are a serious hindrance to the use of gas exchange balances of ecosystems, hydrological and climatological models and estimation methods. Various literature (Falge et al., 2001; Mishurov & Kiely, 2011; Moffat et al., 2007; Teegavarapu & Chandramouli, 2005; Villazón & Willems, 2010; Westerberg et al., 2010; Xia, Fabian, Stohl, & Winterhalter, 1999) pointed out that a range of estimation methods can be used to bridge data gaps. The experiences of these studies are specifically outlined in this section because they revealed other techniques used to estimate missing data than those already revealed in the literature analysis.

2.4.3.1 Gas concentrations

The literature revealed that data gap-filling techniques can be applied to data records of gas exchange balances of ecosystems, and this section sums up the techniques that perform well. For example, Falge et al. (2001) and Moffat et al. (2007) estimated carbon fluxes (movement of the quantity of carbon (as CO_2) occurring in an ecosystem which is absorbed by green plants and respired by various organisms) data gaps with certain data gap-filling techniques, while Mishurov and Kiely (2011) determined nitrous oxide fluxes (the exchange of nitrous oxide (as N_2O) occurring in an ecosystem) data gaps (Table 2-4). Furthermore, Falge et al. (2001) and Mishurov and Kiely (2011) compared three data gap-filling methods in their estimation of the data gaps, while Moffat et al. (2007) compared 15 data gap-filling techniques (Table 2-4). The *look up table* data gap-filling method was the only technique that was applied in all three studies, and the *methods mean diurnal variation* and *non-linear regression* were used in two of the three studies.

The performance of the data gap-filling techniques in the studies by Moffat et al. (2007) and Mishurov and Kiely (2011) were determined with the coefficient of determination, root mean square error, mean absolute error and bias error. In contrast to Moffat et al. (2007) and Mishurov and Kiely (2011), Falge et al. (2001) used mean error, standard deviation of the mean, skewness and kurtosis for the performance measure for the techniques.

Falge et al. (2001) found that the *look up table* and *regression* method were the two best performing methods to determine data occurring within gaps carbon fluxes data. Compared to the findings of the research by Falge et al. (2001), the first comparison of the 15 methods by Moffat et al. (2007) revealed that an *artificial neural network with pre-sampling*, and *smoothing and marginal distribution sampling* were consistently good gap-filling techniques. A more comprehensive comparison applied to more vegetation types (such as wetlands, grassland, crops), then only forest sites, showed that *artificial neural network with Bayesian regularization* and *artificial neural network with pre-sampling and smoothing* performed the best. The study by Mishurov and Kiely (2011) illustrated that the *look up table* method applied to a yearly data set seems to produce the best representation of nitrous oxide fluxes data.

According to Moffat et al. (2007), the performance of the data gap-filling techniques depended on the site, gap, length, and time of the day (night versus day). Similarly, Mishurov and Kiely (2011) discovered that the length of the gap particularly influences the performance of the data gap-filling method for nitrous oxide fluxes data. Falge et al. (2001) claimed that more investigation is required in theory and experiment of the night time problem, especially the use of complementary chamber measurements of soil, stem and leaf respiration at the measure sites and that the accuracy of the data gap-filling techniques depends on the pre-treatment of the data used for the parameterization of filling algorithms.

2.4.3.2 Climatology and hydrology data

Xia et al. (1999) compared seven gap-filling techniques used to estimate climatology data of nine German weather stations (including three forest stations), whereas Henn, Raleigh, Fisher, and Lundquist (2012) compared a number of other gap-filling techniques applied to air temperature data (Table 2-4). Harvey et al. (2010) examined the performance of eleven gap-filling methods used to bridge gaps in flow river data of the UK (Table 2-4).

Xia et al. (1999) measured the performance of the gap-filling techniques with the mean absolute error, while Henn et al. (2012) choose the root mean square as the primary performance measure over the mean absolute error. However, Henn et al. (2012) claimed that both performance measures give relevant information regarding the performance, and their analysis concluded that the magnitude of the mean absolute error was about 75% of that of the root mean square error. Harvey et al. (2010) determined the accuracy of their applied gap-filling methods with Nash-Sutcliffe model efficiency coefficient, root mean square error and percent bias.

Research by Xia et al. (1999) found that the *multiple regression* analysis was the most accurate data gap-filling technique, especially with climatology data of the weather stations situated in the forest, whereas Henn et al. (2012) discovered that the performance of the methods depended highly on the length of the gap and the number of available stations. For example, *MicroMet* *preprocessor* was the most accurate method as long as the numbers of available stations was less than 16, and the *empirical orthogonal functions reconstruction* method performed the best in situations of 16 or more stations. *MicroMet* was also the most accurate method to estimate data gaps of 1 hour – 3 days with data of two stations, while the *long-term lapse rate* method performed the best to determine data gaps of 1-30 days.

The research by Harvey et al. (2010) found out that the *equipercentile, multiple regression* and *multiple regression log* were the most accurate techniques to bridge flow data gaps. Harvey et al. (2010) concluded that the location of the neighbouring stations are critical in bridging data gaps and emphasise more research is required to determine the influence of the choice of neighbouring stations, techniques for various flows, and the improvements by incorporating localising data sets.

2.4.3.3 Rainfall data

Teegavarapu and Chandramouli (2005) investigated for improvements of the performance of the data gap-filling method *inverse distance weighting* with conceptual revisions compared with *ordinary kriging* and *artificial neural networks*, while Villazón and Willems (2010) examined *linear regression* and *multiple linear regression* applied to monthly rainfall of Pirai River Basin in Bolivia (Table 2-4). Westerberg et al. (2010) evaluated two methods (*inverse distance weighting* and *coefficient of correlation weighting* method) to patch daily rainfall data gaps to complete their data record to determine spatiotemporal characteristics of rainfall with SEMs in a mountainous catchment in Honduras (Table 2-4).

The mean absolute error, mean relative error, root mean square error, and the coefficient of determination were used to evaluate the performance of the two data gap-filling techniques by Teegavarapu and Chandramouli (2005), and Westerberg et al. (2010). Also, Villazón and Willems (2010) used the same performance measurements, but extended it with the Nash-Sutcliffe efficiency standard deviation, linear goodness of fit, model skill, and percentage error.

According to Teegavarapu and Chandramouli (2005) three of the eight methods (*artificial neural networks, coefficient of correlation weighting and ordinary kriging*) are the most appropriated techniques to fill rainfall data gaps. They claimed that these three methods directly deal with observed data in space rather than Euclidean distance generally used in traditional *weighted* methods. In comparison with the research by Teegavarapu and Chandramouli (2005), the *coefficient of correlation weighting* also performed well and dominated in all comparisons with *inverse distance weighting* in the study by Westerberg et al. (2010). The *multiple linear regression* applied to monthly rainfall in the study by Villazón and Willems (2010) showed a reduction of 36% in the standard deviation and the root mean square error. However, the other performance measures showed very small differences between the two data gap-filling methods.

Table 2-4: Data gap-filling techniques that perform well

Data gap-filling techniques	Gas concentrations	Climatology and hydrology data	Rainfall data
Artificial neural networks	-	-	Teegavarapu and Chandramouli (2005)
Artificial neural network with Bayesian regularization	Moffat et al. (2007)	-	-
Artificial neural network with pre-sampling and smoothing	Moffat et al. (2007)	-	-
Coefficient of correlation weighting	-	-	Teegavarapu and Chandramouli (2005) and Westerberg et al. (2010)
Empirical orthogonal functions reconstruction	-	Henn et al. (2012)	-
Equipercentile	-	Harvey et al. (2010)	-
Long-term lapse rate		Henn et al. (2012)	-
Look up tables	Falge et al. (2001) and Mishurov and Kiely (2011)	-	-
Marginal distribution sampling	Moffat et al. (2007)	-	-
MicroMet preprocessor	-	Henn et al. (2012)	-
Multiple linear regression	-	-	-
Multiple regression	-	Harvey et al. (2010)	-
Multiple regression analysis, least absolute deviations criteria		Xia et al. (1999)	-
Multiple regression log	-	Harvey et al. (2010)	-
Non-linear regression	Falge et al. (2001)	-	Villazón and Willems (2010)
Ordinary kriging	-	-	Teegavarapu and Chandramouli (2005)

2.4.4 Summary

The literature identified two uncommon SEMs (*empirical Bayesian kriging* and *geostatistical simulation*) and those should be considered in this research based on their performance. For example, one of the studies revealed that *empirical Bayesian kriging* outperformed *ordinary kriging,* the most applied SEM in Li and Heap's review (2008, 2011) and this review, in a study that estimated rainfall of Hawaii, and other literature claimed that this SEM is a straightforward and robust method. *Geostatistical simulation* was applied in rainfall and soil texture estimation and the results showed that it generated more realistic outputs than other SEMs.

Data gaps in a rainfall data set with a particular extent, caused by various reasons, seriously hinder spatial estimation. Importantly, the literature revealed various disciplines of environmental science that are dealing with similar issues, and they bridge the gaps with a number of different data filling techniques. For example *multiple regression* and *coefficient of correlation* methods were used to fill rainfall data gaps and *non-linear regression* and *look up tables* methods were used to bridge natural gas exchange data gaps, and their performances were diverse. However, this research select only data gap-filling techniques used for rainfall data gaps, because the data is different than the data of other disciplines.

2.5 Chapter summary

The two bibliometric analyses revealed similair results, for instance both analyses identifed Stein and Goovaerts as productive authors in the geostatistics. Another publication compared the performance of the SEMs applied to variables from various disciplines in environmental sciences of 53 studies. The analysis revealed that that *ordinary kriging* was the most common SEM, and *ordinary cokriging* and *regression* appeared to be more accurate than other SEMs and it showed that sampling density, coefficient of variation and sampling design affected the performance of various SEMs. Lastly, this study and other studies independently developed decision trees and comparison overviews to make the selection of SEMs simple. However, these overviews and trees are not up to date with new SEMs and they contain mostly common SEMs.

Importantly, these literature reviews do not specifically address particular methods for estimating montane rainfall. Therefore, a literature analysis that compared the performance of SEMs applied to montane rainfall was carried out. In this analysis, 40 studies out of over 10,000 identified publications were selected and compared. This comparison revealed that *ordinary kriging* was the most preferred and effective SEM for estimating montane rainfall. *Regression models, regression kriging, ordinary cokriging* and *inverse distance weighting* completed the top five of the most preferred SEMs. Also, the literature analysis revealed that monthly rainfall was the most temporal applied data set, elevation was the most applied incorporated data set, cross validation was the most preferred method to determine the estimation error, root mean square error was the most applied diagnostic statistic, and ArcGIS was the most used software for estimating montane rainfall. These findings were the foundation for establishing the research design for this study.

In addition to the 40 studies, the performance of two less cited SEMs (*empirical Bayesian kriging* and *geostatistical simulation*) in other publications made them worth considering further. For example, one of the studies revealed that *empirical Bayesian kriging* outperformed the most applied SEM (*ordinary kriging*) in this research literature analysis (40 articles) and the other literature analysis of the 53 studies to estimate rainfall of Hawaii. *Geostatistical simulation* was applied in rainfall and soil texture estimation and the results showed that it generated more realistic outputs than other SEMs.

Data gaps in a rainfall data set are serious hindrance in for a spatial estimation. Importantly, the literature revealed various disciplines of environmental science that are dealing with similar issues and they bridge the gaps with a number of different data filling techniques. For example *multiple regression* and *coefficient of correlation* methods were used to fill rainfall data gaps, and *non-linear regression* and *look up tables* methods were used to bridge natural gas exchange data gaps and their performance was diverse. However, the literature identified a large number of data gap-filling methods, but this research select only data gap-filling techniques used for rainfall data gaps, because the data is different than the data of other disciplines. In addition, scientists usually expect a complete dataset to allow their work to proceed. Unfortunately they also often have little interest in how the gaps have been filled. Thus it need further study and determination of a preferred method.

Chapter 3: Research Design

3.1 Introduction

The previous chapter identified the wide variety of SEMs in use together with the five dominant SEMs. However, questions can be raised about each of the five because the literature review reveals inconsistent performance under different circumstances. At the same time, the literature shows two less frequently cited SEMs that are sufficiently able to estimate rainfall.

This chapter develops a method for assessing the relative efficacy of estimation methods for montane rainfall. It does do this by, firstly, selecting five SEMs, an appropriate software, a performance measure process, supplementary data sets, and data gap-filling techniques based on the findings in the literature. These five SEMs were initially applied to a primary data set. Secondly, these five SEMs were applied to the same primary data set with supplementary data sets with the purpose of improving the accuracy of these SEMs. The performance of each SEM was determined with an appropriate validation data set and diagnostic statistic. The improvement or decline in the accuracy of the SEMs was established by comparing their diagnostic statics results. Thirdly, this chapter describes the spatial estimation process by which the estimated data were computed. Fourthly, it describes the primary data and the supplementary data used in the estimation. Lastly, the validation process and the criteria of the validation data set are specified.

3.2 Selection of methods, software, and data sets

The literature analysis in the previous chapter identified and ranked applied methods, including software and data sets, based on their popularity and performance. The result of the analyses was the foundation of the selection of the appropriate methods for assessing the relative efficacy of estimation methods.

3.2.1 Spatial estimation methods

Firstly, it is necessary to select appropriate SEMs for estimating rainfall. The literature analysis revealed the top five most applied SEMs with their calculated effectiveness (Table 3-1). Based on the top five, the three most effective SEMs (*ordinary kriging, regression models,* and *regression kriging*) with two less cited SEMs (*empirical Bayesian kriging* and *geostatistical simulation)* were selected for the estimation of montane rainfall in this research (Table 3-2). Appendix 10 describes the operation of the five selected SEMs in more detail.

Empirical Bayesian kriging was specifically selected for its performance in a research by Schroeder (2013), because it outperformed two (*ordinary kriging* and *ordinary cokriging*) of the top five most applied SEMs of the literature analysis in this research. Secondly, Krivoruchko (2012a, 2012b) claimed that this SEM is straightforward and robust. *Geostatistical simulation* (Gaussian version) was selected because Mendez-Venegas et al. (2013) considered that this SEM can be an ideal estimation tool to model the spatial distribution of rainfall.

Table 3-1: The effectiveness of the top five of the most used SEMs of the literature analysis

SEM	Times applied	Times Best performed	Effectiveness (%)
Ordinary kriging	26	7	27
Regression models	12	3	25
Regression kriging	8	2	25
Ordinary cokriging	10	2	20
Inverse distance weighting	16	2	13

Table 3-2: The selected SEMs

SEM	Reason for selection
Ordinary kriging	One of the three most effective SEMs in the literature analysis of this research.
Regression models	One of the three most effective SEMs in the literature analysis of this research
Regression kriging	One of the three most effective SEMs in the literature analysis of this research
Empirical Bayesian kriging	Good experiences in other research.
Gaussian geostatistical simulation	Good experiences in other research.

It is necessary to determine an appropriate software for the estimation before developing a comparison efficacy of these models. The 40 studies outlined in the previous chapter identified 15 software products, of which three were mostly used (Table 3-3). These software products were ArcGIS, GSLIB and GSTAT (Deutsch & Schnetzler, 2009; Esri, 2013; Pebesma, 2006). At the same time, the three software products were examined for the inclusion of the five selected SEMs (Table 3-4). Table 3-3 and 3-4 revealed that ArcGIS is the most appropriate software product to select for estimating montane rainfall since it contains all five SEMs, and it was the most applied software in the 40 reviewed studies.

Table 3-3: The three predominant software products

Software	Times applied
ArcGIS	8
GSLIB	6
GSTAT	5

Table 3-4: Software

SEM	ArcGIS	GSLIB	GSTAT
Ordinary kriging	Yes	Yes	Yes
Regression models	Yes	***No***	Yes
Regression kriging	Yes	***No***	***No***
Empirical Bayesian kriging	Yes	***No***	***No***
Gaussian geostatistical simulation	Yes	Yes	Yes

3.2.2 Performance measure

The literature review shows two techniques (cross validation and validation) to establish the estimation error of a SEM. The choice between these two techniques is very dependent on the availability of the number of data sets. Most of the 40 articles in the literature analysis applied cross validation (see glossary) because of a lack of sample points. This method applies the same data set for the spatial estimation and determination of the spatial estimation error. Validation (see glossary) is the other technique that uses two spatial data sets. One data set is used for the spatial estimation and the other one is applied to determine the spatial estimation error (Chang, 2008; Johnston et al., 2001). This last technique is selected for this research because there are enough sample points available from two independent agencies, and according to Hengl (2009a), this technique assesses the 'true' prediction power.

After establishing the estimation error for each measured data point in a spatial estimation, the accuracy of the SEM can be assessed by calculating a diagnostic statistic with these estimation errors (Chang, 2008; Johnston et al., 2001). The literature analysis showed numerous diagnostic statistics used to determine the performance of SEMs. Significantly, the root mean square error was the most applied diagnostic statistic and, according to Willmott (1982), this diagnostic statistic is one of the best overall measures of a model performance (Table 3-5). For these two reasons, root mean square error is selected in this research to determine the performance of the five selected SEMs.

Table 3-5: Top three of the most applied diagnostic statistics of the 40 readings

Ranking	Diagnostic statistics
1	Root mean square error
2	Mean absolute error
3	Mean error

Lastly, the literature analysis revealed a third technique of performance measure, which is visual validation (Carrera-Hernández & Gaskin, 2007). This technique is also selected for this study, which examines the output (a grid (see glossary)) of the estimation on the maintenance of the distinct pattern of rainfall with the reality by comparing it with an elevation model and the measured data points. This elevation model shows high elevated areas that can expect more rainfall than lower areas caused by orographic rainfall (Mays, 2011; Soliman, 2010).

3.2.3 Auxiliary data sets

Incorporating auxiliary data sets in the estimation, especially topographic variables that have great impact on the spatial variation of rainfall, is another way to estimate rainfall closer to the reality by having more data coverage over the area of interest (Hession & Moore, 2011; Wagner, Fiener, Wilken, Kumar, & Schneider, 2012). The literature analysis demonstrated that 35 of the 40 studies incorporated topographic features into their rainfall estimations, with the elevation data set as the predominant auxiliary data set. Based on the literature analysis and their impact on orographic rainfall, elevation and slope (generated from the digital elevation model, Appendix 19) were selected as the two auxiliary data sets. These two data sets can be only incorporated by two of the five SEMs: *regression models* and *regression kriging* (Table 3-6).

Table 3-6: Top three of the most incorporated auxiliary data sets of the 40 readings

Ranking	Diagnostic statistics
1	Elevation
2	Coordinates
3	Slope

3.2.4 Data gap-filling technique

The literature review identified a large number of data gap-filling techniques applied in various disciplines of environmental science. The selection of the data gap-filling technique to bridge data gaps for historical rain gauges in this research is based on the performances of these techniques in the three studies focussed on rain data gaps (Teegavarapu & Chandramouli, 2005; Villazón & Willems, 2010; Westerberg et al., 2010). The *coefficient of correlation weighting* method is selected for this research because namely this technique is recommended in two of the three studies (Appendix 11) (Teegavarapu & Chandramouli, 2005; Westerberg et al., 2010).

Additionally, *inverse distance weighting* was selected as a data gap-filling technique because Teegavarapu and Chandramouli (2005) claimed that this technique is the most common applied method to bridge data gaps, and to compare its performance with the *coefficient of correlation weighting* method (Appendix 11). The performance of both techniques in this research is determined with the cross validation method and the root mean square value. The data generated for the data gap with the best performance (lowest root mean square value) was chosen to be the measured rainfall in the historical data set applied in the spatial estimations.

3.3 Method for assessing the relative efficacy of estimation methods

The previous chapter identifies 24 dominant SEMs, of which five were found to be predominantly used (Table 3-1). These SEMs were *ordinary kriging*, *inverse distance weighting*, *regression models*, *ordinary cokriging* and *regression kriging* (Appendix 9). To briefly recap the literature review, there is a noticeable variability in performance; in difficult circumstances individual SEMs perform well and others not. It is appropriate to accurately validate the performance of each applied SEM and compare their performance against each other by developing a comparison efficacy of these models.

3.3.1 Experiments

The comparison efficacy of these models starts with three experiments for each SEM applied to the same temporal data set. For each experiment, the number of the observed rainfall data points of the temporal data set increases with the purpose of improving the performance of the estimation by having more data coverage over the area of interest (Chang, 2008; Englund, Weber, & Leviant, 1992; Isaaks & Srivastava, 1989; Stahl, Moore, Floyer, Asplin, & McKendry, 2006) (Table 3-7). All three experiments estimate rainfall of the same period of time (day, month, or year) for the same area of interest.

The first experiment uses only the primary rainfall data set in the estimation. The historical rain gauges are added to primary rainfall data set to estimate rainfall in the second experiment. The third experiment estimates rainfall with the primary rainfall data set, historical rain gauges, and rain gauges situated outside and along the border of the area of interest within a buffer of 30 kilometres of the border of the catchment (Table 3-7).

Table 3-7: Experiments

Experiments	Temporary rainfall data set
Experiment 1	primary rainfall data set
Experiment 2	primary rainfall data set + historical rainfall data set
Experiment 3	primary rainfall data set + historical rainfall data set + rainfall data set from rain gauges located outside the area of interest

Each experiment (experiment 1, 2 and 3) runs five times, each time for another SEM applied to the same temporal rainfall data set. An experiment per SEM produces an estimated surface with an estimation error in the form of a root mean square error (Appendix 12). This estimated surface represents the best estimation output that maintains the distinct spatial pattern of rainfall with the reality and with the lowest possible estimation error (root mean square error (Appendix 12)) (Chang, 2008; Johnston et al., 2001; Laslett, 1994; Li & Heap, 2008; Yang & Hodler, 2000). This best estimated surface is generated on the basis of trial and error by fine tuning the estimation by adjusting variables of the SEM till the lowest root mean square value is produced in combination of the maintenance of the distinct spatial pattern of rainfall with the reality.

3.3.2 Comparison

The performance (root mean square error) of the five SEMs is compared per experiment. For example, in the first experiment, the estimation errors (root mean square values) of the five SEMs applied to the primary rainfall data set are compared in a table (Table 3-8). The same comparison process is repeated for the estimation errors (root mean square values) of the estimated surfaces of the five SEMs applied in the second and third experiments.

Also, the performance measure (root mean square error) of each experiment is applied in the ranking assessment. The ranking assessment ranked the five SEMs based on their performance per experiment. The SEM with lowest performance measure of an experiment is ranked as number one (highest ranking), and the SEM with the highest performance measure is ranked as number five (lowest ranking). The average ranking of the five SEMs in the three experiments determines the most suitable SEM for that temporal rainfall data set, which is the SEM with highest average ranking (Table 3-9).

Finally, the average ranking per temporal data set is used to determine the most appropriated SEM for montane rainfall. This assessment is based on average ranking of each SEM applied to all temporal data sets. The SEM with the highest overall ranking is the most appropriated SEM for montane rainfall (Table 3-10).

Table 3-8: Performance comparison of the spatial estimation methods applied to a data set per experiment

SEM	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
Ordinary kriging	-				
Linear regression	-	-			
Regression kriging	-	-	-		
Empirical Bayesian kriging	-	-	-	-	
Gaussian geostatistical simulation	-	-	-	-	-

Table 3-9: Example of the ranking assessment table for a temporal data set

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
Experiment 1					
Experiment 2					
Experiment 3					
Average ranking					

Table 3-10: Example of the final ranking assessment table

Experiments	Ordinary kriging	Linear regression	Regression Kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
Average ranking temporal data set 1					
Average ranking temporal data set 2					
Average ranking temporal data set 3					
Average ranking temporal data set 4					
Average ranking temporal data set 5					
Average ranking temporal data set 6					
Average Overall Ranking					

3.4 Spatial estimation

Spatial estimation plays the main role in the experiments and its result is used in the comparison efficacy. For that reason, it is essential to verify and understand the general process of spatial estimation and the differences between the five selected SEMs because each SEM applied to the same data set performs differently as a result of their own variables (Chang, 2008; Li & Heap, 2008, 2011). Finally, the procedure that determines the accuracy of the SEM is described.

A spatial estimation starts with applying a SEM to a spatial data set containing, for example, temporal rainfall data to be estimated for an area. Each SEM contains its own specific variables, which differentiates each one from other SEMs, generates different estimated outputs, and impacts on its performance (Table 3-11) (Chang, 2008; Li & Heap, 2008, 2011). These variables of the SEM will be adjusted until the best performance is realised; this is represented by a low diagnostic statistic value and a maintenance of the distinct pattern of rainfall at the same time.

Table 3-11: The main variables of the five SEMs

SEM	Variables
Ordinary kriging	The semivariogram model and number of surrounding sample points included in the estimation
Linear regression	The strength of the relationship between the primary rainfall variable and the auxiliary data sets(s)
Regression kriging	The strength of the relationship between the primary rainfall variable and the auxiliary data sets(s), the semivariogram model, and number of surrounding sample points included in the estimation
Empirical Bayesian kriging	The number of surrounding sample points included in the estimation and transformation
Gaussian geostatistical simulation	The semivariogram model, number of surrounding sample points included in the estimation, and the number of simulations

The verification of the performance of the spatial estimation, which is identical for each SEM, begins with determining the estimation error with the same data set used for the estimation (cross validation technique) or with an independent data set (validation technique) (Chang, 2008; Hengl, 2009a; Johnston et al., 2001). The estimation error is used to establish one or more diagnostic statistics (such as root mean square error, bias, variance, mean error and mean absolute error), which defines the SEM's performance (Chang, 2008; Hengl, 2009a; Johnston et al., 2001). In the end, the spatial estimation output is visually validated on the maintenance of the distinct pattern of rainfall by comparing it with the reality, such as an elevation model and the measured data points (Chang, 2008; Laslett, 1994; Yang & Hodler, 2000).

3.5 Data sets

The number of rain gauges increases per experiment, which requires explanation. This section describes the differences between data sets used in these three experiments. Secondly, it outlines the process of determining the historical rain gauges values with the data gap-filling techniques. Finally, the validation data set applied in the performance measure is characterised.

3.5.1 Primary rainfall data set and additional rainfall data points

Numerous studies deals with a sparse network of rain gauges, which impacts on the performance of the spatial estimation (Burrough & McDonnell, 1998; Li & Heap, 2008, 2011). Therefore, the three experiments apply the same temporal data set, but, at the same time, the number of measured data points increases per experiment to examine whether the increase of data points improves the performance of the SEM. The first experiment uses only the primary rainfall data set, which contains data solely from rain gauges within the area of interest. The second experiment uses the primary rainfall data set and historical rain gauges. The rainfall values of the historical rain gauges, also called "virtual rain gauges" by Giambelluca et al. (2011), are determined with a data gap-filling technique that is explained in the following section. The last experiment applies maximum number of rain gauges containing the same data sets as in the previous experiment and rain gauges located in neighbouring areas of the area of interest (Figure 3-1).

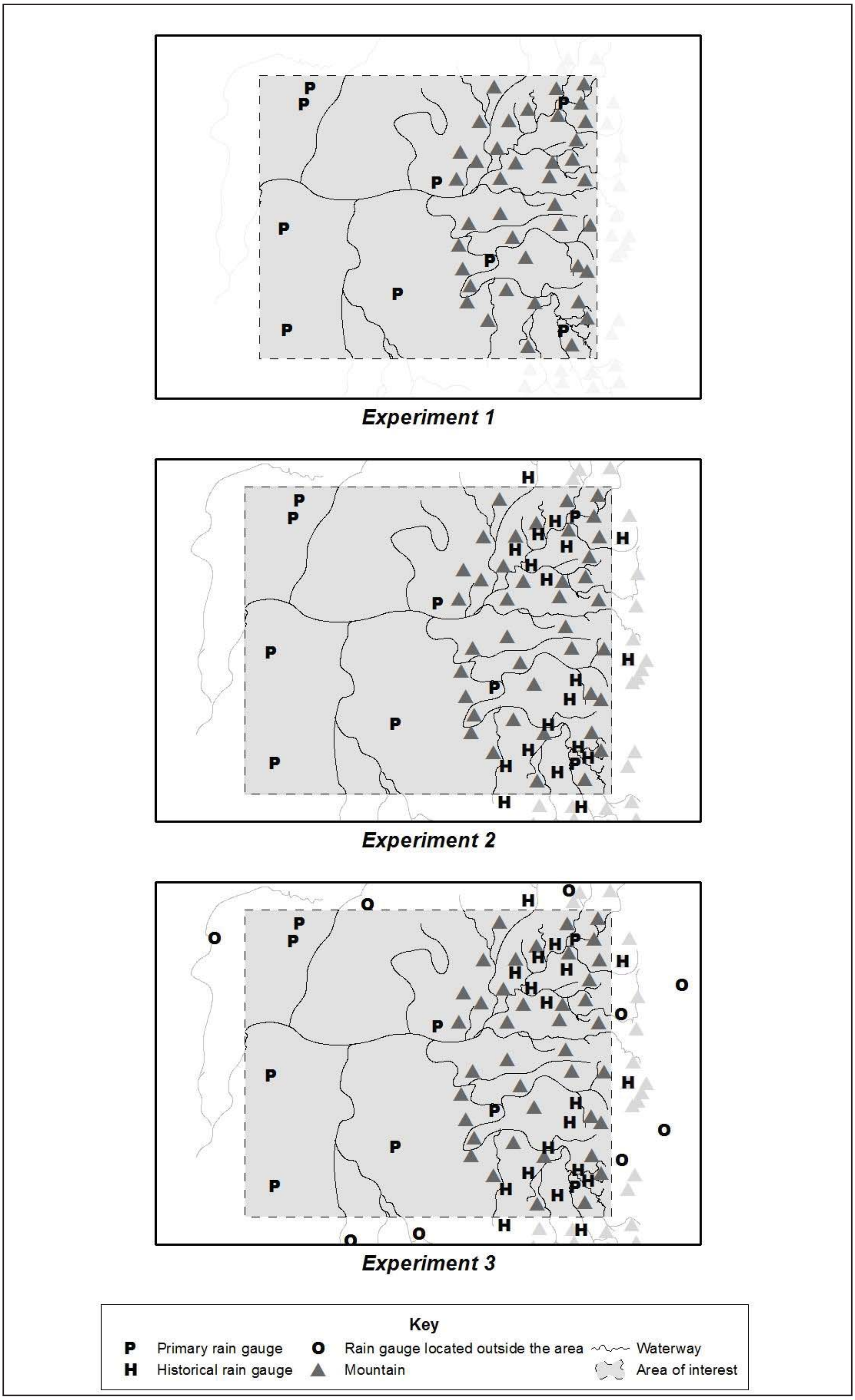

Figure 3-1: The three experiments

3.5.2 Historical rain gauge values determined with data gap-filling techniques

Over many years, a number of rain gauges were set up and operated for various durations and subsequently discontinued. Being able to fill data gaps in the data record of these historical rain gauges by applying data gap-filling techniques increases the spatial coverage of rainfall gauges in the area of interest (Figure 3-1). These techniques use rain gauges that have partly or the same temporal data records extent as the historical rain gauges, and, at the same time, these rain gauges have a data record that also covers the temporal extent of the spatial estimation. The *coefficient of correlation weighting* method and *inverse distance weighting* method were applied as the two data gap-filling techniques.

3.5.3 Validation data set

The validation technique used an independent validation data set to determine the performance of a SEM. All the rain gauges within the validation data set have different spatial locations than all rain gauges included in the primary data set with the additional rainfall data sets (historical and rain gauges situated outside and along the border of the area of interest) but they are situated within the area of interest. At the same time, this validation data set has to cover the same temporal extent and have similar rainfall characteristics as all other data sets incorporated in the spatial estimation. The similarity in the rainfall characteristics (using influential rainfall quantity properties such as elevation and distance to the coast) between the rain gauges within the validation data sets and the data sets used in the spatial estimation were examined with the principal components analysis (PCA). PCA identifies patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Lastly, this validation data set can be a subset of a larger data set or an independent data set from another agency but it can only be used to validate the performance measure of the spatial estimation.

3.6 Summary

The result of the literature analysis in the previous chapter provided a solid foundation for the selection of methods, software, and data sets, which are all incorporated in the comparison efficacy of these models. The selection of SEMs for estimating rainfall was the most important, with *ordinary kriging*, *regression models*, *regression kriging*, *empirical Bayesian kriging*, and *geostatistical simulation* as the chosen SEMs. These five SEMs are used to estimate montane rainfall, and their performances are compared to establish the most suitable SEM for montane rainfall.

The comparison efficacy starts with three experiments for each of the five SEMs applied to the same temporal data set and, for each experiment, the number of observed rainfall data points of the temporal data set increases with the purpose of improving the performance of the spatial estimation. Primary rain gauges situated only in the area of interest are applied in all three experiments. Historical rain gauges, determined with data gap-filling techniques (*coefficient of* *correlation weighting* method and *inverse distance weighting* method) are added in the second and third experiments. Rain gauges located out the area of interest are included only in the third experiment. The performance of all the SEMs are recorded, compared and ranked, and used in the final ranking assessment to determine the most appropriated SEM for montane rainfall.

Chapter 4: Data Sets

4.1 Introduction

The previous chapter developed a method for assessing the relative efficacy of estimation methods for montane rainfall and outlined the criteria of the data sets used in this method to be applied on a case study. This chapter describes the choice of data and data preparation. It firstly clarifies the region selection by illustrating its geography and climatic characteristics. Secondly, it overviews existing data sets fitting the assessment criteria, and covering the region. Finally, the selection of the particular temporal extents of the rainfall data sets is justified.

4.2 Selection of the area

The Manawatu River Catchment (MRC) provides an excellent location to apply the method, because its geography and climate fit the criteria of a mountain region that experiences montane rainfall. Secondly, a numerous of rainfall data sets are available (current rain gauges and historical rain gauges).

4.2.1 Geography characteristics

The MRC is located in Southern part of the North Island of New Zealand (NZ) at 175 to 177º E and 39 to 41º S, and it covers an area of 6000 square kilometres (Figure 4-1). The topography of the area is predominantly hilly and mountainous, and it encompasses three mountain ranges: the Puketoi, Ruahine, and Tararua Ranges. Altitude in the MRC ranges from sea level to the highest peak of 1700 metres of the Ruahine Ranges, with a mean elevation of 845 metres[1]. The rainfall in the MRC is drained by the Manawatu River and its large tributaries, including the Mangahao River, Mangatainoka River, Oroua River, Pohangina River and the Tiraumea River. They all form a large stream network with a total length of 9,648 km, which flows into the Tasman Sea on the western coast of New Zealand.

4.2.2 Rainfall characteristics

The annual rainfall of the MRC ranges from 900 millimetres in the western coastal areas of the MRC to over 3000 millimetres in higher elevated areas of the Tararua and Ruahine Ranges. The rainfall distribution is characterized by a certain seasonality, with January and February as the driest months as a result of more frequent anti-cyclonic weather. The winter months, June, July and August, are the wettest period of the year, and in December, the rainfall intensity is higher in comparison with other months due to convectional rainfall (Burgess & New Zealand Meteorological Service, 1988).

[1] This mean elevation is indicative only.

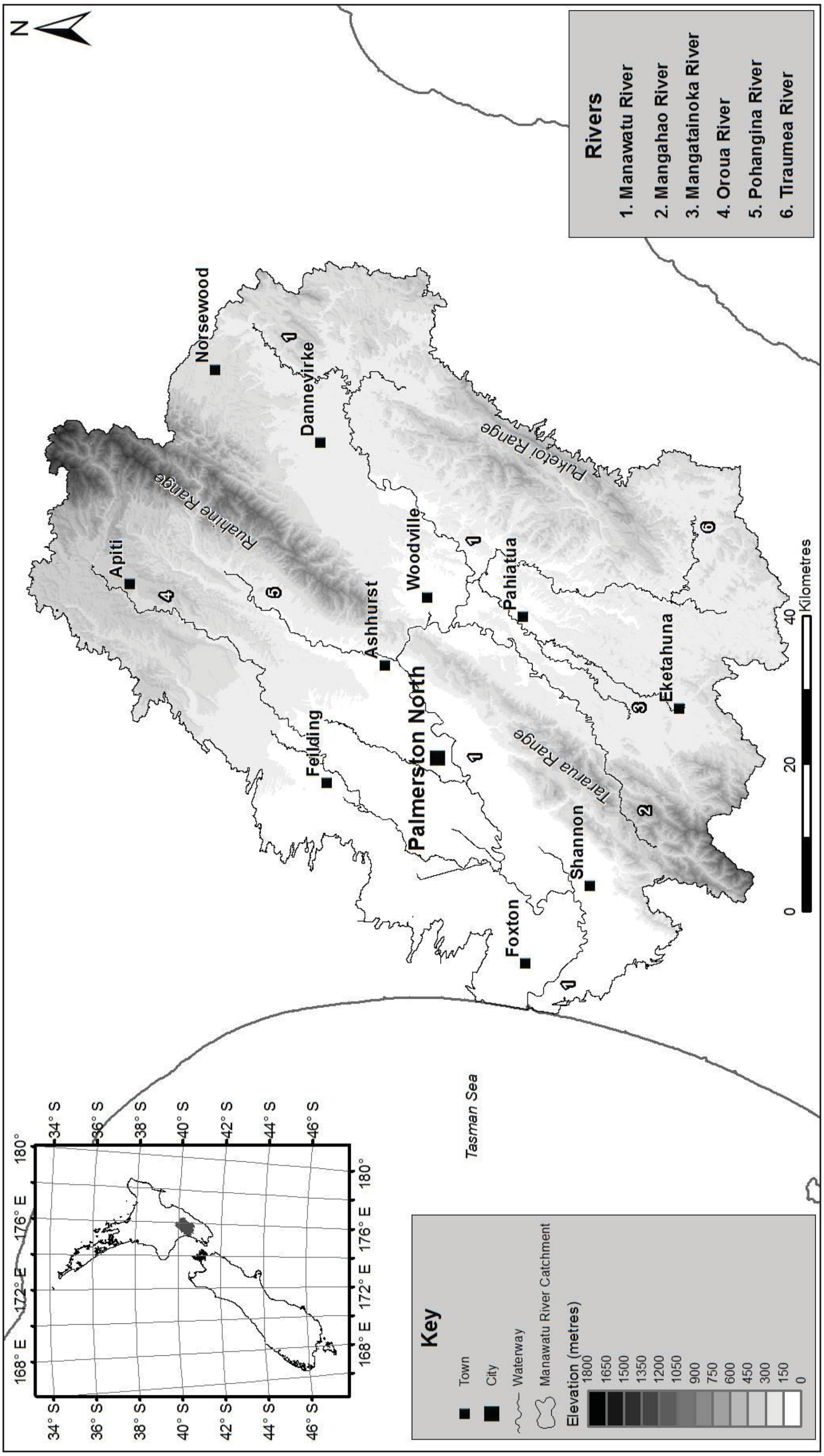

Figure 4-1: The Manawatu River Catchment

The rainfall distribution in the Manawatu River Catchment is influenced by weather systems; most centres of anticyclones passing over New Zealand are located just to the north of the North Island that cause predominantly north-west and south-west airflows. The north-westerly airflows generate showers in the Tararua and Ruahine Ranges and usually light or moderate rainfall throughout the rest of the Manawatu River Catchment. The south-westerly conditions produce fine weather to the south-western side of the North Island, and cold and showery weather in, and east of, the Tararua and Ruahine Ranges (Figure 4-2) (Burgess & New Zealand Meteorological Service, 1988).

4.2.3 Rainfall data

This research used various rainfall data sets supplied by three different agencies. It is necessary to illustrate them because they have all a different purpose within this research. Also, they comply with different standards and cover different temporal extents.

4.2.3.1 Rainfall data for spatial estimation

Rainfall data used for spatial estimation were supplied by Manawatu-Wanganui Regional Council, also known as the Horizons Regional Council. This rainfall data were in three different data sets (Table 3-7): primary rainfall data set (Appendix 13), historical rainfall data set (Appendix 14), and rainfall data set from rain gauges located outside the Manawatu River Catchment, but within a 30 kilometre buffer of the catchment boundary (Appendix 15). (At the time these rain gauges were installed, their locations were captured in New Zealand Map Grid (see glossary).) In the last few years the New Zealand Map Grid has been replaced with the New Zealand Transverse Mercator (see glossary) and the rain gauges' coordinates have been re-projected to this "new" coordinate system.

The primary rainfall data includes 21 automated recorded rain gauges which are irregularly dispersed throughout the Manawatu River Catchment. Most of these rain gauges are located below 500 metres, while only a few gauges are located in higher areas with complex topography (Table 4-1, Figure 4-3, and Appendix 13). In contrast with the rain gauges forming the primary rainfall data set, most of the 18 historical rain gauges are situated on higher elevated areas of the Ruahine and Tararua Ranges, of which 9 are situated outside the Manawatu River catchment (Table 4-1, Figure 4-3, and Appendix 14). The data of these 18 historical rain gauges were manually recorded by Regional Council staff, New Zealand Forest Service staff, and hikers. Lastly, all 11 automated rain gauges located rain outside the Manawatu River Catchment are mostly situated north-west of the Manawatu River Catchment (Table 4-1, Figure 4-3, and Appendix 15).

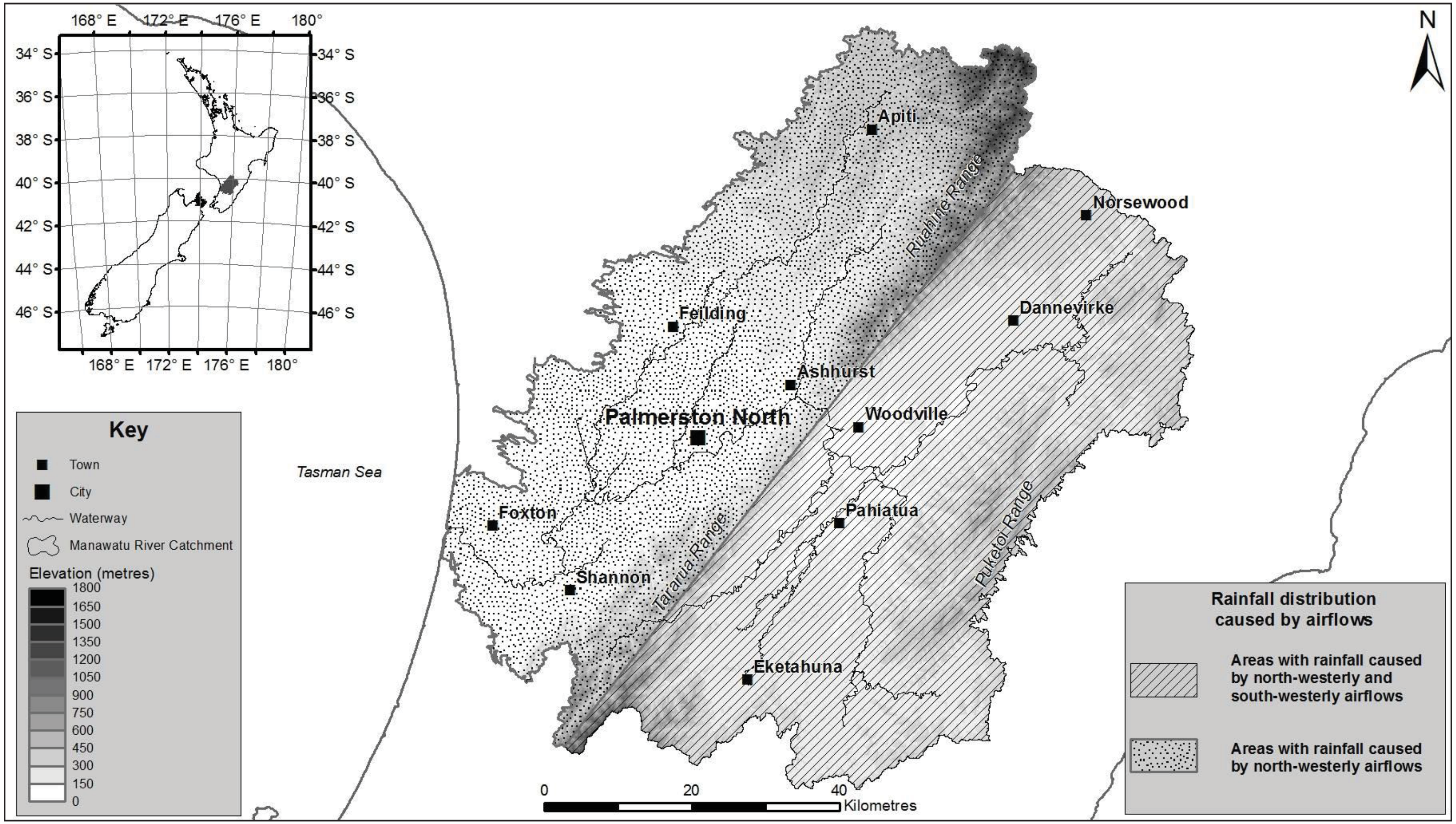

Figure 4-2: The rainfall distribution in the Manawatu River Catchment is influenced by weather systems

All three data sets operated during various timeframes. For example, the 21 automated recorded rain gauges of the primary rainfall data set includes rain gauges that started their first recording in 1974. Most of the 11 automated rain gauges situated outside the Manawatu River Catchment started their recording in the twenty-first century (Table 4-1, Figure 4-3, and Appendix 13). The 21 (primary rainfall data set) and the 11 (located outside the Manawatu River Catchment) rain gauges of these two data sets are still recording rainfall nowadays, whereas the 18 historical rain gauges operated for various numbers of years and were subsequently discontinued, and most of them closed around 1979.

Horizons Regional Council's rainfall data complies with National Environmental Monitoring Standards (NEMS), which is a series of environmental monitoring standards prepared by the National Environmental Monitoring Standards Steering Group on the authority of the Regional Chief Executive Officers and the Ministry for the Environment of New Zealand. Regional and unitary councils across New Zealand, electricity generation industry representatives, and the National Institute of Water and Atmospheric Research Ltd (NIWA) were involved in the development of this standard, which is adopted throughout New Zealand (LAWA, 2013).

The primary purpose of the historical rain gauges was to enable a better understanding of the orographic enhancement and spatial variation of rainfall, but the rain gauges were at times unreliable due to overflowing, being blown over, and harbouring drowned possums. As a result, historical rain gauges and their infrequent recording, the historical rain gauges meet a NEMS quality value of QC200, which means that the rainfall data is raw and it's quality is unknown (Appendix 17) (J. Watson, personal communication, 10 October 2013). In contrast to the historical rain gauges, the automated rain gauges situated within and outside the Manawatu River Catchment fall in higher NEMS' quality value ranges, namely between QC200 and QC600 (Appendix 17).

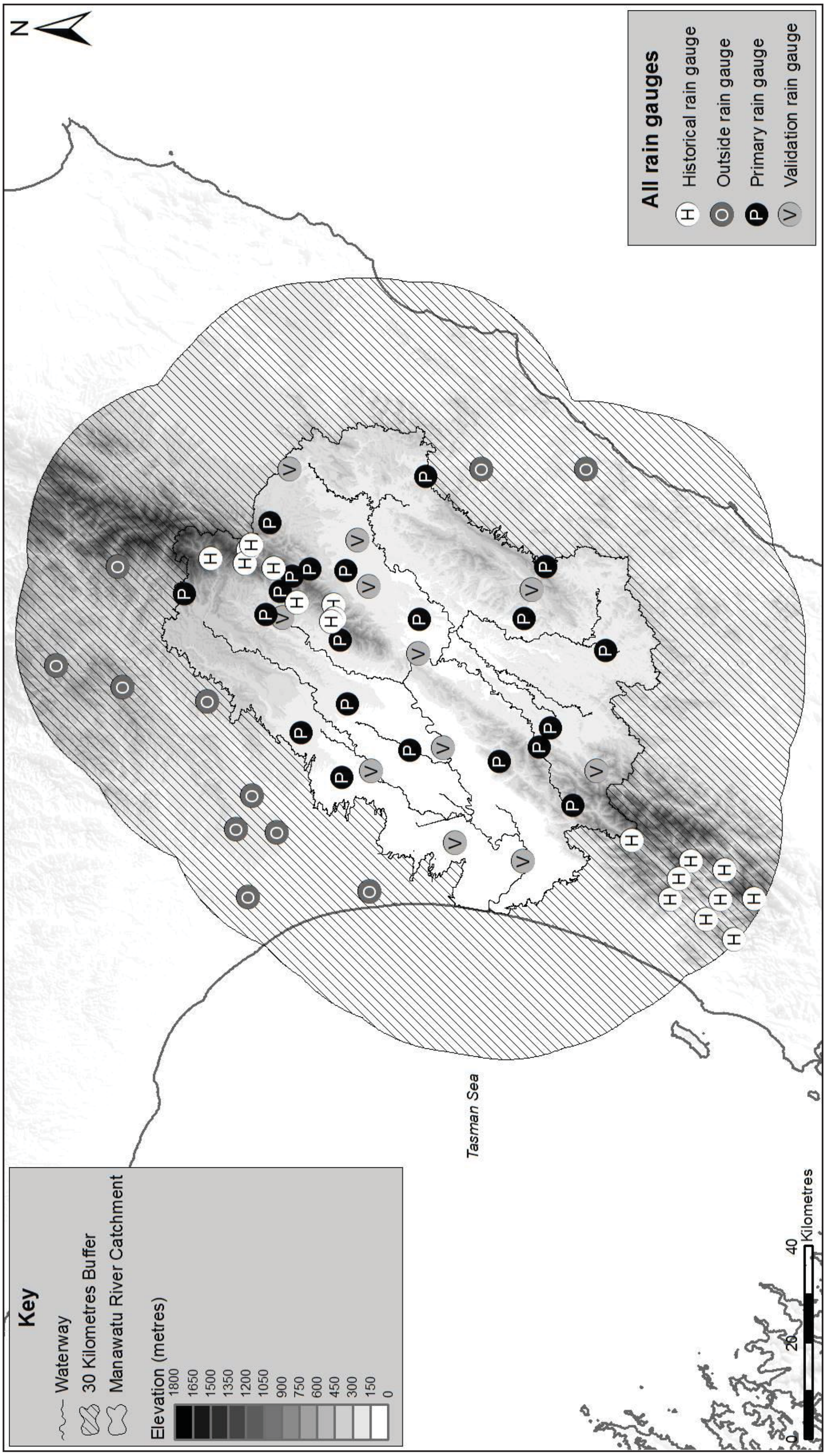

Figure 4-3: The geographical location of all rain gauges involved in the spatial estimation

4.2.3.2 Rainfall data for the validation of the spatial estimation

The SEMs' performance was examined with an independent validation data set supplied by NIWA (National Institute of Water and Atmospheric Research), which is a Crown Research Institute established in NZ in 1992 that undertakes scientific research. This independent validation data set contains rainfall data of 11 automated recorded rain gauges, and they are unevenly distributed throughout the Manawatu River Catchment (Table 4-1, Figure 4-3 and Appendix 16).

The oldest rain gauge of the validation data set started recording in 1913. In comparison with the rain gauges of the Horizons Regional Council data set, the rain gauges within NIWA's data set have a much longer rainfall data recording, with the smallest record of 13 years and the longest record of over 100 years.

NIWA's rainfall data collection and processing meets the World Meteorological Organisation (WMO) standards. The World Meteorological Organisation is a specialized agency of the United Nations for meteorology, hydrology, and geophysical sciences with a membership of 191 Member States and Territories at the start of 2013, and it was established in 1950. These standards are designed by the WMO Congress of Convention to ensure effectively adequate uniformity and standardization in the practices and procedures in meteorology and hydrology between members (World Meteorological Organization, 2014). In comparison with the NEMS this WMO standard is a more open standard that does not indicate the quality status of the data.

4.2.3.3 Rainfall data used in the data gap-filling techniques

The data of the historical rain gauges were determined using two data gap-filling techniques. The *coefficient of correlation weighting* method uses the rainfall data of historical rain gauges and close neighbouring rain gauges with the same temporal extent to establish the data gap, while the *inverse distance weighting* method uses only the data of close neighbouring rain gauges and the distance between the historical and close neighbouring rain gauges.

The historical rain gauges with some rain gauges of the primary data set and two rain gauges provided by the Greater Wellington Regional Council (also known as incorporated data set, Figure 4-4) are used in the data gap-filling techniques (Figure 4-4 and Appendix 18). The Greater Wellington Regional Council is also a regional council, which encompasses the most southern part of the North Island of NZ and is situated south of Horizons Regional Council.

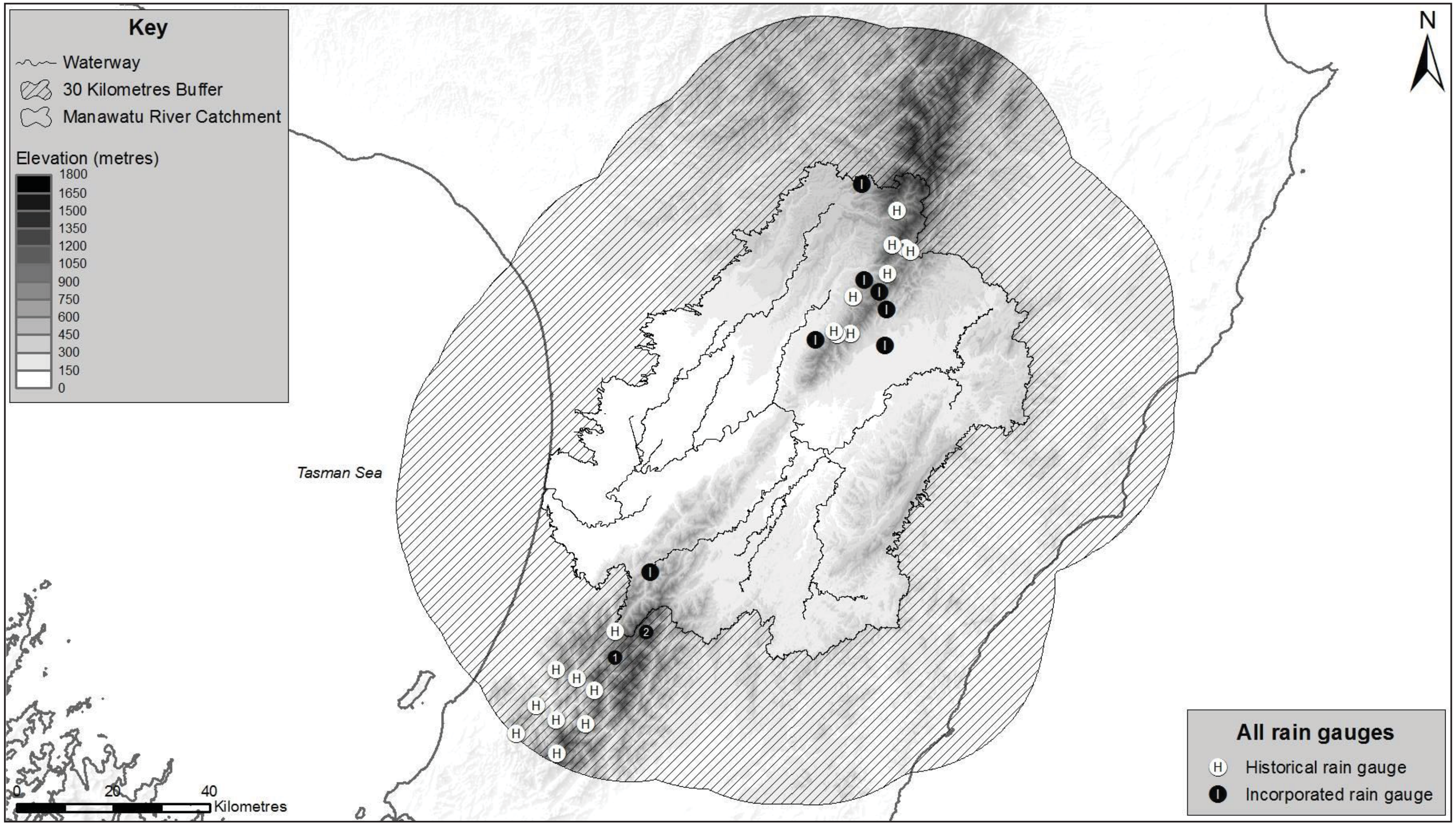

Figure 4-4: The geographical location of all rain gauges involved in the data gap-filling techniques

The two rain gauges monitored by the Greater Wellington Regional Council have been operating since 1974 and are located outside the Manawatu River Catchment. This regional council complies with National Environmental Monitoring Standards (NEMS). According to staff of the Greater Wellington Regional Council, these two rain gauges fall likely in the QC500, which means that the recordings do not meet operational standards, but the data is considered to be fair representation of the monitored rainfall (Appendix 17) (M. Shaw, personal communication, 5 May 2014).

Table 4-1: Summary of all applied rainfall data sets

Data sets	Data obtained	Applied to	Data supplied by	Quality standard	Number of rain gauges
Primary rain gauges	Recorded	Spatial estimation and data gap-filling	Manawatu-Wanganui Regional Council	National Environmental Monitoring Standards	21 (All used for the spatial estimation and 7 of the 21 used for data gap-filling)
Historical rain gauges	Recorded and data gaps determined with data gap-filling techniques	Spatial estimation	Manawatu-Wanganui Regional Council	National Environmental Monitoring Standards	18
Rain gauges located outside the MRC	Recorded	Spatial estimation	Manawatu-Wanganui Regional Council	National Environmental Monitoring Standards	11
Validation rain gauges	Recorded	Validation of the spatial estimation	National Institute of Water and Atmospheric Research	World Meteorological Organisation (WMO) standards	11
Extra rain gauges	Recorded	Data gap-filling	Greater Wellington Regional Council	National Environmental Monitoring Standards	2

4.3 Selection of the temporal data extent

The years 2009 to 2011 were selected as the temporal extent to assess the relative efficacy of estimation methods for montane rainfall, because this selection maximises the number of rain gauges, and the data contains minimum number of gaps (Figure 4-5). The yearly data sets are formed from the same years (2009, 2010, and 2011). The selection of the monthly data set is based on the average monthly rainfall of each year (2009, 2010, and 2011). The month with a total rainfall closest to the average monthly rainfall of a year (based on average of 21 rain gauges of the primary rainfall data set) was selected for this research. The selection of the daily data set was based on the selected months (June 2009, May 2010, and March 2011). The day with a total rainfall closest to the average daily rainfall of the selected month (based on average of 21 rain gauges of the primary rainfall data set) was chosen for this research (Table 4-2).

Table 4-2: The selection of temporal rainfall data sets

Yearly	Monthly	Daily
2009	June 2009	1 June 2009
2010	May 2010	13 May 2010
2011	March 2011	7 March 2011

4.4 Summary

The Manawatu River Catchment fits the criteria to examine the method for assessing the relative efficacy of estimation methods for montane rainfall, because it has a predominantly hilly and mountainous topography with a mean elevation of 845 metres, and it encompasses three mountain ranges (Puketoi, Ruahine, and Tararua Ranges). Secondly, this area, especially the three ranges, experiences montane rainfall. Lastly, two independent rainfall data sets of the catchment covering the selected temporal extent (2009 till 2011) are available to examine the performance of the SEMs fair and accurately.

Figure 4-5: Temporal extents of all applied rain gauges

Chapter 5: Results

5.1 Introduction

The previous chapter describes the selected area that is used to assess the relative efficacy of SEMs and it outlines the criteria of the applied data sets, while this chapter identifies the most appropriate SEM based on the overall ranking in the relative efficacy assessment as outlined in Chapter 3. Firstly, two data gap-filling techniques are assessed to complete all the data sets. Then, the results of the SEMs are outlined and the most appropriate SEM is identified with relative efficacy assessment.

5.2 Data gap-filling

The data gaps of a total of 18 historical rain gauges situated in the Tararua and Ruahine Ranges were bridged with the *coefficient of correlation weighting* and *inverse distance weighting* methods. The data gaps covering a temporal extent of one year, one month and one day (Table 4-2), and they were determined with at least two and a maximum of six current neighbouring rain gauges, depending on the applied data gap-filling technique and data availability. The performance of the two methods is calculated with the root mean square error and this section reports on that and on the challenges experienced during the analysis.

5.2.1 Challenges

The data of the historical rain gauges used in this research were delivered on old graph paper and those data were entered in the system, but the condition of some of the graphs was poor and very hard to read. The impact of this “bad” data on the results of the data gap-filling technique was minimised by running a second round of the *coefficient of correlation weighting* method without “bad” data.

Lastly, the *coefficient of correlation weighting* method relies heavily on correlation between data sets covering the same temporal extent. One of the biggest challenges was finding neighbouring rain gauges with the same temporal extent as the historical rain gauges covering at least one or two years. In some situations, a judgment of using less neighbouring rain gauges with more years of the same temporal data extent to determine a data gap for a historical rain gauge with the *coefficient of correlation weighting* method was preferred over using more surrounding rain gauges with only one year or less of the same temporal data extent.

5.2.2 Comparison

Table 5-1 shows the 2009 data gap-filling results for both data gap-filling methods (*inverse distance weighting* method and the *coefficient of correlation weighting* method (with and without “bad” suspicious data) with their performance measure in the form of a root mean square value. For example the root mean square values of the Andersons Hut in the 2009 data set (Table 5-1) reveal that the *coefficient of correlation weighting* method (after the “bad” data was removed) performed better than the *inverse distance weighting* method. In 11 of the 18 times filling data gaps for the 2009 data set, the *coefficient of correlation weighting* method perform better than the *inverse distance weighting* method, which is 61%. This percentage is higher for all data gap analysis (yearly, monthly, and daily): that is 74 % (Table 5-2).

Table 5-1: The 2009 data gap (1 year data gap) filling results of the 18 historical rain gauges

Historical Rain Gauge	Inverse Distance Weighting Method		Coefficient of Correlation Weighting Method		Coefficient of Correlation Weighting Method (Without "Bad" Data)	
	Estimated Data Gap	Root Mean Square Error	Estimated Data Gap	Root Mean Square Error	Estimated Data Gap	Root Mean Square Error
Andersons Hut	4355.23	1787.93	4446.72	1567.49	4440.90	1567.24
Aston Peaks	4522.28	1800.93	4357.27	1644.82	4478.43	1611.14
Diggers Hut	2328.46	722.55	2190.11	783.83	2189.41	783.50
Fields Hut	4485.28	1922.84	4480.97	1544.90	4474.35	1544.40
Iron Gate	1906.00	694.86	2596.56	753.32	2600.34	733.95
Kumeti	1841.31	666.84	2215.22	794.17	2177.94	784.20
Leon Kinvig	2263.61	727.34	2599.80	774.76	2602.70	731.13
Maharahara	1668.34	646.90	2479.46	580.34	2479.68	579.73
Mid Pohangina	2550.89	728.10	2601.95	731.60	N/A	N/A
Mt Kapakapanui	4505.56	1959.31	4390.75	1603.74	4443.28	1582.25
Ngamoko	2257.21	725.95	2480.00	580.95	2479.68	580.67
Opawe	1636.81	643.96	2572.46	847.82	2599.44	730.63
Roaring Meg	4480.99	1929.69	4464.86	1553.67	N/A	N/A
Tararua Peaks	4488.70	1901.67	4522.68	1635.91	4436.92	1577.13
Taungata	4429.29	1860.33	4439.36	1550.90	4440.24	1532.70
Te Matawai Hut	4746.17	1589.90	4493.99	1578.67	4467.03	1554.24
Toms	2276.69	728.21	2607.06	739.92	N/A	N/A
Waitewaewae Hut	4469.81	1622.60	4469.81	1622.60	4475.90	1550.92

N/A: The historical rain data did not contain "bad" data.

Table 5-2: Overview of the number of times that each data gap technique performed better than the other in percentage for all data gap analysis

Data gap-filling technique	All data sets (Yearly, Monthly, and Daily) (%)	Yearly data sets (2009, 2010, and 2011) (%)	Monthly data sets (June 2009, May 2010, and March 2011) (%)	Daily data sets (1 June 2009, 13 May 2010, and 7 March 2011) (%)
inverse distance weighting method	26	33	15	31
coefficient of correlation weighting method (Without "Bad" Data)	74	67	85	69

The root mean square error value (estimation error) for each data gap was combined for each data gap technique. The first technique, the *inverse distance weighting* method, produced a total root mean square error value of 79451 (total of all data gap analysis). The second and third techniques generated a lower total root mean square error value, with the second run of *coefficient of correlation weighting* method (without “bad” data) increasing the accuracy tremendously, 22% (Table 5-3). The rainfall data generated with this second run of *coefficient of correlation weighting* method was used for relative efficacy assessment of SEMs, with its results described in the following section.

Table 5-3: The total increase in accuracy of the three runs of methods

Data gap-filling technique	Total root mean square error of all data gap analysis	Increase in accuracy – compared with inverse distance weighting method (%)	Increase in accuracy – compared with coefficient of correlation weighting method (%)
inverse distance weighting method	79451	-	-
coefficient of correlation weighting method	74573	6	-
coefficient of correlation weighting method (Without “Bad” Data)	61941	22	17

5.3 Principal components analysis

The rainfall values of the historical rain gauges generated with the data gap-filling technique (*coefficient of correlation weighting* method) are used in the PCA. The average total yearly rainfall (covering 2009 to 2011), distance to the west coast, and the elevation were used to determine if the rain gauges of the validation data set are similar in the characteristic (distance to the west coast, elevation, and average total yearly rainfall) as the historical, and the primary rain gauges, and the rain gauges located outside the MRC.

The results (Appendix 25) revealed four classes, which are class 1 (rain gauges situated in Ruahine Ranges), class 2 (includes rain gauges located in the Tararua Ranges), class 3 (most of rain gauges located west of the Ruahine and Tararua Ranges), and class 4 (rain gauges situated east of the two ranges and a few are located in the north outside the MRC). The rain gauges of the validation data set have at least one rain gauge in class 2, 3 and 4. Only it has no rain gauges in class 1 that encompasses rain gauges in the high elevated areas of the Ruahine Ranges.

5.4 Spatial estimation methods

The most suitable SEM was determined by applying the five SEMs (Table 3-2) to three versions (Table 4-1) of the nine temporal rainfall data sets specified in Table 4-2. Each spatial estimation performance was recorded with a root mean square value and the best performance of each of the 135 spatial estimations was defined by a rainfall map with the lowest root mean square value, and at the same time it maintained the distinct rainfall pattern (Table 5-4). These minimum root mean square values of Table 5-4 were used in the performance comparison, average ranking assessment, and the final ranking assessment. Lastly, the rainfall maps generated from each data set were evaluated.

5.4.1 Performance comparison

The differences in the performances between the five SEMs are shown in Appendix 25. The large differences in the first and third experiments of the yearly data set estimation revealed that *Gaussian geostatistical simulation* is more accurate than the other SEMs. In contrast, the large differences between *empirical Bayesian kriging* and the other SEMs in the second experiment can considered as the bad performance of *empirical Bayesian kriging* in comparison with the rest of SEMs.

Regression kriging perform well, solely based on the statistics, in the spatial estimations with June 2009 and March 2011 data sets. In all three experiments of both data sets estimation, there is a small margin with a maximum of just below 7 between the root mean square values of *regression kriging* and the second lowest root mean square value. In the May 2010 spatial estimation *Gaussian geostatistical simulation* perform well in comparison with the other SEMs, whereby the differences with the rest of the performances of the SEMs are larger in the first experiment and small in the second experiment.

The differences in performances in spatial estimation of 7 March 2011 data set are the smallest, whereby *Gaussian geostatistical simulation* outperforms the rest of the SEMs. The performance of other SEMs used to estimate the two other daily rainfall data sets varied. *Empirical Bayesian kriging* and *ordinary kriging* generated rainfall outputs with the smallest root mean square value for the spatial estimation of 1 June 2009 data set, while three different SEMs (*ordinary kriging*, *linear regression*, and *regression kriging*) perform well in one of three experiments of the spatial estimation of 13 May 2010 data set. All performances were used to rank each SEM per data set spatial estimation and these results are described in the following section.

5.4.2 The ranking assessment per temporal data set

Appendix 26 reveals the average ranking assessment of all nine data sets, determined by average ranking of the each SEM per experiment, which is based on their estimation performance measurement (root mean square value). The SEM with the lowest score performed the best with that data set. *Regression kriging* and/or *Gaussian geostatistical simulation* were predominantly better than the rest of the SEMs in 8 of 9 spatial estimations (Table 5-5). *Empirical Bayesian kriging* was in only one spatial estimation better than the rest, while *ordinary kriging* and *linear regression* never provided the best result based on the average ranking. The results of the average ranking of all SEMs were used to determine the final ranking assessment, which is described in the following section.

Table 5-4: Minimum root mean square values for each experiment and SEM applied to a data set

Data set	Experiment 1 SEMs					Experiment 2 SEMs					Experiment 3 SEMs				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
2009	571.81	552.72	508.58	523.30	315.49	554.25	559.68	520.34	771.25	565.28	456.08	531.73	490.04	552.46	383.94
2010	578.77	522.49	471.66	478.06	305.21	482.45	502.56	479.61	577.08	546.76	408.20	504.33	447.40	455.23	387.53
2011	546.06	503.61	468.58	413.88	313.51	526.60	523.41	491.48	573.72	525.76	440.20	497.24	464.52	462.59	377.19
Jun-09	36.95	33.39	26.82	39.92	33.34	41.51	34.72	29.78	44.85	51.04	37.65	36.56	29.07	42.14	36.03
May-10	33.09	31.97	29.03	26.64	17.44	29.75	28.55	32.06	30.56	29.56	29.97	29.49	34.49	28.99	25.90
Mar-11	47.53	33.01	31.82	43.97	33.10	43.75	36.14	34.31	49.47	74.06	37.29	33.65	31.87	40.75	34.41
1-Jun-09	2.71	3.17	3.05	2.50	3.33	2.34	2.87	2.75	2.39	2.40	2.45	3.22	3.12	2.43	2.49
13-May-10	4.76	4.97	4.92	4.92	5.21	5.35	4.61	4.61	5.68	4.78	5.21	4.71	4.75	5.57	4.95
7-Mar-11	8.75	8.76	8.77	8.73	8.70	8.64	8.73	8.67	8.69	8.57	8.68	8.73	8.67	8.69	8.59

Note:

1. Ordinary kriging,
2. Linear regression,
3. Regression kriging,
4. Empirical Bayesian kriging,
5. Gaussian geostatistical simulation

Table 5-5: Summary of the best method for each data set, as determined by average ranking of each SEM per experiment

Data set	SEM with the best performance based on the average ranking assessment
2009	Regression kriging and Gaussian geostatistical simulation
2010	Regression kriging and Gaussian geostatistical simulation
2011	Gaussian geostatistical simulation
Jun-09	Regression kriging
May-10	Gaussian geostatistical simulation
Mar-11	Regression kriging
1-Jun-09	Empirical Bayesian kriging
13-May-10	Regression kriging
7-Mar-11	Gaussian geostatistical simulation

5.4.3 The final ranking assessment

The final average overall ranking assessment determines the most suitable SEM for estimating montane rainfall, which is based on the mean of all average ranking assessments of all SEMs applied to the nine data sets (Table 5-6). The best method was defined by the highest average overall ranking. *Regression kriging* and *Gaussian geostatistical simulation* were tied as the best methods in the overall ranking, but the final ranking assessment indicated that *Gaussian geostatistical simulation* was the most suitable SEM for montane rainfall (based on their lowest average ranking of a four for *Gaussian geostatistical simulation* and a five for *regression kriging*) (Table 5-6).

Table 5-6: The final ranking assessment

Average ranking per data set	Ordinary kriging	Linear regression	Regression Kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
Average ranking 2009	3	4	1	5	1
Average ranking 2010	3	4	1	4	1
Average ranking 2011	4	4	2	3	1
Average ranking June 2009	4	2	1	5	3
Average ranking May 2010	4	2	5	2	1
Average ranking March2011	4	2	1	5	3
Average ranking 1 June 2009	2	5	3	1	3
Average ranking 13 May 2010	3	2	1	5	4
Average ranking 7 March2011	2	5	3	3	1
Average Overall Ranking	**3**	**4**	**2**	**5**	**1**

5.4.4 Rainfall distribution in the Manawatu River Catchment

Appendix 28 shows all the maps generated by the five SEMs per experiment with the best performance. The yearly and monthly rainfall maps revealed more rainfall in the Tararua and Ruahine Ranges than the rest of the Manawatu River Catchment. The yearly rainfall maps show maximum estimated rainfall values in these two ranges are just under 4000 millimetres (mm) in the first experiment, but they are over 4000mm in the second and third experiment. The monthly rainfall maps reveal a noticeable difference in the estimated maximum monthly rainfall between the two ranges, with an estimated maximum rainfall quantity around 360mm for the Ruahine Ranges and around 270 mm for the Tararua Ranges. The lowest yearly (between 900 and 1000 mm) and monthly (between 80 and 120 mm) estimated values are situated on the north-western side of the Tararua Ranges. The daily rainfall maps (Appendix 28) show a lot of variability in their rainfall distribution and the five SEMs produce significantly different maps.

5.4 Summary

The performance of the data gap-filling techniques *coefficient of correlation weighting* and *inverse distance weighting* were compared by determining the data gaps of the historical rain gauges. The data gaps of the historical rain gauges that were used for comparing the SEMS were defined with *coefficient of correlation* weighting without the 'bad' data, because it performed well in comparison with the other technique and it increased the accuracy by 22% (Table 5-3). The results of performance comparison and the average ranking assessment were already an indicator that *regression kriging* and *Gaussian geostatistical simulation* were two appropriate SEMs for montane rainfall. Good performances by *Gaussian geostatistical simulation* in the yearly data sets spatial estimation and good performances by *regression kriging* in the monthly data sets spatial estimation were the highlights in performance comparisons. Also, both SEMs were dominating the average ranking assessment, whereby both of them were tied as the best methods in two spatial data set estimations, and each of the SEMS were the best in three other spatial data set estimations. It was easy to foretell that one of these two SEMS was the most suitable SEM for estimating montane rainfall. The overall ranking indicated that both were the best methods (*regression kriging* and *Gaussian geostatistical simulation*), but the final ranking assessment indicated that *Gaussian geostatistical simulation* was the most suitable SEM for montane rainfall (based on the lowest average ranking of a four for *Gaussian geostatistical simulation* and a five for *regression kriging*). The yearly and monthly rainfall maps revealed higher estimated rainfall values in the Tararua and Ruahine Ranges and the lowest estimated rainfall values are situated on the north-western side of the Tararua Ranges. The daily rainfall maps do not show a particular rainfall distribution and the five SEMs produce significantly different maps.

Chapter 6: Analysis

6.1 Introduction

The previous chapter describes the results of the data gap-filling techniques applied to the historical rain gauges and relative efficacy assessment, while this chapter discusses the results. Firstly, the results of data gap-filling techniques are discussed and compared with other studies. Secondly, the impact of the increase in the number of rain gauges on the performance of the SEMs is examined. Thirdly, the performance of each SEM is compared. Fourthly, the strategically placing of rain gauges are discussed, and finally the rainfall distribution of the MRC is reviewed with the generated rainfall maps in Appendix 28 and 29.

6.2 Validity of results

The validity of the results presented in this research can be challenged based on the lack of historical data in the study area. In particular, the number of recordings applied in the data gap-filling technique *coefficient of correlation weighting* was very low, varying from 4 to 17 recordings with a temporal coverage ranging from 1 to 3 years. This lack of confidence in historical data is amplified with the spatial estimation performance results, highlighted in Table 6-1, which revealed that yearly and monthly rainfall spatial estimations perform better without the historical rain gauge data. However, the inclusion of the historical rain gauges spatial estimation provides more detailed rainfall quantity in the mountains on the estimation outputs.

Table 6-1: Minimum root mean square values generated by that experiment per SEM per data set

Data set	Empirical Bayesian kriging	Gaussian geostatistical simulation	Linear regression	Ordinary kriging	Regression kriging
2009	1 (523.30)	**1 (315.49)**	3 (531.73)	3 (456.08)	3 (490.04)
2010	3 (455.23)	**1 (305.21)**	2 (502.56)	3 (408.20)	3 (447.40)
2011	1 (413.88)	**1 (313.51)**	3 (497.24)	3 (440.20)	3 (464.52)
June 2009	1 (39.92)	1 (33.34)	1 (33.39)	1 (36.95)	**1 (26.82**)
May 2010	1 (26.64)	**1 (17.44)**	2 (28.55)	2 (29.75)	1 (29.03)
March 2011	3 (40.75)	1 (33.10)	1 (33.01)	3 (37.29)	**1 (31.82)**
1 June 2009	2 (2.39)	2 (2.40)	2 (2.87)	**2 (2.34)**	2 (2.75)
13 May 2010	1 (4.92)	2 (4.78)	2 (4.61)	1 (4.76)	**2 (4.61)**
7 March 2011	2 (8.69)	**2 (8.57)**	2 (8.73)	2 (8.64)	3 (8.67)

On the contrary, the quality of the rainfall data may influence the accuracy of the SEMs. The best quality for rainfall data is preferred for rainfall estimations; however, the current rain gauges (the primary rain gauges and the rain gauges located outside the MRC) do not always comply with the highest quality code of 600, while the historical rain gauge data meets only a NEMS quality code of 100 (Appendix 17). Furthermore, there is an uncertainty about the quality of NIWA's validation data, which complies with the World Meteorological Organisation (WMO) standards, a more open standard that does not indicate the quality status of the data.

In addition, the location of the rain gauges can put the estimated rainfall map in jeopardy, especially in areas with a low density of rain gauges. The rainfall maps generated by experiment two and three (incorporating the historical rain gauges) revealed more detail about the rainfall quantity in the upper Tararua and Ruahine Ranges, compared to the rainfall maps generated in the first experiment (without the historical rain gauges). Importantly, the rain gauge distribution in all three experiments is uneven and the rainfall maps show limited details of rainfall quantity in areas with a few or no rain gauges, especially the north-eastern side of the MRC and the lower elevated areas of the Tararua Ranges.

6.3 Comparison of the data gap filing techniques

Two data gap-filling techniques (*inverse distance weighting* method and the *coefficient of correlation weighting* method) were applied to 18 historical rain gauges and their performance was compared. The method with the best performance (the lowest root mean square value), was selected to generate all data for the historical rain gauges.

The *coefficient of correlation weighting* method outperformed *inverse distance weighting* method in 74% of the all data gap analyses, whereby the "bad" data could be removed in the *coefficient of correlation weighting* method. Other studies, for instance Westerberg et al. (2010), and Teegavarapu and Chandramouli (2005), compared these two methods or more having similar results, whereby the *coefficient of correlation weighting* method outperformed *inverse distance weighting* method, but they have more performance measurements, such as mean absolute error, the mean relative error, the root mean square value, and the coefficient of determination. Importantly, the poor performance by *inverse distance weighting* method can be explained by its limitations, which are that the estimated data gaps are bounded by extreme values in the sample data, and radial symmetry assumed by *inverse distance weighting* method obscures the effects of linear features such as ridges or valleys (Watson & Philip, 1985).

The removal of "bad" data in the *coefficient of correlation weighting* method had noticeable impact on the accuracy of the data gap-filling technique. It increased the overall accuracy of the method by 17% compared to the same technique with all the data and it increased the accuracy 22% compared to the *inverse distance weighting* method (Table 5-2). The *coefficient of correlation weighting* method, the most accurate technique, was selected to patch the data gaps of the historical rain gauges and they were used in the spatial estimation. Their impact on the performance of the SEMs are discussed in the following section.

6.4 Most appropriate spatial estimation method to manage sparse data

The final overall ranking revealed that *Gaussian geostatistical simulation* is the most appropriated spatial estimation method for estimating montane rainfall with sparse data (Appendix 28 show all maps generated by this most suitable SEM) and regression kriging was second best, with minor differences. This final ranking was based on average ranking, which was determined with the performance measure (root mean square value). It is necessary to highlight the possible reasons for the performance differences between the SEMs based on the applied data sets, SEMs' variables (described in Appendix 20 (*ordinary kriging*), 21 (*linear regression*), 22 (*regression kriging*), 23 (*empirical Bayesian kriging*), and 24 (*Gaussian geostatistical simulation*)), and experiences from other studies. This section starts with the lowest ranked SEM (*empirical Bayesian kriging*) and finishes with the most suitable SEM (*Gaussian geostatistical simulation*).

6.4.1 Empirical Bayesian kriging

According to Pilz and Spöck (2008, as cited in Schroeder, 2013) *Empirical Bayesian kriging* (Appendix 23) automatically determines its parameters (such as semivariogram model, number of lags), accounts for the error introduced by estimating the underlying semivariogram, and improves the accuracy of the results (specifically, it is more accurate for small data sets). Nevertheless, the final ranking assessment ranked this SEM as the worst technique for estimating montane rainfall, but in some of the experiments it performed better (lowest root mean square values) than the other SEMs (for example the first and third experiment of the 1 June 2009 spatial estimation).

Importantly, the performance of this SEM may be considered insufficient due to the limited number of rain gauges in all three experiments, which may lead to unstable semivariograms (Nalder & Wein, 1998). Bilonick (1983) suggested a minimum of 50 or more sample points are required to obtain a stable semivariogram. According to Webster and Oliver (1992), researchers should aim for 150 to 200 sample points in a their research area, where the variation is isotropic (see glossary). An anisotropic variation (see glossary) required a larger number of sample points, over 200 (Webster & Oliver, 1992). The number of rain gauges used in the three experiments are 21, 39, and 50, and that may explained the poor fit of the semivariogram, which may lead to large estimation errors. This limitation of the used data, which has negative influence on the performance, has similar implications on the performance of all SEMs that use fewer data points (less than 50) and semivariograms to estimate data, including *ordinary kriging* and *Gaussian geostatistical simulation*.

Appendix 28 showed that most of the estimated rainfall maps generated by e*mpirical Bayesian kriging* are smooth and maintaining the distinct pattern of rainfall, but some of them are crude (for example third experiment of 13 May 2010). Compared to Schroeder's (2013) research, this research dealt with a low data point density and empirical Bayesian kriging performed poorly, and Schroeder's research revealed a good performance by this method, outperforming *ordinary kriging* and *ordinary cokriging*, with a larger rain gauge density in a small area.

6.4.2 Linear regression

Linear regression assumes that data are independent from each other, normally distributed, and homogenous in variance (Li & Heap, 2008). It seeks a possible functional relationship between the dependent variable and explanatory variables (Burrough & McDonnell, 1998). A perfect relationship is illustrated with an R-square value of 1.0, which was not the case in this research. Figure 6-2, revealed a range of R-squared values from 0.03 to 0.725. The results (Figure 6-2) do not reveal that the strength of the relationships impacted the performances, because in 14 cases, a weaker relationship in linear regression generated a lower root mean square value (a better performance) than a stronger relationship (Appendix 21).

Furthermore, the yearly and monthly rainfall maps showed the maintenance of the distinct pattern of rainfall, with high rainfall values on the top of the ranges and lower values on the flats; however, they look very similar as the digital elevation model (Appendix 28). Most of the daily rainfall maps showed a similar pattern with the maps generated by one of the other four SEMs. In contrast, the map of 1 June 2009 does not maintain the distinct pattern of rainfall, by having higher rainfall values in the downstream areas than upstream areas. Overall, *linear regression* applied to the MRC's rainfall data with slope and elevation as explanatory variables do not perform well generally, which the final ranking assessment confirmed with the fourth ranking.

6.4.3 Ordinary kriging

Ordinary kriging assumes a constant but unknown value, and it estimates the average value as a constant in the searching neighbourhood and uses a fitted semivariogram for the estimation (Chang, 2008; Goovaerts, 1999b; Kumar, Maroju, & Bhat, 2007; Pereira, Oliva, & Baltrenaite, 2010). This SEM is commonly applied and it often outperforms other SEMs, which was revealed in the literature analysis by Li and Heap (2008, 2011) and the literature analysis within this research. Interestingly, in only two of the 27 spatial estimations, it outperforms the four other SEMs within this research (Appendix 20).

Similar to *empirical Bayesian kriging* and *Gaussian geostatistical simulation*, *ordinary kriging* requires at least 50 and preferably 300 sample points for semivariogram estimation (Webster & Oliver, 1992). However, this study used 21, 39, and 50, and that may explain the poor fit of the semivariogram (Figure 6-1 and 6-2), which could have led to large estimation errors. A good fit of a semivariogram is represented by a model (represented by a line in Figure 6-1 and 6-2) that passes through the centre of the cloud of binned values (represented by dots in Figure 6-1 and 6-2) and at the same time it passes closely as possible to the average values (represented by crosses in Figure 6-1 and 6-2) (Esri, 2013).

Table 6-2: R-squared values of all rainfall data sets with rainfall and/or slope data

Data set	Experiment 1			Experiment 2			Experiment 3		
	R-squared for rainfall and elevation	R-squared for rainfall and slope	R-squared for rainfall and elevation & slope	R-squared for rainfall and elevation	R-squared for rainfall and slope	R-squared for rainfall and elevation & slope	R-squared for rainfall and elevation	R-squared for rainfall and slope	R-squared for rainfall and elevation & slope
2009	**0.313 (4)**	0.108	0.352	0.316	0.239	**0.431 (3)**	**0.459 (4)**	0.327	0.517
2010	**0.509 (4)**	0.114	0.537	**0.563 (3)**	0.280	0.515	**0.477 (5)**	0.383	0.588
2011	0.370	0.114	**0.407 (4)**	0.436	0.289	**0.495 (2)**	**0.445 (5)**	0.391	0.567
Jun-09	0.682	0.163	**0.725 (3)**	0.623	0.386	**0.694 (2)**	**0.590 (3)**	0.423	0.683
May-10	**0.668 (4)**	0.003	0.670	0.488	0.298	**0.536 (1)**	0.450	0.358	**0.526 (3)**
Mar-11	0.505	0.003	**0.520 (2)**	0.568	0.349	**0.631 (2)**	**0.547 (2)**	0.422	0.221
1-Jun-09	0.336	**0.012 (4)**	0.404	0.247	**0.034 (5)**	0.252	0.306	**0.306 (5)**	0.312
13-May-10	**0.002 (4)**	0.012	0.018	**0.168 (2)**	0.072	0.174	0.229	**0.124 (1)**	0.241
7-Mar-11	0.396	**0.012 (4)**	0.470	0.295	**0.135 (5)**	0.308	0.200	**0.134 (5)**	0.221

Note: the bold numbers represent the best estimations (lowest root mean square value) and the number between brackets are the rankings of the ranking assessment per temporal data set and per experiment.

The rainfall maps generated by ordinary kriging (Appendix 28) revealed that less data points (experiment 1) incorporated in the spatial estimation create more straight isohyets (see glossary), especially the yearly data set estimations. The maps generated in the second (39 rain gauges) and third (50 rain gauges) experiments are smoother. Overall, ordinary kriging maintained the distinct pattern of rainfall in all the maps.

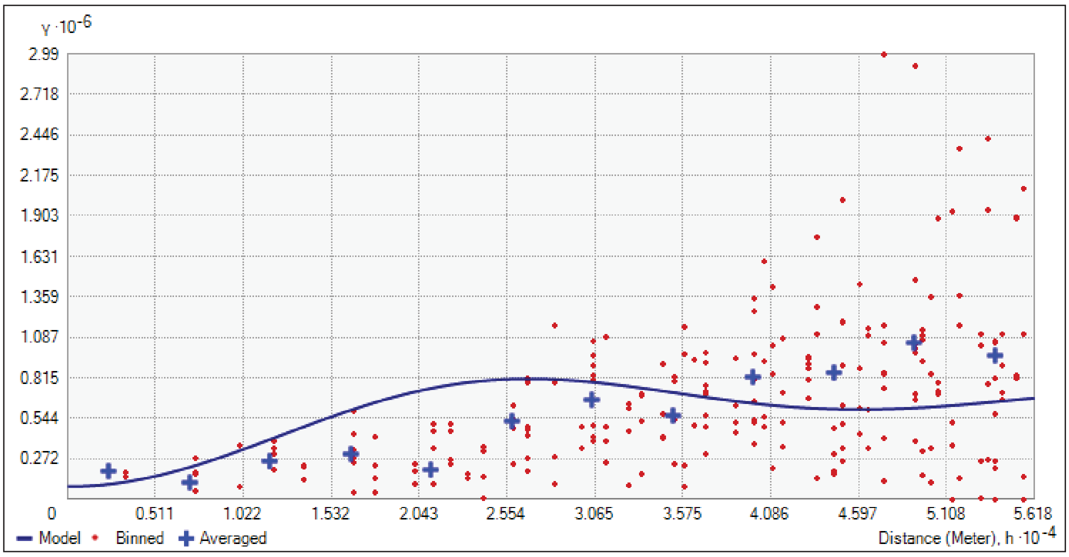

Figure 6-1: The semivariogram of the 2009 data set (experiment 3) in ordinary kriging

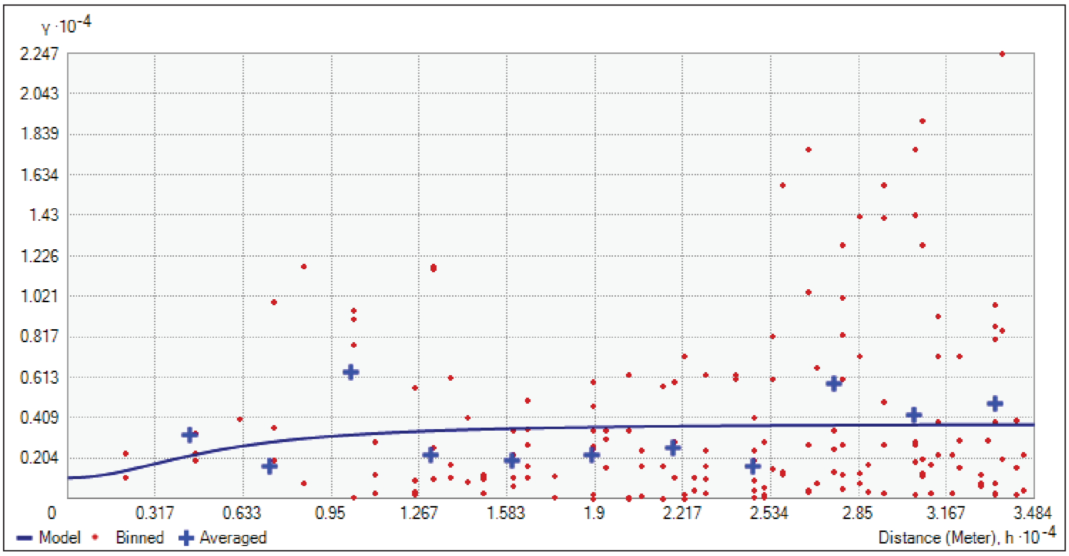

Figure 6-2: The semivariogram of the June 2009 data set (experiment 1) in ordinary kriging

6.4.4 Regression kriging

An alternative form of *kriging* is *regression kriging* that involves modelling the relationship between the main and auxiliary variables at sample points and is followed by kriging of residuals. The literature has revealed several types of regression kriging (Li & Heap, 2008).

According to Li and Heap's (2008) classification, this research applied the C-type of *regression kriging* that involves *regression* and *simple kriging*, also called, *regression with residual simple kriging* by Asli and Marcotte (1995) or *residual kriging* by Mardikis, Kalivas, and Kollias (2005).

After the first final ranking assessment, *regression kriging* was first equal, but this SEM was placed second because it had in one of the average rankings a lower ranking than *Gaussian geostatistical simulation.* Overall, *regression kriging* performed well (Appendix 22) in comparison with the other three SEMs. However, *regression kriging* has factors, listed by Hengl, Heuvelink, and Rossiter (2007), that can influence its performance and which can explain certain poor performances (based on the root mean square values) within this research, such as the May 2010 estimation.

Extrapolation is the first factor that can affect the performance badly, although the third experiment aimed to minimise that factor by incorporating the rain gauges located outside the MRC (Hengl et al., 2007). Interestingly, the performance revealed inconsistent results across all estimations with some of the estimations improving in performance by incorporating these rain gauges located outside MRC, and some of them decreasing in performance.

The second factor is the data quality. According to Hengl et al. (2007), *regression kriging* relies heavily on the data quality and a single bad data point can influence the regression arbitrary badly, which affects the regression kriging estimation over the whole area. This factor may explain the poor performance in the May 2010 estimation, where *regression kriging* in the first experiment still performs average (third ranking), but it performs poorly in the second and third experiments (both fifth ranking). The historical data set, generated by the data gap-filling technique (the *coefficient of correlation weighting* method), may introduce bad data points.

The last factor is an uneven relation between the main variable (rainfall in this research) and the auxiliary variables (elevation and slope in this research), which can cause artefacts in the estimated output (grid) (Hengl et al., 2007). According Hengl et al. (2007), the auxiliary data sets should have a constant physical relationship with the main variable. Although, the grids generated with *regression kriging* revealing no signs of artefacts (Appendix 28), maintaining the distinct pattern of rainfall, and these grids look like a "smooth copy" of the maps generated by *linear regression*.

6.4.5 Gaussian geostatistical simulation

Conditional Gaussian geostatistical simulation, applied in this research, produces a set of values in a grid format that agrees to a standard normal distribution with a specified semivariogram and mean value of 0 and variance of 1, but it maintains the measured values at the locations (Krivoruchko, 2011). The maintenance of the measured values could be the justification of the best overall performance by this SEM (Appendix 24). However, *Gaussian* *geostatistical simulation* does not always perform well in all the spatial estimations within this research.

Similar to *empirical Bayesian kriging* and *ordinary kriging*, *Gaussian geostatistical simulation* requires at least 50 and preferably 300 sample points for semivariogram estimation (Webster & Oliver, 1992). In comparison, this study used only 50 rain gauges in the last experiment and less in the first two experiments, which may explain why this SEM did not always perform well in comparison with the other four SEMs.

According to Vann, Bertoli, and Jackson (2002), the biggest challenge is the number of neighbouring sample points included in the estimation. A small quantity of neighbouring sample points included in the spatial estimation can cause poor condition and replication of the semivariogram, which can lead to poor estimation. This research selected a maximum of five neighbouring rain gauges (Appendix 24), which could be the reason that *Gaussian geostatistical simulation* did not always perform better than the rest of the SEMs.

During the running of *Gaussian geostatistical simulation*, there were computer performance issues. In particular, increasing the number of realisations (number of simulations) impacted the computer performance heavily, which is also mentioned in Burrough and McDonnell's (1998) comparison overview of SEMs (Appendix 1). More realisation (more than 30) may increase the accuracy of *Gaussian* geostatistical simulation.

Some of the rainfall maps (appendix 28) generated with *Gaussian geostatistical simulation* look significantly different than the other rainfall maps generated with the other SEMs. The maps (for example 2010 experiment 2 and 2011 experiment 1) look more like a rainfall radar map, very coarse and blocky. Some of the maps revealed a lot of variance (looks very patchy), such as June 2009 experiment 1 and March 2011 experiment 1; however, these maps do not represent the best performance (based on the root mean square values).

6.4.6 Summary

The previous sections describes certain factors that can cause poor performances, which can explain the performances of the five SEMs within this research. These factors are summarised in table 6-3.

Table 6-3: Factors that may impact the performance of the SEM

Spatial estimation methods	Factors
empirical Bayesian kriging	Less than 50 sample points can cause unstable semivariograms (Webster & Oliver, 1992). Low sample point density, based on the performance differences of this SEM and the used sample point density in Schroeder (2013) research and this research.
linear regression	Poor relationship between the dependent variable and explanatory variables.
ordinary kriging	Less than 50 sample points can cause unstable semivariograms (Webster & Oliver, 1992).
regression kriging	Extrapolation (Hengl et al., 2007). Data quality, a single bad data point can influence the regression arbitrary bad (Hengl et al., 2007). An uneven relation between main variable (rainfall in this research) and the auxiliary variables (elevation and slope in this research) can cause artefacts in the estimated output (grid) (Hengl et al., 2007).
Gaussian geostatistical simulation	Less than 50 sample points can cause unstable semivariograms (Webster & Oliver, 1992). Small quantity of neighbouring sample points included in the spatial estimation can cause poor condition and replication of the semivariogram, which lead to poor estimation (Vann et al., 2002). This SEM requires more computer resources than there were, which limited the number of variables to be examined (Burrough & McDonnell, 1998).

6.5 Strategically placing limited rain gauges in montane country

The previous section describes possible factors of each SEM that can influence the performance; however, the strategic placing of rain gauges can also be a factor that can cause a poor performance by the spatial estimation. The impact of the strategic placing (also called, sample design by Li and Heap (2008, 2011)) of the rain gauges on the accuracy of the spatial estimation is discussed in a number of studies and it is also examined in this study by the three spatial estimation experiments with an increasing number of rain gauges per experiment (21, 39, and 50 rain gauges). The impact of the quantity of the rain gauges on the performance (statistical and visually) of each SEM is discussed and compared with other studies in this section.

Interestingly, the best performances of all spatial estimation methods in this research were not generated with the data sets of experiment 3 (Table 6-1), but with less rain gauges (21 and 39 rain gauges). In contrast, Bregt (1992) and Dirks, Hay, Stow, and Harris (1998) did not find significant differences in the performance of the applied SEMs with any data point density. On the other hand, Englund et al. (1992), Isaaks and Srivastava (1989), and Stahl et al. (2006) explained that the performance of the SEMs is better when the measured data point density is greater, and Puente and Bras (1986) claimed that low quantity data points applied to their selected SEMs (*disjunctive* and *universal kriging*), may seriously over- or under-estimate.

Gotway, Ferguson, Hergert, and Peterson (1996) claimed that a low density of data points generated by enlarging the sample spacing reduced the information on the estimation maps (Gotway et al., 1996). In contrast, the rainfall maps generated in the second and third experiment shows more definition and variation of the rainfall quantity, especially in the Tararua and Ruahine Ranges, than the rainfall generated with the number of rain gauges used in the first experiment.

An increase of the density of the monitoring networks is utopian because it is very costly and in many cases impossible due to inaccessible steep hill country (Buytaert et al., 2006). Additionally, other research (included this research) proved that high density networks do not always improve the spatial estimation accuracy (statistically), but a high density network of rain gauges show more definition and variation of the rainfall quantity. A more even and strategic distribution of rain gauges, for example a transect of three rain gauges covering both sides and the ridge of the mountain, could be an alternative to increase the accuracy of the spatial estimation of rainfall, which models montane rainfall with its large variability caused by processes such as rain shading and strong winds. However, the literature (Li & Heap, 2008) revealed various results of the impact of the data point distribution. For example, Collins and Bolstad (1996) discovered that *splines*, a SEM not applied in this research, performed much better with dense, regularly-spaced data, while various sample patterns (random, cellular stratified, and regular grid) applied to *ordinary kriging* examined by Englund et al. (1992) did not reveal significant differences in the performance. In conclusion, a more strategic and even distribution of rain gauges could be a good alternative for a better coverage of the montane rainfall variability to archive better rainfall outputs, but it may not increase the statistical performance (root mean square values).

6.6 Rainfall distribution in the Manawatu River Catchment

The previous sections describe the factors that can influence the accuracy of the SEMs, while this section examined the montane rainfall spatial distribution in the MRC of three different temporal extents revealed on the rainfall maps in Appendix 28. Firstly, the yearly and monthly rainfall maps are discussed followed with the review of the more diverse daily rainfall maps.

According to Burgess and New Zealand Meteorological Service (1988) the coastal and low downstream areas of the MRC are dry, which the rainfall maps of this study confirmed with values around 1000 mm in these areas, while the highest tops of the Tararua and Ruahine Ranges experience over 4000 mm rainfall (Appendix 28). Interestingly, the annual rainfall map (1951-1980) by Burgess and New Zealand Meteorological Service (1988) revealed show higher rainfall values (3200 – 4800mm) on the Tararua Ranges than on the Ruahine Ranges (2000 – 3200mm), while NIWA's (2013) annual rainfall map (1971-2000) revealed a more similar rainfall distribution as the yearly rainfall maps of this study, which shows values between 2000 and 4000mm on the higher elevated areas of both Ranges (Appendix 30). The monthly rainfall maps generated in this study revealed a similar distribution as the yearly rainfall maps with high (270 – 360 mm) rainfall values on the Tararua and Ruahine Ranges and low (80 – 120 mm) rainfall quantity in the coastal and low downstream areas of the MRC. The monthly rainfall recordings by Burgess and New Zealand Meteorological Service (1988) confirmed a similar rainfall quantity distribution. Overall, yearly and monthly rainfall maps in Appendix 28 generated by the five SEMs confirmed that the rainfall distribution is mostly maintained. There are some exceptions, for example, the March 2011 rainfall map generated in the first experiment by *ordinary kriging* that shows less rainfall on the western side of the Tararua Ranges. In addition, the statistical performance of this estimation generating this output is the worst in comparison with the four other SEMs. Lastly, for the SEMs that performed statistically well with monthly (*regression kriging*) and yearly rainfall data (*Gaussian geostatistical simulation*), their rainfall maps confirmed the maintenance of the distinct pattern of rainfall.

The daily rainfall maps revealed more variance in the rainfall distribution and in the statistical performance of all SEMs. The three daily data set spatial estimations revealed three different SEMs (*regression kriging*, *Gaussian geostatistical simulation* and *empirical Bayesian kriging*) that performed the best, which is revealed in appendix 27. The rainfall maps with the measured values in Appendix 29, revealed these three SEMs maintain mostly the measured rainfall values. However, the maps generated with ordinary kriging (perform average well with daily rainfall (Appendix 27)) revealed perfectly the distinct pattern of rainfall of these particular days. In conclusion, the statistical and visual performance of daily montane rainfall estimation in this research showed too much variation, which means more investigation is required to determine a more reliable method to estimate accurately daily montane rainfall.

Chapter 7: Conclusion

The previous chapter discusses and compares the results of this research with findings of other studies, where a number of important aspects in the field of montane rainfall estimation were established for future research. These aspects are highlighted in this section and followed with a number of recommendations.

This study sought to establish how hill county rainfall can be estimated in absence of full data sets for bridging the hydrological knowledge gap of upstream areas of river catchments for preventing flooding of downstream areas across the world. This research identifies with a thorough process (literature analyses, and applying and comparing a number of SEMs applied to rainfall data) a reliable SEM, determined by a ranking assessment. The final ranking assessment revealed that *Gaussian geostatistical simulation* was the best method (their spatial estimation outputs are mapped in Appendix 31), with *regression kriging* the second best with only a small difference. Importantly, both methods are recommendable for yearly and monthly montane rainfall estimation because the results show that *Gaussian geostatistical simulation* performs the best with yearly rainfall, while *regression kriging* performs the best with monthly rainfall. Additionally, both methods can also be used for flood models to determine the height of the stopbanks in downstream areas of the catchment for protecting urban areas during heavy rainfall events. The results of the daily rainfall estimation revealed inconsistent performance across the five selected SEMs, which means that more investigation is required in daily montane rainfall estimation.

The selection of SEMs is important; however, this research identifies that the removal of "bad data" is significant in the accuracy of the data gap-filling technique. This study proved that the removal of 'bad data' increases the accuracy of the *coefficient of correlation weighting* method by 17% for patching up data gaps of the historical data and, more significantly, overall the *coefficient of correlation weighting* method without 'bad data' is 22% more accurate than the *inverse distance weighting* method. The *coefficient of correlation weighting* method is the best data gap filling technique in this research, and other studies by Westerberg et al. (2010), and Teegavarapu and Chandramouli (2005) find similar results. In conclusion, it is highly recommendable to fill rainfall data gaps with the *coefficient of correlation weighting* method and remove 'bad data' before applying this technique.

Importantly, the strategic placing of rain gauges is crucial in the accuracy of spatial estimation. The impact of the strategic placing of the rain gauges on the accuracy of the spatial estimation is examined in this study by the three spatial estimation experiments with an increasing amount of rain gauges per experiment (21, 39, and 50 rain gauges). However, including more rain gauges does not improve the accuracy of the spatial estimation in the research, but it does increase definition and variation of the rainfall quantity on the maps. Importantly, a more even and strategic distribution of rain gauges, for example a transect of three rain gauges covering both sides and the ridge of the mountain, could be an alternative to increase the accuracy of the spatial estimation of rainfall, which models montane rainfall with its large variability caused by processes such as rain shading and strong winds. The literature (Li & Heap, 2008) revealed various results of the impact of the data point distribution.

The statistical and visual performance of daily montane rainfall estimation in this research shows too much variation, while the yearly and monthly rainfall maps generated in this study revealed a similar distribution of rainfall, where the Tararua and Ruahine Ranges experience high rainfall quantities and the coastal and low downstream areas of the MRC experience low rainfall quantities. Importantly, the annual rainfall maps by Burgess and New Zealand Meteorological Service (1988) and NIWA (2013) revealed lower rainfall quantities than the rainfall maps generated in three experiments of this research. The differences in the montane rainfall quantities can be part of the knowledge gap in the quantity of rainfall montane rainfall identified at the beginning of this research.

Nevertheless, worldwide montane rainfall causes catastrophes resulting from a lack of hydrological knowledge of upstream areas of river catchments, while these areas are inaccessible to monitor rainfall. This research clearly identifies that montane rainfall can be accurately estimated with *regression kriging* and *Gaussian geostatistical simulation* and more accuracy can be acquired with the strategic placing of rain gauges and removal of “bad data”. Finally, these three aspects fill a part of the hydrological knowledge gap of upstream areas, however the results of this study suggest that more research is required to fill the knowledge gap.

7.1 Recommendations

Minimising this knowledge gap, future work in montane rainfall estimation requires adoption of the findings in this research, but more research can bridge more of that knowledge gap. Therefore, the following section lists recommendations, firstly for practitioners, secondly for scientists and thirdly for the Horizons Regional Council.

Practitioners

- The results of this research show little difference in the performance between *regression kriging* and *Gaussian geostatistical simulation* in yearly and monthly montane rainfall estimation. Therefore, this study recommends using *regression kriging* and *Gaussian geostatistical simulation* for yearly and monthly montane rainfall estimation and comparing their performance for selecting the most accurate spatial estimation method for the applied data.
- The data gap analyses in this research suggest using the *coefficient of correlation weighting* method for patching rainfall data gaps. Importantly, this research highly

recommends that ‘bad data’ must be removed before applying the *coefficient of correlation weighting* method for more accurate results.

Scientists

- The daily rainfall estimation in this study revealed inconsistent performances across the five selected SEMs, which means that more investigation is required in the spatial estimation of daily montane rainfall.
- The results of the three experiments revealed that fewer rain gauges performed better than more rain gauges. However, other research (Li & Heap, 2008) revealed various results of the impact of the data point distribution. The two aspects of incorporating more rain gauges in the spatial estimation and the strategic placing of rain gauges requires more research, because this research and other literature shows inconsistent results.

Horizons Regional Council

- The results of the monthly and yearly montane rainfall estimation, recommend using *regression kriging* and *Gaussian geostatistical simulation* to estimate rainfall yearly and monthly rainfall and for flood models to determine stop banks heights.
- The results of spatial estimation of daily rainfall suggest that more investigation in the rainfall spatial distribution and spatial estimation methods is required
- This research and other research revealed that the placing of rain gauges can influence the performance of the spatial estimation. A more even and strategic distribution of rain gauges (for example, a transect of three rain gauges covering both sides and the ridge of the mountain, especially the northern side of the Ruahine Range, the Tararua Ranges and the Puketoi Range) is recommended to archive a more accurate spatial estimation of montane rainfall in the MRC.

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Appendix 1: Comparison overview of SEMs by Burrough and McDonnell (1998)

Method	Deterministic/ Stochastic	Local/Global	Transitions abrupt/ gradual	Exact interpolator	Limitations of the procedure	Best for	Computing load	Output data structure	Assumptions of interpolation model
Classification	Deterministic 'soft' information	Global	Abrupt if used alone	No	Delineation of areas and classes may be subjective. Error assessment limited to within-class standard deviations.	Quick assessments when data are sparse. Removing systematic differences before continuous interpolation from data points.	Small	Classified polygons	Homogeneity within boundaries
Trend surfaces	Essentially deterministic (empirical)	Global	Gradual	No	Physical meaning of trend may unclear. Outliers and edge effect may distort surface. Error assessment limited to goodness of fit.	Quick assessment and removal of spatial trends.	Small	Continuous, gridded surface	Phenomenological explanation of trend, normally distributed data
Regression models	Essentially deterministic (empirical-statistical)	Global with local refinements	Gradual if inputs have gradual variation	No	Result depends on the fit of the regression model and the quality and detail of the input data surfaces. Error assessment possible if input errors are known.	Simple numerical modelling of expensive data when better methods are not available for budgets are limited.	Small	Polygons or continuous, gridded surface	Phenomenological explanation of regression model
Thiessen polygons (proximal mapping)	Deterministic	Local	Abrupt	Yes	No error assessment, only one data point per polygon. Tessellation pattern depends on distribution of data.	Nominal data from point observation.	Small	Polygons or gridded surface	Best local predictor is nearest data point.
Pycnophylactic interpolation	Deterministic	Local	Gradual	No, but conserves volumes	Data inputs are counts or densities.	Transforming step-wise patterns of population counts to continuous surfaces.	Small-moderate	Gridded surface or contours	Continuous, smooth variation is better than ad hoc areas

Method	Deterministic/ Stochastic	Local/Global	Transitions abrupt/ gradual	Exact interpolator	Limitations of the procedure	Best for	Computing load	Output data structure	Assumptions of interpolation model
Linear interpolation	Deterministic	Local	Gradual	Yes	No error assessment.	Interpolating from point data when data densities are high as in converting gridded data from one projection to another.	Small	Gridded surface	Data densities are so large that linear approximation is no problem
Moving averages and inverse distance weighting	Deterministic	Local	Gradual	Not with regular smoothing window, but can be forced	No error assessment. Results depend on size search window and choice of weighting parameter. Poor choice of window can give artefacts when used with high data densities such as digitized contours.	Quick interpolation from sparse data on regular grid or irregularly spaced samples.	Small	Gridded surfaces, contour lines	Underlying surface is smooth
Thin plate splines	Deterministic with local stochastic component	Local	Gradual	Yes, within smoothing limits	Goodness of fit possible, but within the assumptions that the fitted surface is perfectly smooth.	Quick interpolation (univariate or multivariate) of digital elevation data and related attributes to create DEMs from moderately detailed data.	Small	Gridded surfaces, contour lines	Underlying surface is smooth everywhere

Method	Deterministic/ Stochastic	Local/Global	Transitions abrupt/ gradual	Exact interpolator	Limitations of the procedure	Best for	Computing load	Output data structure	Assumptions of interpolation model
Kriging	Stochastic	Local with global variograms Local with local variograms when stratified Local with global trends	Gradual	Yes	Error assessment depends on variogram and distribution of data points and size of interpolated blocks. Requires care when modelling spatial correlation structures.	When data are sufficient to compute variograms, kriging provides a good interpolator for sparse data. Binary and nominal data can be interpolated with indicator kriging. Soft information can be also be incorporated as trends or stratification. Multivariate data can be interpolated with co-kriging.	Moderate	Gridded surfaces	Interpolated surface is smooth Statistical stationarity and the intrinsic hypothesis
Conditional simulation	Stochastic	Local with global variograms Local with local variograms when stratified Local with global trends	Irregular	No	Understanding of underlying stochastic process and models is necessary.	Provides an excellent estimate of the range of possible values of an attribute at unsampled locations that are necessary for Monte Carlo analysis of numerical models, also for error assessments that do not depend on distribution of the data but on local values.	Moderate-Heavy	Gridded surfaces	Statistical stationarity and the intrinsic hypothesis

Reference

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Appendix 2: Comparison overview of SEMs by Johnston, et al. (2001)

Method	Deterministic/ Stochastic	Output surface types	Computing time/ Modelling time[1]	Exact interpolator	Advantages	Disadvantages	Assumptions[2]
Inverse distance weighted	Deterministic	Prediction	Fast/Fast	Yes	Few parameter decisions	No assessment of prediction errors; produces "bulls eyes" around data locations	None
Global polynomial	Deterministic	Prediction	Fast/Fast	No	Few parameter decisions	No assessment of prediction errors; may be too smooth; edge points have large influence	None
Local polynomial	Deterministic	Prediction	Moderately Fast/Moderate	No	More parameter decisions	No assessment of prediction errors; may be too automatic	None
Radial basis functions	Deterministic	Prediction	Moderately Fast/Moderate	Yes	Flexible and automatic with some parameter decisions	No assessment of prediction errors; may be too automatic	None
Kriging	Stochastic	Prediction; Prediction Standard Errors; Probability; Quantile	Moderately Fast/Slower	Yes without measurement error; No with measurement error	Very flexible; allows assessment of spatial autocorrelation; can obtain prediction standard errors; many parameter decisions	Need to make many decisions on transformations, trends, models, parameters, and neighbourhoods	Data comes from a stationary stochastic process, and some methods require that the data comes from normal distribution
Cokriging	Deterministic	Prediction; Prediction Standard Errors; Probability; Quantile	Moderate/ Slowest	Yes without measurement error; No with measurement error	Very flexible; allows assessment of spatial autocorrelation; can obtain prediction standard errors; many parameter decisions	Need to make many decisions on transformations, trends, models, parameters, and neighbourhoods	Data comes from a stationary stochastic process, and some methods require that the data comes from normal distribution

1. Computingtime is computer-processing time to create a surface. Modelling time includes user-processing time to make decisions on model parameters and search neighbourhoods.
2. We assume that all methods are predicting a smooth surface from noisy data.

Reference

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Appendix 3: Comparison overview of SEMs by Basistha, et al. (2008)

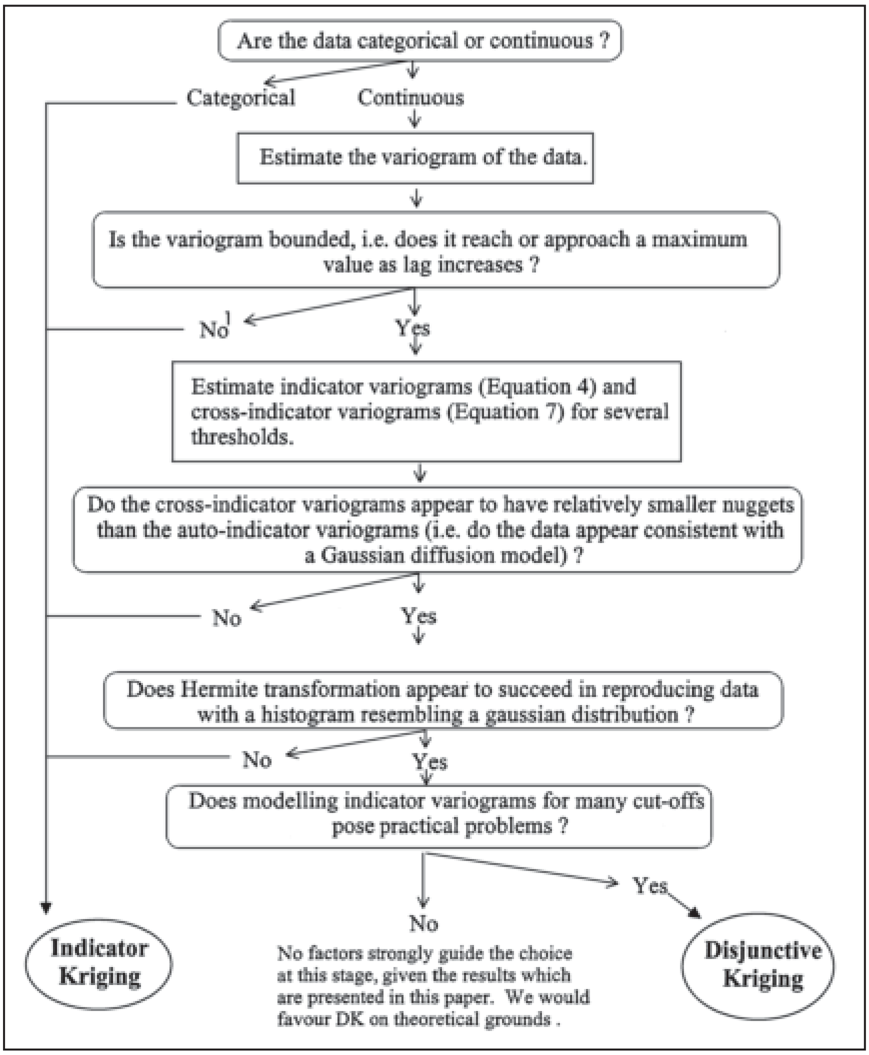
Method	Advantages	Limitations
Thiessen polygon method	Simple, most popular.	Not suitable for mountainous regions, because of orographic influence on rainfall (Goovaerts 1999)
		Unrealistic patchy maps with sudden changes at the polygon boundaries are obtained (Goovaerts 1999)
		Information on rainfall gradients is lost (Dirks et al. 1998)
Inverse distance weighted method	Compared with other methods, most notably Kriging, this method is simpler and does not require pre-modelling or subjective assumptions in selecting a semi-variogram model. The method runs faster, being of value in an emergency situation requiring rapid yet justifiable results (Tomczak 1998).	When two or more sampling points are close to each other, the redundant information from these stations are not discriminated against (Tabios and Salas 1985). Commonly have a "duck-egg" pattern around solitary data points with values that differ greatly from their surroundings (Burrough and McDonnel 1998). The surface generated is sensitive to outliers, as it is an exact interpolator.
Polynomial method	Technique is superficially easy to understand, at least with respect to the way the surfaces are calculated.	The surfaces are highly susceptible to edge effects, waving the edges to fit the points in the centre of the area, with the result that second order and higher surfaces may reach ridiculously large or small values just outside the area covered by the data.
	Broad features of the data can be modelled by low order trend surfaces.	Because it is a general interpolator, the trend surfaces are very susceptible to outliers in the data.
	Local polynomial estimators, with weaker assumptions than the parametric estimators (e.g. Kriging), adapt better to heterogeneous and non-stationary data sets (Rajagopalan and Lall 1998).	Trend surfaces are smoothing functions, rarely passing exactly through the original data points unless these are few and the order of the surface is large. The deviations from a trend surface are almost always to some degree spatially dependent. It becomes increasingly difficult to ascribe a physical meaning to complex, higher polynomials (Burrough and McDonnel 1998).

Method	Advantages	Limitations
Splines method	Because Splines are piecewise functions using few points at a time, the interpolated values can be quickly calculated.	The most critical disadvantage may be that the Thin Plate Splines provide a view that is unrealistically smooth (Burrough and McDonnel 1998).
	In contrast to trend surfaces and weighted averages, Splines retain small-scale features (Burrough and McDonnel 1998).	Another major problem with Thin Plate Splines is the steep gradients in poor data areas (Chang 2002).
	Thin Plate Smoothing Splines enjoy the significant practical advantage of having no range parameter. This makes the associated covariance structure more robustly determined when data are limited (Hutchinson 1998).	
Kriging	Geostatistical methods have the advantage of providing information on spatial anisotropy.	Like other interpolation algorithms, kriging tends to smooth out local details of the spatial variability of the attribute, leading to overestimation of small values and underestimation of large ones (Goovaerts 1997).
	External information can be combined to get the most out of expensive data.	The quality of estimates produced by Ordinary Kriging depends on the time taken to choose an appropriate model of the spatial continuity. Ordinary Kriging with a poor model may produce worse estimates than the other simpler methods (Isaaks and Srivastava 1989).
	Geostatistical methods are generally superior when there is sufficient data to estimate a variogram because, unlike splines, such methods do not treat noise as part of the signal (Burrough and McDonnel 1998). Kriging accounts both for the clustering of nearby samples and for their distance to the point being estimated. By considering statistical distance, through the variogram model, rather than Euclidian distance, it offers tremendous possibilities for customizing the estimation method to the particular problem at hand. If the pattern of spatial continuity can be described and adequately captured in a variogram model, it is hard to improve on the estimates produced by Ordinary Kriging (Isaaks and Srivastava 1989).	Though, normally the impact of different models on interpolation results is compared through cross validation, the model that produces the best cross-validated results may not yield the best predictions at unsampled locations as sample data, particularly when they are scarce and preferentially located, may not be representative of the study area (Goovaerts 1997).

Reference

Basistha, A., Arya, D. S., & Goel, N. K. (2008). Spatial distribution of rainfall in Indian Himalayas - A case study of Uttarakhand Region. *Water Resources Management*, *22*(10), 1325-1346.

Appendix 4: Decision tree for selecting Gaussian disjunctive kriging and indicator kriging by Lark and Ferguson (2004)



Equation 4:

$$\hat{\gamma}_{\Omega_c}(h) = \frac{1}{2M_h}\sum_{i=1}^{M_h}\{\omega_c(x_i) - \omega_c(x_i - h)\}^2$$

$\hat{\gamma}_{\Omega_c}$ = estimated indicator variogram

ω_c = indicator variable

$\mathrm{M_h}$ = pairs of observations

h = lag interval

x = location

Equation 7:

$$\hat{\gamma}_{\Omega_{u,v}}(h) = \frac{1}{2M_h}\sum_{i=1}^{M_h}\{\omega_u(x_i) - \omega_u(x_i + h)\} \times \{\omega_v(x_i) - \omega_v(x_i + h)\}$$

$\hat{\gamma}_{\Omega_{u,v}}$ = cross-indicator variogram

ω = indicator variable

$\mathrm{M_h}$ = pairs of observations

h = lag interval

x = location

Reference

Lark, R., & Ferguson, R. (2004). Mapping risk of soil nutrient deficiency or excess by disjunctive and indicator kriging. *Geoderma, 118*(1), 39-53.

Appendix 5: Decision tree for selecting a SEM by Li and Heap (2008)

1 Data or residuals show spatial structure
  2 Estimation of continuous variable
    3 No information of secondary variables available
      4 Global mean known ……………………………………………………………………**SK**
      4* Global mean unknown and using local means
        5 Point estimation………………………………………………………………**OK**
        5* Block estimation………………………………………………………………**BK**
    3* Information of secondary variables available
      6 Global mean known
        7 Secondary variable is only categorical
          8 Stratification……………………………………………………………**SKWS**
          8* Non-stratification……………………………………………………**SKlm**
        7* Secondary variable is not only categorical
          9 Stratification……………………………………………………………**SCKWS**
          9* Non-stratification
            10 Sparse samples of secondary variable and multiple samples in search window……………………………………………………………**SCK**
            10* Dense samples of secondary variable and single sample in search window……………………………………………………………**SCCK**
      6* Global mean unknown and using local means
        11 Secondary information available for each point being estimated
          12 Spatial trend is apparent and only coordinates available ……………**UK**
          12* Other secondary variable available
            13 An apparent global relation with the secondary variable……………**SKlm**
            13* The relation is not so apparent………………………………………**KED**
        11* Secondary information not available for each point being estimated
          14 Secondary variables including a categorical variable
            15 Only a categorical variable available
              16 Multiple samples in search window……………………………………**OKWS**
              16* Dense samples of secondary variable and single sample in search window……………………………………………………………**OCCK**
              15* Other secondary information available…………………………………**OCKWS**
            14* Secondary variables without categorical variable
              17 Sparse samples of secondary variable and multiple samples in search window
                18 Many secondary variables and PCA needed………………………………**PCK**
                18* PCA not needed to reduce the number of secondary variables
                  19 Avoid negative weights and artificially limiting the effect of secondary variable……………………………………………………**SOCK**
                  19* Accept above two drawbacks……………………………………………**OCK**
              17* Dense samples of secondary variable and single sample in search window……………………………………………………………………**OCCK**
  2* Estimation of categorical variable or uncertainty assessment………………**IK & its variants**
1* Data or residuals show no spatial structure
  20 No secondary variables available
    21 Abrupt estimation acceptable
      22 Using single sample for estimation………………………………………………**NN**
      22* Using multiple samples for estimation
        23 Using three samples for estimation………………………………………………**TIN**
        23* Using more than three natural neighbour samples for estimation……………**NaN**

21* Abrupt estimation unacceptable
24 Using more than three natural neighbour samples weighted by area...……………….**NaN**
24* Using nearest several samples weighted by distance…………..………………………**IDW**
20* Secondary variable available
25 Using information of coordinates
26 Only coordinates information used with inexact estimation
27 Using nearby samples……..……………………………..........................**Splines & LTS**
27* Using all samples…………………………………………...………………………...**TSA**
26* May use other variables with exact estimation…………....…………………………...**TPS**
25* Not using information of coordinates
28 Only categorical secondary information available
29 Only one variable available……………………...……………………………………….**CI**
29* Multiple variables available…………………………………………………………..**CART**
28* Continuous secondary information available
30 Univariate or multiple secondary information……………………..……………………..**LM**
30* Require multiple secondary information………………………………………………**CART**

Abbreviations (SEMs):
BK: block kriging
CART: regression tree
CI: classification
IDW: inverse distance weighting
IK: indicator kriging
KED: kriging with an external drift
LM: linear regression model
LTS: local trend surfaces
NaN: natural neighbours
NN: nearest neighbours
OCCK: ordinary colocated cokriging
OCK: ordinary cokriging
OCKWS: ordinary cokriging within strata
OK: ordinary kriging
OKWS: ordinary kriging within strata
PCK: principal component kriging
SCCK: simple colocated cokriging
SCK: simple cokriging
SCKWS: simple cokriging within strata
SK: simple kriging
SKlm: simple kriging with varying local means
SKWS: simple kriging within strata
SOCK: standardised ordinary cokriging
TIN: triangular irregular network
TPS: thin plate splines or Laplacian smoothing splines
TSA: trend surface analysis
UK: universal kriging

Reference

Li, J., & Heap, A. D. (2008). A review of spatial interpolation methods for environmental scientists. *Record - Geoscience Australia*, 137-137.

Appendix 6: The 40 selected studies

No	Reference	Country	Applied SEM(s)	Best performed SEM(s)
1	Apaydin et al. (2004)	Turkey	Inverse distance weighting, splines, trend surfaces, disjunctive kriging, ordinary kriging, simple kriging, disjunctive cokriging, ordinary cokriging, simple cokriging, universal cokriging and universal kriging	Splines
2	Bankanza (2011)	Czech Republic	Regression models	Regression models
3	Brown and Comrie (2002)	United States of America	Regression models	Regression models
4	Brunsdon et al. (2001)	Great Britain	Gradient plus inverse distance squared	Gradient plus inverse distance squared
5	Buytaert et al. (2006)	Ecuador	Nearest neighbours, ordinary kriging and universal kriging	Universal kriging
6	Carrera-Hernández & Gaskin (2007)	Mexico	Block kriging, ordinary kriging and kriging with an external drift	Kriging with an external drift
7	Daly et al. (1994)	United States of America	Regression models, ordinary kriging, ordinary cokriging and regression kriging	Regression models
8	Di Piazza et al. (2011)	Italy	Inverse distance weighting, regression models, ordinary kriging, gradient plus inverse distance squared and regression kriging	Ordinary kriging
9	Dingman et al. (1988)	United States of America	Universal kriging	Universal kriging
10	Diodato (2005)	Italy	Ordinary kriging and ordinary cokriging	Ordinary cokriging
11	Drogue et al. (2002)	France	Regression Models, colocated cokriging and kriging with an external drift	Regression models
12	Goovaerts (2000)	Portugal	Inverse distance weighting, ordinary kriging and simple kriging with varying local Means	Simple kriging with varying local means
13	Haberlandt (2007)	Germany	Nearest neighbours, indicator kriging, ordinary kriging, kriging with an external drift and simple kriging with varying local means	Kriging with an external drift
14	Hession and Moore (2011)	Kenya	Regression models	Regression models
15	Krishna and Abbaia (2008)	India	Trend surfaces , ordinary kriging and ordinary cokriging	Ordinary kriging

No	Reference	Country	Applied SEM (s)	Best performed SEM(s)
16	Kurtzman et al. (2009)	Israel	Inverse distance weighting and gradient plus inverse distance squared	Inverse distance weighting
17	Kyriakidis et al. (2001)	United States of America	Ordinary kriging, kriging with an external drift and simple kriging with varying local means	Simple kriging with varying local means
18	Lloyd (2005)	Great Britain	Inverse distance weighting, regression Models, ordinary kriging, kriging with an external drift and simple kriging with varying local means	Ordinary kriging and kriging with an external drift
19	Mair and Fares (2011)	United States of America	Inverse distance weighting, nearest neighbours, regression models, ordinary kriging and simple kriging with varying local means	Ordinary kriging
20	Marquinez et al (2003)	Spain	Regression models	Regression models
21	Moral (2010)	Spain	Ordinary kriging, simple kriging, colocated cokriging, simple kriging with varying local means, universal kriging and regression kriging	Regression kriging
22	Nalder and Wein (1998)	Canada	Inverse distance weighting, nearest neighbours, ordinary kriging, ordinary cokriging, universal kriging, gradient plus inverse distance squared and regression kriging	Gradient plus inverse distance squared
23	Ninyerola et al. (2000)	Spain	Regression models	Regression models
24	Oettli and Camberlin (2005)	Kenya and Tanzania	Regression kriging	Regression kriging
25	Pereira et al. (2010)	Portugal	Inverse distance Weighting, splines, thin plate splines, ordinary kriging and ordinary cokriging	Splines
26	Phillips et al. (1992)	United States of America	Ordinary kriging, ordinary kriging and regression kriging	Regression kriging
27	Price et al. (2000)	Canada	Inverse distance weighting and thin plate splines	Thin plate Splines
28	Prudhomme and Reed (1999)	Great Britain	Ordinary kriging and regression kriging	Regression kriging
29	Saghafian & Bondarabadi (2008)	Iran	Inverse distance weighting, regression models, thin plate splines, ordinary kriging and ordinary cokriging	Ordinary cokriging
30	Saveliev et al. (1998)	Switzerland	Thin plate splines, ordinary kriging and ordinary kriging	Thin plate splines and ordinary kriging

No	Reference	Country	Applied SEM(s)	Best performed SEM(s)
31	Subyani (2004)	Saudi Arabia	Ordinary Kriging	Ordinary kriging
32	Suprit and Shankar (2008)	India	Splines	Splines
33	Szolgay et al. (2009)	Slovakia	Inverse distance weighting, nearest neighbours and ordinary kriging	Inverse distance weighting and ordinary kriging
34	Tait and Turner (2005)	New Zealand	Thin plate splines	Thin plate splines
35	Vicente-Serrano et al. (2003)	Spain	Inverse distance weighting, lapse rate, nearest neighbours, regression models, splines, trend surfaces, block kriging, ordinary kriging, directional kriging, simple kriging, ordinary cokriging and universal kriging	Regression models
36	Wagner et al. (2012)	India	Inverse distance weighting, splines, trend surfaces, disjunctive kriging, ordinary kriging, simple kriging, disjunctive cokriging, ordinary cokriging, simple cokriging, universal cokriging and universal kriging	Trend surfaces
37	Westerberg et al. (2010)	Honduras	Inverse distance weighting, ordinary kriging and universal kriging	Universal kriging
38	Wüest et al. (2010)	Switzerland	Classification combined other interpolation methods	Classification combined other interpolation methods
39	Yavuz and Erdoğan (2012)	Turkey	Inverse distance weighting, splines and ordinary kriging	Ordinary kriging
40	Zhang and Srinivasan (2009)	China	Inverse distance weighting, nearest neighbours, ordinary kriging, simple kriging, kriging with an external drift and simple kriging with varying local means	Simple kriging with varying local means

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Nalder, I. A., & Wein, R. W. (1998). Spatial interpolation of climatic normals: test of a new method in the Canadian boreal forest. *Agricultural and Forest Meteorology, 92*(4), 211-225.

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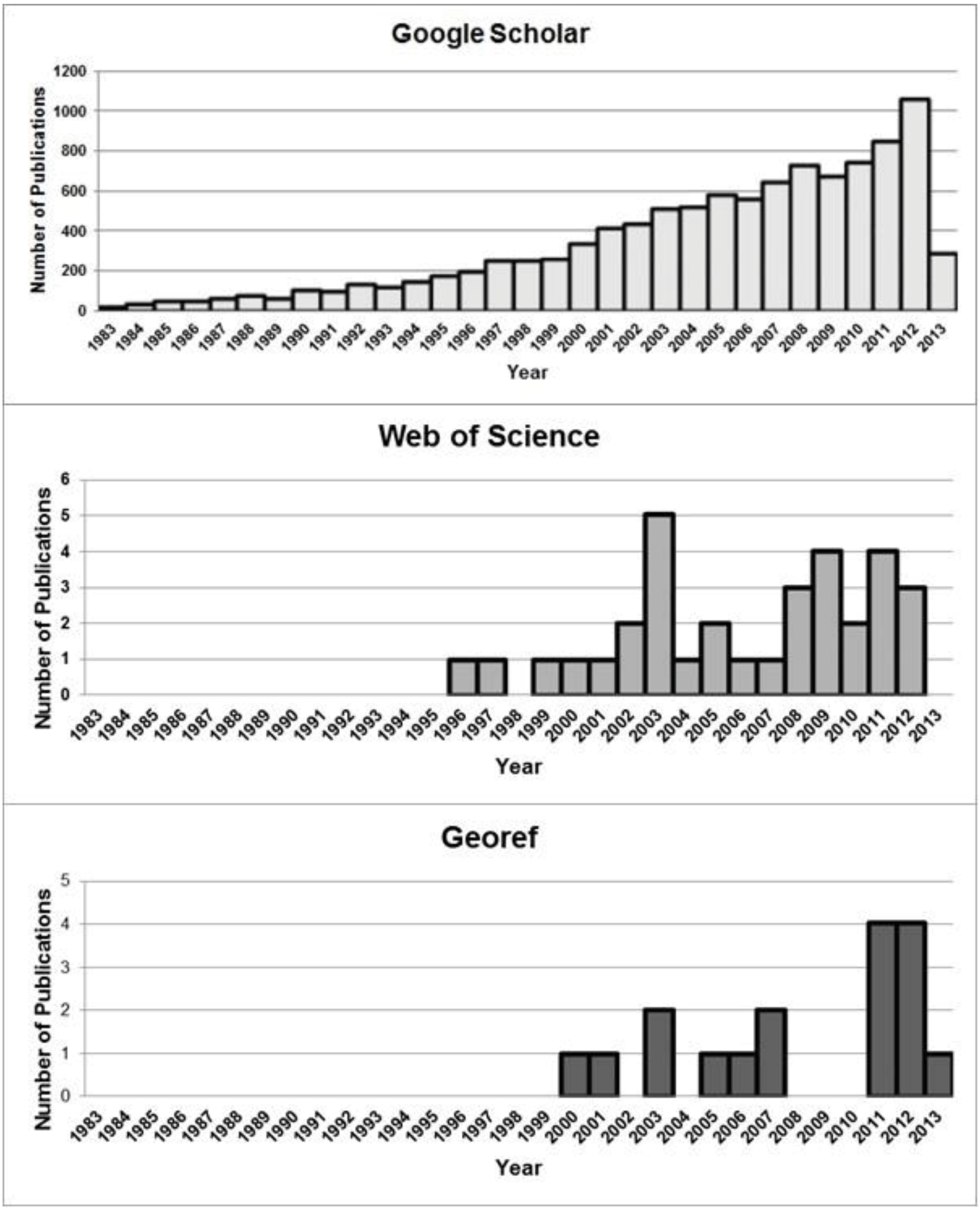
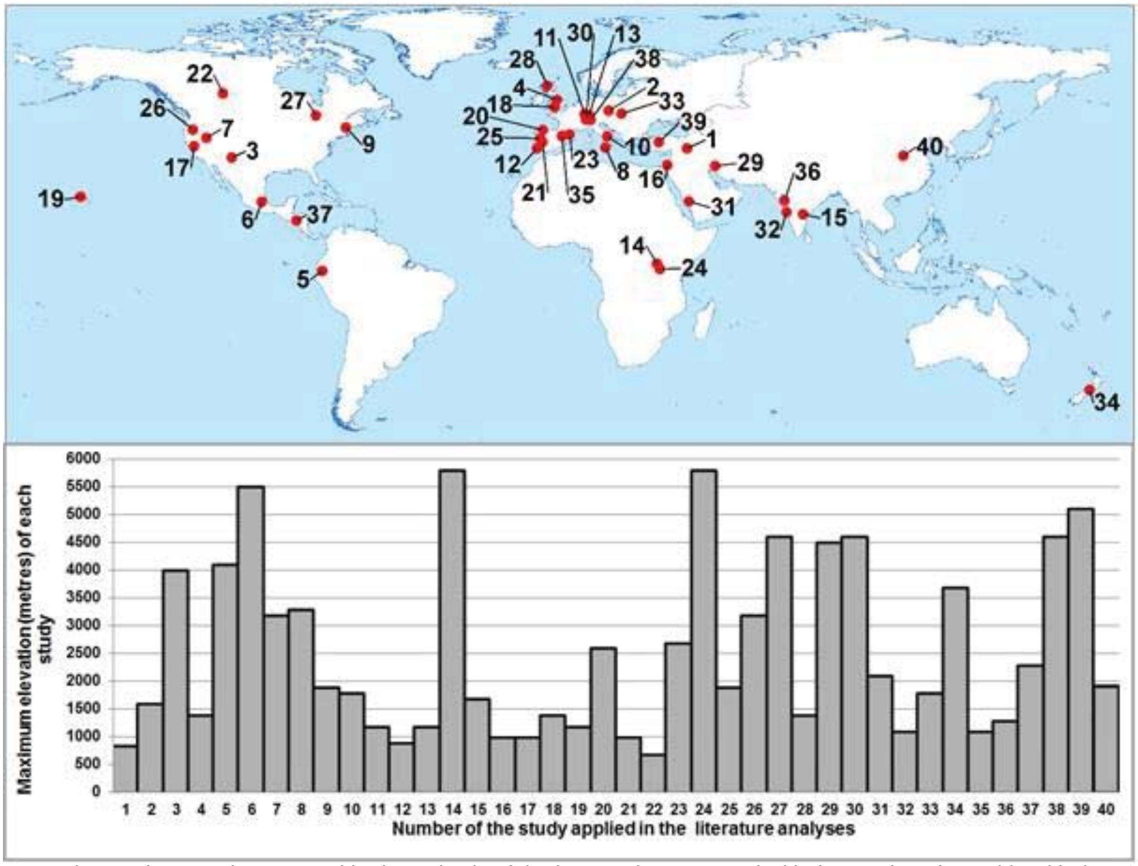
Yavuz, H., & Erdoğan, S. (2012). Spatial analysis of monthly and annual precipitation trends in Turkey. *Water Resources Management, 26*(3), 609.

Zhang, X., & Srinivasan, R. (2009). GIS-based spatial precipitation estimation: A comparison of geostatistical approaches. *Journal of the American Water Resources Association, 45*(4), 894-906.

Appendix 7: The three databases with the number of identified publications per year



Appendix 8: Background information of the literature analysis



Note: The numbers on the map and horizontal axis of the bar graph correspond with the numbers in a table with the 40 journal articles applied in the literature analyses in Appendix 6.

Figure 1: The geographical location and maximum elevation (metres) of the 40 studies applied in the literature analyses

Europe, with 17 studies, and the US, with six studies, were the hotspots of research in SEMs applied to montane rainfall (Figure 1). At the same time, Figure 1 shows more research in SEMs applied to montane rainfall were conducted in developed countries and in the northern hemisphere. The same figure (Figure 1) displays the maximum elevation of each of the 40 studies and they range from 700 metres (above sea level) in Canada (Nalder & Wein, 1998) to 5800 metres (above sea level) in Kenya (Hession & Moore, 2011; Oettli & Camberlin, 2005). The 700 metres in Canada represents the lower areas of the Rocky Mountains and 5800 metres represents Mt Kilimanjaro in Kenya.

The area around Mt Kilimanjaro, Great Britain and Turkey were used in two or more studies (Figure 2). The duplication of study areas in the selection of 40 studies was intentional because they applied different estimation methods and there were limited articles available fitting the criteria of this research. Furthermore, some of the 40 studies were done in different areas of the same country, such as six studies in the US and two studies in Italy. In total, 23 different countries are covered with the selection of 40 articles, and with only one publication by Oettli and Camberlin (2005) determining montane rainfall in two countries (Kenya and Tanzania).

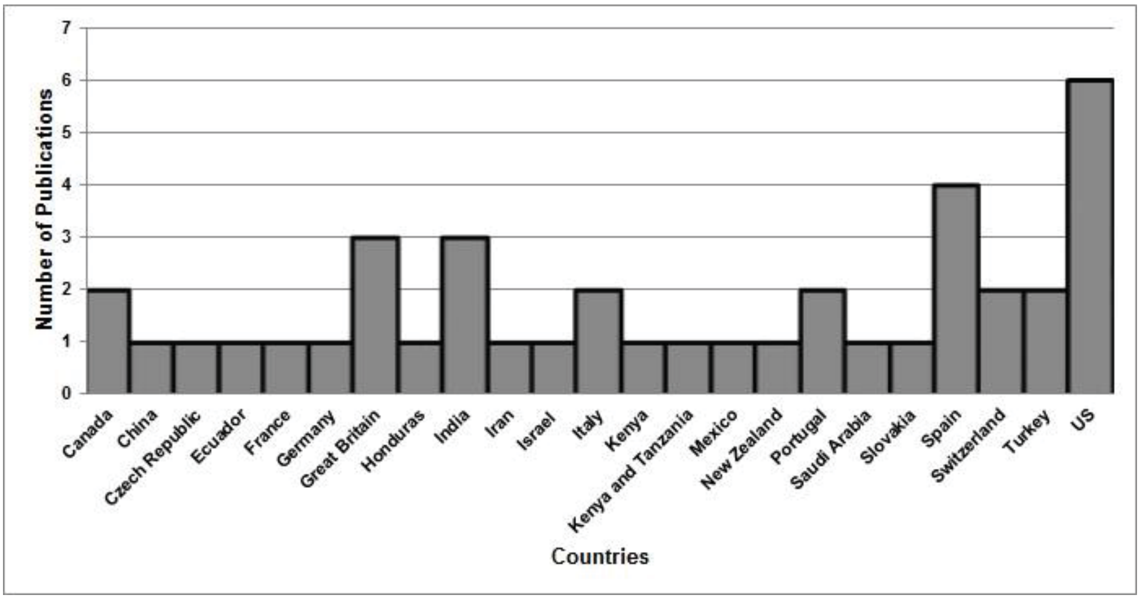


Figure 2: Number of publications per country of the 40 selected articles

Reference

Hession, S. L., & Moore, N. (2011). A spatial regression analysis of the influence of topography on monthly rainfall in East Africa. *International Journal of Climatology, 31*(10), 1440-1456.

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Oettli, P., & Camberlin, P. (2005). Influence of topography on monthly rainfall distribution over East Africa. *Climate Research, 28*, 199-212.

Appendix 9: The frequency and number times best performed of all SEMs in a review of 53 studies by Li and Heap (2008, 2011) and in this review of 40 studies

SEM	Review by Li and Heap (2008, 2011) – 53 articles		This review – 40 articles	
	Times applied	Times best performed	Times applied	Times best performed
Block kriging	2	0	2	0
Classification	3	0	Not applied	
Classification combined with other spatial interpolation methods	7	3	1	0
Cokriging	4	0	Not applied	
Colocated cokriging	2	0	1	0
Directional kriging	Not applied		1	0
Disjunctive cokriging	Not applied		1	0
Disjunctive kriging	5	0	1	0
Global mean	3	0	Not applied	
Gradient plus inverse distance squared	6	4	5	2
Indicator cokriging	1	0	1	0
Indicator kriging	4	0	Not applied	
Inverse distance weighting	30	2	16	2
Kriging	3	2	Not applied	
Kriging with an external drift	9	6	5	3
Lapse rate	1	1	1	0
Lapse rate combined with kriging	1	0	Not applied	
Local mean	1	0	Not applied	
Lognormal ordinary kriging	4	1	Not applied	

SEM	Review by Li and Heap (2008, 2011) – 53 articles		This review – 40 articles	
	Times applied	Times best performed	Times applied	Times best performed
Natural neighbours	1	0	Not applied	
Nearest neighbours	11	0	8	0
Ordinary cokriging	14	4	10	2
Ordinary kriging	37	8	26	7
Projected slope	1	0	Not applied	
Regression kriging	15	4	8	2
Regression models	13	2	12	3
Regression tree	1	0	Not applied	
Regression tree combined with kriging	2	2	Not applied	
Residual maximum likelihood-empirical best linear unbiased predictor	2	1	Not applied	
Simple cokriging	Not applied		1	0
Simple kriging	8	2	4	0
Simple kriging with varying local means	3	1	7	4
Splines and local trend surfaces	16	0	5	2
Standardised ordinary cokriging	1	1		
Thin plate splines	6	3	5	2
Topo to raster	1	0		
Trend surfaces	Not applied		3	0
Trend surface analysis combined with kriging	1	1	Not applied	
Triangular irregular network	1	0	Not applied	
Universal cokriging	Not applied		1	0
Universal kriging	8	2	7	2
Universal kriging + ordinary cokriging	1	1	Not applied	

Reference

Li, J., & Heap, A. D. (2008). A review of spatial interpolation methods for environmental scientists. *Record - Geoscience Australia*, 137-137.

Li, J., & Heap, A. D. (2011). A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors. *Ecological Informatics, 6*(3), 228-241.

Appendix 10: Spatial estimation methods

Details of the five selected SEMs are described with their own variables and equation.

Ordinary kriging

Ordinary kriging is one of the most widespread incorporated estimation method in Geographic Information System (GIS) packages (Pereira et al., 2010, p. 332). This method applies point or block computations, resulting in smoothed surface. *Ordinary kriging* assumes a constant value, but unknown, and it estimates the average value as a constant in the searching neighbourhood (Goovaerts, 1999b; Kumar et al., 2007; Pereira et al., 2010). The formula for *ordinary kriging* is:

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i (s_0) Z(s_i) + \left[1 - \sum_{i=}^{N} \lambda_i (s_0) \right] m$$

where $\hat{Z}$ represents the variable to estimate for location s_0. N is the number of measured sample points surrounding the estimation location that is applied in the estimation. λ_i represents the weights assigned to each measured point used in the estimation. These weights will decrease with distance. Z is the measured variable at location s_i, situated around s_0 calculated from the spatial covariance matrix based on the spatial continuity and m is the mean of the distribution (Kumar et al., 2007; Pereira et al., 2010).

Regression models

Regression models are based on a *linear regression* model in this research. This model assumes that the data are independent of each other and normally distributed and homogeneous in variance (Li & Heap, 2008, p. 8). This SEM explores a possible functional relationship between the primary variable (rainfall in this study) and explanatory variables (for instance elevation and slope). The formula for regression:

$$\hat{Z}(s_0) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots \beta_n X_n$$

where $\hat{Z}$ represents the variable to estimate for location s_0. β is a coefficient represent the strength and the type of relationship between the primary rainfall variable and the explanatory variable. X in the formula of regression represents the explanatory variables at location s_0.

Regression kriging

Regression kriging combines *regression* and *simple kriging*, and has the advantage that it explicitly separates trend estimation from the residual estimation, allowing the use of arbitrarily complex forms of regression (Hengl, Heuvelink, & Stein, 2004, p. 1303). Regression is applied to fit the explanatory variation and simple kriging with the expected value of zero is applied to fit the residuals (Hengl et al., 2007, p. 1302). The formula for *regression kriging* (Hengl et al., 2007; Hengl et al., 2004):

$$\hat{Z}(s_0) = \hat{m}(s_0) + \hat{e}(s_0) = \sum_{k=0}^{p} \hat{\beta}_k \cdot q_k(s_0) + \sum_{i=1}^{N} \lambda_i e(s_i)$$

where $\hat{Z}$ represents the variable to estimate for location s_0. $\hat{m}(s_0)$ is the fitted drift (drift is functional relationship between the primary variable and explanatory variables), $\hat{e}(s_0)$ is the estimated residual. $\hat{\beta}_k$ are estimated drift model coefficients. λ_i are kriging weights determined by the spatial dependence structure of the residual and where e is the residual at location s_i (Hengl, 2009a; Hengl et al., 2007; Hengl et al., 2004).

Empirical Bayesian kriging

Empirical Bayesian kriging is additional method of kriging. It differs from the classical kriging methods by automatically determining rather than manually adjusting parameters, improving the accuracy of results (Schroeder, 2013).

The semivariogram in *empirical Bayesian kriging* accounts the error introduced by estimating the semivariogram model by estimating, and then using, many semivariogram models rather than a single semivariogram used in classic kriging methods. The spectrum of semivariograms is created by a large number of simulations from multivariate distributions using Markov chain Monte Carlo techniques (Krivoruchko, 2011). The semivariogram of this additional method of kriging can be defined with the following equation (Esri, 2013):

$$\gamma(h) = Nugget + b|h|^{\alpha}$$

where γ represent the semivariogram model for a given distance h. b is the slope and α represent the power. The nugget is another semivariogram variable which represents micro scale variation at spatial scales that are too fine to detect. All these variables are estimated using the restricted maximum likelihood (Esri, 2013).

As a result of computer performance limitations by the restricted maximum likelihood, the input data is divided into subsets. These subsets are used to estimate semivariograms. These estimated semivariograms are used to simulate a new set of data at the input locations, and the simulated data is used to estimate a new semivariogram (Esri, 2013).

The overlap factor in *empirical Bayesian kriging* represents the degree of overlap between subsets which impact the smoothness of the estimated output surface and the processing time. The higher the overlap factor, the more smoother the estimated output surface will be and the longer the processing will take.

Empirical Bayesian kriging can be applied with (Empirical (requires positive input data values which guarantee that all estimated will be positive) and Log Empirical) or without transformation. This method without transformation is called the intrinsic random function of order 0. The applied spatial correlation model is the power model (Cressie, 1993):

$$\gamma(h;\theta) = \begin{cases} 0, & h = 0, \\ c_0 + b\|h\|^{\lambda}, & h \neq 0, \end{cases}$$

where b, c and λ (the power value of λ is between 0 and 2) are the model parameters and h represents the distance (Krivoruchko, 2012a). This correlation model is identical to the fractional Brownian motion that is also known as the random walk process (Krivoruchko, 2012a). This process corresponds with steps in a random direction and it filters out a moderate trend in the applied data.

Gaussian geostatistical simulation

This SEM has an unconditional and a conditional stream. Unconditional *Gaussian geostatistical simulation* produces a set of values in a grid format that agrees to a standard normal distribution with a specified semivariogram and mean value of 0 and variance of 1. Conditional geostatistical simulation, also known as spatially consistent Monte Carlo simulation, does exactly the same, but it maintains the measured values at the locations (Krivoruchko, 2011).

Simulated realisations are produced by a randomly sampling from conditionally distributions of grid nodes. The grid nodes are defined with a preliminary semivariogram model. Each realisation can be a possible representation of the reality of the measured variable (Zhang, Huang & Zeng, 2009). The values from locations in a number of realisations correspond to the Gaussian distribution, with a mean equal to the simple kriging estimation and a spread given by the simple kriging variance.

The end result is a number of surfaces (depended on the selected number of realisations) created by simulation. There also surfaces created that represent the mean, median value, maximum value, minimum value and standard deviation of any cell in all realisations that fall within the area of interest (Esri, 2013). The mean surface represents the estimated surface of the variable.

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Appendix 11: Data gap-filling techniques

Details of the two data gap-filling techniques are described with their own variables and equation.

Coefficient of correlation weighting method

$$\theta_m = \frac{\sum_{i=1}^{n} \theta_i R_{m,i}}{\sum_{i=1}^{n} R_{m,i}}$$

where Θ_m is the missing data value at rain gauge *m*. *R* represents the Pearson's correlation coefficient between rain gauge *m* and another rain gauge *i and* Θ_i is the measured rainfall at rain gauge *i*. *n* is the number of gauges considered for the correlations (Roudier et al., 2012).

Inverse distance weighting method

$$\theta_m = \frac{\sum_{i=1}^{n} \theta_i d_{mi}^{-k}}{\sum_{i=1}^{n} d_{mi}^{-k}}$$

where Θ_m is the missing data value at rain gauge *m*. *d* represents distance between rain gauge *i* and *m, and* Θ_i is the measured rainfall at rain gauge *i*. *k* is the power that controls the degree of local influence, with two as the most applied value for *k* (Teegavarapu & Chandramouli, 2005).

References

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Appendix 12: Root mean square error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(z_{i,act} - z_{i,est}\right)^2}$$

where n represents the number of sample points, $z_{i,act}$ is the known value of the sample point i, and $z_{i,est}$ represents the estimated value of sample point i (Li & Heap, 2008).

References

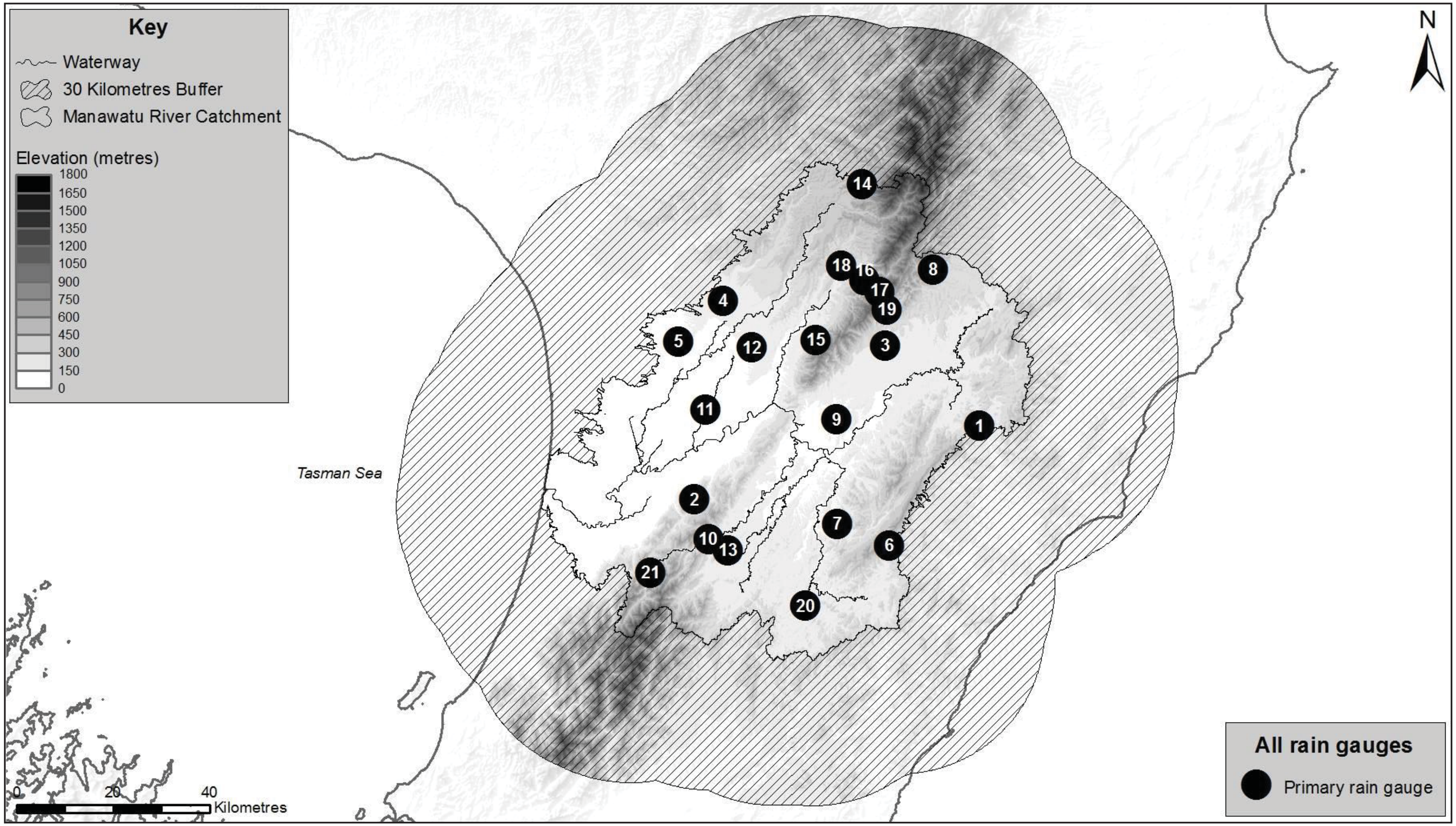
Li, J., & Heap, A. D. (2008). A review of spatial interpolation methods for environmental scientists. *Record - Geoscience Australia*, 137-137.

Appendix 13: Primary rainfall data set

Geographical location details of the rain gauges:

Site number	Site name	Altitude (metres)	Geographical location	
			Latitude	Longitude
1	Akitio at Toi Flat	274	-40.33	176.27
2	Kahuterawa at Scotts Road	378	-40.49	175.58
3	Kumeti at Rua Roa	262	-40.19	176.03
4	Makino at Cheltenham	227	-40.12	175.64
5	Makino at Halcombe Road	123	-40.19	175.53
6	Makuri at Bee 4 Trig	479	-40.56	176.06
7	Makuri at Tuscan Hills	120	-40.52	175.93
8	Manawatu at Apiti Track	507	-40.04	176.14
9	Manga-atua at Hutchinsons	106	-40.33	175.92
10	Mangahao at Kakariki	217	-40.56	175.62
11	Mangaone at Milson Line	32	-40.32	175.60
12	Mangaone at Valley Road	140	-40.20	175.71
13	Mangatainoka at Hillwood Hukanui	212	-40.58	175.67
14	Oroua at Rangiwahia	641	-39.89	175.96
15	Pohangina at Alphabet Hut	414	-40.18	175.86
16	Pohangina at Delaware Ridge	903	-40.07	175.98
17	Pohangina at Makawakawa Divide	1143	-40.09	176.02
18	Pohangina at Range View Farm	405	-40.04	175.92
19	Tamaki at Tamaki Reserve	384	-40.12	176.03
20	Tiraumea at Alfredton	154	-40.68	175.86
21	Upper Mangahao at No.1 Dam	359	-40.63	175.48

Geographical location of the rain gauges:



Temporal extent details of the rain gauges:

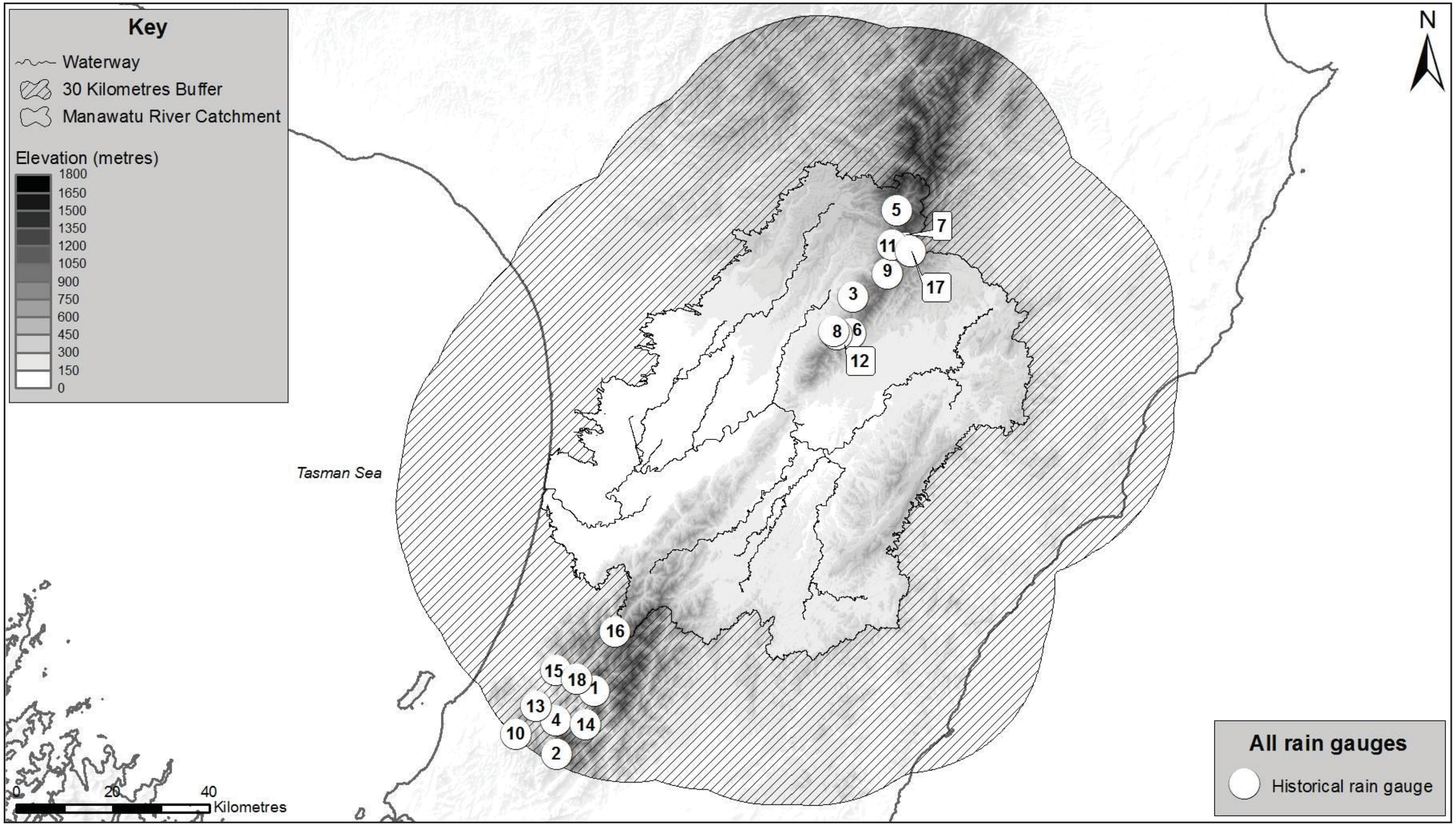
Site number	Site name	Temporal extent		
		Start date	**Finish date**	**Total number of years of data**
1	Akitio at Toi Flat	22/07/1978	1/05/2013	35
2	Kahuterawa at Scotts Road	22/12/1998	1/05/2013	15
3	Kumeti at Rua Roa	17/12/1975	1/05/2013	38
4	Makino at Cheltenham	20/12/1989	1/05/2013	24
5	Makino at Halcombe Road	16/12/1998	1/05/2013	15
6	Makuri at Bee 4 Trig	18/12/2003	1/05/2013	10
7	Makuri at Tuscan Hills	22/02/2002	1/05/2013	11
8	Manawatu at Apiti Track	19/06/1987	1/05/2013	26
9	Manga-atua at Hutchinsons	21/02/2003	1/05/2013	10
10	Mangahao at Kakariki	27/07/1989	1/05/2013	24
11	Mangaone at Milson Line	18/05/2001	1/05/2013	12
12	Mangaone at Valley Road	3/03/1987	1/05/2013	26
13	Mangatainoka at Hillwood Hukanui	20/01/1987	1/05/2013	26
14	Oroua at Rangiwahia	3/08/1977	1/05/2013	36
15	Pohangina at Alphabet Hut	10/07/1977	1/05/2013	36
16	Pohangina at Delaware Ridge	19/12/1975	1/05/2013	38
17	Pohangina at Makawakawa Divide	2/10/1974	1/05/2013	39
18	Pohangina at Range View Farm	1/07/2008	1/05/2013	5
19	Tamaki at Tamaki Reserve	3/10/1974	1/05/2013	39
20	Tiraumea at Alfredton	22/07/1978	1/05/2013	35
21	Upper Mangahao at No.1 Dam	2/07/1977	1/05/2013	36

Appendix 14: Historical rainfall data set

Geographical location details of the rain gauges:

Site number	Site name	Altitude (metres)	Geographical location	
			Latitude	Longitude
1	Andersons Hut	865	-40.85	175.35
2	Aston Peaks	1338	-40.97	175.26
3	Diggers Hut	504	-40.10	175.95
4	Fields Hut	739	-40.91	175.26
5	Iron Gate	681	-39.94	176.05
6	Kumeti	710	-40.17	175.95
7	Leon Kinvig	819	-40.01	176.08
8	Maharahara	947	-40.17	175.92
9	Mid Pohangina	561	-40.06	176.03
10	Mt Kapakapanui	1020	-40.93	175.16
11	Ngamoko	1368	-40.00	176.04
12	Opawe	648	-40.17	175.91
13	Roaring Meg	461	-40.88	175.21
14	Tararua Peaks	1060	-40.91	175.33
15	Taungata	882	-40.81	175.25
16	Te Matawai Hut	880	-40.74	175.40
17	Toms	1083	-40.01	176.09
18	Waitewaewae Hut	322	-40.83	175.31

Geographical location of the rain gauges:



Temporal extent details of the rain gauges:

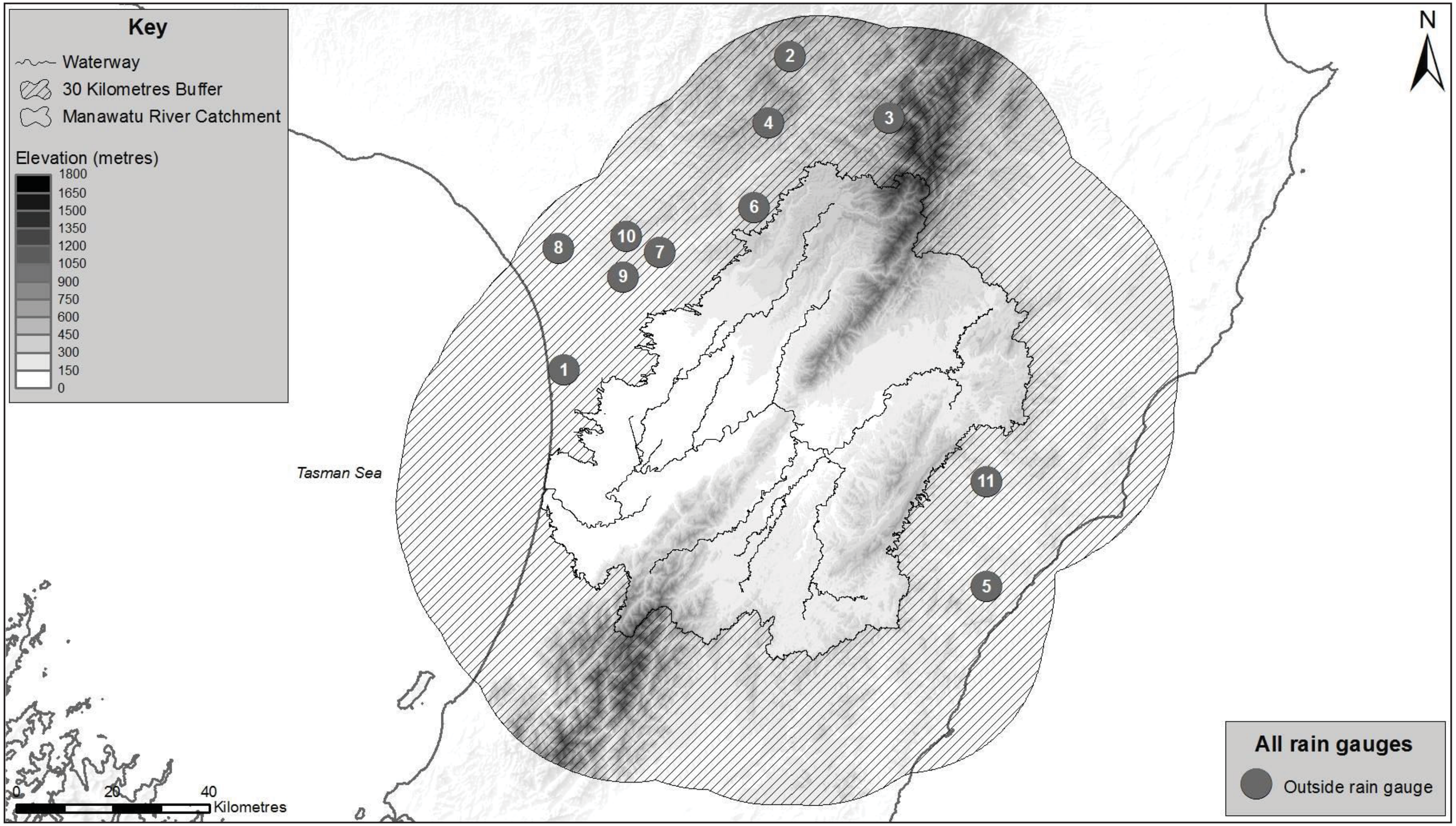
Site number	Site name	Temporal extent		
		Start date	Finish date	Total number of years of data
1	Andersons Hut	5/02/1967	25/09/1980	13
2	Aston Peaks	22/08/1976	25/09/1980	4
3	Diggers Hut	27/01/1965	30/10/1977	12
4	Fields Hut	25/06/1966	8/02/1979	13
5	Iron Gate	15/02/1965	31/08/1976	11
6	Kumeti	26/02/1968	30/11/1977	9
7	Leon Kinvig	9/01/1965	5/04/1977	12
8	Maharahara	24/02/1965	10/01/1979	14
9	Mid Pohangina	8/01/1965	2/01/1978	13
10	Mt Kapakapanui	26/08/1971	8/05/1980	9
11	Ngamoko	14/01/1965	16/04/1979	14
12	Opawe	26/01/1965	6/12/1977	12
13	Roaring Meg	22/08/1976	8/05/1980	4
14	Tararua Peaks	22/08/1976	25/09/1980	4
15	Taungata	12/07/1975	8/05/1980	5
16	Te Matawai Hut	12/07/1975	8/05/1980	5
17	Toms	12/01/1965	6/12/1977	12
18	Waitewaewae Hut	5/07/1966	8/05/1980	14

Appendix 15: Rainfall data set covering rain gauges outside the catchment

Geographical location details of the rain gauges:

Site number	Site name	Altitude (metres)	Geographical location	
			Latitude	Longitude
1	Forest Rd Drain at Drop Structure	17	-40.25	175.26
2	Hautapu at Alabasters	435	-39.66	175.78
3	Kawhatau Catchment at Upper Kawhatau	623	-39.77	176.02
4	Makohine at Zohs Road	430	-39.78	175.73
5	Owahanga at Branscombe Bridge	33	-40.63	176.30
6	Pakihikura at Pakihikura Airstrip	279	-39.94	175.71
7	Porewa Catchment at Tututotara	160	-40.03	175.48
8	Turakina at O'Neills Bridge	20	-40.03	175.23
9	Tutaenui at Green Haven Farm	155	-40.08	175.39
10	Tutaenui at Ribby Farm	244	-40.00	175.40
11	Waihi at S.H.52	53	-40.44	176.29

Geographical location of the rain gauges:



Temporal extent details of the rain gauges:

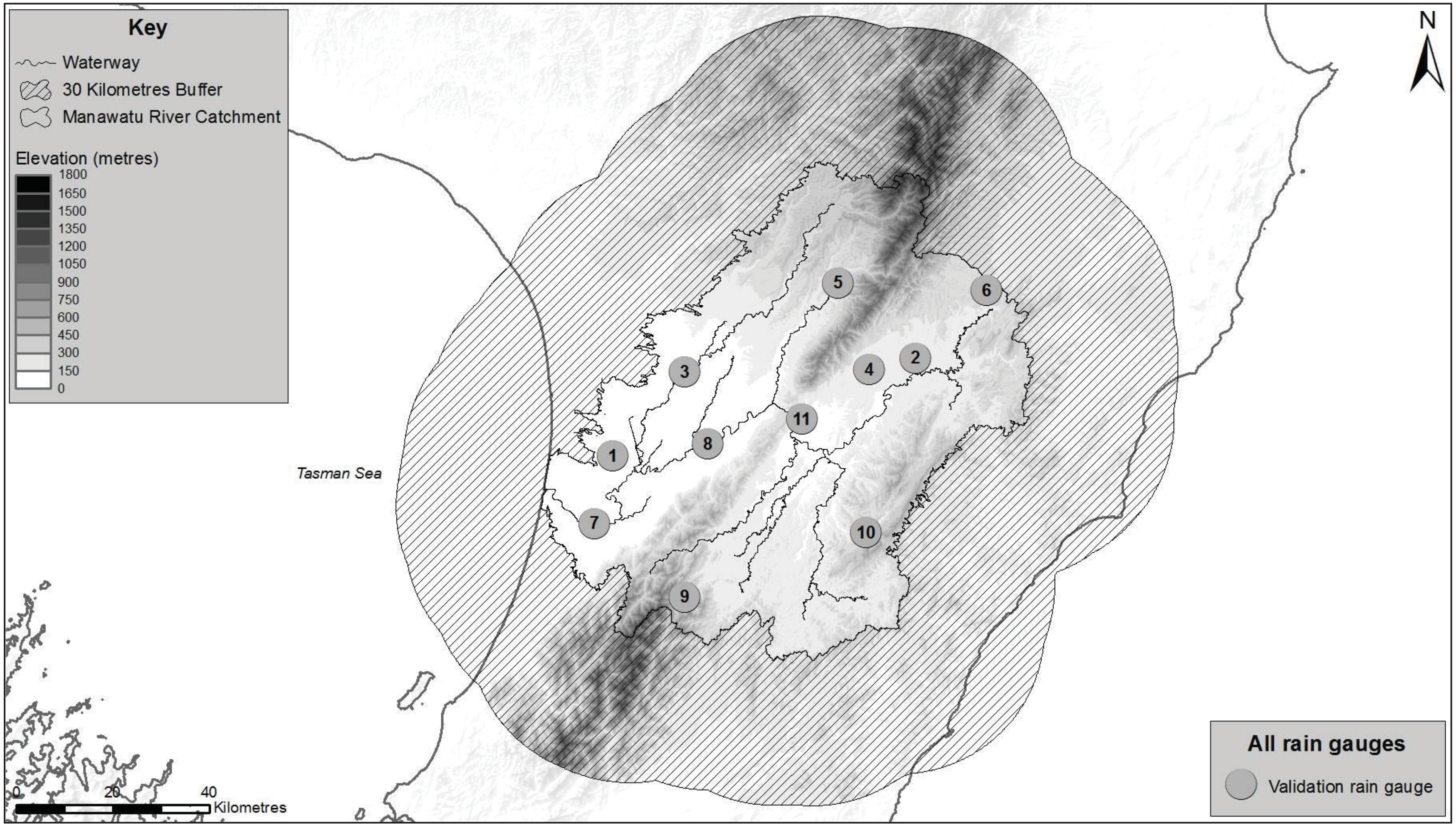
Site number	Site name	Temporal extent		
		Start date	Finish date	Total number of years of data
1	Forest Rd Drain at Drop Structure	13/08/2003	1/05/2013	10
2	Hautapu at Alabasters	13/04/2005	1/05/2013	8
3	Kawhatau Catchment at Upper Kawhatau	2/01/1995	1/05/2013	18
4	Makohine at Zohs Road	17/06/2005	1/05/2013	8
5	Owahanga at Branscombe Bridge	23/12/2002	1/05/2013	11
6	Pakihikura at Pakihikura Airstrip	6/05/2005	1/05/2013	8
7	Porewa Catchment at Tututotara	21/01/2005	1/05/2013	8
8	Turakina at O'Neills Bridge	6/05/2005	1/05/2013	8
9	Tutaenui at Green Haven Farm	14/07/2007	1/05/2013	6
10	Tutaenui at Ribby Farm	29/05/2007	1/05/2013	6
11	Waihi at S.H.52	29/09/2005	1/05/2013	8

Appendix 16: Validation rainfall data set

Geographical location details of the rain gauges:

Site number	Site name	Altitude (metres)	Geographical location	
			Latitude	Longitude
1	Bainesse	28	-40.41	175.38
2	Dannevirke	200	-40.21	176.11
3	Feilding Sewage Pt	53	-40.25	175.55
4	Kiritaki	220	-40.23	176.00
5	Komako	298	-40.07	175.91
6	Kopua	288	-40.08	176.27
7	Moutoa	3	-40.54	175.34
8	Palmerston North Ews	34	-40.38	175.61
9	Putara	316	-40.67	175.57
10	Tataramoa Makuri	260	-40.54	176.00
11	Waipuna Woodville	76	-40.33	175.84

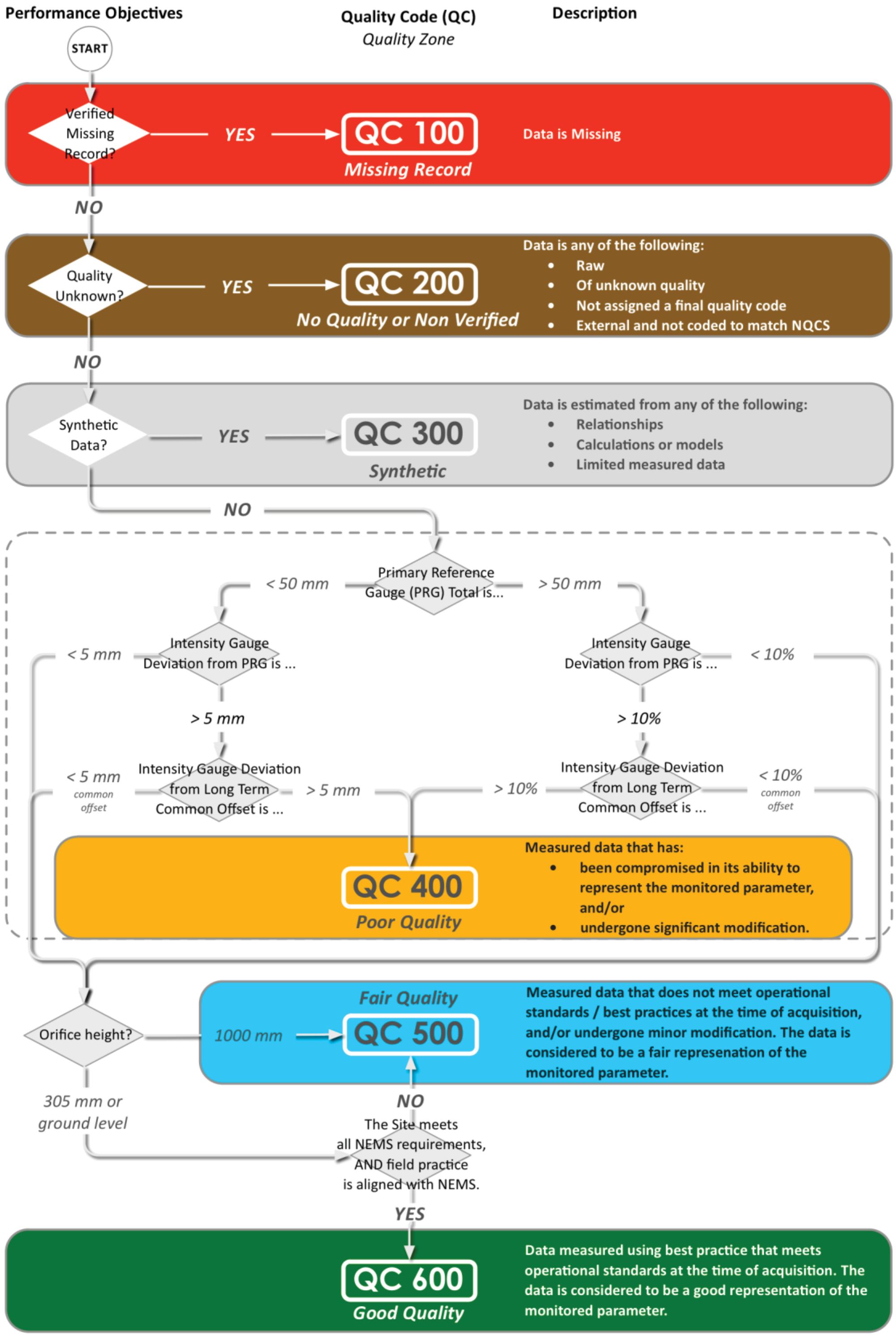
Geographical location of the rain gauges:



Temporal extent details of the rain gauges:

Site number	Site name	Temporal extent		
		Start date	Finish date	Total number of years of data
1	Bainesse	1/01/1974	31/03/2013	39
2	Dannevirke	1/01/1951	31/03/2013	62
3	Feilding Sewage Pt	1/01/1967	31/08/2012	45
4	Kiritaki	1/02/1971	28/02/2013	42
5	Komako	1/01/1913	31/03/2013	100
6	Kopua	1/07/1962	31/03/2013	51
7	Moutoa	1/10/1941	30/04/2012	71
8	Palmerston North Ews	1/04/2001	30/04/2013	12
9	Putara	1/12/1917	31/03/2013	96
10	Tataramoa Makuri	1/04/1943	31/01/2013	70
11	Waipuna Woodville	1/11/1924	31/03/2013	89

Appendix 17: NEMS' quality code schema for rainfall recording



Reference

LAWA. (2013). *Factsheet: (NEMS) National Environmental Monitoring Standards*. Retrieved 7 December, 2014, from http://www.lawa.org.nz/learn/factsheets/(nems)-national-environmental-monitoring-standards/

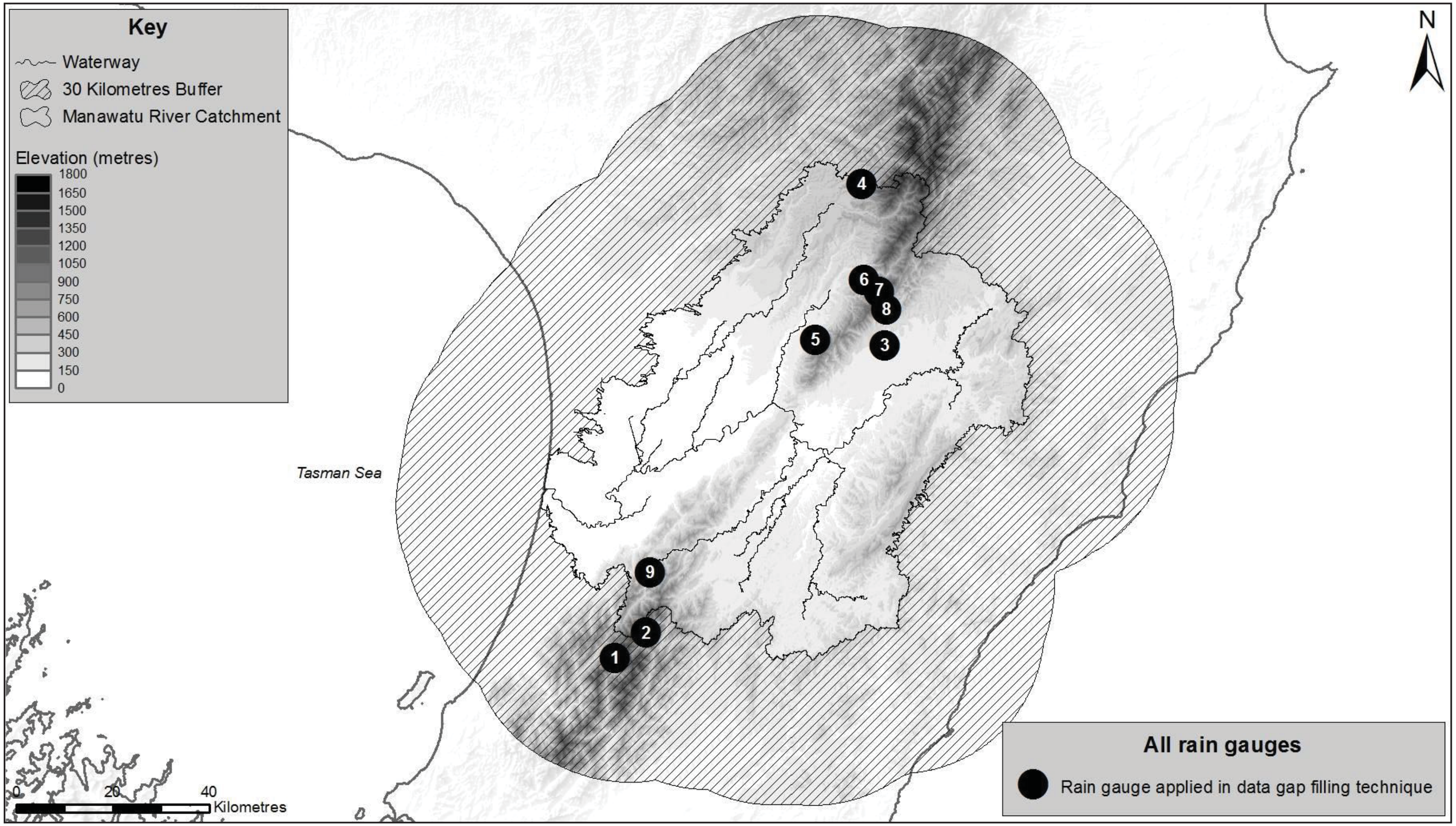
Appendix 18: Rain gauges used to determine the historical data with data gap-filling techniques

Geographical location details of the rain gauges:

Site number	Site name	Altitude (metres)	Geographical location	
			X coordinate	Y coordinate
1	Carkeek*	1159	1802385	5482185
2	Bannister Basin*	943	1808833	5487428
3	Kumeti at Rua Roa	262	1858200	5546806
4	Oroua at Rangiwahia	641	1853391	5580221
5	Pohangina at Alphabet Hut	414	1843894	5548005
6	Pohangina at Delaware Ridge	903	1853896	5560412
7	Pohangina at Makawakawa Divide	1143	1857098	5557911
8	Tamaki at Tamaki Reserve	384	1858499	5554209
9	Upper Mangahao at No.1 Dam	359	1809587	5499888

*This rain gauge is under management by the Greater Wellington Regional Council.

Geographical location of the rain gauges:



Appendix 19: Generating slope data

The slope tool in ArcMap is applied in this research to generate the slope data. This appendix explains the principle of how the slope tool works.

For each cell in the DEM (Digital Elevation Model), the Slope tool calculates the maximum rate of change in value from that cell to its neighbours. The maximum change over distance between the cell and the eight neighbours (3 x 3 cell neighbourhood) determines the steepest descent from the cell. The slope value of this plane is calculated by applying the average maximum technique (Burrough & McDonnell, 1998).

The rate of change (delta) of the surface in the horizontal (dz/dx) and vertical (dz/dy) directions from the centre cell determines the slope (Esri). The basic algorithm used to calculate the slope is (Esri):

Slope radians = ATAN (√ ([dz/dx]2 + [dz/dy]2))

The slope is in degrees, which uses the algorithm:
Slope degrees = ATAN (√ ([dz/dx]2 + [dz/dy]2)) * 57.29578

The slope algorithm can also be interpreted as:
Slope degrees = ATAN (rise run) * 57.29578

where:
rise run = √ ([dz/dx]2 + [dz/dy]2]

An example of a slope calculation (Esri):

50	45	50
30	30	30
8	10	10

The cell size is 5 units and the slope measure of degrees is used.

The rate of change in the x direction for the centre cell 'e' is:
[dz/dx] = ((c + 2f + i) - (a + 2d + g)) / (8 * x_cell_size)
[dz/dx] = ((50 + 60 + 10) - (50 + 60 + 8)) / (8 * 5)
[dz/dx] = (120 - 118) / 40
[dz/dx] = 0.05

The rate of change in the y direction for the centre cell 'e' is:

[dz/dy] = ((g + 2h + i) - (a + 2b + c)) / (8 * y_cell_size)

[dz/dy] = ((8 + 20 + 10) - (50 + 90 + 50)) / (8 * 5)

[dz/dy] = (38 - 190) / 40

[dz/dy] = -3.8

The slope for the centre cell 'e' is calculated using the rate of change in the x and y direction:

Rise run = √ ([dz/dx]2 + [dz/dy]2)

Rise run = √ ((0.05)2 + (-3.8)2]

Rise run = √ [0.0025 + 14.44]

Rise run = 3.80032

Slope degrees = ATAN (rise_run) * 57.29578

Slope degrees = ATAN (3.80032) * 57.29578

Slope degrees = 1.31349 * 57.29578

Slope degrees = 75.25762

The slope value for cell 'e' is 75 degrees (Esri).

59	56	59
71	75	70
60	63	57

References

Burrough, P. A., & McDonnell, R. (1998). *Principles of geographical information systems*. Oxford New York: Oxford University Press.

Esri. (2013). *ArcGIS*. Retrieved December 12, 2013, from http://www.arcgis.com/features/

Appendix 20: Ordinary kriging

The tested variables of *ordinary kriging*

No	Model	Maximum neighbours	Minimum neighbours
1	Circular	5	2
2	Spherical	5	2
3	Tetraspherical	5	2
4	Pentaspherical	5	2
5	Exponential	5	2
6	Gaussian	5	2
7	Rational Quadratic	5	2
8	Hole Effect	5	2
9	K-Bessel	5	2
10	J-Bessel	5	2
11	Stable	5	2
12	Stable	5	2
13	Circular	10	4
14	Spherical	10	4
15	Tetraspherical	10	4
16	Pentaspherical	10	4
17	Exponential	10	4
18	Gaussian	10	4
19	Rational Quadratic	10	4
20	Hole Effect	10	4
21	K-Bessel	10	4
22	J-Bessel	10	4
23	Stable	10	4
24	Stable	10	4
25	Circular	2	1
26	Spherical	2	1
27	Tetraspherical	2	1
28	Pentaspherical	2	1
29	Exponential	2	1
30	Gaussian	2	1
31	Rational Quadratic	2	1
32	Hole Effect	2	1
33	K-Bessel	2	1
34	J-Bessel	2	1
35	Stable	2	1
36	Stable	2	1

The performances of *ordinary kriging* applied to the data sets with a number of different variables – experiment 1

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	604.28	630.55	583.14	39.53	39.06	54.74	***2.71***	4.90	8.77
2	598.69	635.91	583.14	39.07	39.06	54.74	***2.71***	4.90	8.77
3	597.66	635.91	583.14	38.93	39.06	54.74	***2.71***	4.90	8.78
4	598.94	635.91	583.14	38.95	39.06	54.74	***2.71***	4.92	8.78
5	597.96	635.91	583.14	38.74	39.06	54.74	***2.71***	4.91	8.78
6	604.34	631.07	583.14	39.71	39.06	54.74	***2.71***	4.90	8.77
7	601.02	635.91	583.14	38.30	39.06	54.74	***2.71***	4.97	8.78
8	607.10	635.91	583.14	41.47	39.06	54.74	***2.71***	5.34	8.77
9	604.00	628.57	583.77	39.52	41.01	54.74	***2.71***	4.92	8.78
10	608.79	635.91	583.14	39.92	39.06	54.74	***2.71***	5.08	8.78
11	***571.81***	628.88	583.14	39.88	39.06	54.74	***2.71***	4.96	8.78
12	***571.81***	628.88	583.14	41.50	39.06	54.74	***2.71***	4.96	8.78
13	585.55	646.48	593.35	37.33	***33.09***	***47.53***	2.93	5.04	8.75
14	578.09	654.29	593.35	37.12	***33.09***	***47.53***	2.93	5.04	8.75
15	579.58	654.29	593.35	37.17	***33.09***	***47.53***	2.93	5.04	8.75
16	583.23	654.29	593.35	37.34	***33.09***	***47.53***	2.93	5.06	8.75
17	598.17	654.29	593.35	37.05	***33.09***	***47.53***	2.93	5.06	8.76
18	582.32	647.27	593.35	37.63	***33.09***	***47.53***	2.93	5.04	8.75
19	608.54	654.29	593.35	***36.95***	***33.09***	***47.53***	2.93	5.07	8.76
20	589.55	654.29	593.35	38.89	***33.09***	***47.53***	2.93	5.64	8.79
21	603.04	640.62	589.31	37.86	33.19	***47.53***	2.93	5.06	8.76
22	590.19	654.29	593.35	38.58	***33.09***	***47.53***	2.93	***4.76***	8.76
23	585.60	641.82	593.35	38.32	***33.09***	***47.53***	2.93	5.10	8.76
24	585.60	641.82	593.35	38.32	***33.09***	***47.53***	2.93	5.10	8.76
25	611.92	581.40	547.75	42.82	33.88	52.56	2.77	5.39	8.78
26	595.81	583.11	547.75	42.36	33.88	52.56	2.77	5.39	8.79
27	591.92	583.11	547.75	42.11	33.88	52.56	2.77	5.39	8.79
28	589.87	583.11	547.75	42.00	33.88	52.56	2.77	5.39	8.79
29	600.51	583.11	547.75	41.81	33.88	52.56	2.77	5.39	8.79
30	602.81	581.55	547.75	42.86	33.88	52.56	2.77	5.39	8.79
31	600.10	583.11	547.75	41.30	33.88	52.56	2.77	5.38	8.75
32	608.05	583.11	547.75	40.93	33.88	52.56	2.77	5.67	8.80
33	604.30	579.19	***546.06***	42.28	36.38	52.56	2.77	5.39	8.79
34	606.94	583.11	547.75	42.30	33.88	52.56	2.77	5.21	***8.75***
35	603.12	***578.77***	547.75	42.45	33.88	52.56	2.77	5.39	8.79
36	603.12	***578.77***	547.75	42.45	33.88	52.56	2.77	5.39	8.79

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *ordinary kriging* applied to the data sets with a number of different variables - experiment 2

No	**2009**	**2010**	**2011**	**June 2009**	**May 2010**	**March 2011**	**1 June 2009**	**13 May 2010**	**7 March 2011**
1	685.32	599.99	582.07	44.17	35.41	51.34	2.39	5.46	8.72
2	681.47	597.01	577.99	47.15	35.41	51.17	2.37	5.51	8.73
3	675.91	595.12	561.82	46.15	36.58	51.44	2.40	5.48	8.73
4	667.91	593.71	585.14	45.73	34.65	51.39	2.41	5.47	8.73
5	696.81	649.54	621.08	45.13	37.73	51.89	2.45	5.38	8.72
6	645.57	585.52	625.30	45.31	37.49	50.95	***2.34***	5.55	8.73
7	692.56	655.54	610.53	43.44	30.46	52.14	2.57	***5.35***	8.71
8	***554.25***	501.90	533.51	41.60	39.54	54.87	2.36	5.65	8.69
9	681.26	629.80	632.27	41.78	36.20	52.33	2.35	5.46	8.74
10	660.94	532.60	581.70	43.26	37.19	53.83	2.56	5.47	8.73
11	682.07	639.63	627.10	42.26	35.58	52.25	2.35	5.48	8.73
12	682.07	639.63	627.10	42.26	35.58	52.25	2.35	5.48	8.73
13	673.39	597.28	576.95	44.19	34.53	48.66	2.44	5.52	8.69
14	663.96	585.31	564.41	47.00	35.15	48.84	2.45	5.57	8.69
15	654.66	579.34	542.59	45.96	36.39	49.23	2.48	5.54	8.69
16	643.82	576.03	588.07	44.57	34.45	49.21	2.49	5.52	8.70
17	687.70	649.40	602.25	46.51	36.73	49.55	2.51	5.49	8.70
18	631.91	580.14	627.09	49.01	37.65	48.65	2.39	5.49	8.70
19	673.65	642.75	621.49	43.09	***29.75***	50.00	2.59	5.45	8.71
20	577.50	***482.45***	564.03	44.60	44.10	58.06	2.60	5.69	***8.64***
21	665.42	626.33	617.30	***41.51***	35.35	50.09	2.47	5.55	8.70
22	744.40	585.38	666.08	47.28	37.78	51.59	2.59	5.54	8.69
23	666.71	626.35	643.21	42.06	34.79	50.00	2.45	5.58	8.70
24	666.71	626.35	643.21	42.06	34.79	50.00	2.45	5.58	8.70
25	695.68	618.79	589.33	44.38	31.66	***43.75***	2.61	5.79	8.70
26	715.94	635.45	598.29	45.55	32.23	44.68	2.65	5.81	8.70
27	713.64	638.99	598.83	44.95	32.62	44.58	2.59	5.77	8.71
28	716.46	644.63	579.61	44.59	34.55	45.42	2.59	5.74	8.69
29	665.64	600.45	576.23	44.62	38.26	46.92	2.61	5.59	8.71
30	684.68	621.64	622.29	45.35	32.93	44.23	2.67	5.66	8.71
31	647.95	579.86	647.99	43.07	31.26	52.73	2.64	5.58	8.70
32	647.10	564.08	***526.60***	50.02	39.14	46.88	2.57	5.79	8.66
33	721.68	587.59	585.36	42.93	37.27	47.19	2.66	5.78	8.71
34	656.30	579.87	551.38	47.16	33.07	53.79	2.60	5.76	8.73
35	719.98	588.58	646.29	43.27	36.84	52.62	2.65	5.80	8.71
36	719.98	588.58	646.29	43.27	36.84	52.62	2.65	5.80	8.71

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *ordinary kriging* applied to the data sets with a number of different variables - experiment 3

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	604.85	535.76	524.56	41.53	37.90	42.88	2.51	5.86	8.72
2	594.09	518.06	523.81	40.56	36.92	42.59	2.51	5.82	8.74
3	586.48	519.89	508.07	40.06	37.12	42.64	2.50	5.79	8.74
4	591.73	513.44	493.86	40.61	34.29	41.96	2.52	5.77	8.75
5	616.20	570.72	526.11	41.09	32.18	42.60	2.48	5.61	8.73
6	514.00	497.87	558.51	44.44	40.11	42.89	2.48	5.40	8.75
7	630.60	595.97	558.40	39.46	30.34	42.72	2.49	5.59	8.74
8	510.87	***408.20***	***440.20***	41.30	42.53	46.67	2.53	5.52	8.69
9	596.83	560.43	552.56	40.74	34.38	43.25	2.48	5.79	8.70
10	475.17	617.55	568.96	43.73	39.68	43.59	2.51	5.78	8.71
11	597.16	564.58	538.32	40.44	38.06	43.32	2.48	5.81	8.70
12	597.16	564.58	538.32	40.44	38.06	43.32	2.48	5.81	8.70
13	591.07	523.91	518.13	39.38	36.49	43.59	2.45	5.70	8.69
14	581.15	505.60	533.20	38.27	36.33	43.55	***2.51***	5.64	8.72
15	568.23	538.90	525.61	***37.65***	36.54	43.80	2.52	5.61	8.72
16	606.02	529.52	508.35	38.64	33.61	40.89	2.54	5.59	8.74
17	606.13	561.65	517.24	39.52	31.48	42.41	2.51	5.55	8.73
18	500.56	485.25	567.12	44.49	39.68	43.85	2.45	***5.21***	8.71
19	606.37	576.63	546.95	38.35	***29.97***	42.69	2.54	5.52	8.73
20	***456.08***	492.49	507.79	40.30	39.78	41.44	2.61	5.23	***8.68***
21	586.84	551.27	534.76	38.86	33.22	41.99	2.46	5.64	8.70
22	487.20	604.71	557.73	40.79	39.79	41.97	2.58	5.61	8.70
23	587.65	555.45	536.78	39.53	36.95	42.08	2.45	5.67	8.71
24	587.65	555.45	536.78	39.53	36.95	42.08	2.45	5.67	8.71
25	621.60	561.58	515.17	41.11	36.69	***37.29***	2.48	5.83	8.71
26	594.46	531.79	509.51	40.80	36.48	38.10	2.57	5.77	8.72
27	599.82	527.02	502.06	40.56	37.16	37.83	2.56	5.61	8.72
28	593.34	528.72	498.00	40.26	37.84	40.24	2.56	5.70	8.73
29	630.63	581.16	541.99	40.93	34.24	41.50	2.55	5.59	8.73
30	596.95	552.05	540.79	43.09	37.86	37.82	2.57	5.52	8.71
31	600.92	545.35	545.26	40.89	32.45	41.13	2.63	5.59	8.72
32	630.14	471.89	465.22	41.24	43.01	45.19	2.56	5.52	8.70
33	613.89	573.27	531.15	41.95	35.60	42.82	2.57	5.76	8.73
34	549.67	671.80	628.11	47.25	38.01	41.08	2.56	5.71	8.70
35	612.83	576.46	547.46	41.38	40.01	42.90	2.57	5.78	8.73
36	612.83	576.46	547.46	41.38	40.01	42.90	2.57	5.78	8.73

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

Appendix 21: Linear regression

Three spatial estimations per data set per experiment were performed. The first estimation incorporated the relationship between rainfall and elevation in the *linear regression*, while the second spatial estimated used the correlation between rainfall and slope in the *linear regression* with rainfall. The third estimation combined the relationship between rainfall and elevation, and rainfall and slope and include these in the *linear regression*.

This SEM is based on the functional relationship between the primary variable (rainfall) and explanatory variables (elevation and slope). The functional relationship was compared between the experiments, to determine if an increase of rain gauges improved the strength of the relationship, which was determined by the regression coefficient. When the relationship is strong, the coefficient is large (the number before the x), and a weak relationship is associated with a coefficient near zero (Esri, 2013). Lastly, the influence of the relationship (strong or weak) and the increase of rain gauges to the performance of *linear regression* was analysed.

The three experiments of *linear regression* with rainfall and elevation revealed that an increase of the number data points in the data set (rainfall) does not always improves the strength of the relationship between rainfall and elevation. In only 4 of the 9 data sets (2009, 2011, March 2011, and 13 May 2010) showed an increase the strength in performance per experiment, whereas the other data sets used in *linear regression* don not required the quantity of data points (rain gauges) used in experiment 3.

The functional relationship between rainfall and elevation for the three experiments per data set

Data set	Experiment 1	Experiment 2	Experiment 3
2009	y = 1.4649x + 1154.1	y = 1.8507x + 1365.3	y = 2.3409x + 1025.1
2010	y = 1.971x + 952.1	y = 2.5556x + 974	y = 2.4247x + 979.75
2011	y = 1.5596x + 1150	y = 2.0979x + 1303.7	y = 2.1384x + 1125.7
June 2009	y = 0.1814x + 76.189	y = 0.1315x + 103.45	y = 0.1548x + 80.158
May 2010	y = 0.2237x + 59.85	y = 0.1578x + 93.11	y = 0.1447x + 99.597
March 2011	y = 0.153x + 86.88	y = 0.1607x + 106.92	y = 0.1671x + 93.077
1 June 2009	y = 0.0086x - 0.0734	y = 0.0043x + 1.4055	y = 0.0051x + 0.8483
13 May 2010	y = 0.0007x + 2.4652	y = 0.0059x + 2.0105	y = 0.0066x + 1.1995
7 March 2011	y = 0.0017x + 0.065	y = 0.0011x + 0.3473	y = 0.001x + 0.4645

The functional relationship between rainfall and slope show the stronger relationships, with higher regression coefficients, for yearly data sets compared to the monthly and daily data sets. In nearly all data sets, except 1 June 2009, the relationship between rainfall and slope became stronger. The results showed a very high increase of the regression coefficient between experiment one and two, with some of them with an increase over 100% (May 2010, March 2011, 1 June 2009, 13 May 2010, and 7 March 2011).

The functional relationship between rainfall and slope for the three experiments per data set

Data set	Experiment 1	Experiment 2	Experiment 3
2009	y = 23.108x + 1478.7	y = 40.401x + 1738.1	y = 50.391x + 1428.8
2010	y = 25.027x + 1440.6	y = 45.57x + 1720.6	y = 53.25x + 1375
2011	y = 23.254x + 1507	y = 42.223x + 1752.3	y = 49.138x + 1443.4
June 2009	y = 2.3782x + 120.51	y = 2.559x + 133.12	y = 3.2814x + 108.56
May 2010	y = 1.2051x + 129.24	y = 3.029x + 130.65	y = 3.2926x + 121.86
March 2011	y = 0.3199x + 138.65	y = 3.1109x + 143.47	y = 3.745x + 119.69
1 June 2009	y = -0.0439x + 3.3743	y = 0.0397x + 3.167	y = 0.0051x + 0.8483
13 May 2010	y = -0.0428x + 3.0794	y = 0.0956x + 3.7052	y = 0.1231x + 2.6108
7 March 2011	y = -0.0078x + 0.7329	y = 0.018x + 0.6498	y = 0.0199x + 0.6378

The three experiments of *linear regression* with rainfall, elevation, and slope revealed that the relationship between rainfall and elevation and rainfall and slope become stronger for the yearly data sets, while only the regression coefficient between rainfall and slope for monthly data sets increased per experiment. The *linear regression* of the daily data sets show very minimum differences in the regression coefficients between the experiments, but an increase of rain gauges in the data set (rainfall) does not always improves the strength of the relationship between rainfall and elevation and rainfall and slope.

The functional relationship between rainfall and elevation (e) and slope (s) for the three experiments per data set

Data set	Experiment 1	Experiment 2	Experiment 3
2009	y = (1.33*e) + (14.28*s) + 1078.99	y =(1.72*e) + (20.96*s) + 1144.88	y =(1.80*e) + (25.26*s) + 914.69
2010	y =(1.85*e) + (12.76*s) + 884.98	y =(1.94*e) + (21.91*s) + 1031.28	y =(1.98*e) + (26.52*s) + 825.52
2011	y =(1.43*e) + (13.77*s) + 1077.52	y =(1.66*e) + (21.98*s) + 1162.56	y =(1.71*e) + (25.86*s) + 968.53
June 2009	y =(0.17*e) + (1.25*s) + 69.59	y =(0.11*e) + (1.26*s) + 95.34	y =(0.11*e) + (1.73*s) + 77.31
May 2010	y =(0.23*e) + (-0.29*s) + 61.39	y =(0.13*e) + (1.50*s) + 85.97	y =(0.11*e) + (1.82*s) + 91.66
March 2011	y =(0.16*e) + (-0.74*s) + 90.76	y =(0.13*e) + (1.52*s) + 97.15	y =(0.12*e) + (2.014*s) + 84.28
1 June 2009	y =(0.01*e) + (-0.12*s) + 0.49	y =(0.01*e) + (-0.017*s) + 1.51	y =(0.01*e) + (-0.02*s) + 0.95
13 May 2010	y =(0.001*e) + (-0.05*s) + 2.73	y =(0.01*e) + (0.03*s) + 1.81	y =(0.01*e) + (0.04*s) + 1.00
7 March 2011	y =(0.002*e) + (-0.02*s) + 0.17	y =(0.001*e) + (0.01*s) + 0.31	y =(0.001*e) + (0.01*s) + 0.42

The performance of *linear regression* that incorporates the relationships between rainfall and the auxiliary data sets (elevation and slope) were compared per experiment. The first experiment revealed that the *linear regression* of yearly rainfall and elevation performed better (lower root mean square values) than the other *linear regression*s with slope and elevation-slope. The differences in the root mean square values of the *linear regression* of monthly rainfall with elevation and elevation-slope are small, with one regression with elevation (May 2010) and two regressions with elevation-slope (June 2009 and 2011 March) representing the most accurate spatial estimation of monthly rainfall for experiment one. *Linear regression* of two daily rainfall data sets (1 June 2009 and 7 March 2011) with slope and one daily rainfall (13 May 2010) data set with elevation appeared to generate lower root mean square values than the other regressions.

The results of experiment 2, expressed in root mean square values, revealed 5 of the 9 *linear regressions* produced the lowest root mean square value by applying *linear regression* to yearly and monthly rainfall with elevation-slope. Two of the rest of the *linear regression* produces the lowest root mean square with slope and the other two with elevation.

Regression with elevation produces in experiment three the lowest root mean square values with 3 yearly and 2 monthly data sets. The remainder produce a lower root mean square value with slope or elevation-slope.

The visual comparison of the yearly, monthly and daily rainfall maps of the three experiments generated with *linear regression* show the same coarseness as the digital elevation model used for the regression; however, the maps generated with *linear regression* including slope had lower rainfall quantities on the higher elevated areas, especially the Ruahine and Tararua Ranges, than the maps created with *linear regression* incorporating elevation and elevation-slope. Comparing the rainfall maps with other SEMS, the geographical features defined by slope and elevation (such as the ranges and the flats) appearing clearly on the maps using *linear regression* as a SEM.

All root mean square values of all estimation

Data set	Experiment 1			Experiment 2			Experiment 3		
	Linear regression rainfall and elevation	Linear regression rainfall and slope	Linear regression rainfall, elevation and slope	Linear regression rainfall and elevation	Linear regression rainfall and slope	Linear regression rainfall, elevation and slope	Linear regression rainfall and elevation	Linear regression rainfall and slope	Linear regression rainfall, elevation and slope
2009	***552.72***	632.96	559.04	596.35	791.59	***559.68***	***531.73***	665.21	562.78
2010	***522.49***	633.94	529.51	***502.56***	827.24	526.63	***504.33***	658.49	529.13
2011	***503.61***	584.72	513.07	540.06	759.73	***523.41***	***497.24***	618.42	524.31
Jun-09	34.28	44.22	***33.39***	36.42	49.10	***34.72***	***36.56***	40.97	37.19
May-10	***31.97***	46.68	32.65	33.98	48.14	***28.55***	36.24	42.06	***29.49***
Mar-11	33.40	45.60	***33.01***	37.83	57.21	***36.14***	***33.65***	1557.10	35.55
1-Jun-09	3.28	***3.17***	3.29	3.05	2.87	3.02	3.26	4.19	***3.22***
13-May-10	***4.97***	5.02	5.01	***4.61***	5.72	4.63	4.76	***4.71***	4.80
7-Mar-11	8.88	**8.76**	8.85	8.80	***8.73***	8.82	8.74	***8.73***	8.77

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

Appendix 22: Regression kriging

No	Model	Maximum neighbours	Minimum neighbours
1	Circular	2	1
2	Spherical	2	1
3	Tetraspherical	2	1
4	Pentaspherical	2	1
5	Exponential	2	1
6	Gaussian	2	1
7	Rational Quadratic	2	1
8	Hole Effect	2	1
9	K-Bessel	2	1
10	J-Bessel	2	1
11	Stable	2	1
12	Circular	10	4
13	Spherical	10	4
14	Tetraspherical	10	4
15	Pentaspherical	10	4
16	Exponential	10	4
17	Gaussian	10	4
18	Rational Quadratic	10	4
19	Hole Effect	10	4
20	K-Bessel	10	4
21	J-Bessel	10	4
22	Stable	10	4

The performances of *regression kriging* applied to the data sets with a number of different variables - experiment 1

No	2009			2010			2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	547.42	604.61	520.53	512.70	604.12	482.85	499.06	570.93	479.26
2	547.73	604.49	520.76	513.23	604.23	483.16	499.32	559.70	479.44
3	547.76	604.50	520.88	513.28	603.97	481.05	499.35	559.71	479.53
4	547.76	604.65	520.58	513.28	604.16	481.81	499.35	559.85	479.32
5	547.67	607.24	520.33	513.13	607.95	482.51	499.27	562.53	479.24
6	549.54	607.29	519.65	515.52	606.87	483.94	501.46	561.75	478.57
7	550.07	601.41	519.87	516.28	600.37	484.21	501.92	556.59	478.74
8	532.36	613.09	512.34	492.78	614.65	474.36	487.75	568.61	475.82
9	552.75	614.14	526.84	519.73	616.53	484.43	504.21	569.07	477.02
10	539.35	599.64	526.77	501.05	598.18	484.01	490.79	555.05	484.41
11	549.54	613.35	519.65	515.52	615.50	483.94	501.46	568.22	478.57
12	547.56	601.82	522.18	512.89	600.36	484.37	499.14	557.95	480.77
13	547.80	601.88	522.27	513.33	600.33	485.02	499.35	558.00	480.93
14	547.82	601.89	522.30	513.38	600.41	480.92	499.37	558.00	480.98
15	547.82	601.81	522.20	513.38	600.36	481.60	499.37	557.93	480.83
16	547.77	601.71	521.81	513.27	600.67	484.09	499.32	558.09	480.62
17	544.51	590.93	535.41	509.34	589.25	497.98	495.66	547.38	492.73
18	546.67	617.42	534.96	511.89	613.33	497.09	498.08	572.49	492.15
19	553.90	592.80	541.18	520.11	590.57	505.20	503.09	550.24	494.33
20	552.36	595.53	508.70	519.15	595.28	***471.66***	504.24	552.36	486.98
21	532.07	617.98	***508.58***	489.84	615.37	484.01	484.51	573.06	***468.58***
22	544.51	595.00	535.41	509.34	594.63	497.98	495.66	551.80	492.73

Notes:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 1

No	June 2009			May 2010			March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	32.50	43.17	28.47	29.99	49.38	30.07	32.89	45.35	34.28
2	32.58	43.19	28.56	30.01	49.37	30.09	32.92	45.35	34.27
3	32.59	43.19	27.81	30.01	49.37	30.09	32.92	45.35	34.12
4	32.59	43.18	27.92	30.01	49.38	30.09	32.92	45.35	34.30
5	32.57	43.55	28.36	30.01	49.59	30.08	32.91	45.41	34.02
6	32.62	43.64	28.85	30.01	49.40	29.90	33.11	45.35	33.64
7	32.72	42.84	28.89	30.02	49.09	29.91	33.14	45.28	33.57
8	29.21	44.23	***26.82***	29.57	49.99	29.20	32.41	45.28	33.27
9	33.15	44.57	28.80	30.11	50.01	30.28	33.30	45.51	33.88
10	33.03	42.60	28.86	29.59	49.08	29.43	32.05	45.27	33.04
11	32.62	44.47	28.85	30.01	49.94	29.90	33.11	45.49	33.64
12	32.56	42.47	28.73	30.01	49.52	30.10	32.90	45.33	34.33
13	32.63	42.47	28.80	30.02	49.52	30.12	32.93	45.33	34.33
14	32.64	42.47	27.87	30.03	49.52	30.12	32.93	45.33	34.16
15	32.62	42.47	27.97	30.03	49.52	30.12	32.93	45.33	34.35
16	32.62	42.50	28.62	30.02	49.64	30.12	32.92	45.35	34.05
17	32.72	41.75	30.42	29.66	49.61	29.42	32.46	45.23	32.57
18	32.72	43.54	30.36	29.80	49.43	29.64	32.75	45.41	32.69
19	34.25	41.35	31.74	29.13	49.38	29.11	32.66	45.20	33.58
20	32.87	42.26	28.35	30.48	49.88	30.62	33.40	45.33	33.90
21	29.81	43.65	27.43	29.45	49.39	***29.03***	***31.82***	45.41	32.67
22	32.72	42.20	30.42	29.66	49.85	29.42	32.46	45.32	32.57

Notes:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 1

No	1 June 2009			13 May 2010			7 March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	3.19	3.24	3.51	4.97	4.96	4.93	8.86	8.78	8.89
2	3.19	3.24	3.51	4.97	4.96	4.93	8.86	8.78	8.89
3	3.19	3.24	3.51	4.97	4.96	4.93	8.86	8.78	8.90
4	3.19	3.24	3.50	4.97	4.96	4.93	8.86	8.78	8.89
5	3.18	3.24	3.50	4.97	4.96	4.93	8.86	8.78	8.89
6	3.17	3.23	3.50	4.97	4.96	4.92	8.87	8.78	8.89
7	3.18	3.25	3.50	4.97	4.95	***4.92***	8.87	8.78	8.89
8	3.07	3.23	3.27	4.97	4.96	4.93	8.84	8.78	8.85
9	3.19	3.22	3.58	4.97	4.96	4.94	8.87	8.78	8.90
10	3.15	3.22	3.49	4.97	4.95	4.92	8.87	8.78	8.89
11	3.17	3.22	3.50	4.97	4.96	4.93	8.87	8.78	8.89
12	3.19	3.27	3.53	4.97	4.97	4.94	8.86	8.78	8.89
13	3.19	3.27	3.54	4.97	4.97	4.94	8.87	8.78	8.89
14	3.19	3.27	3.53	4.97	4.97	4.94	8.87	8.78	8.90
15	3.19	3.27	3.53	4.97	4.97	4.94	8.87	8.78	8.89
16	3.19	3.27	3.53	4.97	4.97	4.94	8.87	8.78	8.89
17	3.21	3.27	3.48	4.97	4.97	4.93	8.87	8.78	8.87
18	3.20	3.26	3.48	4.97	4.96	4.93	8.87	8.77	8.87
19	3.22	3.30	3.23	4.98	4.97	4.92	8.87	8.78	8.85
20	3.17	3.27	3.59	4.97	4.98	4.95	8.87	8.79	8.90
21	***3.05***	3.26	3.43	4.97	4.96	4.93	N/A	***8.77***	8.87
22	3.21	3.27	3.39	4.97	4.98	4.94	8.87	8.79	8.87

Notes:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *regression kriging* applied to the data sets with a number of different variables - experiment 2

No	2009			2010			2011		
	Elevation	**Slope**	**Elevation and Slope**	**Elevation**	**Slope**	**Elevation and Slope**	**Elevation**	**Slope**	**Elevation and Slope**
1	597.55	781.47	527.81	496.05	820.52	487.79	543.00	756.87	497.76
2	597.57	781.52	527.59	496.51	820.28	488.09	542.94	756.69	497.94
3	597.58	781.51	527.69	496.50	820.26	488.26	542.93	756.68	497.66
4	597.58	781.42	527.92	496.51	820.52	487.92	542.93	756.60	497.84
5	597.54	783.42	528.53	496.33	822.69	488.64	542.92	759.04	499.10
6	599.78	771.52	523.13	499.86	815.54	483.90	545.82	751.15	492.62
7	600.29	772.00	523.39	500.65	808.56	484.16	546.21	747.06	492.80
8	584.04	800.40	543.51	***479.61***	844.41	479.93	535.38	776.55	513.20
9	603.75	798.71	522.46	504.89	841.84	492.06	549.18	773.29	498.30
10	590.15	771.56	530.21	502.87	808.28	483.40	534.55	747.04	***491.48***
11	599.78	795.97	523.13	499.86	838.97	483.90	545.82	770.86	492.62
12	597.44	784.16	529.86	496.05	823.38	489.89	542.78	761.45	500.00
13	597.36	784.13	529.65	496.37	823.32	490.16	542.62	761.42	500.18
14	597.35	784.13	529.75	496.36	823.32	490.30	542.60	761.41	499.88
15	597.35	784.13	529.95	496.37	823.37	490.01	542.60	761.41	500.09
16	597.37	786.23	530.42	496.27	825.69	490.57	542.64	763.66	501.17
17	591.97	794.74	541.45	489.31	809.27	503.20	536.15	747.73	510.17
18	594.89	793.24	540.99	493.36	827.65	502.64	539.73	768.63	509.77
19	610.30	775.60	526.49	505.72	814.52	523.70	551.96	755.02	502.35
20	603.96	783.39	527.64	505.43	826.08	481.03	550.17	762.01	492.43
21	591.45	792.23	***520.34***	N/A	828.49	484.52	538.46	767.63	498.68
22	591.97	781.74	541.45	489.31	824.37	503.20	536.15	760.55	510.17

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 2

No	June 2009			May 2010			March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	35.64	49.10	31.92	33.30	55.71	32.75	38.09	57.22	34.84
2	35.68	49.11	31.97	33.29	55.71	32.75	38.08	57.21	34.82
3	35.68	49.11	31.99	33.29	55.71	32.75	38.07	57.21	34.87
4	35.68	49.10	31.93	33.29	55.70	32.75	38.07	57.21	34.84
5	35.67	49.60	31.87	33.29	55.87	32.77	38.07	57.73	34.91
6	35.68	49.32	32.00	33.25	55.01	32.80	38.25	56.65	34.41
7	35.75	48.58	32.04	33.27	54.96	32.82	38.28	56.50	34.41
8	32.87	50.52	33.06	***32.06***	57.17	33.43	37.72	58.84	34.90
9	36.17	50.68	32.32	33.53	57.04	32.80	38.50	58.35	***34.31***
10	35.11	48.41	32.90	33.21	55.02	32.72	37.57	56.57	34.44
11	35.68	50.53	32.00	33.25	56.83	32.80	38.25	58.15	34.41
12	35.67	48.60	31.97	33.29	56.49	32.98	38.07	57.84	34.98
13	35.69	48.60	31.98	33.27	56.50	33.00	38.05	57.83	34.98
14	35.69	48.60	31.99	33.27	56.50	32.95	38.05	57.83	34.98
15	35.69	48.60	31.97	33.27	56.49	32.98	38.05	57.83	34.98
16	35.69	48.76	31.92	33.27	56.55	32.98	38.06	58.13	35.04
17	35.68	47.95	33.16	32.94	55.78	32.95	37.49	57.11	35.14
18	35.67	49.21	33.16	33.02	55.85	32.98	37.78	57.85	35.11
19	37.78	47.58	***29.78***	34.37	56.42	34.36	38.60	57.52	36.12
20	35.94	48.75	31.21	33.68	57.49	33.82	38.62	58.18	34.83
21	34.37	49.28	30.85	33.60	55.77	33.98	38.15	57.84	34.86
22	35.68	48.66	33.16	32.94	57.39	32.95	37.49	58.06	34.89

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 2

No	1 June 2009			13 May 2010			7 March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	3.01	2.80	3.05	4.63	5.74	4.69	8.79	8.69	8.79
2	3.01	2.80	3.05	4.63	5.74	4.70	8.79	8.69	8.79
3	3.01	2.80	3.05	4.63	5.74	4.69	8.79	8.69	8.79
4	3.01	2.80	3.05	4.63	5.74	4.69	8.79	8.69	8.79
5	3.01	2.80	3.04	4.63	5.74	4.70	8.79	8.69	8.79
6	3.00	2.81	3.02	4.63	5.74	4.71	8.79	8.70	8.79
7	3.00	2.79	3.02	4.62	5.74	4.71	8.79	8.69	8.79
8	2.93	2.81	2.95	***4.61***	5.73	4.70	8.77	8.69	8.78
9	3.01	2.82	2.98	4.62	5.73	4.72	8.79	8.69	8.79
10	3.01	2.79	3.00	4.65	5.74	4.72	8.78	8.69	8.79
11	3.00	2.82	3.02	4.63	5.74	4.68	8.79	8.69	8.79
12	3.01	2.77	3.05	4.63	5.73	4.69	8.79	8.69	8.79
13	3.01	2.77	3.05	4.63	5.73	4.70	8.79	8.69	8.79
14	3.01	2.77	3.05	4.63	5.73	4.69	8.79	8.69	8.79
15	3.01	2.77	3.05	4.63	5.73	4.69	8.79	8.69	8.79
16	3.01	2.77	3.04	4.63	5.73	4.70	8.79	8.69	8.79
17	3.02	2.77	3.02	4.65	5.73	4.72	8.79	8.68	8.80
18	3.01	2.78	3.03	4.64	5.74	4.72	8.79	8.71	8.80
19	3.05	***2.75***	3.06	4.66	5.73	4.72	8.79	8.68	8.80
20	3.00	2.77	2.94	4.61	5.73	4.68	8.79	***8.67***	8.78
21	N/A	2.78	2.98	4.63	5.74	4.69	8.77	8.71	8.78
22	3.02	2.77	3.02	4.65	5.73	4.72	8.79	8.67	8.80

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *regression kriging* applied to the data sets with a number of different variables - experiment 3

No	2009			2010			2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	525.98	623.16	505.94	497.16	613.59	463.65	494.92	583.70	476.78
2	526.36	623.00	506.18	497.56	613.72	464.02	495.11	583.55	476.96
3	526.40	623.00	506.29	497.61	613.75	464.18	495.11	583.55	477.05
4	526.40	623.20	505.98	497.61	613.65	463.74	495.11	583.49	476.81
5	526.28	623.88	506.04	497.47	621.13	463.97	495.04	584.76	477.12
6	529.91	621.97	500.93	500.74	612.89	459.09	498.37	581.29	471.10
7	530.51	615.32	501.01	501.53	603.86	459.27	498.81	576.53	471.19
8	513.23	638.64	511.22	478.94	633.72	472.82	487.03	598.63	482.97
9	533.55	638.43	513.14	505.56	633.75	473.24	501.36	597.08	481.97
10	513.33	613.79	513.25	482.99	601.74	473.28	485.85	575.50	481.89
11	529.91	636.48	500.93	500.74	630.86	459.09	498.37	595.20	484.34
12	526.08	626.32	505.94	497.20	615.83	466.36	494.87	588.54	479.46
13	526.38	626.43	508.45	497.49	615.74	466.44	494.99	588.63	479.48
14	526.42	626.42	508.44	497.53	615.73	466.45	494.99	588.62	479.49
15	526.42	626.25	508.47	497.52	615.78	466.39	494.99	588.68	479.49
16	526.34	629.07	508.38	497.45	617.83	466.36	494.96	591.23	479.79
17	520.02	603.41	528.94	491.16	592.89	488.76	488.85	567.28	497.25
18	524.19	652.84	528.20	494.87	635.24	488.08	492.67	611.58	496.69
19	529.24	619.82	491.14	506.39	608.42	448.64	498.04	584.65	470.40
20	534.39	614.25	490.16	505.72	606.55	447.50	502.37	577.81	464.69
21	506.92	653.59	***490.04***	477.74	640.46	***447.40***	485.85	612.53	***464.52***
22	520.02	612.94	528.94	491.16	604.66	488.76	488.85	576.54	497.25

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 3

No	June 2009			May 2010			March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	35.06	38.88	32.61	35.75	50.60	34.94	33.49	42.81	32.31
2	35.13	38.90	32.64	35.74	50.61	34.94	33.49	42.80	32.30
3	35.13	38.91	32.65	35.74	50.58	34.94	33.49	42.80	32.30
4	35.13	38.90	32.60	35.74	50.60	34.94	33.49	42.80	32.29
5	35.11	38.73	32.45	35.74	50.73	34.98	33.49	43.00	32.33
6	35.14	39.59	32.52	35.70	50.30	35.02	33.70	42.26	***31.87***
7	35.22	38.57	32.56	35.72	49.86	34.89	33.74	42.14	31.88
8	32.21	39.76	32.83	***34.49***	52.03	35.76	33.17	44.06	32.43
9	35.61	40.49	33.85	35.97	51.94	34.98	33.93	43.69	32.17
10	34.31	38.24	32.61	35.65	49.91	34.87	32.68	42.19	32.16
11	35.14	40.38	32.52	35.70	51.73	35.02	33.70	43.52	***31.87***
12	35.12	37.91	32.42	35.74	51.51	35.30	33.48	43.62	32.62
13	35.18	37.90	32.41	35.72	51.52	35.36	33.49	43.62	32.62
14	35.18	37.90	32.40	35.72	51.50	35.37	33.49	43.62	32.62
15	35.17	37.91	32.42	35.72	51.51	35.39	33.49	43.62	32.61
16	35.16	37.97	32.30	35.72	51.54	35.43	33.49	43.82	32.64
17	35.27	36.75	34.39	35.43	51.68	35.25	32.91	42.37	33.41
18	35.25	39.75	34.37	35.49	51.00	35.27	33.24	44.38	33.38
19	36.73	36.64	***29.07***	36.91	51.56	36.59	33.47	43.39	32.54
20	35.35	37.20	30.68	36.09	52.44	36.06	34.07	43.28	31.95
21	32.57	39.91	32.24	36.24	50.93	36.29	32.79	44.53	31.94
22	35.27	37.14	34.39	35.43	52.35	35.25	32.91	43.17	33.41

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of regression kriging applied to the data sets with a number of different variables - experiment 3

No	1 June 2009			13 May 2010			7 March 2011		
	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope	Elevation	Slope	Elevation and Slope
1	3.20	4.18	3.26	4.76	4.94	4.87	8.73	8.69	8.74
2	3.20	4.18	3.26	4.77	4.94	4.88	8.73	8.69	8.74
3	3.20	4.18	3.26	4.77	4.94	4.86	8.73	8.69	8.74
4	3.20	4.18	3.26	4.77	4.94	4.86	8.73	8.69	8.74
5	3.20	4.18	3.25	4.77	4.93	4.86	8.73	8.69	8.74
6	3.20	4.18	3.22	4.77	4.95	4.89	8.74	8.70	8.74
7	3.20	4.18	3.22	4.76	4.95	4.89	8.74	8.69	8.74
8	3.12	4.18	3.14	***4.75***	4.92	4.89	8.72	8.68	8.74
9	3.21	4.18	3.17	4.76	4.93	4.90	8.74	8.69	8.75
10	3.21	4.18	3.20	4.79	4.96	4.90	8.73	8.69	8.75
11	3.20	4.18	3.22	4.77	4.93	4.89	8.74	8.69	8.74
12	3.20	4.18	3.26	4.77	4.92	4.88	8.73	8.68	8.74
13	3.21	4.18	3.26	4.77	4.92	4.88	8.73	8.68	8.74
14	3.21	4.18	3.26	4.77	4.92	4.86	8.73	8.68	8.74
15	3.21	4.18	3.26	4.77	4.92	4.86	8.73	8.68	8.74
16	3.21	4.18	3.26	4.77	4.91	4.86	8.73	8.68	8.74
17	3.22	4.18	3.23	4.79	4.91	4.90	8.73	8.67	8.75
18	3.21	4.18	3.23	4.78	4.92	4.90	8.74	8.70	8.75
19	3.24	4.18	3.26	4.80	4.92	4.89	8.74	8.68	8.72
20	3.20	4.18	***3.12***	4.75	4.89	4.86	8.74	***8.67***	8.73
21	3.20	4.18	3.15	4.76	4.94	4.86	8.72	8.70	8.73
22	3.22	4.18	3.23	4.79	4.89	4.90	8.73	8.67	8.75

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

Appendix 23: Empirical Bayesian kriging

The tested variables of *empirical Bayesian kriging*

No	Subset Size (20-500)	Overlap Factor (0.01 - 5)	Number of Simulations (30 - 500)	Trans-formation	Neighbourhood Type	Maximum neighbours	Minimum neighbours
1	100	1	100	None	Standard Circular	15	10
2	20	1	100	None	Standard Circular	15	10
3	200	1	100	None	Standard Circular	15	10
4	400	1	100	None	Standard Circular	15	10
5	500	1	100	None	Standard Circular	15	10
6	100	2.5	100	None	Standard Circular	15	10
7	100	5	100	None	Standard Circular	15	10
8	100	1	30	None	Standard Circular	15	10
9	100	1	200	None	Standard Circular	15	10
10	100	1	400	None	Standard Circular	15	10
11	100	1	500	None	Standard Circular	15	10
12	100	1	100	None	Standard Circular	2	1
13	100	1	100	None	Standard Circular	5	2
14	100	1	100	None	Standard Circular	10	4
15	100	1	100	Empirical	Standard Circular	15	10
16	100	1	500	Empirical	Standard Circular	15	10
17	100	2.5	500	Empirical	Standard Circular	15	10
18	100	5	500	Empirical	Standard Circular	15	10
19	100	2.5	200	Empirical	Standard Circular	15	10
20	400	2.5	200	Empirical	Standard Circular	15	10
21	200	5	200	Empirical	Standard Circular	15	10
22	200	5	200	Empirical	Smooth Circular, smoothing factor 0.2	N/A	N/A
23	100	1	100	Empirical	Smooth Circular, smoothing factor 1	N/A	N/A
24	100	1	100	Empirical	Smooth Circular, smoothing factor 0.2	N/A	N/A
25	100	1	100	Empirical	Smooth Circular, smoothing factor 0.8	N/A	N/A

No	Subset Size (20-500)	Overlap Factor (0.01 - 5)	Number of Simulations (30 - 500)	Trans-formation	Neighbourhood Type	Maximum neighbours	Minimum neighbours
26	100	1	100	Log Empirical	Smooth Circular, smoothing factor 0.8	N/A	N/A
27	100	1	100	Log Empirical	Standard Circular	15	10
28	100	1	100	Empirical	Standard Circular	5	2
29	100	1	500	Empirical	Standard Circular	5	2
30	100	2.5	500	Empirical	Standard Circular	5	2
31	100	5	500	Empirical	Standard Circular	5	2
32	100	2.5	200	Empirical	Standard Circular	5	2
33	400	2.5	200	Empirical	Standard Circular	5	2
34	200	5	200	Empirical	Standard Circular	5	2
35	100	1	100	Log Empirical	Standard Circular	5	2

The performances of *empirical Bayesian kriging* applied to the data sets with a number of different variables - experiment 1

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
2	604.14	572.55	525.37	41.67	29.88	47.17	2.61	4.94	***8.73***
3	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
4	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
5	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
6	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
7	607.81	564.70	522.85	41.86	29.57	47.30	2.57	4.93	8.74
8	614.27	568.11	528.21	40.92	28.82	47.25	**2.50**	4.94	8.73
9	612.27	569.05	528.10	41.44	29.39	47.24	2.53	4.94	8.74
10	614.67	571.40	526.55	41.60	29.65	47.21	2.55	4.94	8.74
11	612.81	568.46	527.61	41.48	29.39	47.14	2.54	4.94	8.74
12	640.46	560.34	560.92	46.15	29.40	52.67	3.09	5.16	8.74
13	660.58	655.96	630.12	45.39	38.02	63.27	2.61	5.22	8.73
14	618.19	581.01	541.69	42.42	30.01	48.89	2.66	***4.92***	8.75
15	526.46	484.36	416.61	***39.92***	27.40	44.33	2.55	5.00	8.77
16	525.86	***478.06***	427.45	40.40	27.82	45.21	2.64	5.03	8.75
17	525.86	***478.06***	427.45	40.40	27.82	45.21	2.64	5.03	8.75
18	525.86	***478.06***	427.45	40.40	27.82	45.21	2.64	5.03	8.75
19	528.90	480.57	435.71	40.83	27.49	45.47	2.58	5.04	8.79
20	528.90	480.57	435.71	40.83	27.49	45.47	2.58	5.04	8.79
21	528.90	480.57	435.71	40.83	27.49	45.47	2.58	5.04	8.79
22	525.57	481.38	433.25	41.08	27.61	45.65	2.59	5.04	8.79
23	526.24	485.12	416.09	39.98	27.40	44.47	2.58	5.00	8.77
24	***523.30***	484.60	***413.88***	40.17	27.54	44.42	2.56	5.00	8.77
25	526.47	485.16	416.21	40.02	27.42	44.52	2.57	5.00	8.77
26	566.55	512.09	488.16	41.93	***26.64***	44.13	N/A	N/A	N/A
27	565.57	510.25	486.49	41.80	26.66	***43.97***	N/A	N/A	N/A
28	530.42	498.10	447.94	41.07	28.52	45.29	2.57	5.01	8.78
29	529.30	493.36	461.86	41.48	29.96	47.10	2.65	5.04	8.75
30	529.30	493.36	461.86	41.48	29.96	47.10	2.65	5.04	8.75
31	529.30	493.36	461.86	41.48	29.96	47.10	2.57	5.04	8.75
32	532.62	497.07	468.74	41.98	28.99	47.30	2.60	5.05	8.80
33	532.62	497.07	468.74	41.98	28.99	47.30	2.60	5.05	8.80
34	532.62	497.07	468.74	41.98	28.99	47.30	2.60	5.05	8.80
35	570.19	521.76	504.75	42.75	27.37	44.82	N/A	N/A	N/A

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *empirical Bayesian kriging* applied to the data sets with a number of different variables - experiment 2

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
2	828.86	743.52	726.25	51.20	34.46	51.46	2.40	6.44	8.71
3	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
4	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
5	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
6	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
7	786.60	705.24	670.33	47.34	39.01	54.34	2.46	6.03	8.70
8	786.16	703.80	671.50	47.35	39.32	55.12	2.46	6.09	8.70
9	785.51	705.09	671.51	47.36	40.09	54.40	2.45	5.98	8.70
10	785.44	705.28	670.11	47.32	39.59	54.41	2.45	6.01	8.70
11	786.07	704.51	671.40	47.33	39.53	54.27	2.45	6.02	8.70
12	788.55	***577.08***	587.21	48.00	35.94	53.84	2.55	5.75	***8.69***
13	788.55	718.68	712.69	52.24	43.60	60.88	***2.39***	6.02	8.69
14	***771.25***	699.92	682.61	48.24	38.93	57.40	2.45	6.03	8.70
15	845.63	721.83	584.33	45.82	30.86	50.33	2.49	5.82	8.74
16	848.01	768.69	597.95	47.20	31.05	***49.47***	2.49	5.79	8.73
17	848.01	768.69	597.95	47.20	31.05	***49.47***	2.49	5.79	8.73
18	848.01	768.69	597.95	47.20	31.05	***49.47***	2.49	5.79	8.73
19	846.58	742.32	***573.72***	46.98	31.07	49.87	2.51	5.78	8.73
20	846.58	742.32	***573.72***	46.98	31.07	49.87	2.51	5.78	8.73
21	846.58	742.32	***573.72***	46.98	31.07	49.87	2.51	5.78	8.73
22	852.84	751.00	577.87	47.20	30.86	50.01	2.50	5.76	8.73
23	850.10	721.78	586.24	46.03	***30.56***	50.44	2.47	5.79	8.74
24	851.92	724.38	588.52	46.06	30.60	50.44	2.48	5.79	8.74
25	850.28	721.88	586.27	46.04	30.60	50.44	2.47	5.79	8.74
26	811.10	666.36	676.31	45.05	31.11	51.97	N/A	N/A	N/A
27	808.17	668.74	674.38	***44.85***	31.30	51.88	N/A	N/A	N/A
28	838.83	713.76	624.88	46.75	31.56	51.77	2.45	5.74	8.73
29	837.10	780.28	646.21	48.28	31.91	50.86	2.43	5.69	8.73
30	837.10	780.28	646.21	48.28	31.91	50.86	2.43	5.69	8.73
31	837.10	780.28	646.21	48.28	31.91	50.86	2.43	5.69	8.73
32	842.55	773.71	618.73	47.96	31.88	51.35	2.47	***5.68***	8.73
33	842.55	773.71	618.73	47.96	31.88	51.35	2.47	***5.68***	8.73
34	842.55	773.71	618.73	47.96	31.88	51.35	2.47	***5.68***	8.73
35	829.35	706.36	718.11	46.46	32.46	53.66	N/A	N/A	N/A

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *empirical Bayesian kriging* applied to the data sets with a number of different variables - experiment 3

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
2	677.80	643.61	621.32	46.81	36.67	47.71	2.45	6.32	8.72
3	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
4	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
5	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
6	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
7	657.85	603.23	582.65	44.65	40.85	49.35	2.51	5.82	8.70
8	677.80	602.86	578.61	44.75	41.23	49.15	2.51	5.81	8.70
9	657.85	600.84	582.86	44.76	40.77	49.45	2.51	5.83	8.70
10	657.85	601.95	582.40	44.79	41.15	49.17	2.51	5.84	8.70
11	657.85	601.58	581.62	44.73	40.83	49.11	2.51	5.82	8.70
12	652.03	578.23	590.07	48.33	38.40	51.83	2.55	***5.57***	***8.69***
13	769.64	713.56	709.08	51.59	46.49	59.88	***2.43***	5.75	8.69
14	664.15	613.35	606.12	44.80	41.57	52.19	2.48	5.79	8.69
15	557.13	461.16	476.94	***42.14***	29.68	41.72	2.53	5.87	8.76
16	580.23	***455.23***	***462.59***	42.71	29.49	41.71	2.50	5.81	8.76
17	580.23	***455.23***	***462.59***	42.71	29.49	41.71	2.50	5.81	8.76
18	580.23	***455.23***	***462.59***	42.71	29.49	41.71	2.50	5.81	8.76
19	577.46	464.20	486.74	42.42	29.22	41.44	2.53	5.84	8.78
20	577.46	464.20	486.74	42.42	29.22	41.44	2.53	5.84	8.78
21	577.46	464.20	486.74	42.42	29.22	41.44	2.53	5.84	8.78
22	573.31	459.77	482.63	42.47	***28.99***	***40.75***	*2.53*	5.83	8.78
23	569.20	467.23	479.91	42.41	29.40	41.14	2.56	5.84	8.76
24	***552.46***	456.51	472.75	42.20	29.39	40.92	2.59	5.86	8.75
25	571.02	469.54	481.62	42.44	29.40	41.15	2.57	5.85	8.76
26	632.24	585.79	575.55	42.92	30.38	40.94	N/A	N/A	N/A
27	615.37	567.70	568.64	42.64	30.56	41.01	N/A	N/A	N/A
28	713.06	644.82	625.24	45.75	30.28	47.82	2.54	5.76	8.76
29	718.14	624.64	614.58	46.81	30.02	47.04	2.53	5.71	8.76
30	718.14	624.64	614.58	46.81	30.02	47.04	2.53	5.71	8.76
31	718.14	624.64	614.58	46.81	30.02	47.04	2.53	5.71	8.76
32	731.10	628.59	637.48	46.38	29.80	47.05	2.56	5.74	8.78
33	731.10	628.59	637.48	46.38	29.80	47.05	2.56	5.74	8.78
34	731.10	628.59	637.48	46.38	29.80	47.05	2.56	5.74	8.78
35	615.37	705.68	713.63	45.98	31.67	44.94	N/A	N/A	N/A

Note:

- N/A are spatial estimations that the software could not processed.
- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

Appendix 24: Gaussian geostatistical simulation

The tested variables of the *Gaussian geostatistical simulation*

No	Model	Maximum neighbours	Minimum neighbours	Number of realisations
1	Stable	5	2	10
2	Circular	5	2	10
3	Spherical	5	2	10
4	Tetraspherical	5	2	10
5	Pentaspherical	5	2	10
6	Exponential	5	2	10
7	Gaussian	5	2	10
8	Rational Quadratic	5	2	10
9	Hole Effect	5	2	10
10	K-Bessel	5	2	10
11	J-Bessel	5	2	10
12	Stable	2	1	10
13	Circular	2	1	10
14	Spherical	2	1	10
15	Tetraspherical	2	1	10
16	Pentaspherical	2	1	10
17	Exponential	2	1	10
18	Gaussian	2	1	10
19	Rational Quadratic	2	1	10
20	Hole Effect	2	1	10
21	K-Bessel	2	1	10
22	J-Bessel	2	1	10
23	Stable	5	2	30
24	Circular	5	2	30
25	Spherical	5	2	30
26	Tetraspherical	5	2	30
27	Pentaspherical	5	2	30
28	Exponential	5	2	30
29	Gaussian	5	2	30
30	Rational Quadratic	5	2	30
31	Hole Effect	5	2	30
32	K-Bessel	5	2	30
33	J-Bessel	5	2	30
34	Stable	2	1	30
35	Circular	2	1	30
36	Spherical	2	1	30
37	Tetraspherical	2	1	30
38	Pentaspherical	2	1	30
39	Exponential	2	1	30
40	Gaussian	2	1	30
41	Rational Quadratic	2	1	30
42	Hole Effect	2	1	30
43	K-Bessel	2	1	30
44	J-Bessel	2	1	30

The performances of *Gaussian geostatistical simulation* applied to the data sets with a number of different variables - experiment 1

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	***315.49***	532.28	421.50	47.71	***17.44***	46.99	3.65	5.35	8.85
2	607.96	519.93	409.61	41.94	34.91	41.52	3.66	5.35	8.82
3	473.21	447.81	358.07	41.06	39.05	42.57	3.57	5.35	8.78
4	514.72	660.96	***313.51***	47.68	33.89	48.65	3.61	5.35	8.88
5	659.14	469.73	405.11	41.20	29.52	39.39	3.63	5.31	8.81
6	522.26	652.65	531.34	42.77	32.21	41.16	3.70	5.35	8.74
7	406.68	581.01	360.88	51.77	37.74	40.82	3.58	5.35	8.79
8	526.32	446.86	503.28	46.56	29.77	39.25	3.71	5.27	8.83
9	802.16	588.00	555.45	56.83	56.59	38.94	3.58	5.74	8.73
10	459.16	***305.21***	650.17	40.67	27.55	43.50	3.68	5.35	8.81
11	684.58	746.90	577.17	57.33	39.44	34.98	3.42	10.46	8.71
12	525.06	485.92	420.93	42.73	23.70	43.13	3.65	5.35	8.79
13	595.87	460.98	505.61	51.58	34.40	39.41	3.56	5.35	8.87
14	702.85	419.17	406.54	43.76	24.80	52.62	3.59	5.35	8.74
15	608.13	505.01	491.29	43.69	23.95	40.39	3.70	5.35	8.78
16	605.54	516.33	458.72	37.05	24.87	50.16	3.61	5.25	8.86
17	562.65	595.05	448.17	50.35	27.94	51.77	3.70	5.35	***8.70***
18	421.58	544.63	466.42	48.94	32.27	49.04	3.78	5.35	8.80
19	562.29	589.72	490.11	***33.34***	26.90	***33.10***	3.71	5.28	8.72
20	581.46	549.53	460.08	47.49	52.92	36.31	3.57	5.41	8.75
21	462.48	343.47	390.81	35.46	24.88	37.28	3.71	5.35	8.82
22	603.26	707.43	390.14	39.42	46.94	55.12	3.50	5.26	8.78
23	383.05	515.86	402.00	44.22	24.02	42.85	3.68	5.35	8.84
24	491.32	486.74	349.20	48.23	39.51	39.53	3.64	5.35	8.80
25	501.83	479.53	448.22	40.99	28.82	38.68	3.61	5.35	8.76
26	619.28	484.61	470.64	42.48	24.23	41.57	3.63	5.35	8.83
27	536.54	434.34	410.61	45.60	27.33	41.70	3.65	***5.21***	8.80
28	538.83	455.94	520.06	41.57	23.10	44.94	3.70	5.35	8.83
29	397.34	521.00	432.98	49.43	33.52	38.20	3.62	5.35	8.78
30	539.78	537.11	439.76	37.24	22.38	42.47	3.71	5.33	8.77
31	681.88	561.13	486.39	51.89	52.98	36.34	3.53	5.44	8.81
32	415.73	398.01	357.42	48.62	24.56	40.98	3.68	5.35	8.79
33	725.85	600.81	587.37	39.03	48.19	40.50	***3.33***	10.11	8.76
34	396.72	511.68	468.82	43.43	23.33	39.38	3.68	5.35	8.77
35	498.97	490.63	504.51	46.49	25.39	39.24	3.63	5.35	8.84
36	531.86	488.40	378.12	41.53	29.23	40.28	3.64	5.35	8.78
37	495.62	479.44	459.86	46.20	26.93	41.56	3.63	5.35	8.85
38	482.18	451.24	464.15	45.23	29.50	39.06	3.64	5.30	8.72
39	497.31	486.52	430.20	42.67	26.23	42.93	3.70	5.35	8.80
40	621.35	474.02	485.08	42.93	32.69	40.41	3.64	5.35	8.81
41	579.89	565.65	453.17	49.33	24.77	40.22	3.71	5.30	8.71
42	629.65	533.14	471.76	52.03	55.64	39.02	3.54	5.40	8.79
43	433.55	500.73	474.33	47.71	25.31	40.37	3.68	5.35	8.85
44	645.94	512.19	494.74	36.97	48.75	41.18	3.61	5.58	8.82

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *Gaussian geostatistical simulation* applied to the data sets with a number of different variables - experiment 2

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	794.95	709.11	819.73	64.68	57.25	81.62	2.64	5.19	8.66
2	854.32	637.99	783.79	60.66	42.45	88.14	2.69	4.80	8.64
3	854.24	636.07	760.15	60.25	46.72	86.15	2.43	4.94	8.74
4	617.25	755.87	765.13	57.04	37.49	82.59	2.56	4.91	8.57
5	805.75	858.44	886.55	61.78	47.95	86.83	2.80	5.24	8.71
6	938.08	682.07	766.72	56.00	40.14	78.70	2.66	5.21	8.68
7	603.69	911.20	656.75	71.79	53.27	87.44	2.52	4.94	8.67
8	819.41	810.20	567.85	65.58	38.77	79.63	2.65	5.02	8.64
9	905.21	800.62	679.79	68.68	53.77	81.96	2.40	4.78	8.67
10	566.83	751.03	789.14	68.26	52.62	79.69	***2.61***	***4.88***	8.70
11	720.00	597.75	711.07	68.33	47.46	88.12	2.60	4.95	8.60
12	752.74	741.10	664.32	69.61	46.50	79.53	2.67	5.21	8.65
13	679.77	711.21	744.54	62.91	39.52	95.10	2.57	5.16	8.71
14	643.93	728.36	726.33	60.44	40.07	78.26	2.70	5.36	8.68
15	740.42	648.24	681.96	63.48	36.69	87.46	2.70	4.91	8.70
16	780.93	***546.76***	636.32	66.06	***29.56***	93.19	2.59	5.04	8.75
17	653.98	869.47	618.68	61.44	41.39	95.87	2.65	4.85	8.57
18	902.24	665.24	589.81	68.02	45.66	90.05	2.64	4.97	***8.57***
19	790.75	905.59	608.13	***51.04***	35.45	82.48	2.82	5.02	8.82
20	***565.28***	908.26	***525.76***	66.09	53.19	87.14	2.67	5.28	8.65
21	796.21	752.13	763.37	58.41	44.06	83.64	2.66	5.01	8.63
22	790.94	735.62	672.25	68.98	48.64	84.68	2.76	5.13	8.75
23	829.93	747.98	701.94	56.79	39.72	79.26	2.68	4.92	8.66
24	799.80	676.30	741.86	63.94	34.31	89.96	2.53	5.02	8.65
25	687.67	675.19	629.83	64.77	44.17	90.39	2.59	4.96	8.70
26	757.40	646.20	681.47	61.07	52.58	83.86	2.59	5.02	8.68
27	701.27	661.95	766.20	57.96	44.90	85.03	2.63	4.95	8.64
28	825.69	822.82	596.50	61.55	43.25	78.40	2.71	5.06	8.68
29	834.69	833.62	646.17	65.36	46.57	81.88	2.66	5.00	8.69
30	823.43	747.79	631.40	56.68	37.40	***74.06***	2.71	4.99	8.67
31	764.41	743.63	697.48	71.71	57.55	86.42	2.54	5.10	8.63
32	755.62	699.68	691.56	62.87	45.42	76.19	2.53	5.12	8.63
33	762.84	609.02	637.11	68.90	41.76	88.66	2.64	5.18	8.67
34	639.02	649.56	622.80	61.22	40.59	85.72	2.61	4.96	8.73
35	648.71	753.02	613.21	65.25	42.77	83.81	2.87	4.87	8.66
36	693.86	661.93	604.37	61.67	39.43	86.62	2.74	5.04	8.62
37	676.70	756.42	548.33	60.35	47.86	87.99	2.78	5.02	8.69
38	675.05	713.88	589.06	61.83	35.67	81.07	2.67	4.87	8.63
39	681.32	682.23	709.75	55.51	44.26	83.99	2.80	4.95	8.67
40	720.90	686.96	655.28	63.99	51.39	80.62	2.65	5.05	8.66
41	804.14	603.34	634.55	53.21	37.67	75.94	2.68	4.95	8.69
42	649.49	735.67	578.13	64.91	49.15	87.05	2.59	5.15	8.68
43	789.98	740.25	645.90	60.76	43.17	87.06	2.60	5.11	8.72
44	778.53	764.71	636.59	59.42	45.28	85.85	2.84	5.09	8.67

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

The performances of *Gaussian geostatistical simulation* applied to the data sets with a number of different variables - experiment 3

No	2009	2010	2011	June 2009	May 2010	March 2011	1 June 2009	13 May 2010	7 March 2011
1	505.60	453.39	529.65	43.02	39.85	***34.41***	2.58	5.18	8.72
2	614.65	613.29	479.32	52.71	41.80	60.28	2.88	5.38	8.74
3	628.28	390.09	518.45	48.58	34.60	41.62	2.91	4.97	8.60
4	725.28	578.88	494.12	46.45	34.54	64.68	2.73	5.46	8.76
5	489.06	590.97	679.02	43.31	26.61	55.35	2.79	5.05	8.72
6	990.36	554.82	642.71	40.29	35.79	62.78	2.76	5.43	8.70
7	493.77	597.65	528.94	45.32	26.68	44.80	2.87	5.09	8.70
8	509.25	643.67	717.36	44.59	33.08	51.18	2.68	***4.95***	8.75
9	530.28	667.82	577.32	61.40	44.90	59.68	2.71	5.03	8.69
10	679.50	424.22	625.98	57.50	28.56	46.19	2.86	5.51	8.80
11	652.85	471.52	498.57	61.69	31.79	70.54	**2.49**	5.36	8.75
12	654.79	545.57	443.85	38.88	32.76	46.98	2.53	5.33	8.69
13	607.10	503.67	612.99	46.72	27.61	70.34	2.76	5.31	***8.59***
14	665.10	543.60	531.98	39.84	29.22	54.96	2.70	5.29	8.78
15	642.46	543.37	436.50	48.28	26.31	43.57	2.74	5.42	8.65
16	479.50	469.93	473.14	36.17	35.64	53.40	2.69	5.32	8.82
17	754.15	474.67	506.09	45.81	37.32	43.52	2.65	5.02	8.77
18	409.46	563.43	***377.19***	49.75	30.36	43.02	2.88	5.33	8.70
19	586.08	675.27	485.81	***36.03***	44.33	56.71	2.84	5.66	8.67
20	585.79	536.35	520.47	62.02	30.62	54.77	2.85	5.22	8.64
21	529.93	392.67	612.43	40.92	36.59	35.77	2.72	5.69	8.62
22	619.47	572.45	505.36	43.51	26.28	60.69	2.89	5.46	8.66
23	518.66	521.91	461.46	49.94	38.22	46.77	2.65	5.33	8.71
24	477.46	625.27	465.57	48.13	31.77	45.19	2.74	5.26	8.68
25	651.30	623.92	491.30	47.43	28.71	56.52	2.75	5.35	8.73
26	506.94	558.59	532.54	48.09	30.62	54.23	2.77	5.23	8.79
27	621.41	519.65	474.93	48.21	33.37	51.54	2.70	5.21	8.75
28	714.00	588.73	572.97	47.60	35.60	55.11	2.74	5.19	8.66
29	403.99	518.08	478.74	45.84	29.91	46.43	2.73	5.15	8.71
30	610.41	548.15	512.52	46.23	32.40	55.96	2.68	5.36	8.75
31	586.04	649.07	617.32	60.09	45.71	59.50	2.84	5.07	8.65
32	470.66	452.37	481.52	55.50	32.05	45.65	2.80	5.35	8.78
33	622.95	***387.53***	528.29	58.20	36.69	64.98	2.81	5.31	8.76
34	***383.94***	643.86	488.84	49.11	39.91	43.19	2.58	5.28	8.68
35	604.71	547.24	584.88	42.17	26.58	48.58	2.79	5.24	8.66
36	573.36	519.79	431.93	51.08	30.32	46.30	2.85	5.32	8.73
37	634.64	497.15	566.71	46.97	30.52	52.87	2.75	5.30	8.69
38	540.45	579.47	546.06	40.79	***25.90***	41.28	2.75	5.51	8.71
39	706.18	538.13	521.91	43.64	38.50	50.23	2.93	5.27	8.70
40	550.42	415.75	523.47	45.87	28.52	48.60	2.73	5.24	8.69
41	644.47	561.65	534.57	50.04	30.33	46.79	2.87	5.33	8.72
42	460.22	596.12	422.64	52.69	30.62	54.12	2.87	5.20	8.73
43	545.98	449.34	486.71	46.51	29.52	43.90	2.82	5.41	8.74
44	546.93	529.30	508.87	51.08	26.27	61.85	2.71	5.34	8.68

Note:

- Numbers in bold and italics are the minimum root mean square values for those data set spatial estimations.

Appendix 25: Principal components analysis

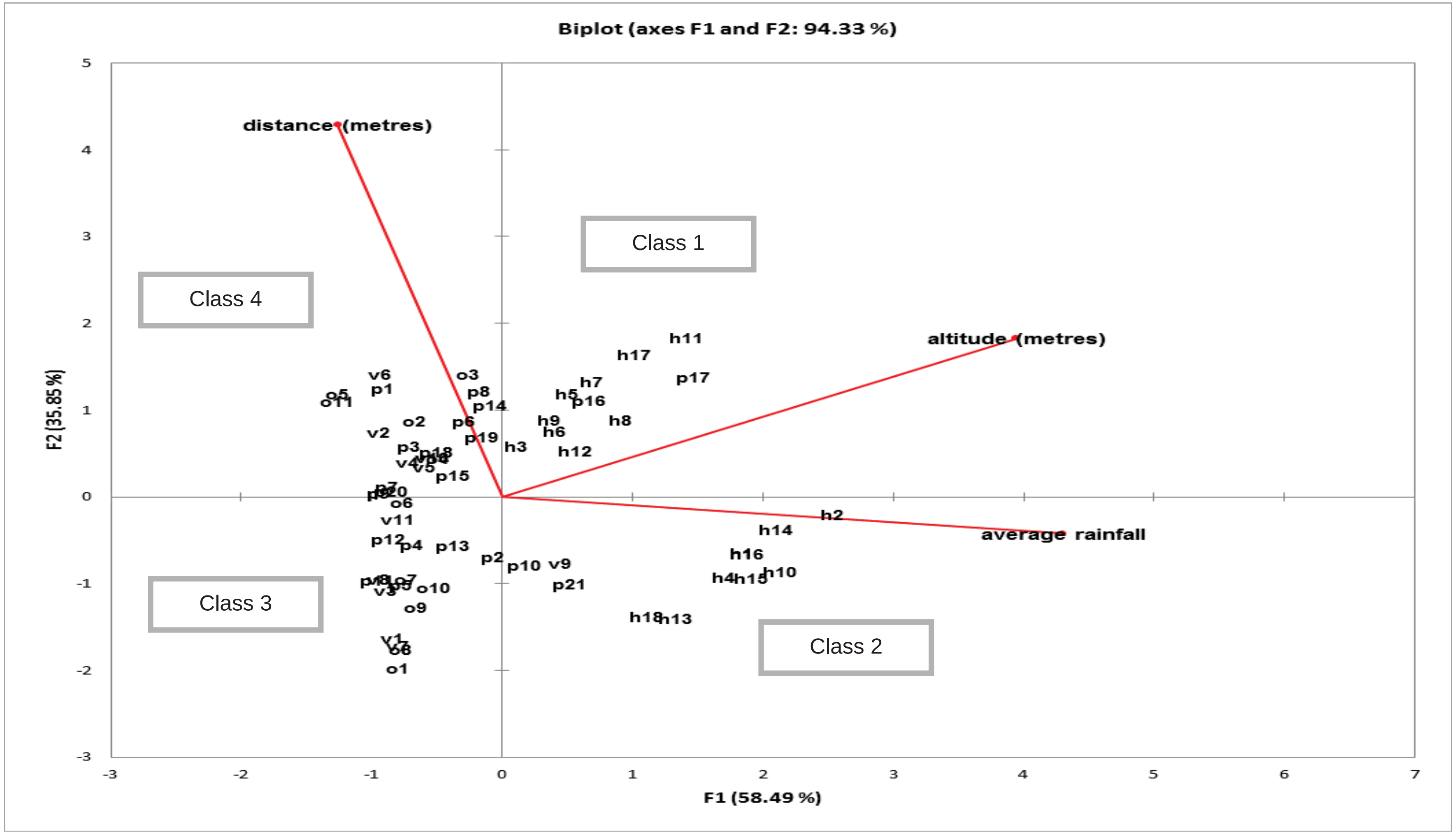
The PCA generated four classes based on the all rain gauges characteristics (manual rainfall (based on the 2009 – 2011 yearly rainfall), altitude of the rain gauge, and the distance to the west coast) (see graph next page). The first class encompasses the rain gauges situated in Ruahine Ranges, class two includes rain gauges located in the Tararua Ranges, class three contains mainly rain gauges located west of the Ruahine and Tararua Ranges, and class four covers rain gauges situated east of the two ranges and a few are located in the north outside the MRC (see map).

Note: (h = historical rain gauge, o = rain gauge situated outside MRC, p = primary rain gauge, and v = validation rain gauge)

Table that defines the rain gauges divided in the four class (determined with PCA)

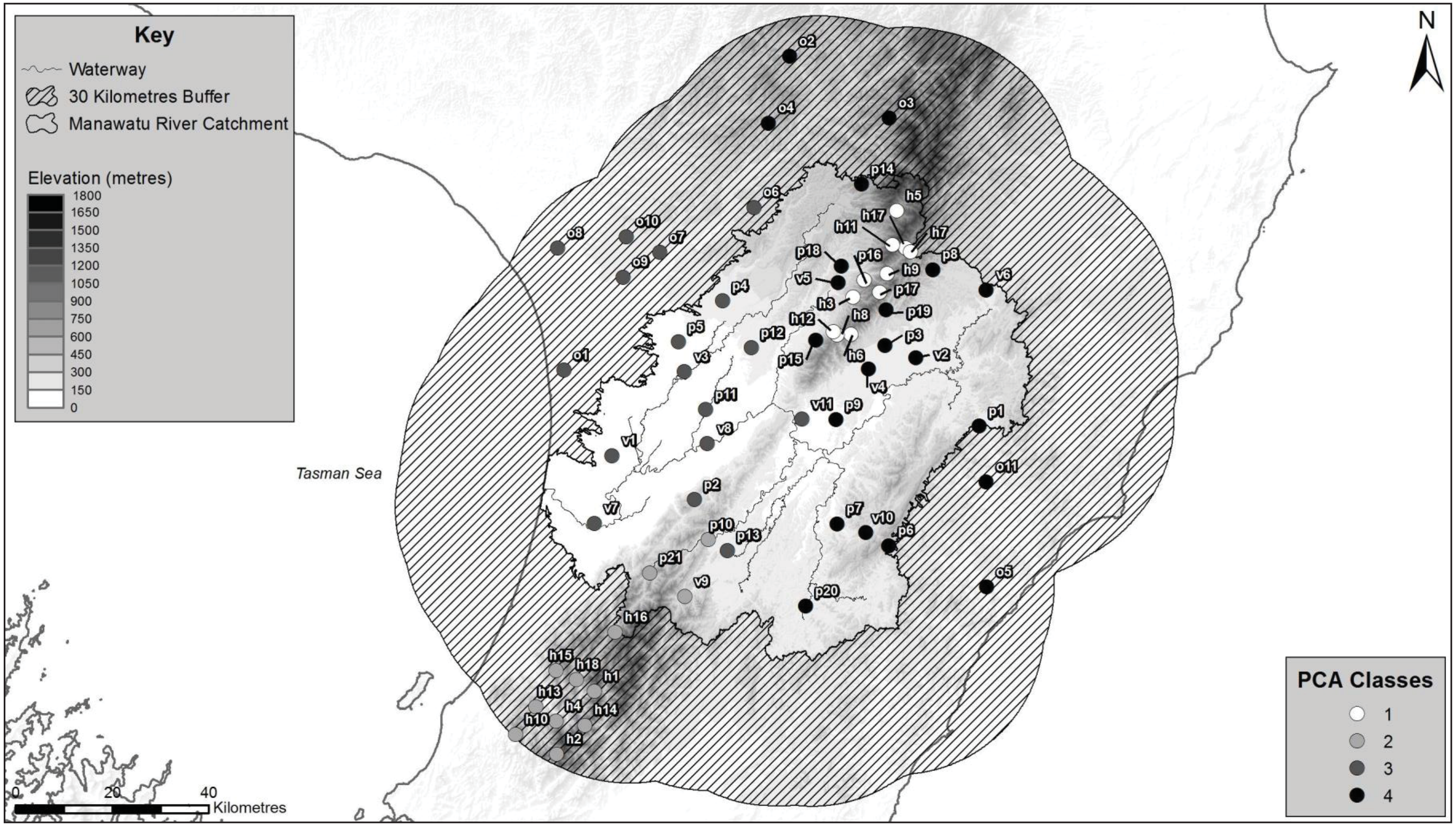
Class 1	Class 2	Class 3	Class 4
h3 - Diggers Hut	h1 - Andersons Hut	o1 - Forest Rd Drain at Drop Structure	o2 - Hautapu at Alabasters
h5 - Iron Gate	h2 - Aston Peaks	o6 - Pakihikura at Pakihikura Airstrip	o3 - Kawhatau Catchment at Upper Kawhatau
h6 - Kumeti	h4 - Fields Hut	o7 - Porewa Catchment at Tututotara	o4 - Makohine at Zohs Road
h7 - Leon Kinvig	h13 - Roaring Meg	o8 - Turakina at O'Neills Bridge	o5 - Owahanga at Branscombe Bridge
h8 - Maharahara	h14 - Tararua Peaks	o9 - Tutaenui at Green Haven Farm	o11 - Waihi at S.H.52
h9 - Mid Pohangina	h15 - Taungata	o10 - Tutaenui at Ribby Farm	p1 - Akitio at Toi Flat
h11 - Ngamoko	h16 - Te Matawai Hut	p2 - Kahuterawa at Scotts Road	p3 - Kumeti at Rua Roa
h12 - Opawe	h18 - Waitewaewae Hut	p4 - Makino at Cheltenham	p6 - Makuri at Bee 4 Trig
h17 - Toms	p21 - Upper Mangahao at No.1 Dam	p5 - Makino at Halcombe Road	p7 - Makuri at Tuscan Hills
p16 - Pohangina at Delaware Ridge	v9 - Putara	p11 - Mangaone at Milson Line	p8 - Manawatu at Apiti Track
p17 - Pohangina at Makawakawa Divide		p12 - Mangaone at Valley Road	p9 - Manga-atua at Hutchinsons
		p13 - Mangatainoka at Hillwood Hukanui	p14 - Oroua at Rangiwahia
		v1 - Bainesse	p15 - Pohangina at Alphabet Hut
		v3 - Feilding Sewage Pt	p18 - Pohangina at Range View Farm
		v7 - Moutoa	p19 - Tamaki at Tamaki Reserve
		v8 - Palmerston North Ews	p20 - Tiraumea at Alfredton
		v11 - Waipuna Woodville	v2 - Dannevirke
			v4 - Kiritaki
			v5 - Komako
			v6 - Kopua
			v10 - Tataramoa Makuri

PCA Graph



Biplot (axes F1 and F2: 94.33 %)
distance (metres)
altitude (metres)
average rainfall
Class 1
Class 2
Class 3
Class 4
F1 (58.49 %)
F2 (35.85 %)

Map that revealed the geographical locations of the four classes (defined by PCA) of the rain gauges



Appendix 26: Performance comparison of the spatial estimation methods applied to a data set per experiment

Data set: 2009

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	19.09	63.22	48.51	256.32
Regression models	-	-	44.14	29.42	237.23
Regression kriging	-	-	-	-14.71	193.09
Empirical Bayesian kriging	-	-	-	-	207.81
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-5.43	33.92	-217.00	-11.03
Regression models	-	-	39.34	-211.57	-5.60
Regression kriging	-	-	-	-250.91	-44.95
Empirical Bayesian kriging	-	-	-	-	205.97
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-75.65	-33.96	-96.38	72.14
Regression models	-	-	41.69	-20.73	147.79
Regression kriging	-	-	-	-62.42	106.10
Empirical Bayesian kriging	-	-	-	-	168.52
Gaussian geostatistical simulation	-	-	-	-	-

Data set: 2010

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	56.28	107.12	100.71	273.56
Regression models	-	-	50.83	44.43	217.28
Regression kriging	-	-	-	-6.40	166.45
Empirical Bayesian kriging	-	-	-	-	172.85
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-20.11	2.84	-94.63	-64.31
Regression models	-	-	22.95	-74.52	-44.20
Regression kriging	-	-	-	-97.47	-67.15
Empirical Bayesian kriging	-	-	-	-	30.32
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Geostatistical simulation**
Ordinary kriging	-	-96.13	-39.20	-47.03	20.66
Regression models	-	-	56.93	49.10	116.80
Regression kriging	-	-	-	-7.83	59.87
Empirical Bayesian kriging	-	-	-	-	67.69
Gaussian geostatistical simulation	-	-	-	-	-

Data set: 2011

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	42.45	77.48	132.19	232.55
Regression models	-	-	35.03	89.74	190.10
Regression kriging	-	-	-	54.70	155.07
Empirical Bayesian kriging	-	-	-	-	100.36
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	3.19	35.12	-47.12	0.85
Regression models	-	-	31.93	-50.31	-2.34
Regression kriging	-	-	-	-82.24	-34.27
Empirical Bayesian kriging	-	-	-	-	47.97
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-57.03	-24.32	-22.39	63.01
Regression models	-	-	32.72	34.65	120.05
Regression kriging	-	-	-	1.93	87.33
Empirical Bayesian kriging	-	-	-	-	85.40
Gaussian geostatistical simulation	-	-	-	-	-

Data set: June 2009

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	3.56	10.13	-2.96	3.61
Regression models	-	-	6.57	-6.53	0.05
Regression kriging	-	-	-	-13.10	-6.52
Empirical Bayesian kriging	-	-	-	-	6.58
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	6.79	11.72	-3.35	-9.53
Regression models	-	-	4.93	-10.14	-0.05
Regression kriging	-	-	-	-15.07	-21.26
Empirical Bayesian kriging	-	-	-	-	-6.19
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	1.09	8.58	-4.49	1.62
Regression models	-	-	7.49	-5.58	0.54
Regression kriging	-	-	-	-13.07	-6.96
Empirical Bayesian kriging	-	-	-	-	6.11
Gaussian geostatistical simulation	-	-	-	-	-

Data set: May 2010

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	1.13	4.07	6.45	15.65
Regression models	-	-	2.94	5.33	14.52
Regression kriging	-	-	-	2.39	11.58
Empirical Bayesian kriging	-	-	-	-	9.20
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	1.20	-2.31	-0.80	0.19
Regression models	-	-	-3.51	-2.00	-1.01
Regression kriging	-	-	-	1.50	2.50
Empirical Bayesian kriging	-	-	-	-	0.99
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	0.48	-4.52	0.98	4.07
Regression models	-	-	-5.00	0.50	3.58
Regression kriging	-	-	-	5.50	8.59
Empirical Bayesian kriging	-	-	-	-	3.09
Gaussian geostatistical simulation	-	-	-	-	-

Data set: March 2011

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	14.51	15.71	3.56	14.42
Regression models	-	-	1.19	-10.96	-0.09
Regression kriging	-	-	-	-12.15	-1.28
Empirical Bayesian kriging	-	-	-	-	10.87
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	7.61	9.44	-5.72	-30.31
Regression models	-	-	1.83	-13.34	-37.92
Regression kriging	-	-	-	-15.16	-39.75
Empirical Bayesian kriging	-	-	-	-	-24.59
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	3.63	5.41	-3.46	2.88
Regression models	-	-	1.78	-7.10	-0.76
Regression kriging	-	-	-	-8.88	-2.54
Empirical Bayesian kriging	-	-	-	-	6.34
Gaussian geostatistical simulation	-	-	-	-	-

Data set: 1 June 2009

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.46	-0.34	0.21	-0.63
Regression models	-	-	0.12	0.67	-0.16
Regression kriging	-	-	-	0.55	-0.28
Empirical Bayesian kriging	-	-	-	-	-0.84
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.52	-0.41	-0.04	-0.05
Regression models	-	-	0.11	0.48	0.47
Regression kriging	-	-	-	0.36	0.35
Empirical Bayesian kriging	-	-	-	-	-0.01
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.77	-0.67	0.01	-0.04
Regression models	-	-	0.10	0.79	0.73
Regression kriging	-	-	-	0.69	0.63
Empirical Bayesian kriging	-	-	-	-	-0.06
Gaussian geostatistical simulation	-	-	-	-	-

Data set: 13 May 2010

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.21	-0.17	-0.16	-0.45
Regression models	-	-	0.05	0.05	-0.24
Regression kriging	-	-	-	0.00	-0.29
Empirical Bayesian kriging	-	-	-	-	-0.29
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	0.74	0.74	-0.33	0.57
Regression models	-	-	0.01	-1.07	-0.17
Regression kriging	-	-	-	-1.08	-0.18
Empirical Bayesian kriging	-	-	-	-	0.90
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	0.49	0.46	-0.37	0.25
Regression models	-	-	-0.03	-0.86	-0.24
Regression kriging	-	-	-	-0.83	-0.21
Empirical Bayesian kriging	-	-	-	-	0.62
Gaussian geostatistical simulation	-	-	-	-	-

Data set: 7 March 2011

Experiment 1					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.01	-0.02	0.02	0.05
Regression models	-	-	-0.01	0.03	0.06
Regression kriging	-	-	-	0.04	0.08
Empirical Bayesian kriging	-	-	-	-	0.03
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 2					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.08	-0.03	-0.04	0.08
Regression models	-	-	0.05	0.04	0.16
Regression kriging	-	-	-	-0.01	0.11
Empirical Bayesian kriging	-	-	-	-	0.12
Gaussian geostatistical simulation	-	-	-	-	-

Experiment 3					
SEM	**Ordinary kriging**	**Linear regression**	**Regression kriging**	**Empirical Bayesian kriging**	**Gaussian geostatistical simulation**
Ordinary kriging	-	-0.05	0.01	-0.01	0.08
Regression models	-	-	0.06	0.04	0.14
Regression kriging	-	-	-	-0.02	0.08
Empirical Bayesian kriging	-	-	-	-	0.10
Gaussian geostatistical simulation	-	-	-	-	-

Appendix 27: The ranking assessment per temporal data set

Data set: 2009

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	5	4	2	3	1
2	2	3	1	5	4
3	2	4	3	5	1
Average ranking	**3**	**4**	**1**	**5**	**1**

Data set: 2010

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	5	4	2	3	1
2	2	3	1	5	4
3	2	5	3	4	1
Average ranking	**3**	**4**	**1**	**4**	**1**

Data set: 2011

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	5	4	3	2	1
2	4	2	1	5	3
3	2	5	4	3	1
Average ranking	**4**	**4**	**2**	**3**	**1**

Data set: June 2009

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	4	3	1	5	2
2	3	2	1	4	5
3	4	3	1	5	2
Average ranking	**4**	**2**	**1**	**5**	**3**

Data set: May 2010

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	5	4	3	2	1
2	3	1	5	4	2
3	4	3	5	2	1
Average ranking	**4**	**2**	**5**	**2**	**1**

Data set: March 2011

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	5	2	1	4	3
2	3	2	1	4	5
3	4	2	1	5	3
Average ranking	**4**	**2**	**1**	**5**	**3**

Data set: 1 June 2009

Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	2	4	3	1	5
2	1	5	4	2	3
3	2	5	4	1	3
Average ranking	**2**	**5**	**3**	**1**	**3**

Data set: 13 May 2010

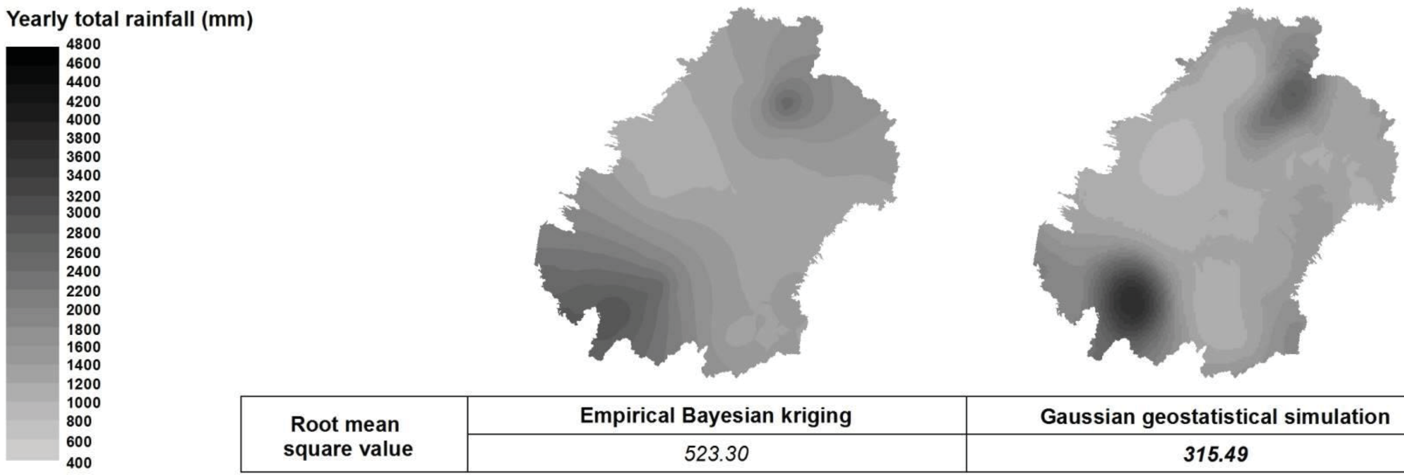
Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	1	4	3	2	5
2	4	2	1	5	3
3	4	1	2	5	3
Average ranking	**3**	**2**	**1**	**5**	**4**

Data set: 7 March 2011

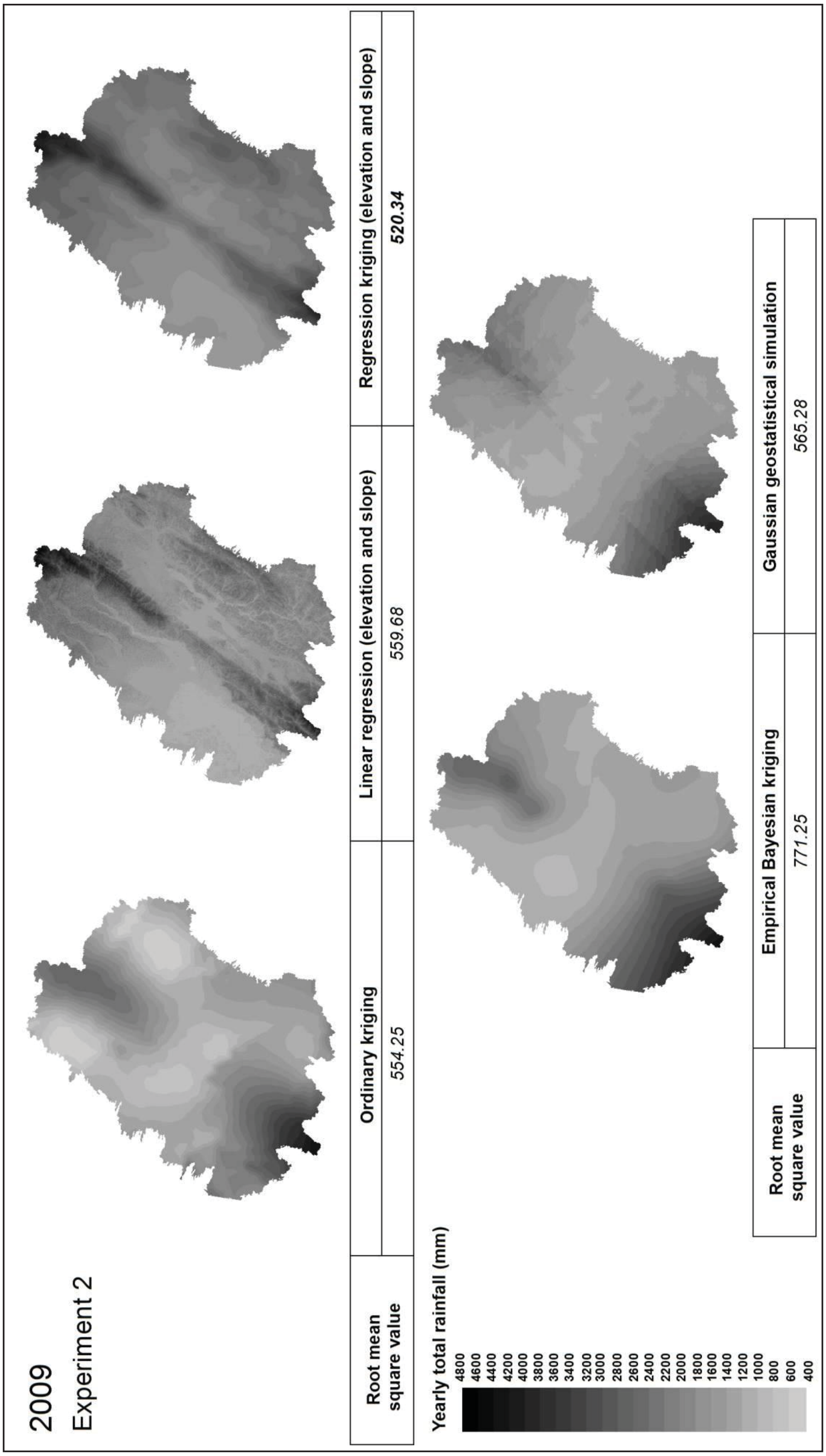
Experiments	Ordinary kriging	Linear regression	Regression kriging	Empirical Bayesian kriging	Gaussian geostatistical simulation
1	3	4	5	2	1
2	2	5	3	4	1
3	3	5	2	4	1
Average ranking	**2**	**5**	**3**	**3**	**1**

Appendix 28: Maps of all experiments and spatial estimation methods that generated the lowest root mean square value

Root mean square value	Ordinary kriging	Linear regression (elevation)	Regression kriging (elevation and slope)
	571.81	*552.72*	*508.58*

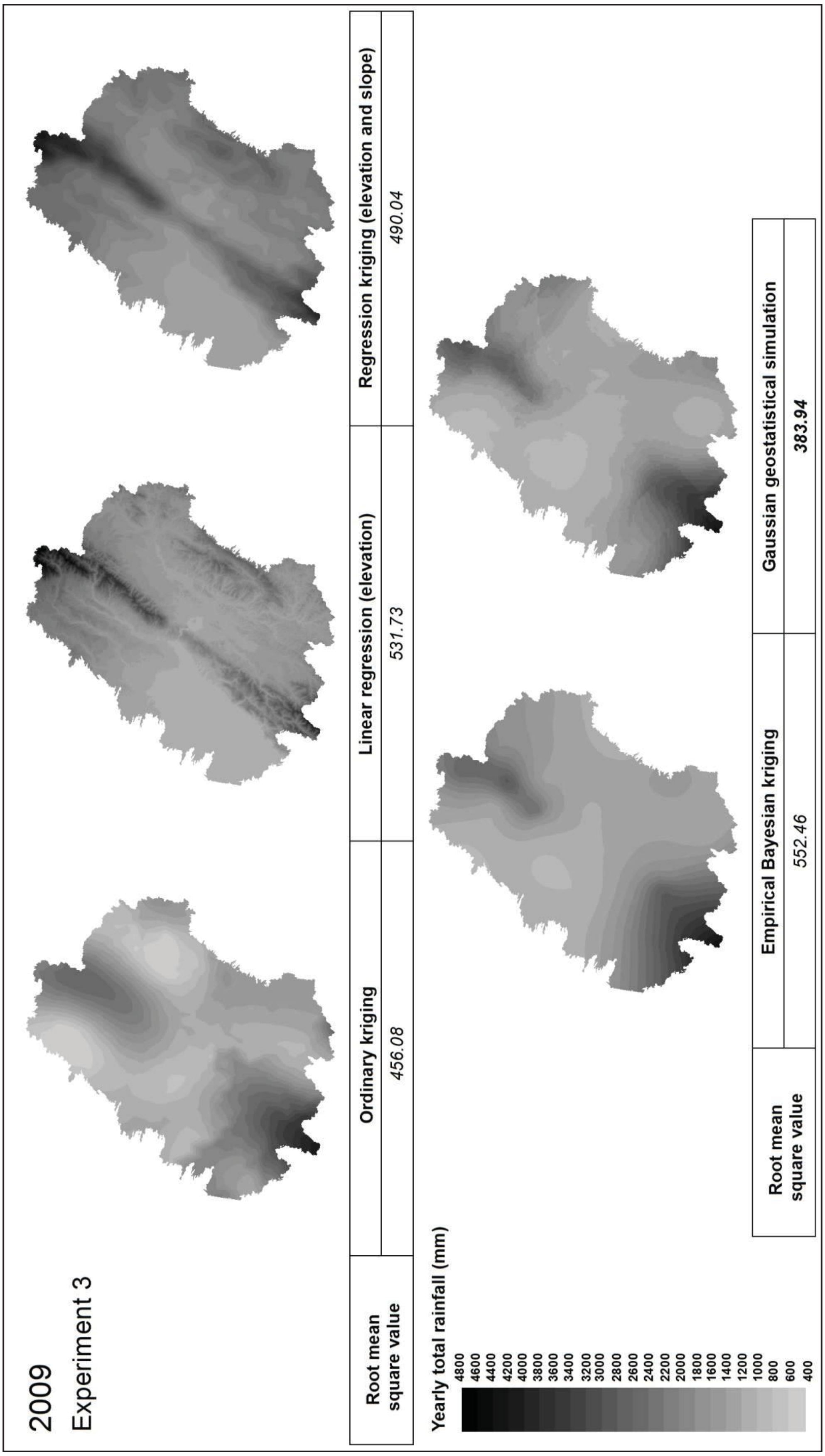


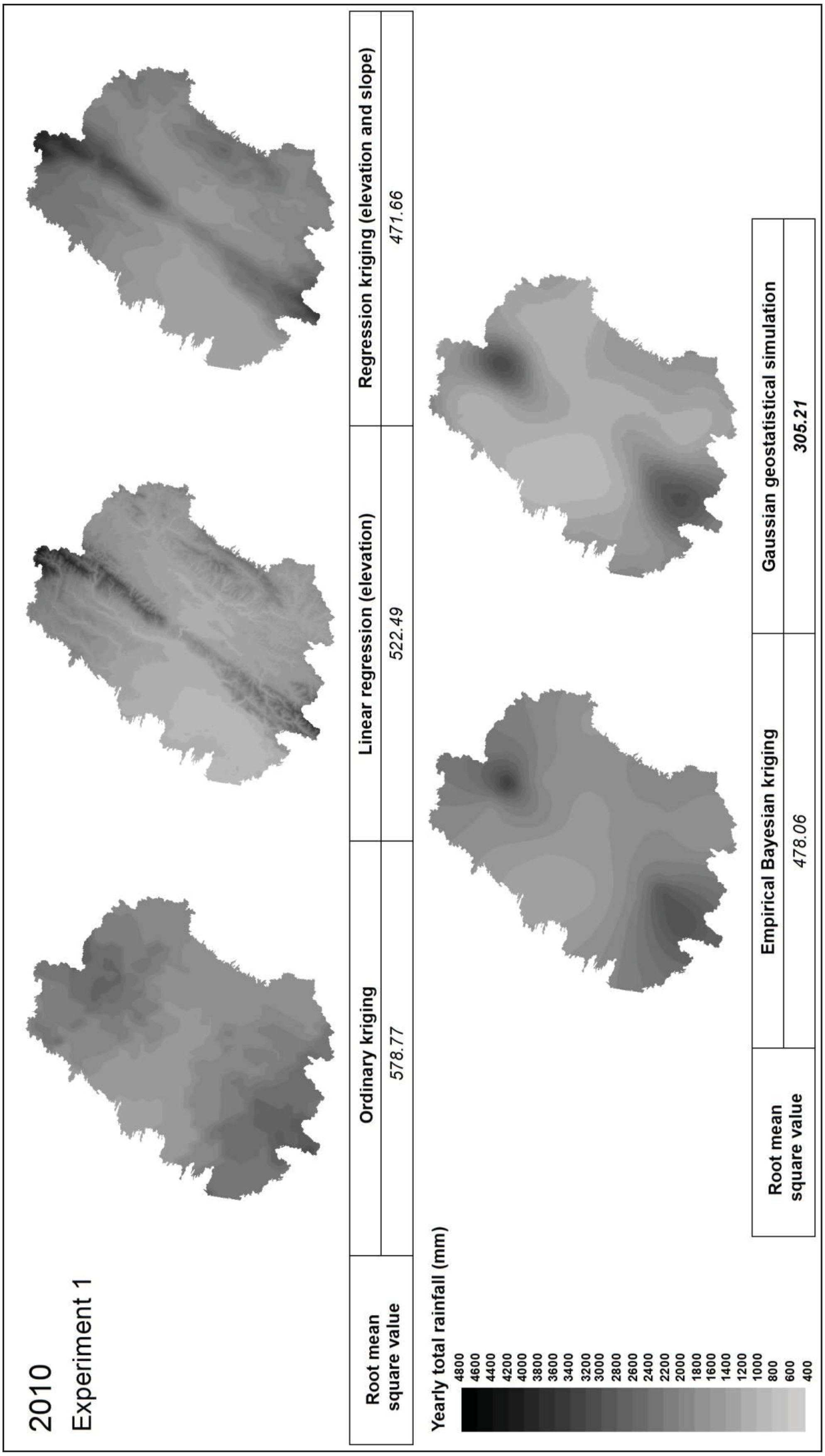
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	523.30	***315.49***



	Ordinary kriging	Linear regression (elevation and slope)	Regression kriging (elevation and slope)
Root mean square value	*554.25*	*559.68*	***520.34***

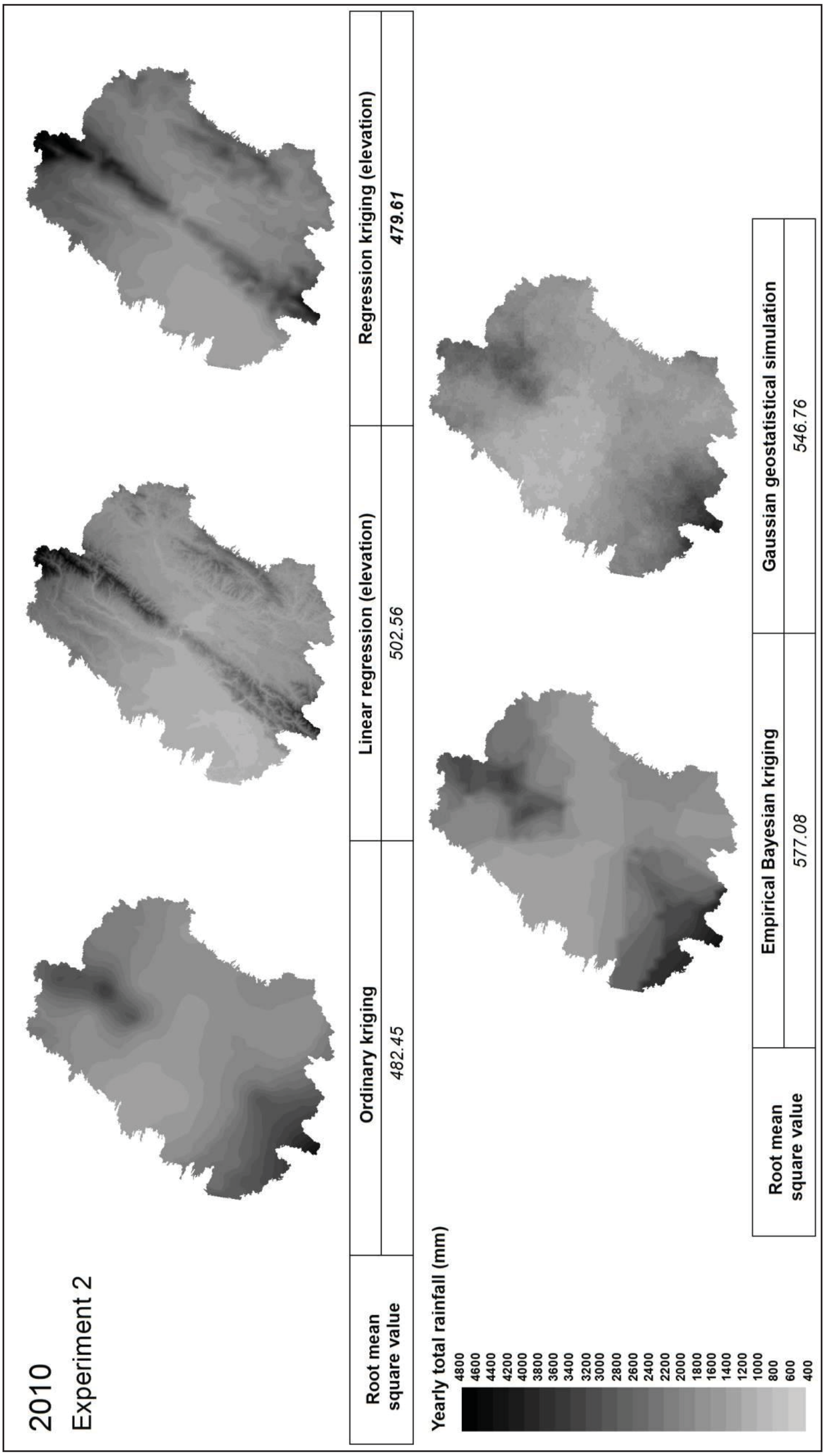
	Empirical Bayesian kriging	Gaussian geostatistical simulation
Root mean square value	*771.25*	*565.28*

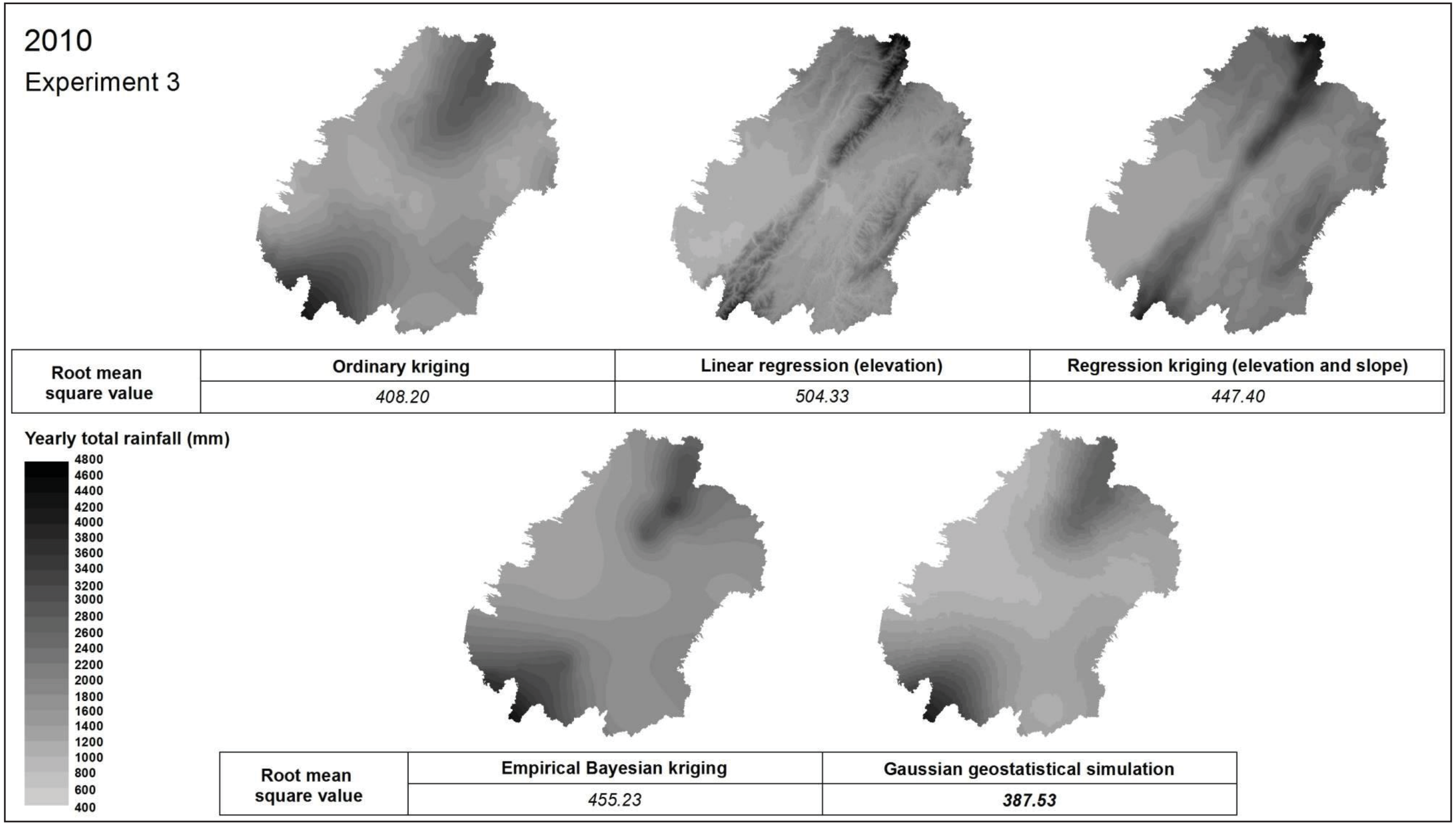

2009
Experiment 3
Root mean square value
Ordinary kriging
456.08
Linear regression (elevation)
531.73
Regression kriging (elevation and slope)
490.04
Root mean square value
Empirical Bayesian kriging
552.46
Gaussian geostatistical simulation
383.94
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400



Root mean square value	Ordinary kriging	Linear regression (elevation)	Regression kriging (elevation and slope)
	578.77	*522.49*	*471.66*

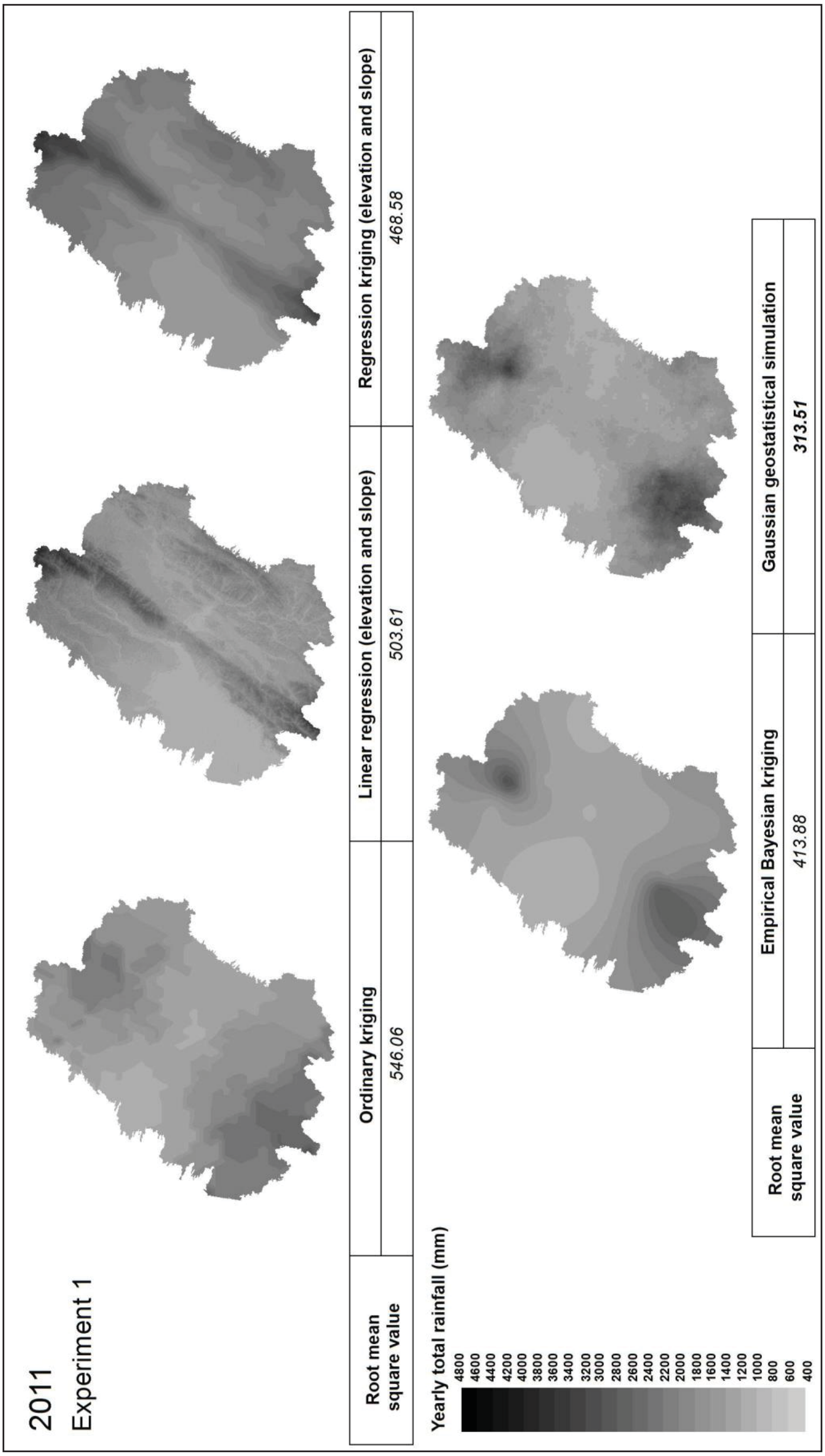
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	478.06	***305.21***

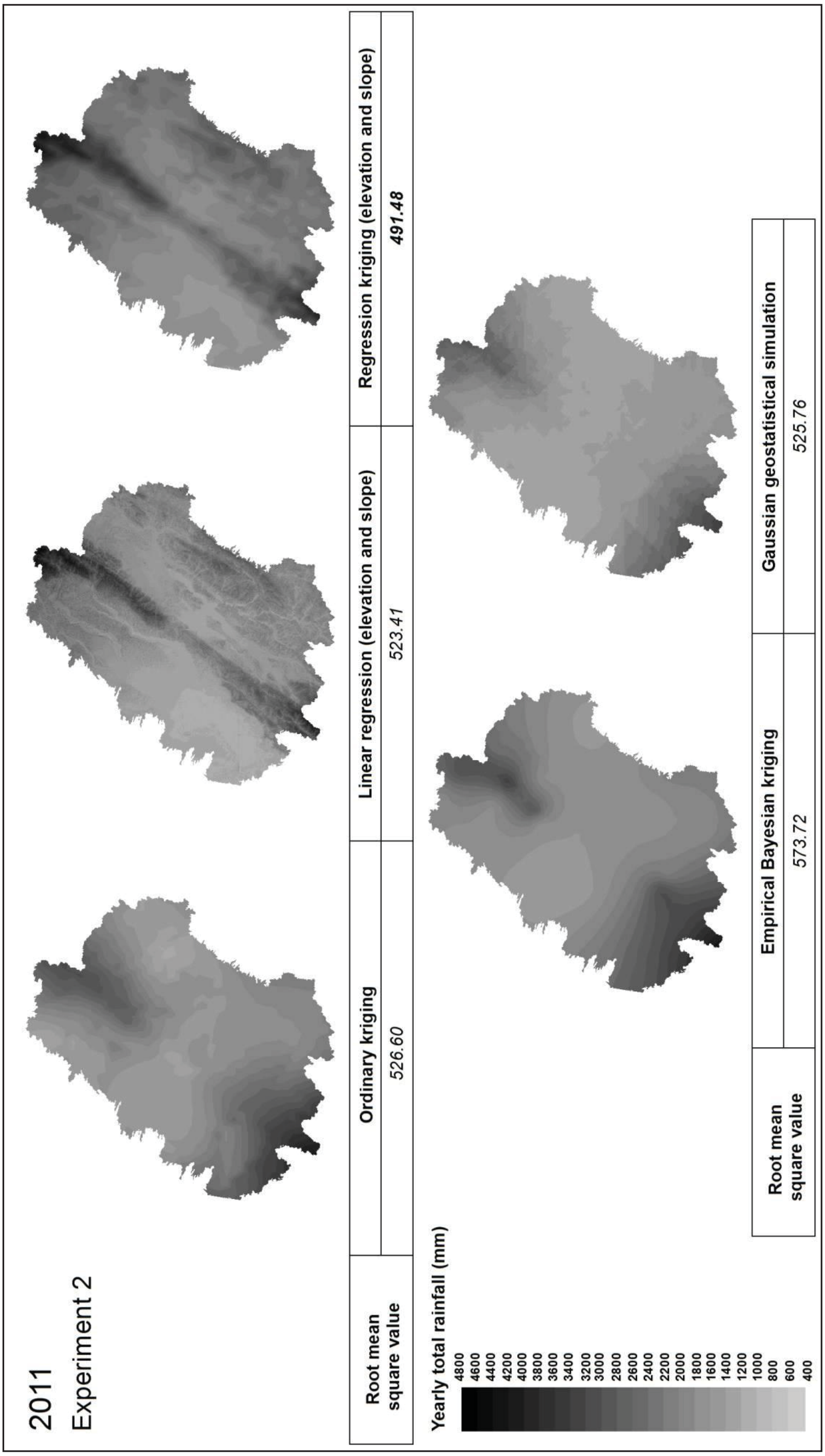

2010
Experiment 2
Root mean square value
Ordinary kriging
482.45
Linear regression (elevation)
502.56
Regression kriging (elevation)
479.61
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
Root mean square value
Empirical Bayesian kriging
577.08
Gaussian geostatistical simulation
546.76

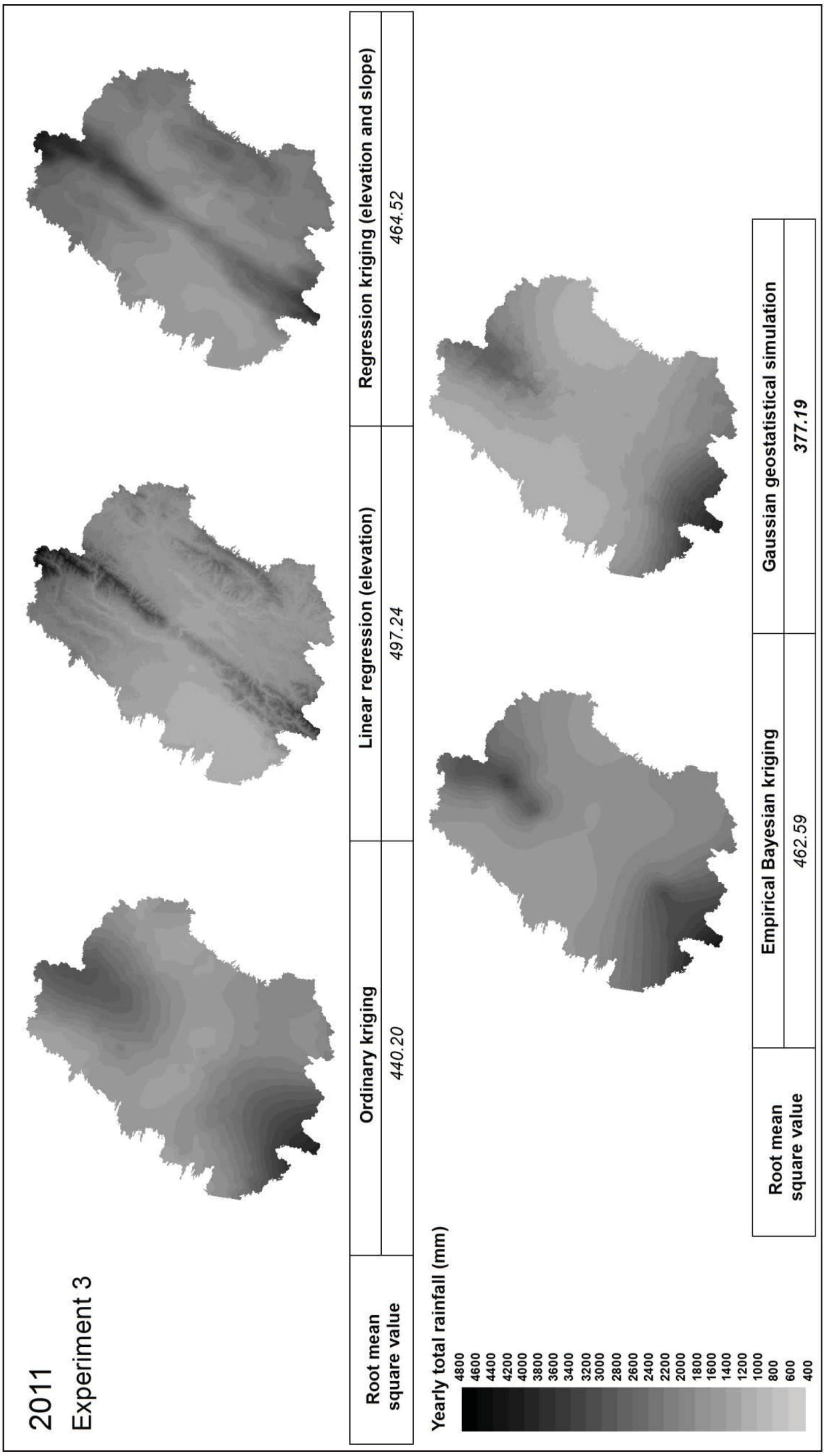


Root mean square value	Ordinary kriging	Linear regression (elevation)	Regression kriging (elevation and slope)
	408.20	*504.33*	*447.40*

Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	455.23	***387.53***

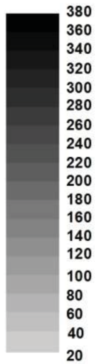

2011
Experiment 1
Root mean square value
Ordinary kriging
546.06
Linear regression (elevation and slope)
503.61
Regression kriging (elevation and slope)
468.58
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
Root mean square value
Empirical Bayesian kriging
413.88
Gaussian geostatistical simulation
313.51

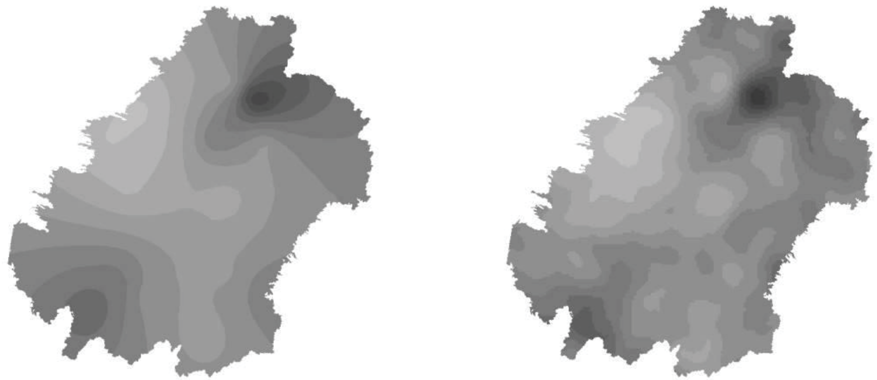

2011
Experiment 2
Root mean square value
Ordinary kriging
526.60
Linear regression (elevation and slope)
523.41
Regression kriging (elevation and slope)
491.48
Root mean square value
Empirical Bayesian kriging
573.72
Gaussian geostatistical simulation
525.76
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400


2011
Experiment 3
Root mean square value
Ordinary kriging
440.20
Linear regression (elevation)
497.24
Regression kriging (elevation and slope)
464.52
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
Root mean square value
Empirical Bayesian kriging
462.59
Gaussian geostatistical simulation
377.19

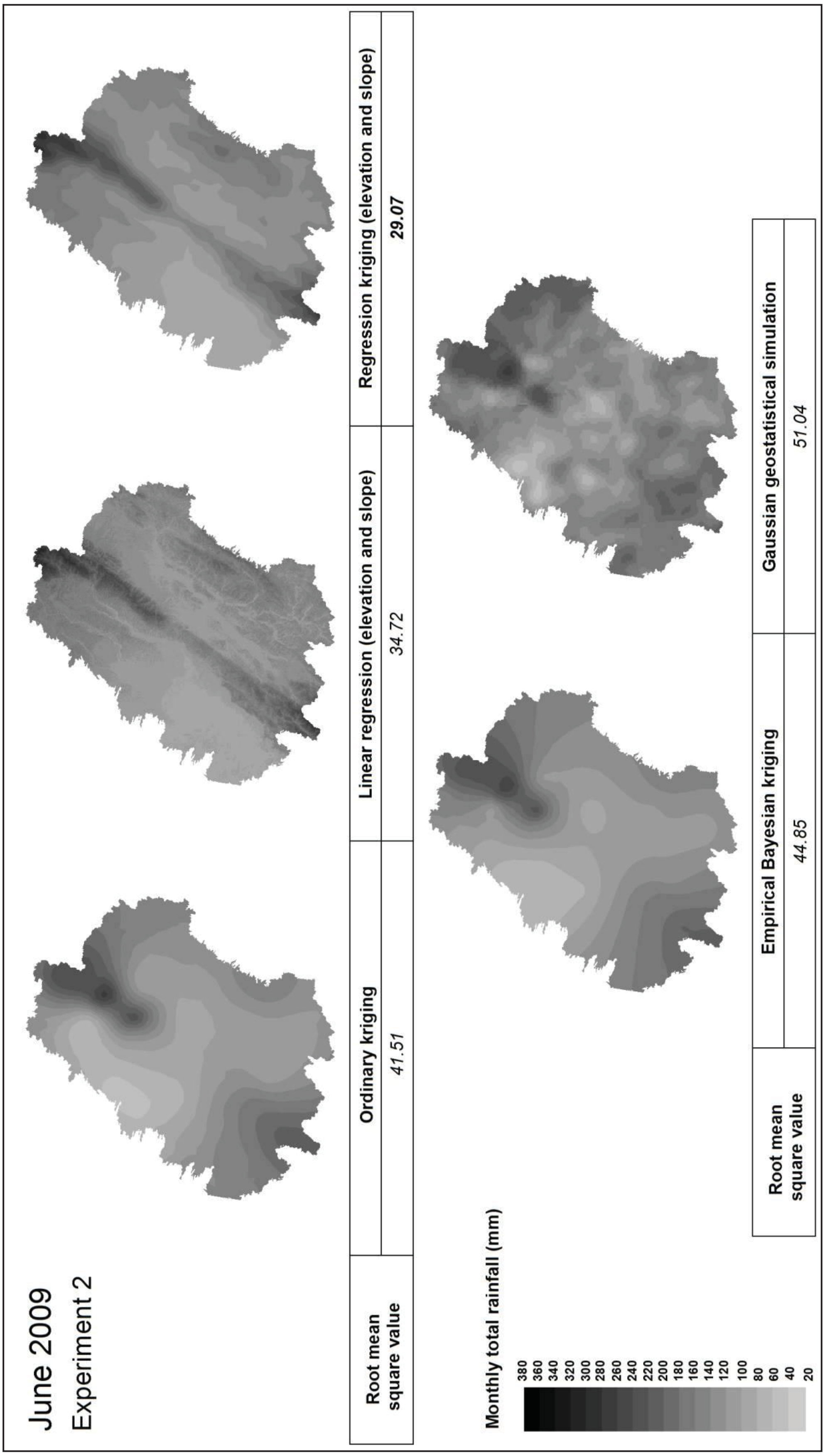
June 2009
Experiment 1

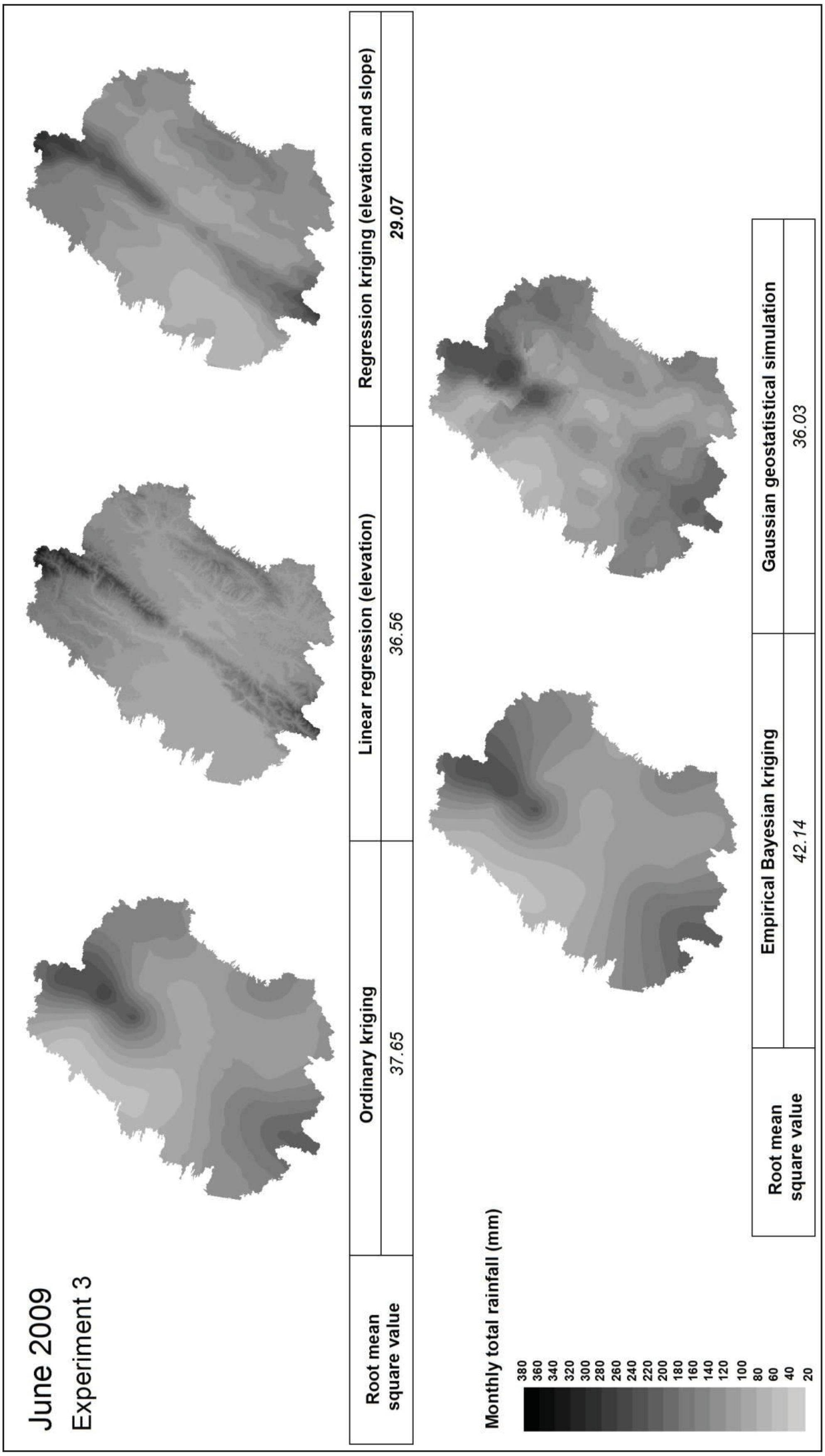
Root mean square value	Ordinary kriging	Linear regression (elevation and slope)	Regression kriging (elevation and slope)
	36.95	*33.39*	***26.82***

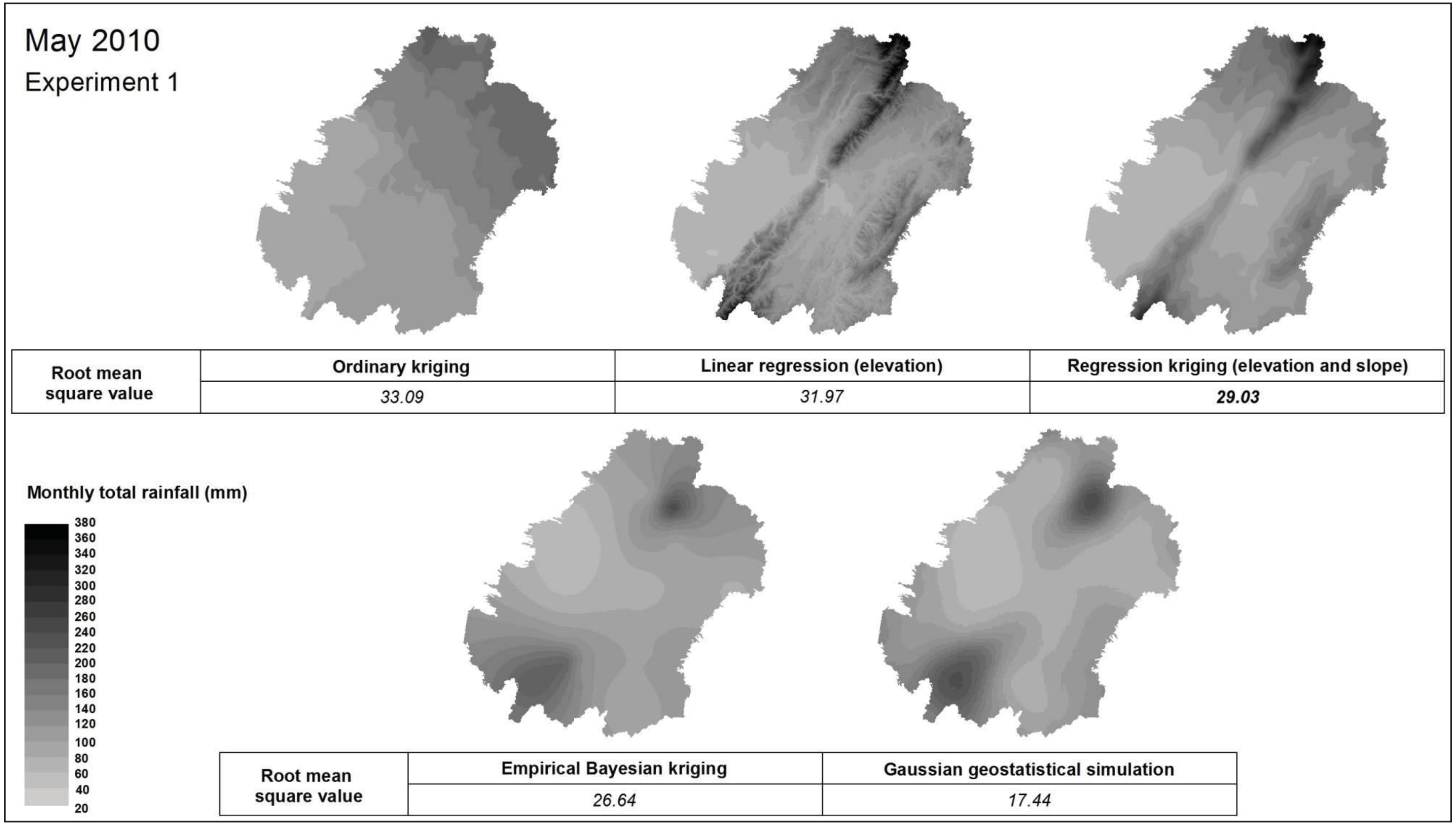


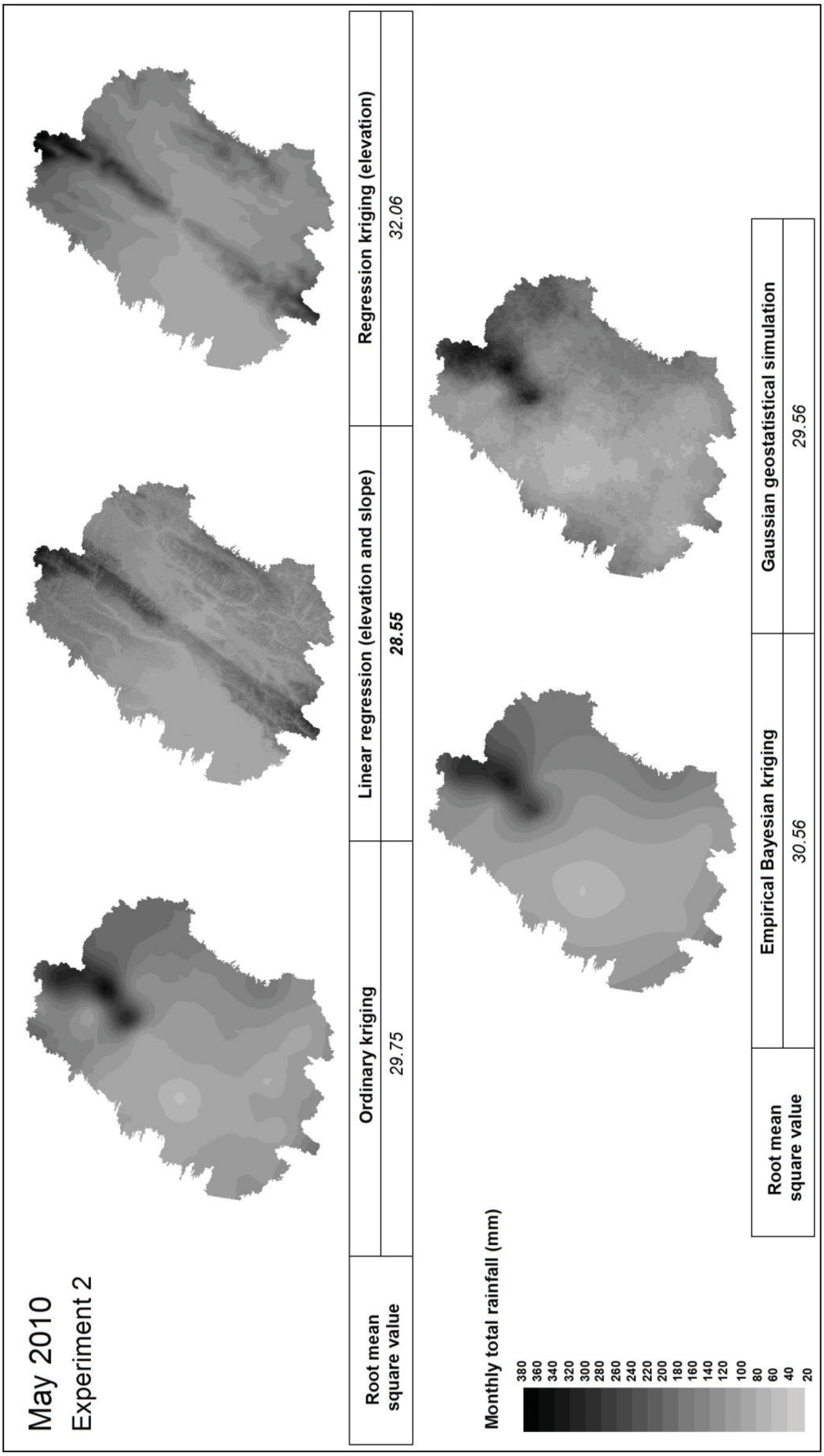


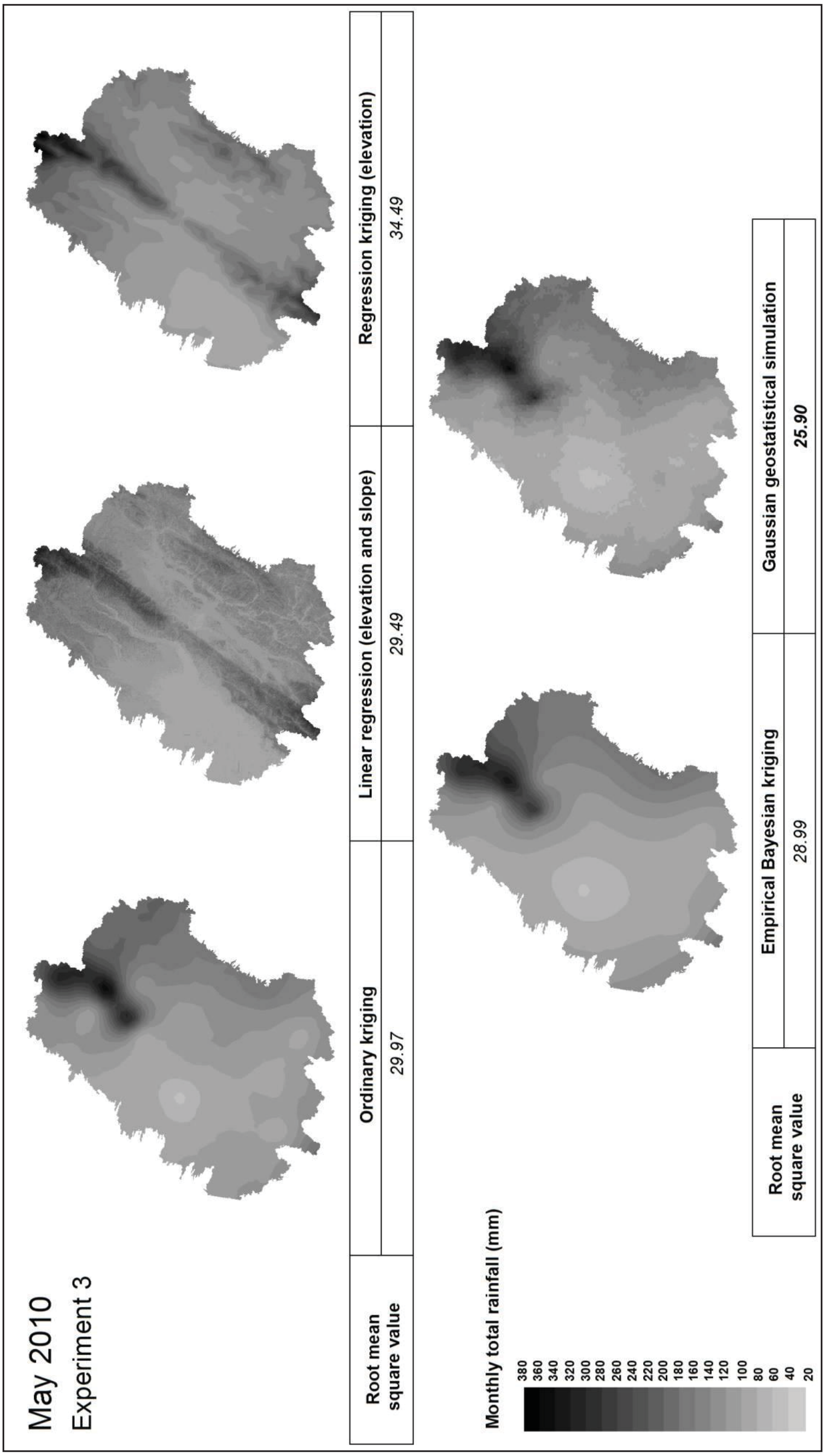
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	39.92	*33.34*


June 2009
Experiment 2
Root mean square value
Ordinary kriging
41.51
Linear regression (elevation and slope)
34.72
Regression kriging (elevation and slope)
29.07
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
44.85
Gaussian geostatistical simulation
51.04


June 2009
Experiment 3
Root mean square value
Ordinary kriging
37.65
Linear regression (elevation)
36.56
Regression kriging (elevation and slope)
29.07
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
42.14
Gaussian geostatistical simulation
36.03


May 2010
Experiment 1
Root mean square value
Ordinary kriging
33.09
Linear regression (elevation)
31.97
Regression kriging (elevation and slope)
29.03
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
26.64
Gaussian geostatistical simulation
17.44

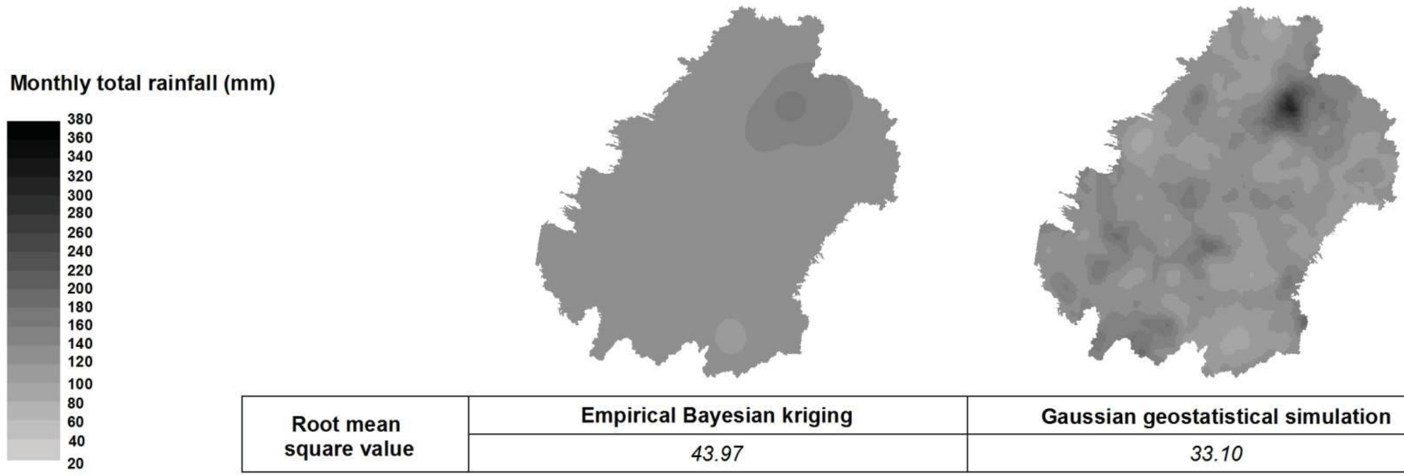

May 2010
Experiment 2
Root mean square value
Ordinary kriging
29.75
Linear regression (elevation and slope)
28.55
Regression kriging (elevation)
32.06
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
30.56
Gaussian geostatistical simulation
29.56


May 2010
Experiment 3
Root mean square value
Ordinary kriging
29.97
Linear regression (elevation and slope)
29.49
Regression kriging (elevation)
34.49
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
28.99
Gaussian geostatistical simulation
25.90

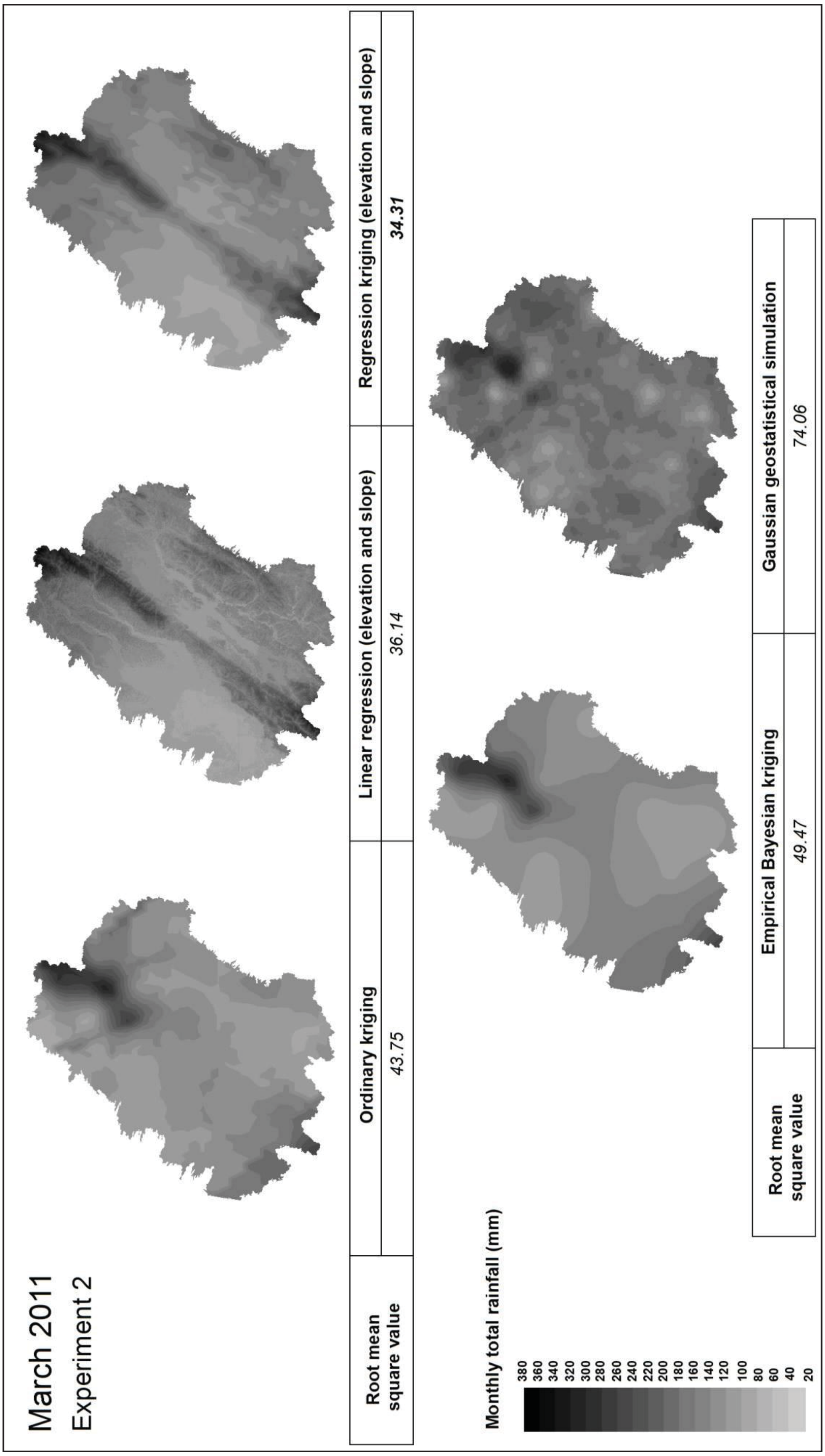
March 2011

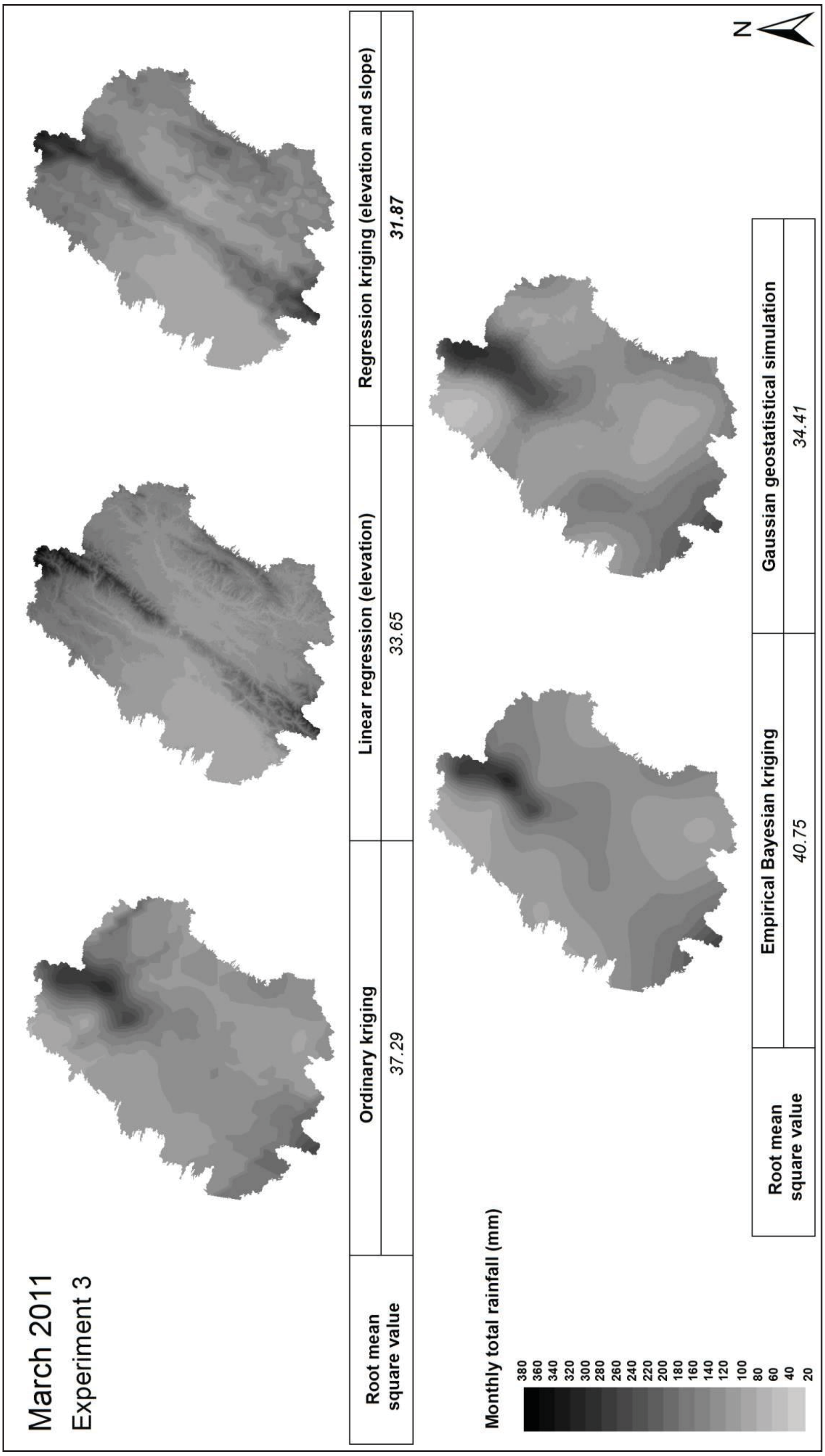
Experiment 1

Root mean square value	Ordinary kriging	Linear regression (elevation and slope)	Regression kriging (elevation)
	47.53	*33.01*	***31.82***

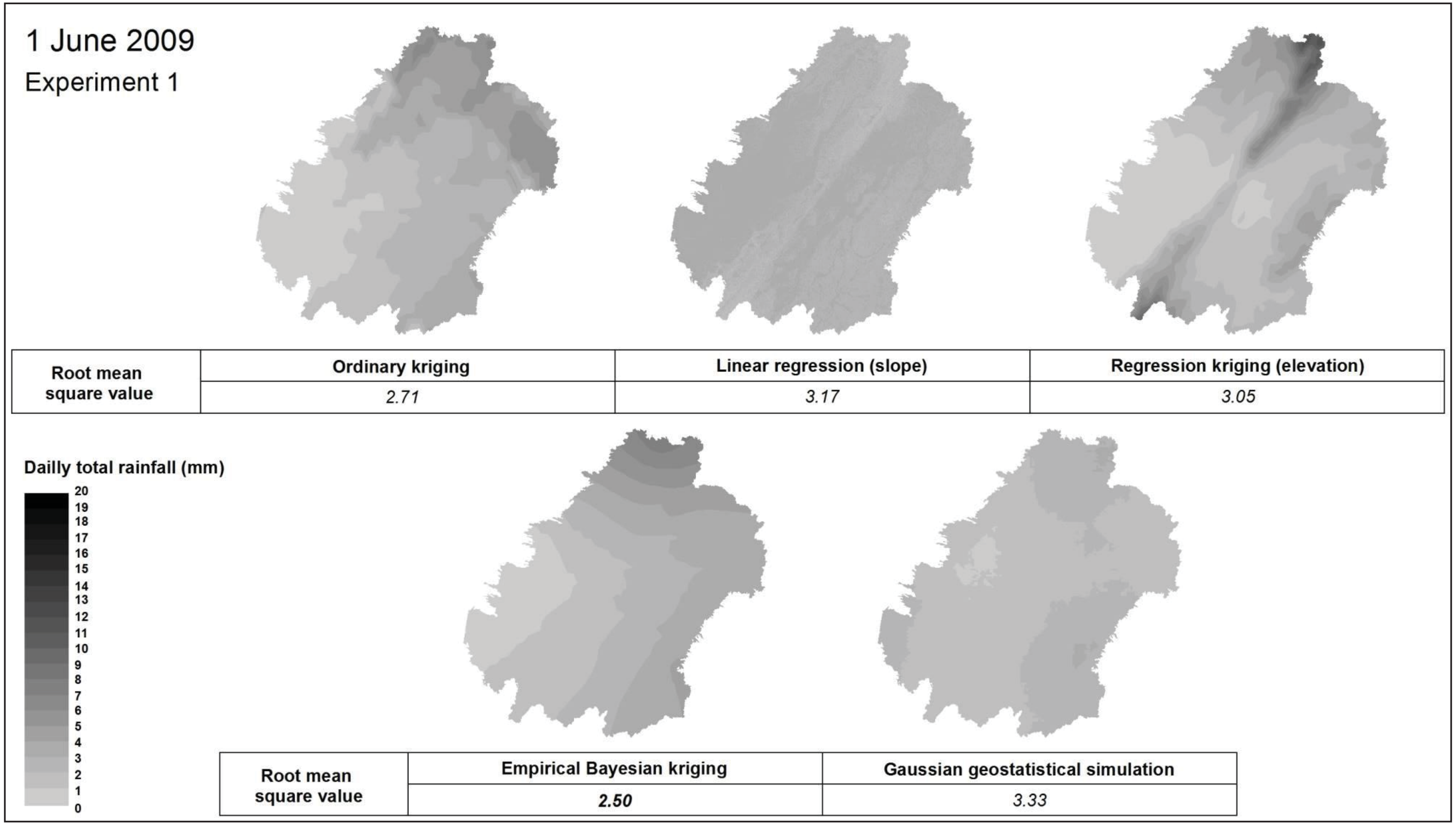


Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	43.97	*33.10*


March 2011
Experiment 2
Root mean square value
Ordinary kriging
43.75
Linear regression (elevation and slope)
36.14
Regression kriging (elevation and slope)
34.31
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Root mean square value
Empirical Bayesian kriging
49.47
Gaussian geostatistical simulation
74.06

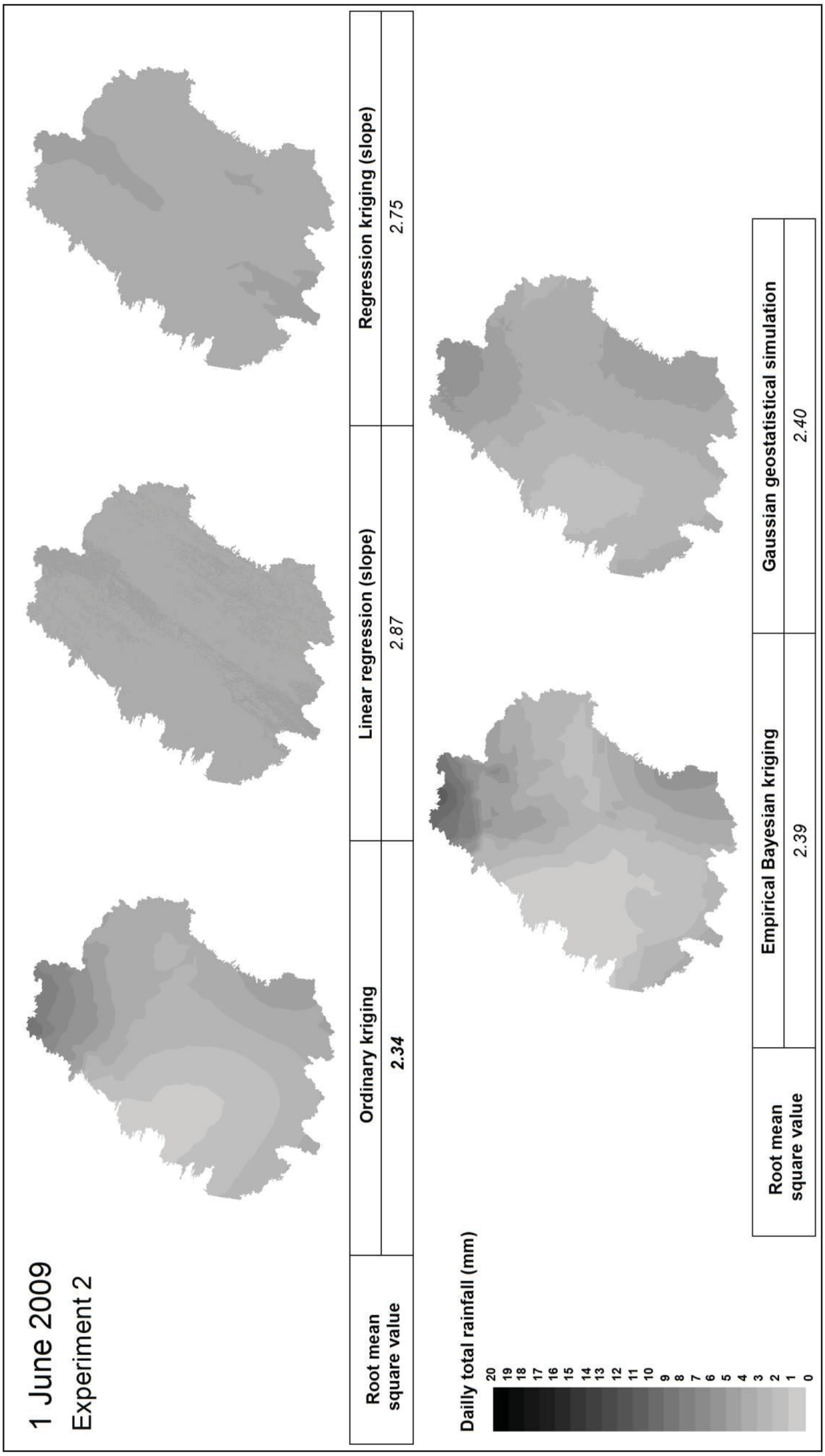


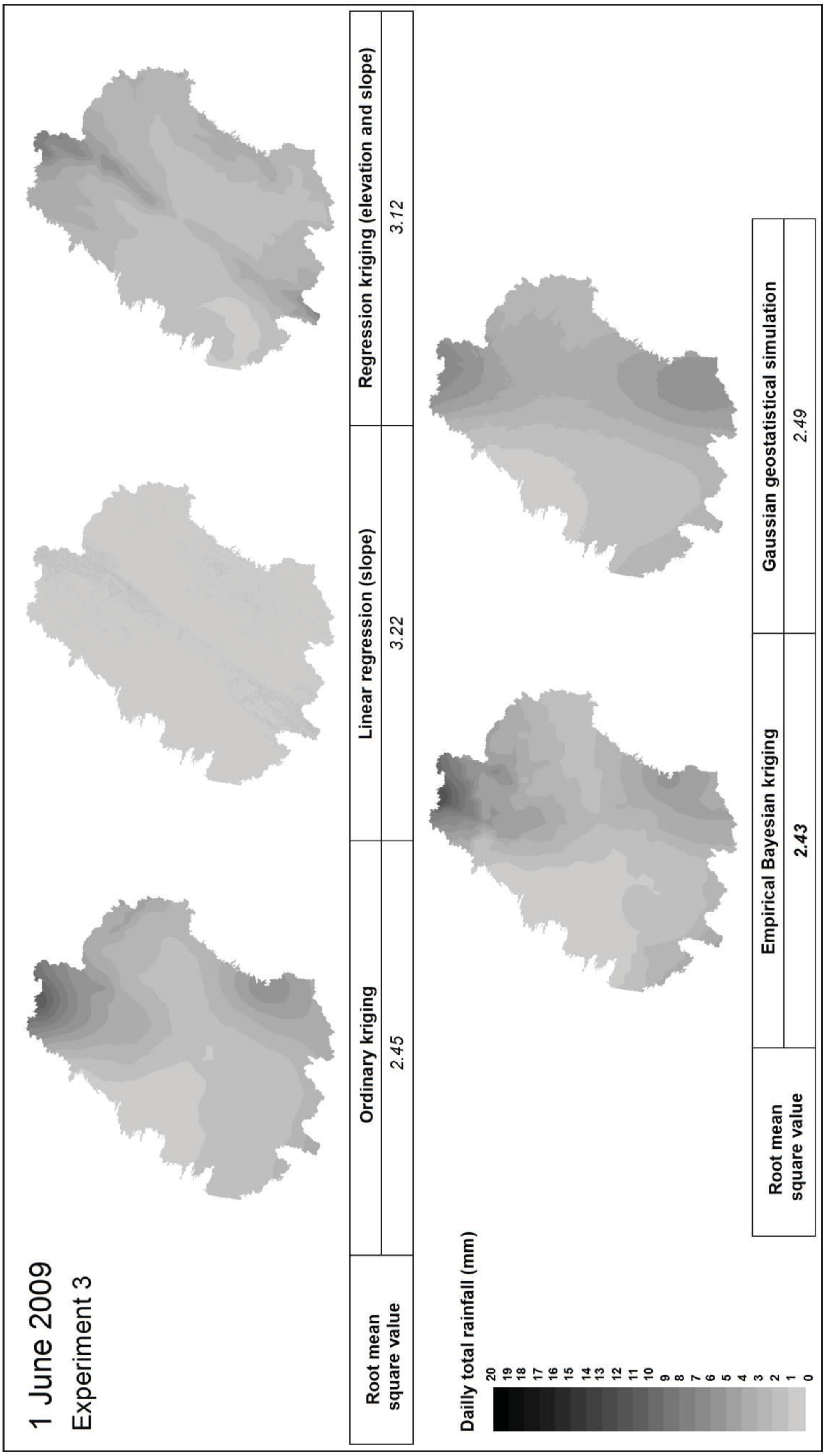
March 2011
Experiment 3
Root mean square value
Ordinary kriging
37.29
Linear regression (elevation)
33.65
Regression kriging (elevation and slope)
31.87
Root mean square value
Empirical Bayesian kriging
40.75
Gaussian geostatistical simulation
34.41
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
N

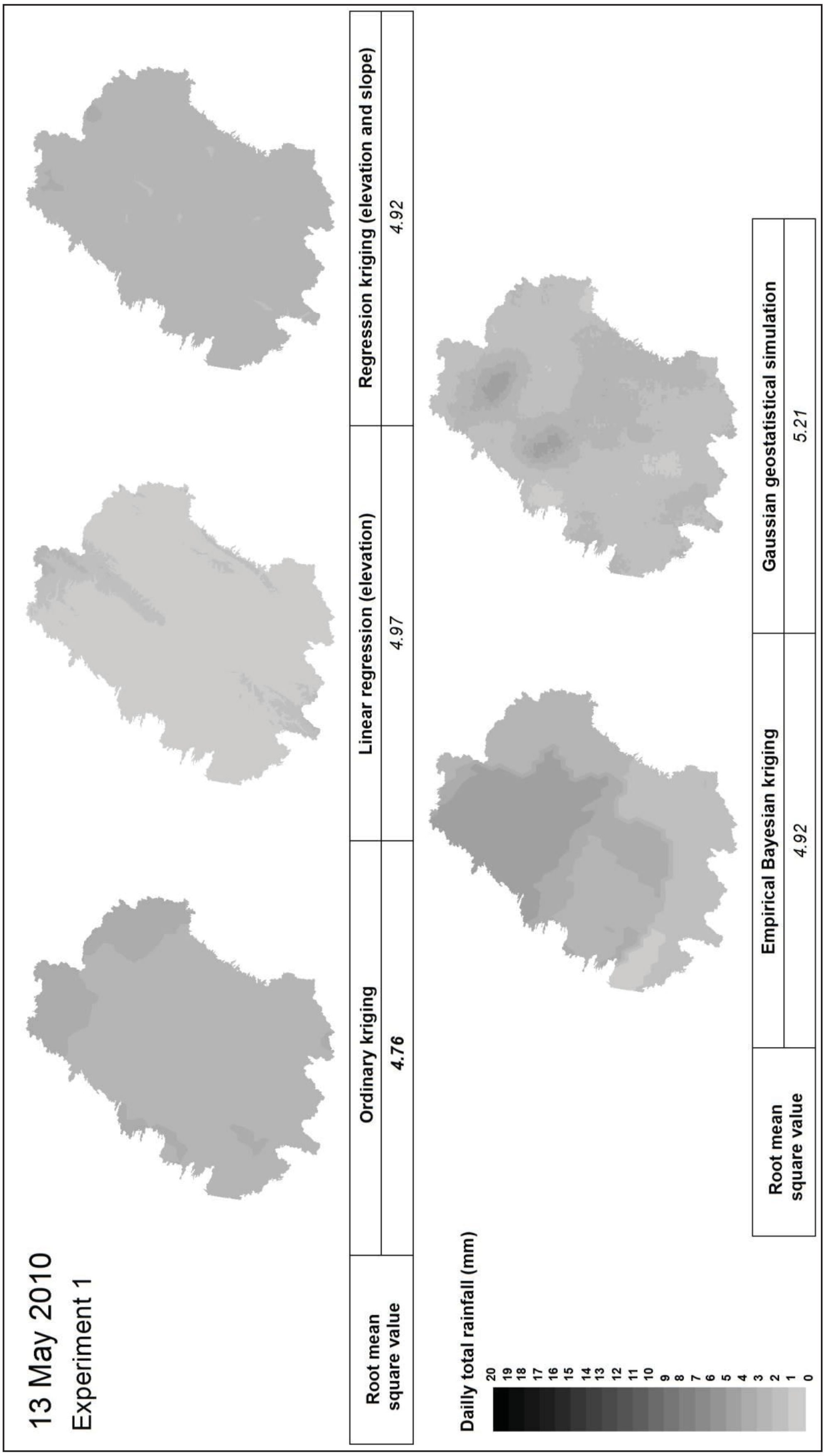


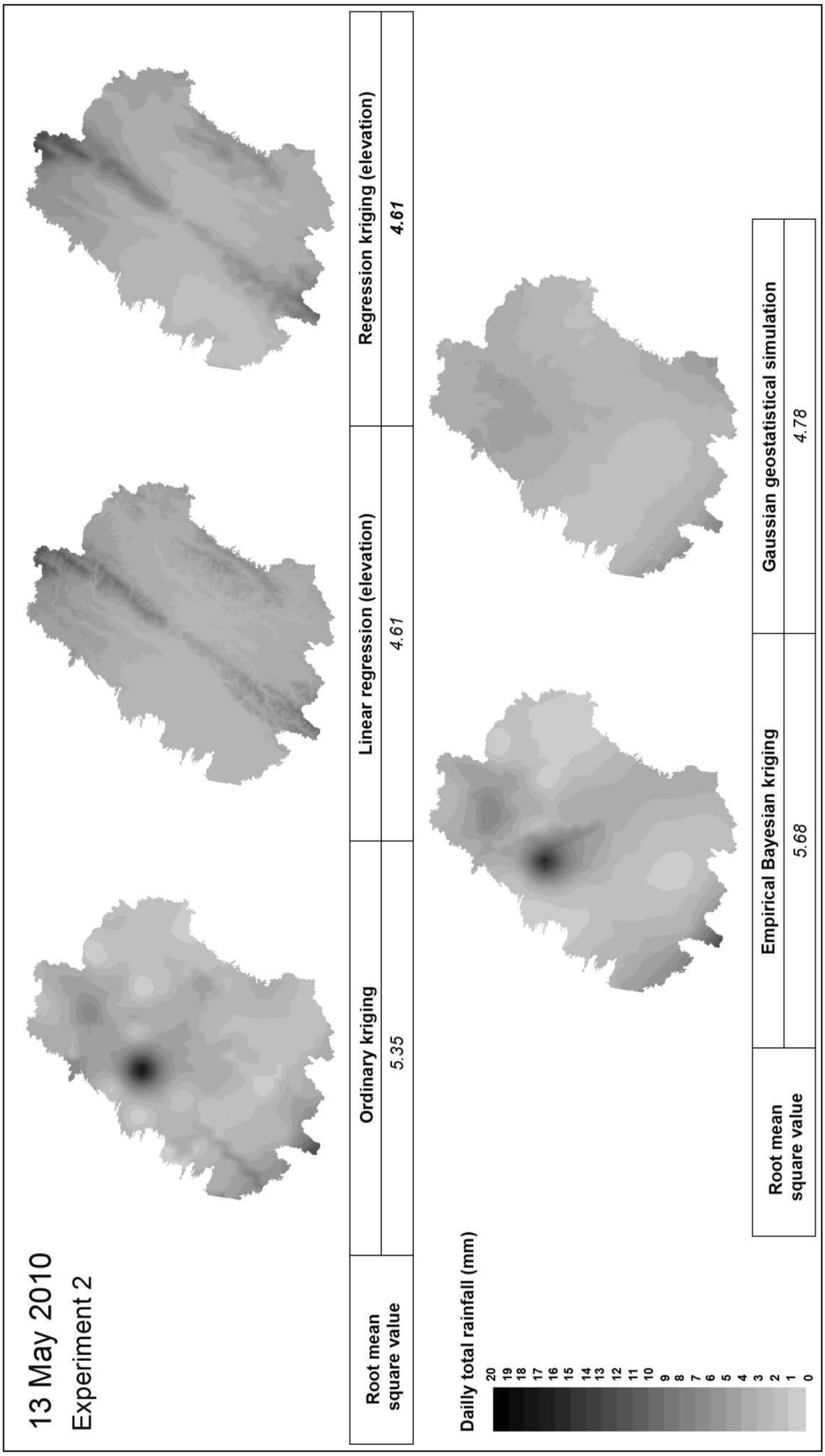
Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (elevation)
	2.71	*3.17*	*3.05*

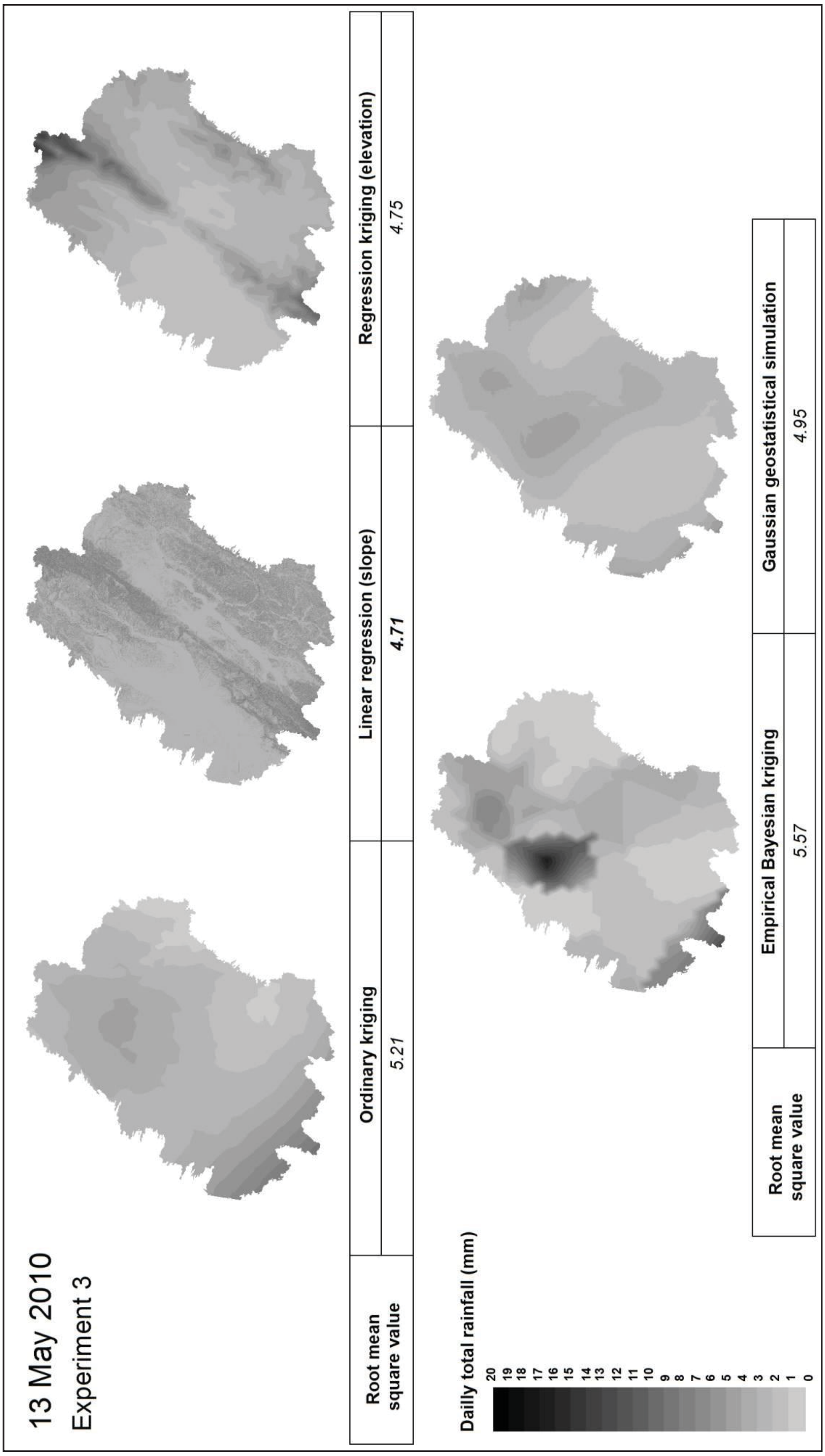
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	2.50	*3.33*


1 June 2009
Experiment 2
Root mean square value
Ordinary kriging
2.34
Linear regression (slope)
2.87
Regression kriging (slope)
2.75
Root mean square value
Empirical Bayesian kriging
2.39
Gaussian geostatistical simulation
2.40
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0


1 June 2009
Experiment 3
Ordinary kriging
Linear regression (slope)
Regression kriging (elevation and slope)
Root mean square value
2.45
3.22
3.12
Empirical Bayesian kriging
Gaussian geostatistical simulation
Root mean square value
2.43
2.49
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0

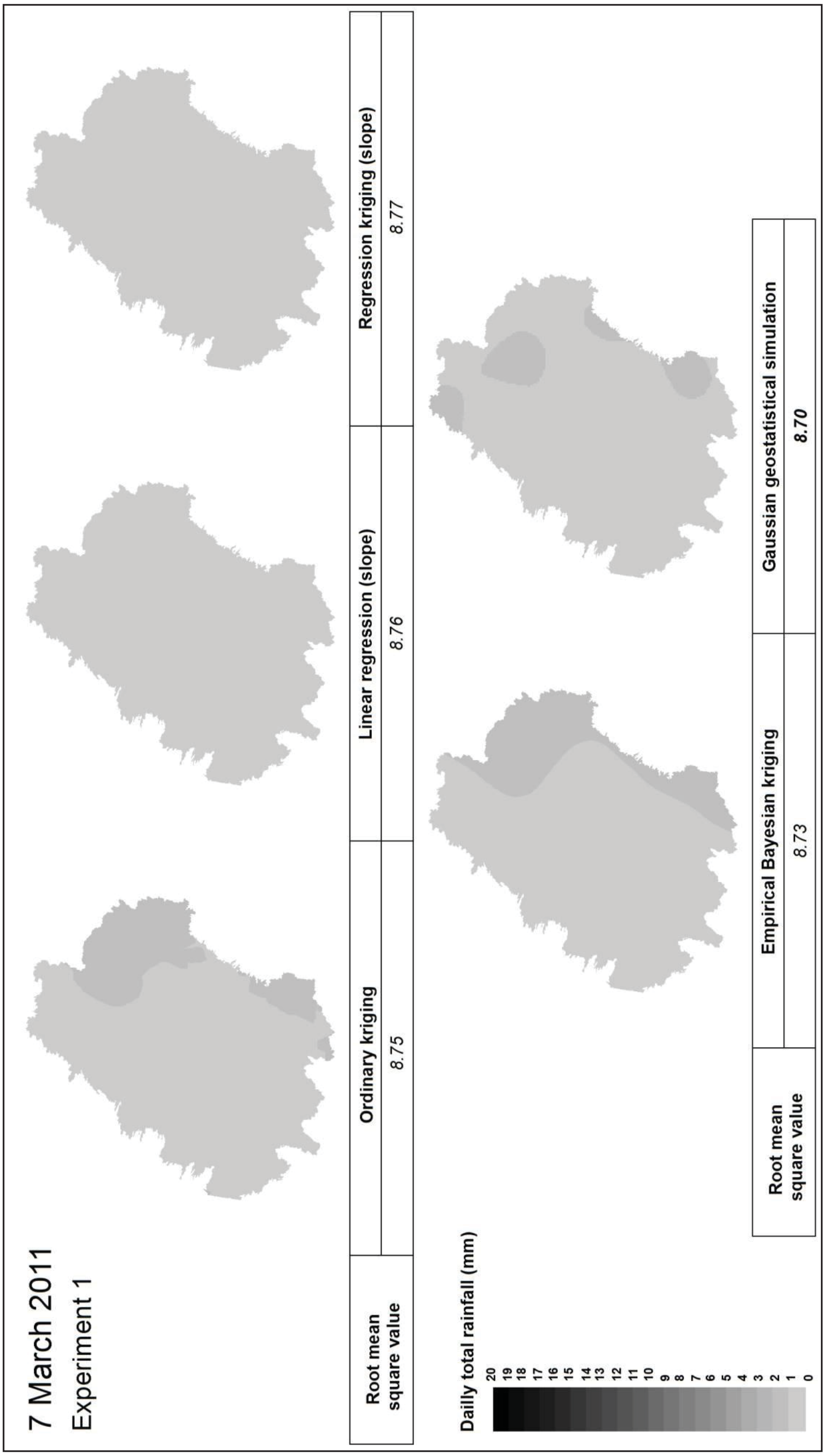

13 May 2010
Experiment 1
Root mean square value
Ordinary kriging
4.76
Linear regression (elevation)
4.97
Regression kriging (elevation and slope)
4.92
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Root mean square value
Empirical Bayesian kriging
4.92
Gaussian geostatistical simulation
5.21

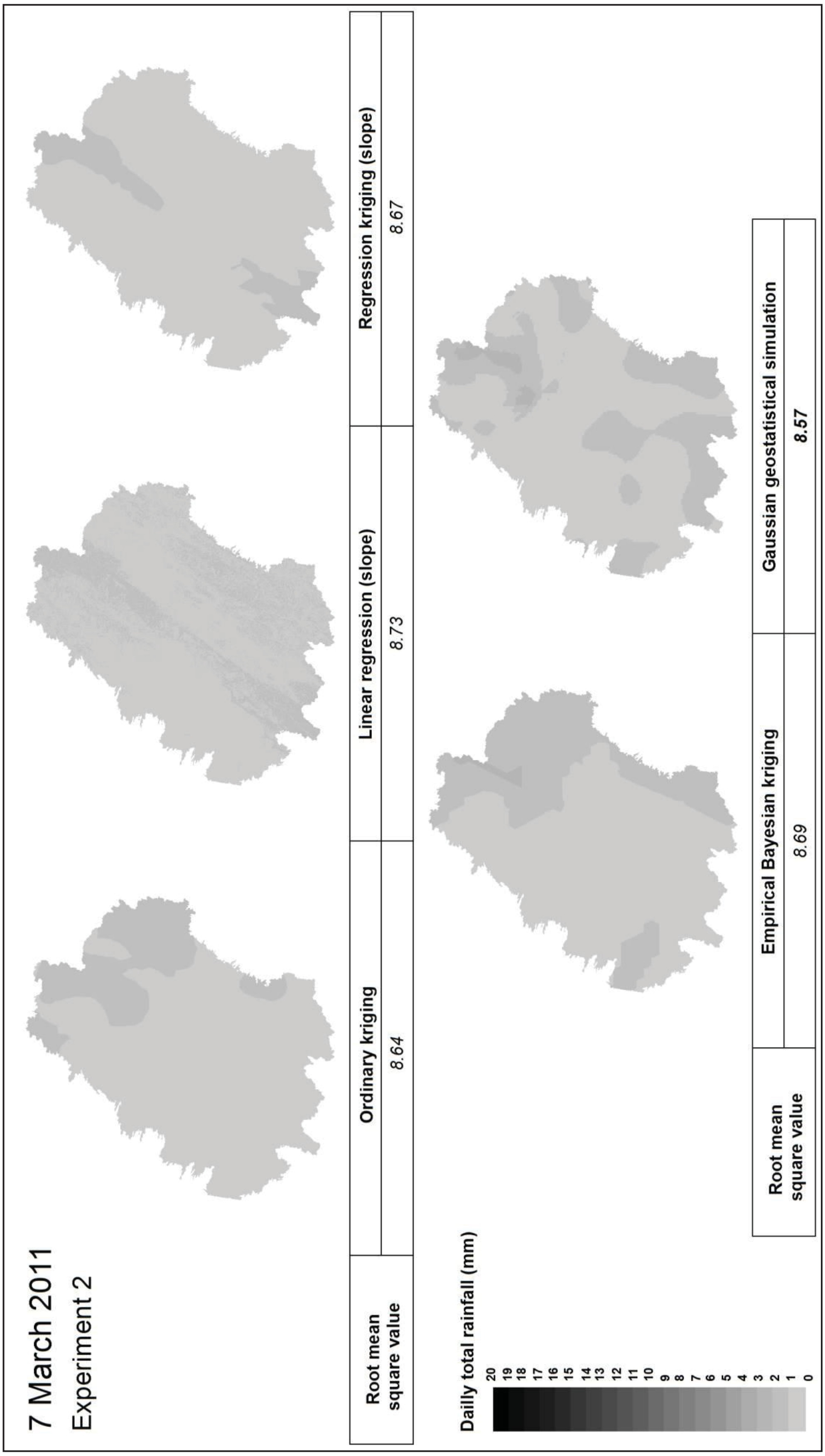

13 May 2010
Experiment 2
Root mean square value
Ordinary kriging
5.35
Linear regression (elevation)
4.61
Regression kriging (elevation)
4.61
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Root mean square value
Empirical Bayesian kriging
5.68
Gaussian geostatistical simulation
4.78



Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (elevation)
	5.21	***4.71***	*4.75*

Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	5.57	*4.95*


7 March 2011
Experiment 1
Root mean square value
Ordinary kriging
8.75
Linear regression (slope)
8.76
Regression kriging (slope)
8.77
Daily total rainfall (mm)
20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
Root mean square value
Empirical Bayesian kriging
8.73
Gaussian geostatistical simulation
8.70

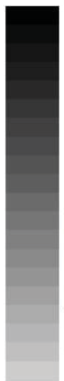

7 March 2011
Experiment 2
Root mean square value
Ordinary kriging
8.64
Linear regression (slope)
8.73
Regression kriging (slope)
8.67
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Root mean square value
Empirical Bayesian kriging
8.69
Gaussian geostatistical simulation
8.57

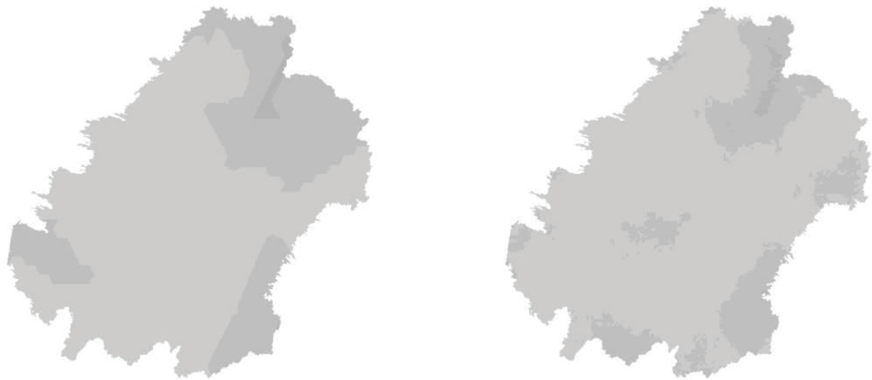
7 March 2011

Experiment 3

Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (slope)
	8.68	*8.73*	*8.67*

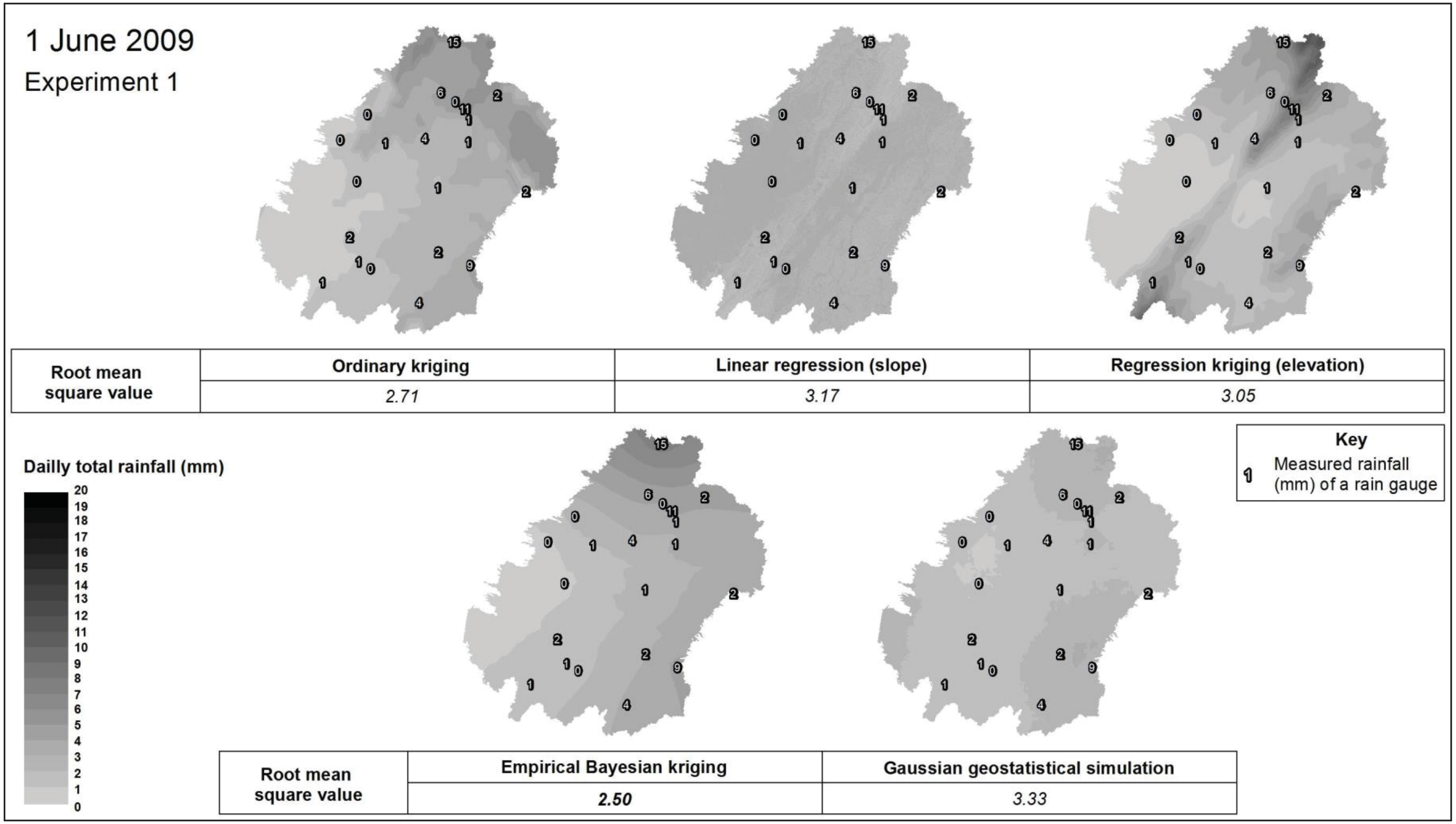
Daily total rainfall (mm)





Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	8.69	***8.59***

Appendix 29: Comparing the daily rainfall maps with the measured rainfall

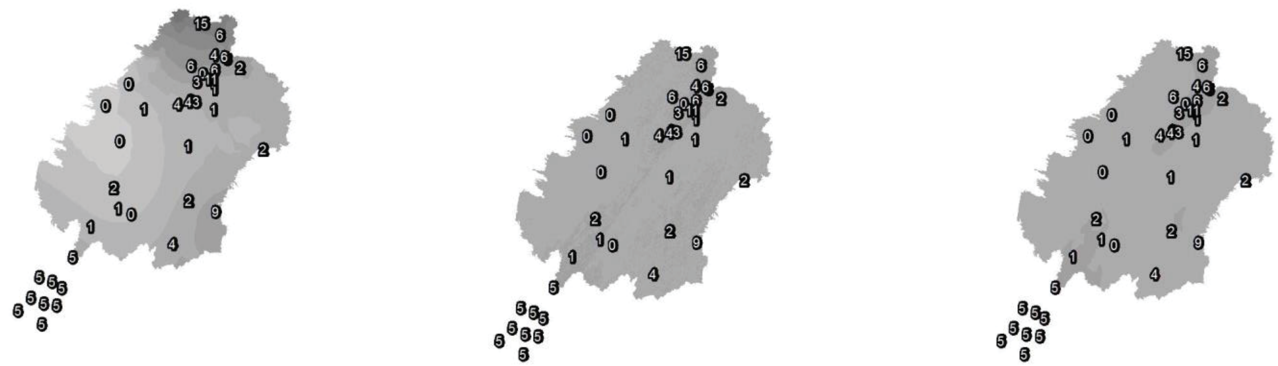


Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (elevation)
	2.71	*3.17*	*3.05*

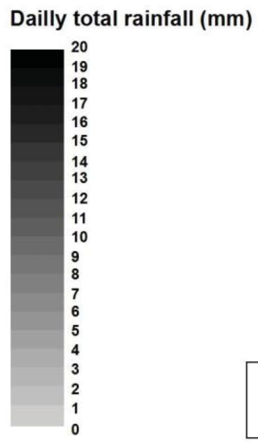
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	2.50	*3.33*

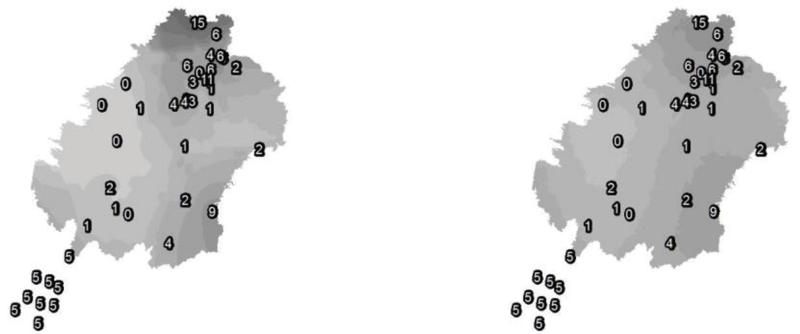
1 June 2009

Experiment 2



Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (slope)
	2.34	*2.87*	*2.75*

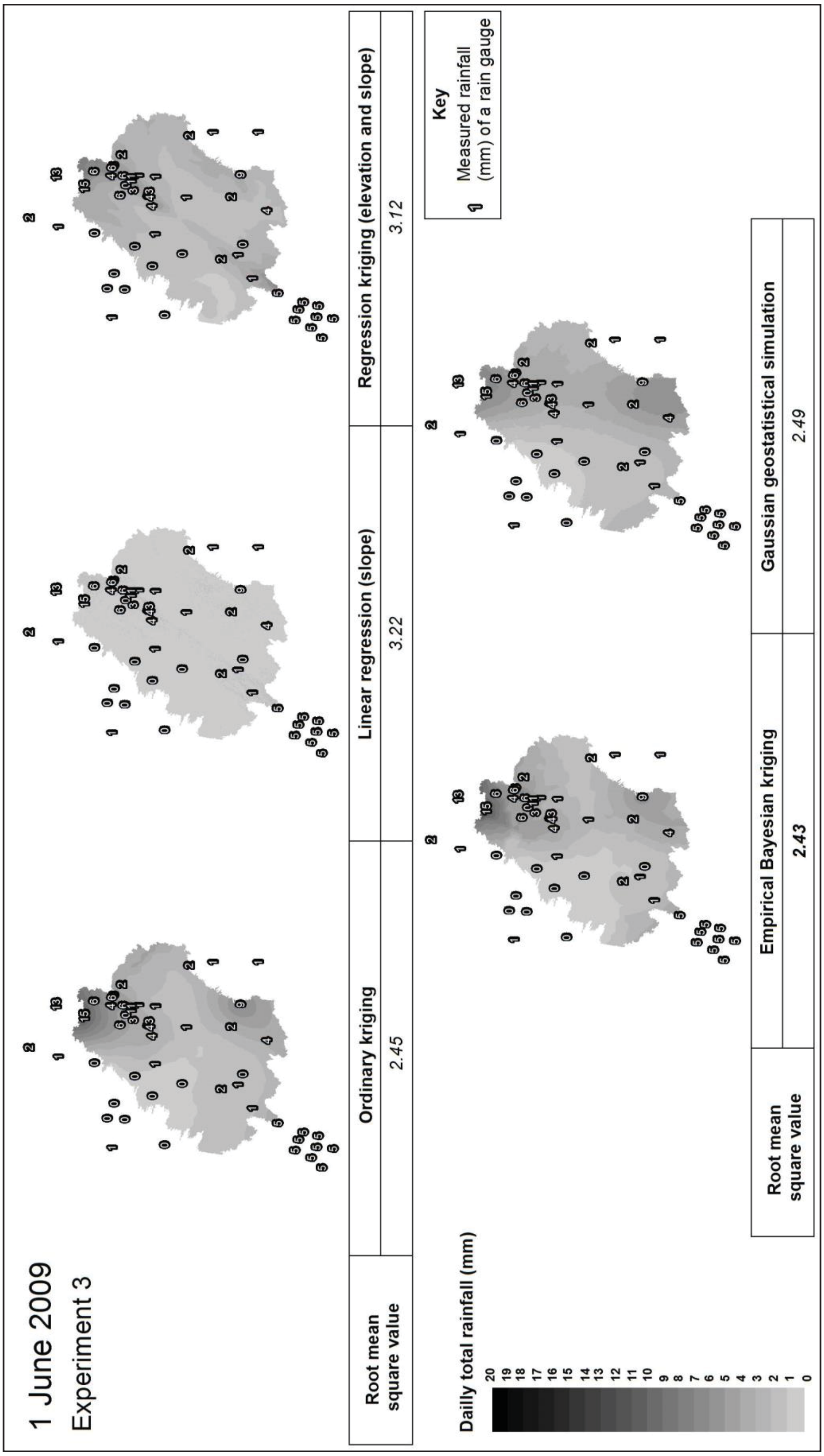




Key

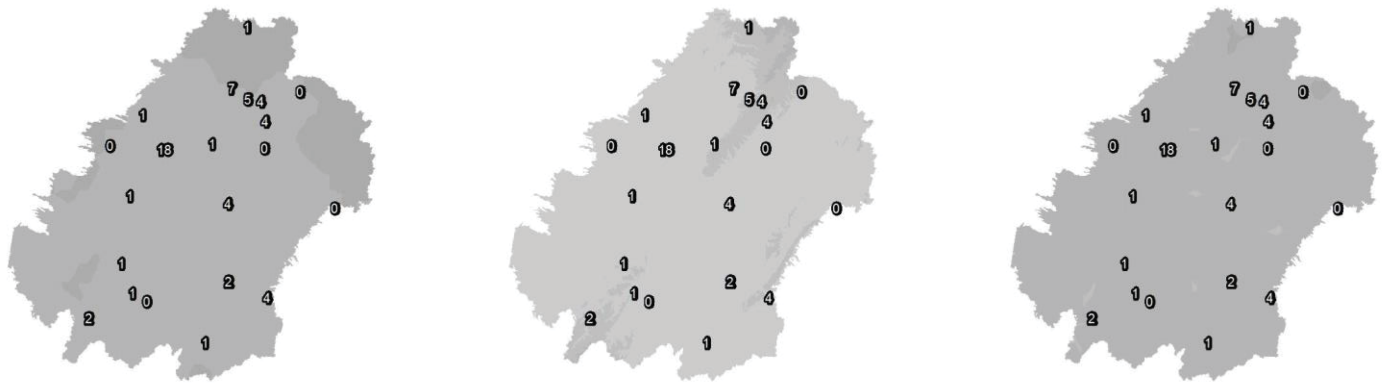
1 Measured rainfall (mm) of a rain gauge

Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	2.39	*2.40*

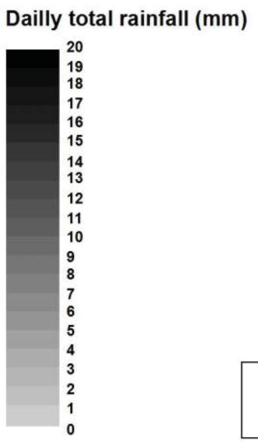

1 June 2009
Experiment 3
Root mean square value
Ordinary kriging
2.45
Linear regression (slope)
3.22
Regression kriging (elevation and slope)
3.12
Key
Measured rainfall (mm) of a rain gauge
Daily total rainfall (mm)
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Root mean square value
Empirical Bayesian kriging
2.43
Gaussian geostatistical simulation
2.49

13 May 2010

Experiment 1



Root mean square value	Ordinary kriging	Linear regression (elevation)	Regression kriging (elevation and slope)
	4.76	*4.97*	*4.92*



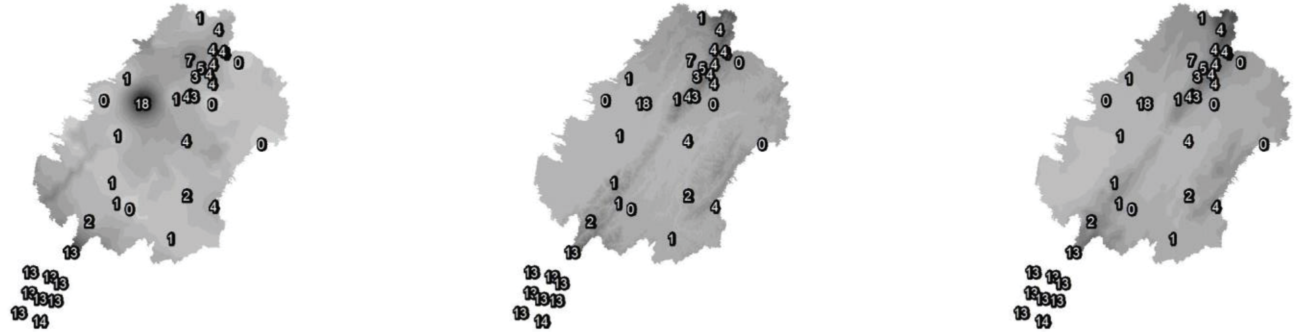
Key

1 Measured rainfall (mm) of a rain gauge

Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	4.92	*5.21*

13 May 2010

Experiment 2

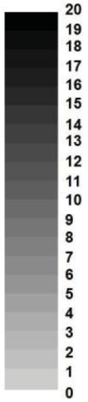


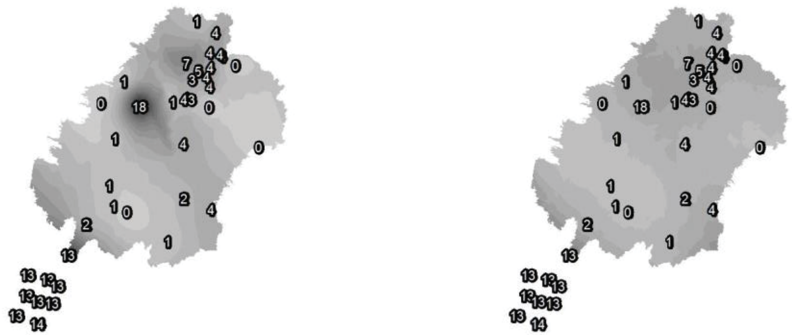
Root mean square value	Ordinary kriging	Linear regression (elevation)	Regression kriging (elevation)
	5.35	*4.61*	***4.61***

Key

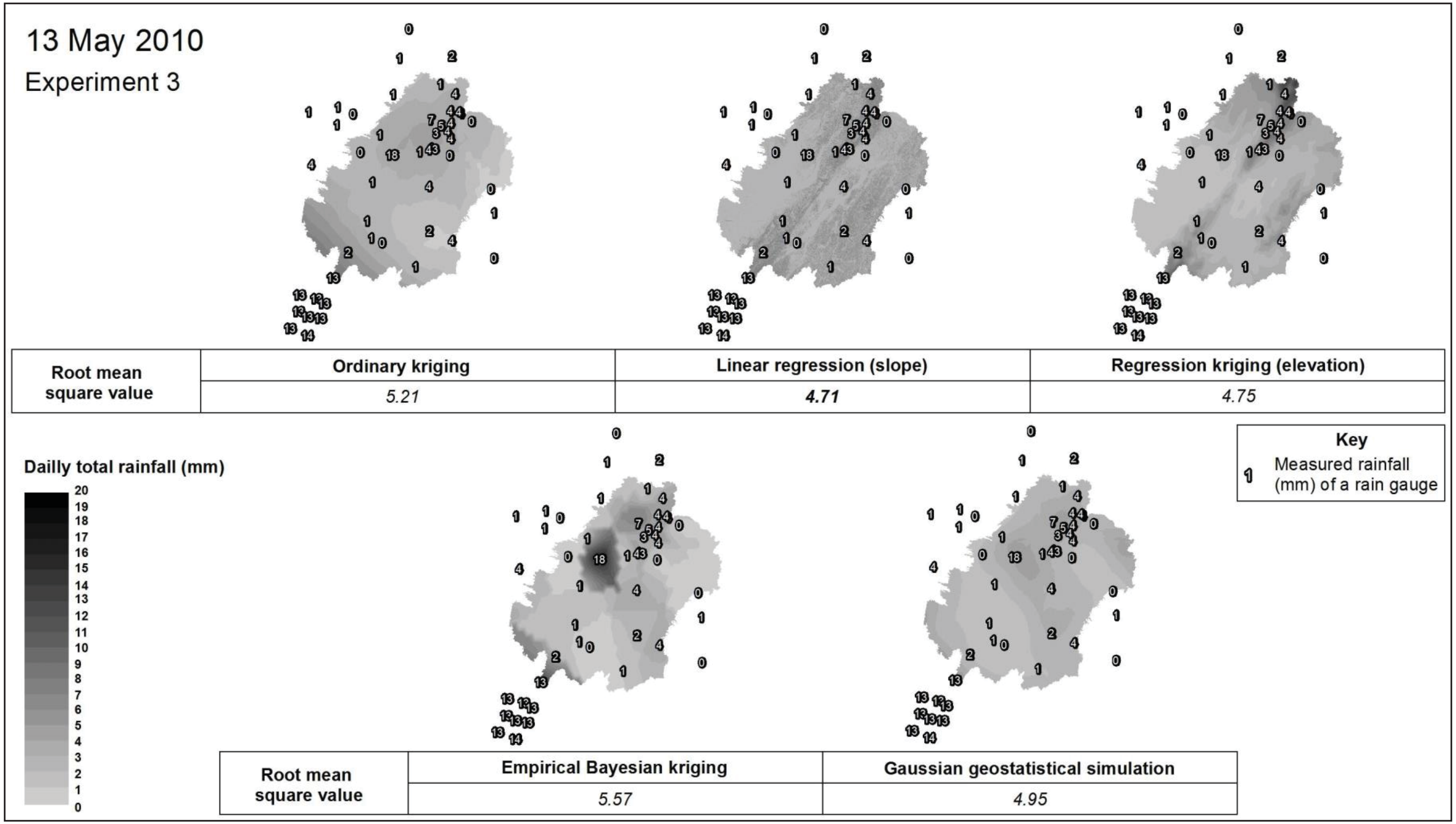
Measured rainfall (mm) of a rain gauge

Daily total rainfall (mm)

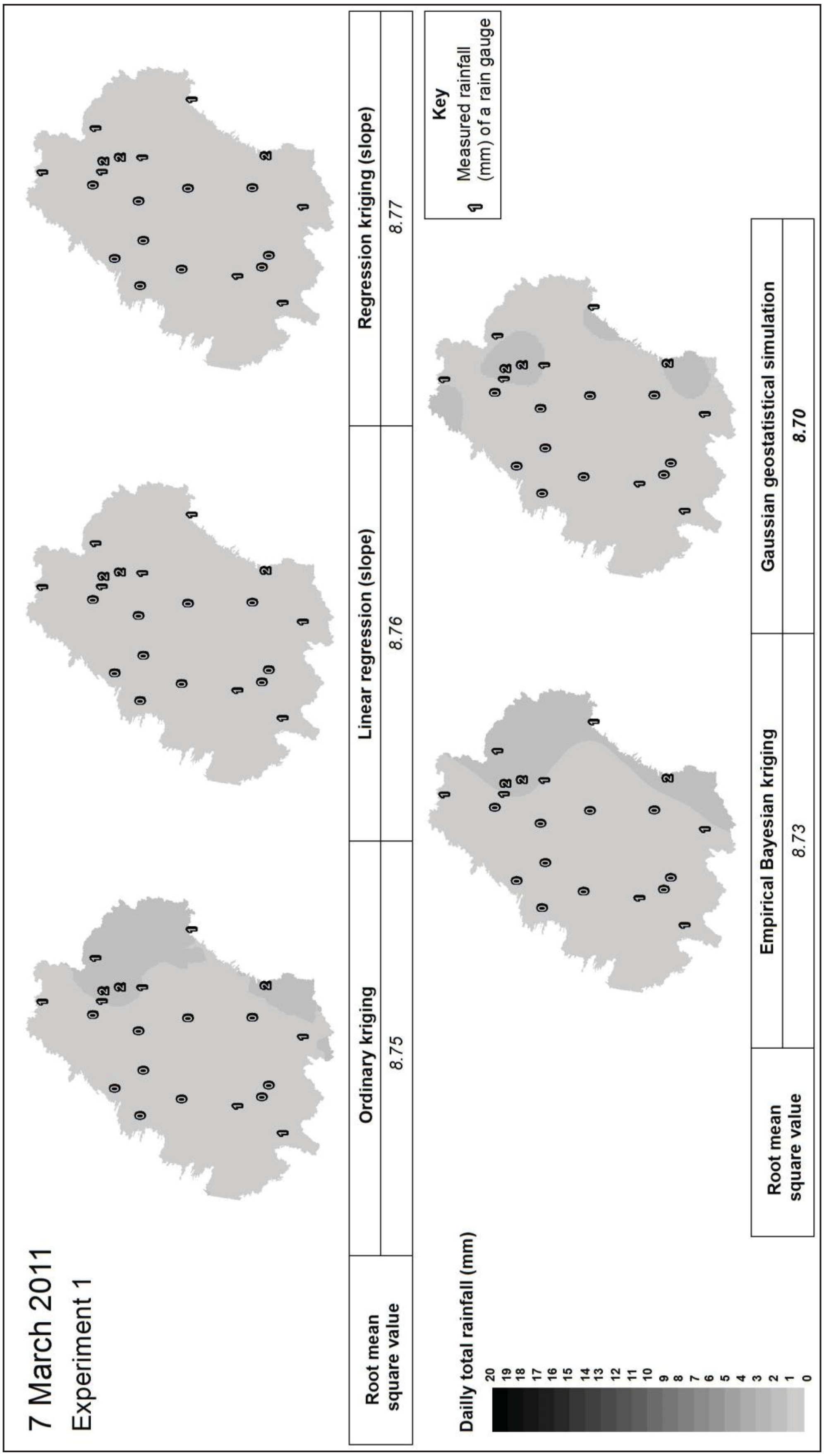




Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	5.68	*4.78*



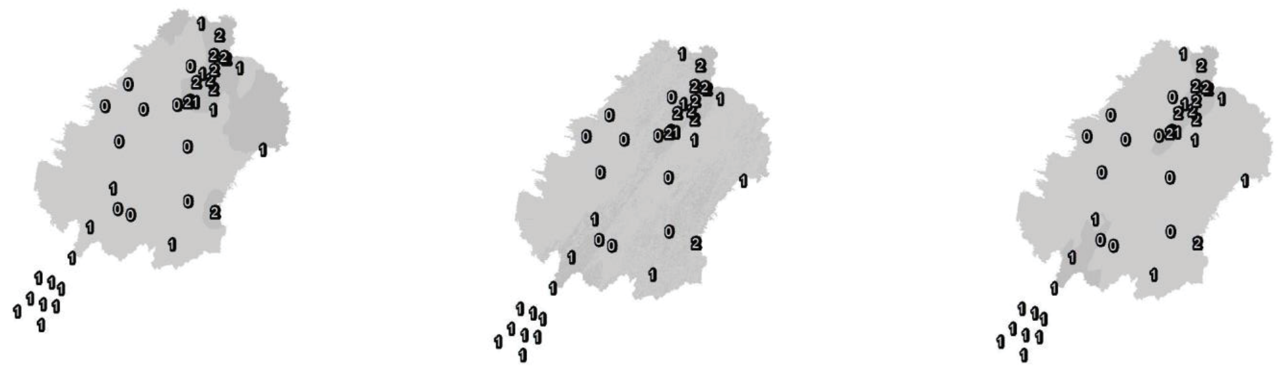
13 May 2010
Experiment 3
Root mean square value
Ordinary kriging
5.21
Linear regression (slope)
4.71
Regression kriging (elevation)
4.75
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Root mean square value
Empirical Bayesian kriging
5.57
Gaussian geostatistical simulation
4.95
Key
Measured rainfall (mm) of a rain gauge



7 March 2011
Experiment 1
Root mean square value
Ordinary kriging
8.75
Linear regression (slope)
8.76
Regression kriging (slope)
8.77
Key
Measured rainfall (mm) of a rain gauge
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Root mean square value
Empirical Bayesian kriging
8.73
Gaussian geostatistical simulation
8.70

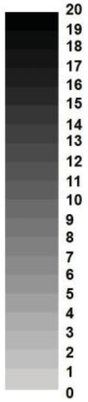
7 March 2011

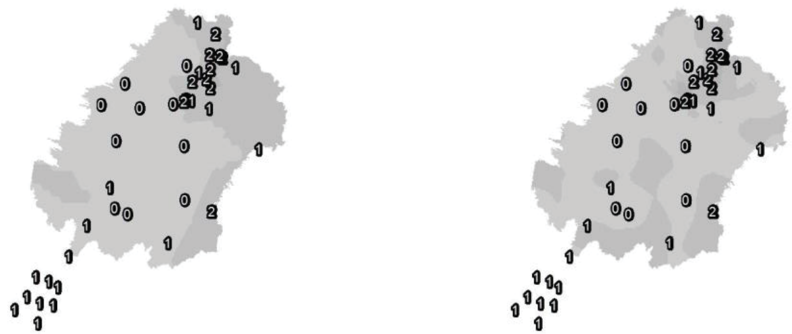
Experiment 2



Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (slope)
	8.64	*8.73*	*8.67*

Daily total rainfall (mm)

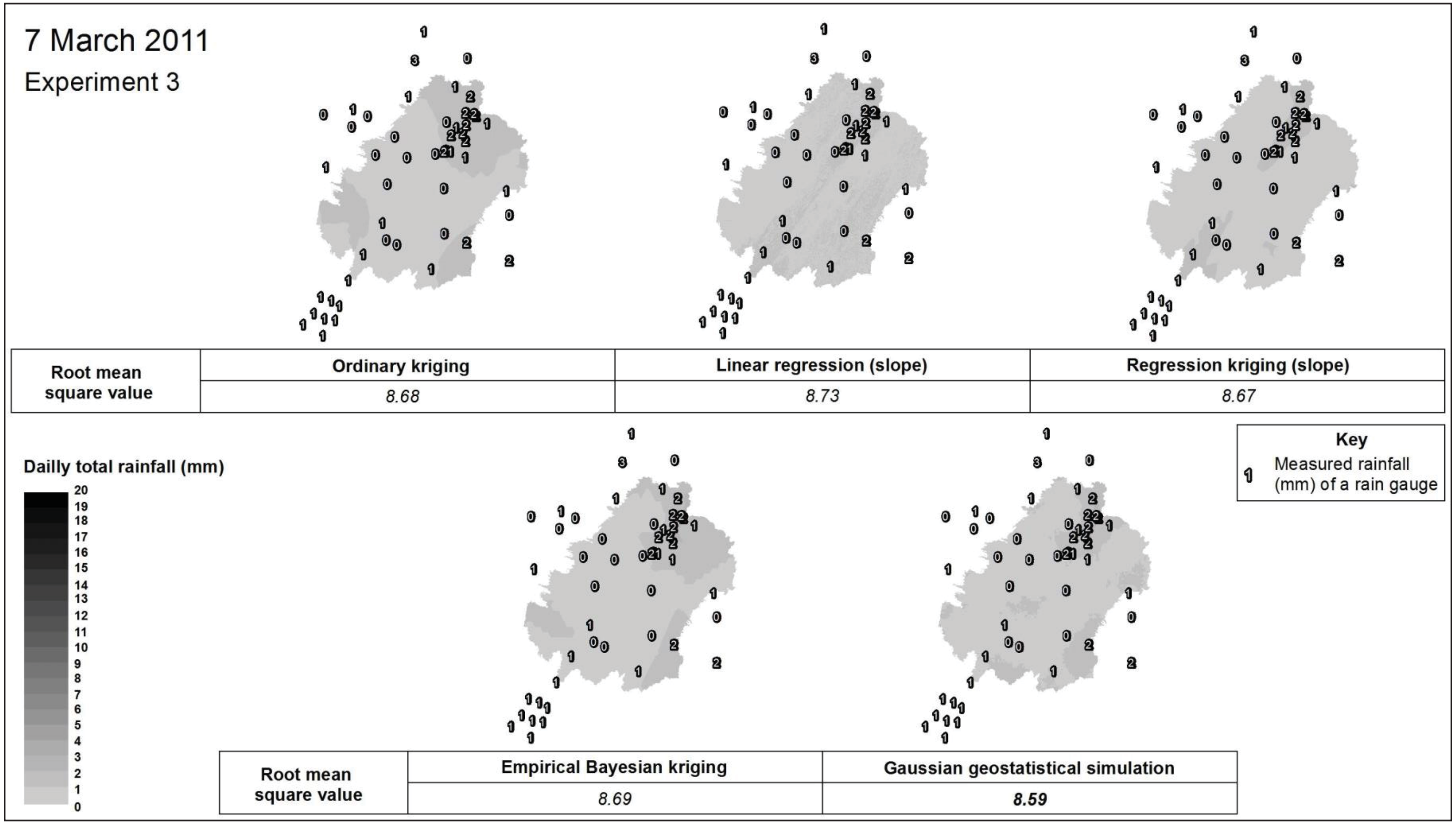




Key

1 Measured rainfall (mm) of a rain gauge

Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	8.69	***8.57***

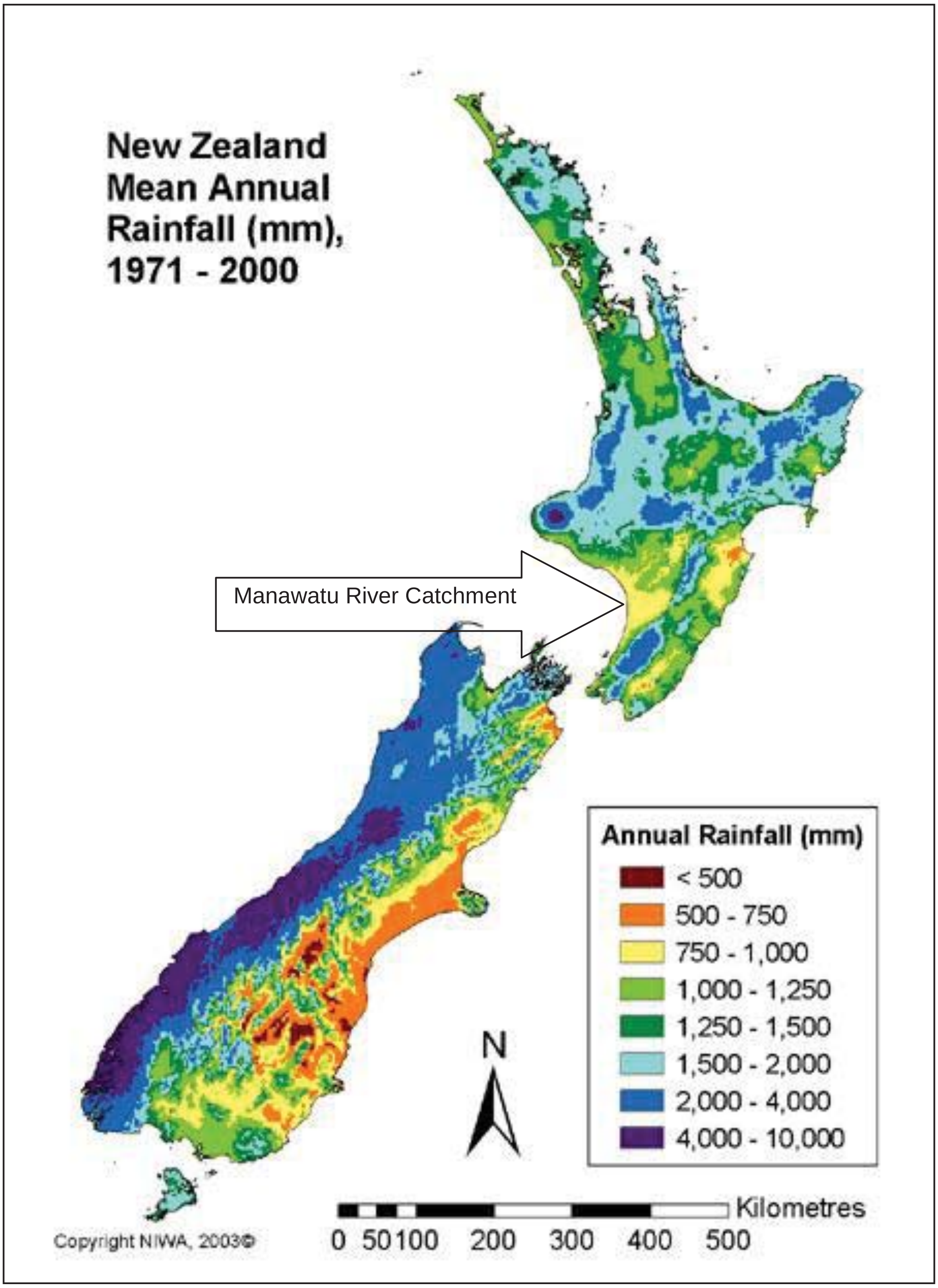


Root mean square value	Ordinary kriging	Linear regression (slope)	Regression kriging (slope)
	8.68	*8.73*	*8.67*

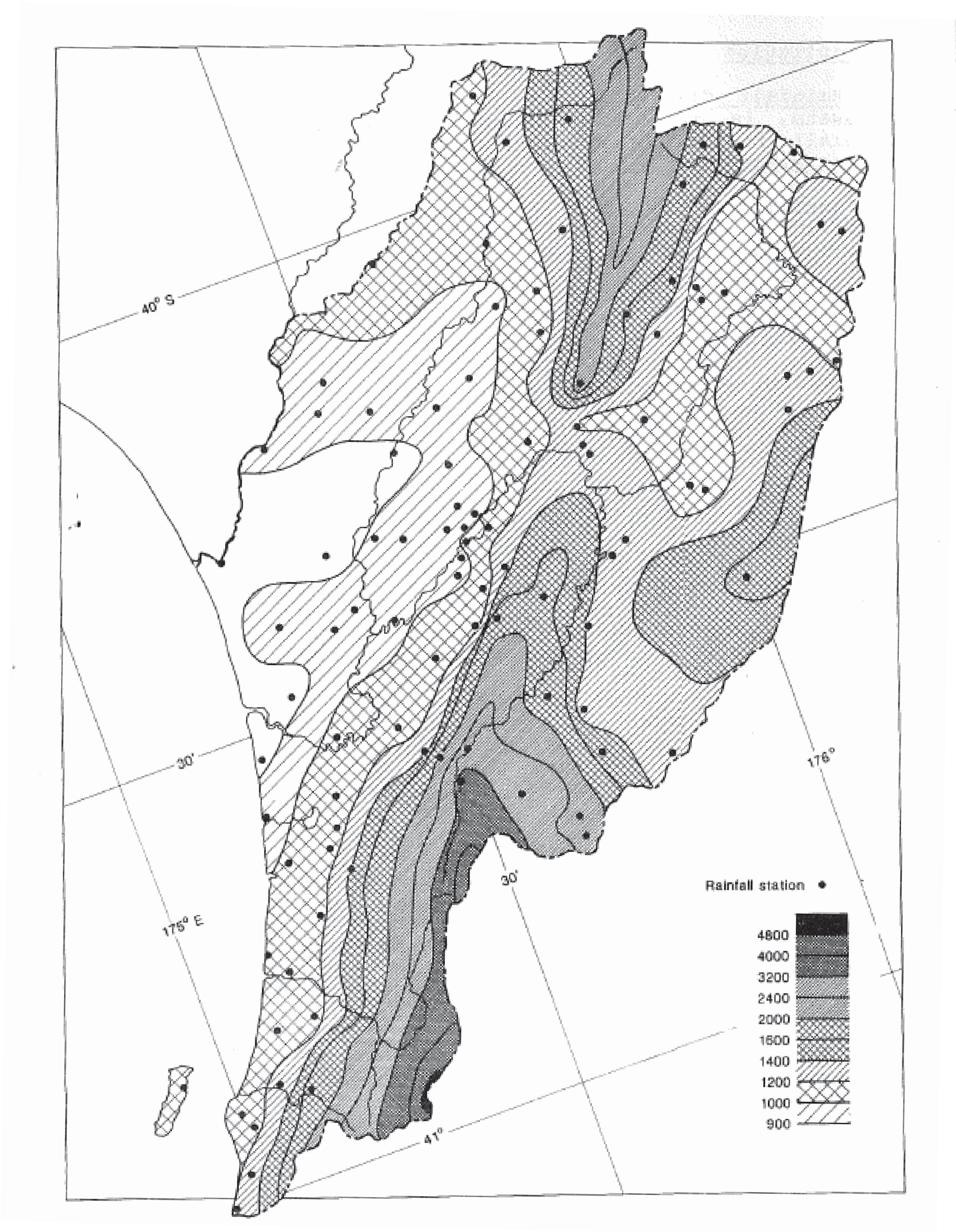
Root mean square value	Empirical Bayesian kriging	Gaussian geostatistical simulation
	8.69	***8.59***

Appendix 30: Annual rainfall maps by NIWA (2013) and by Burgess and New Zealand Meteorological Service (1988)

Annual rainfall (1971-2000) map by NIWA (2013)



Annual rainfall map (1951-1980) by Burgess and New Zealand Meteorological Service (1988)

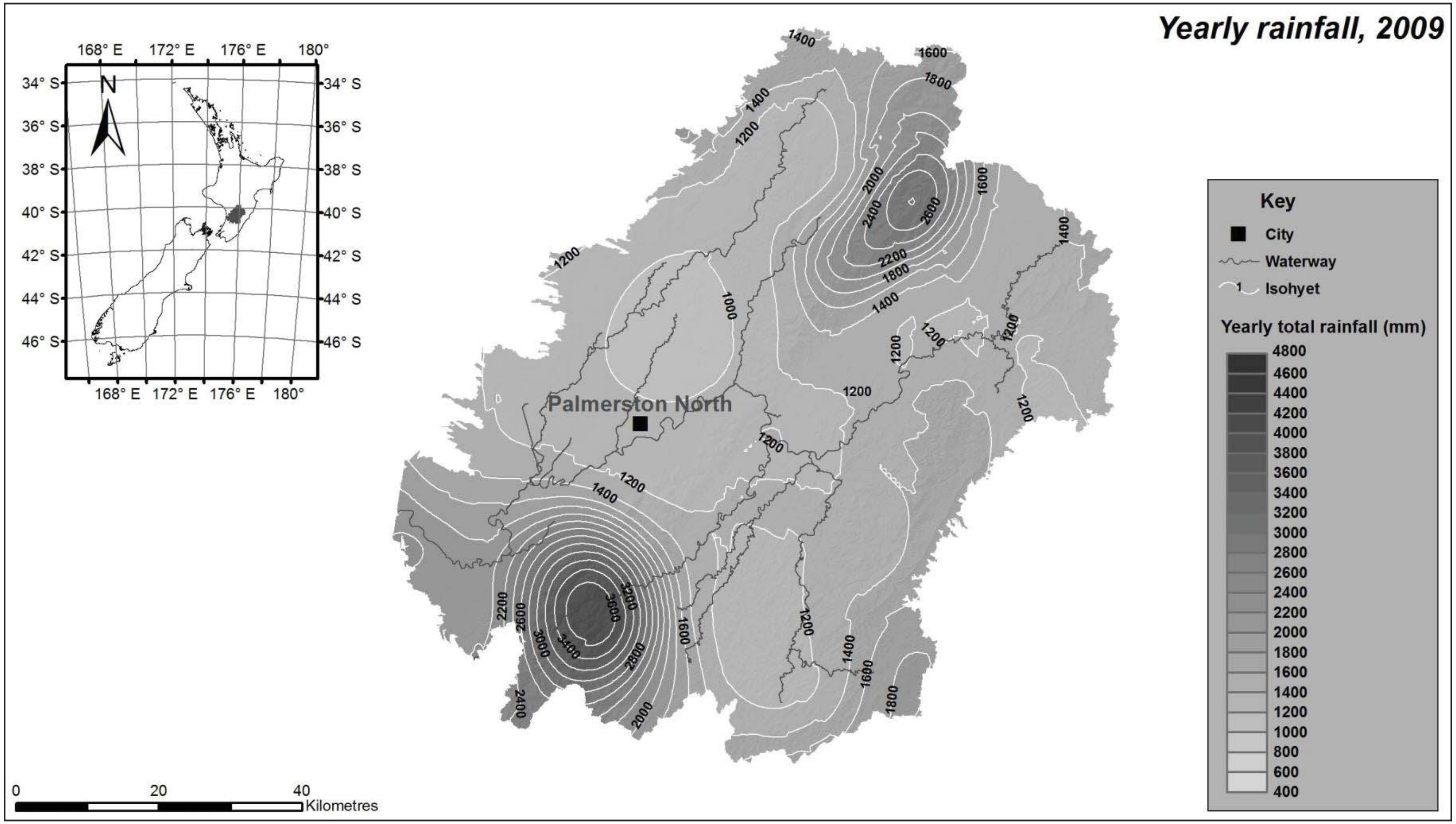


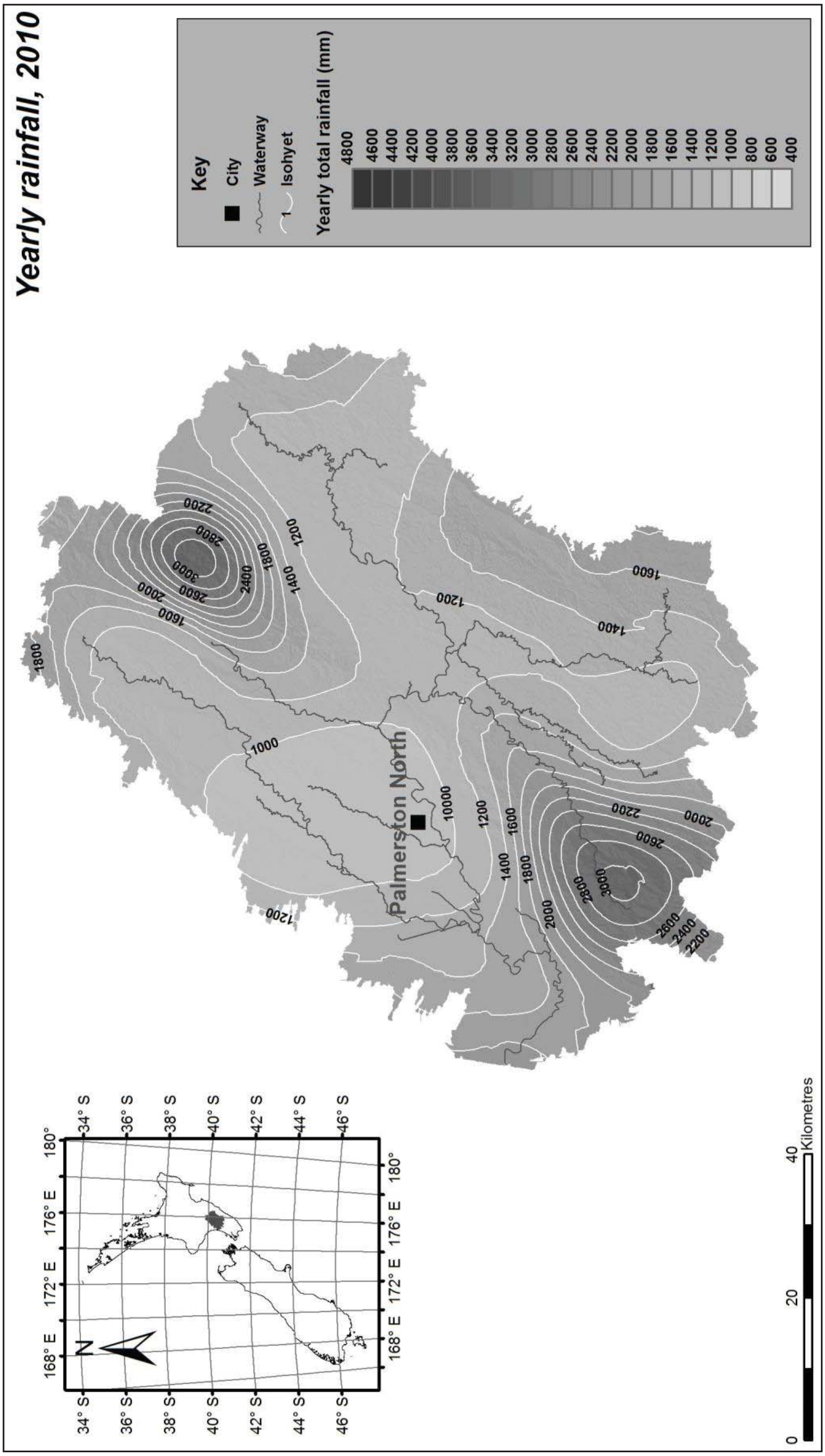
Reference

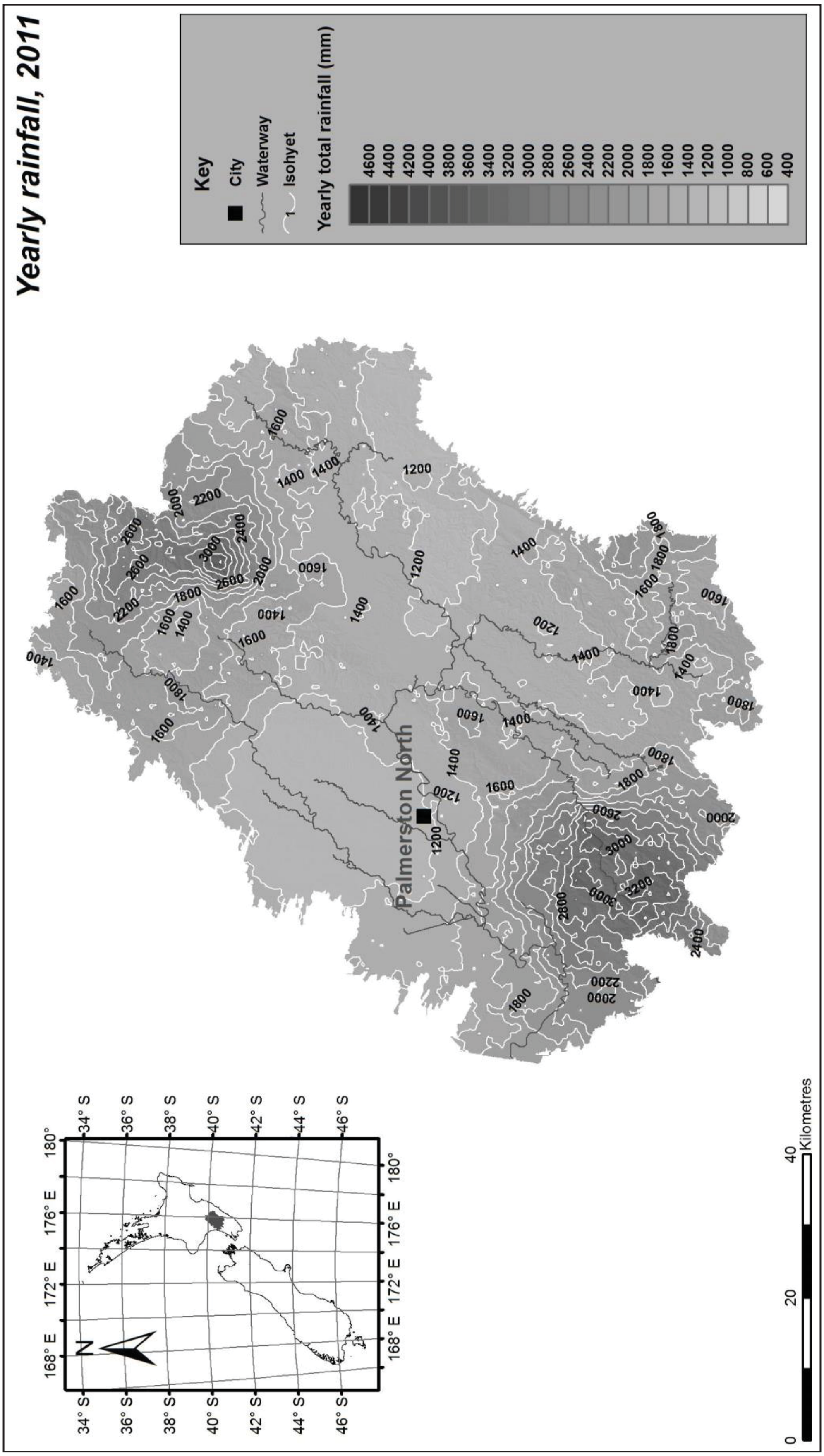
Burgess, S. M., & New Zealand Meteorological Service. (1988). *The climate and weather of Manawatu and Horowhenua*. Wellington, N.Z.: New Zealand Meteorological Service.

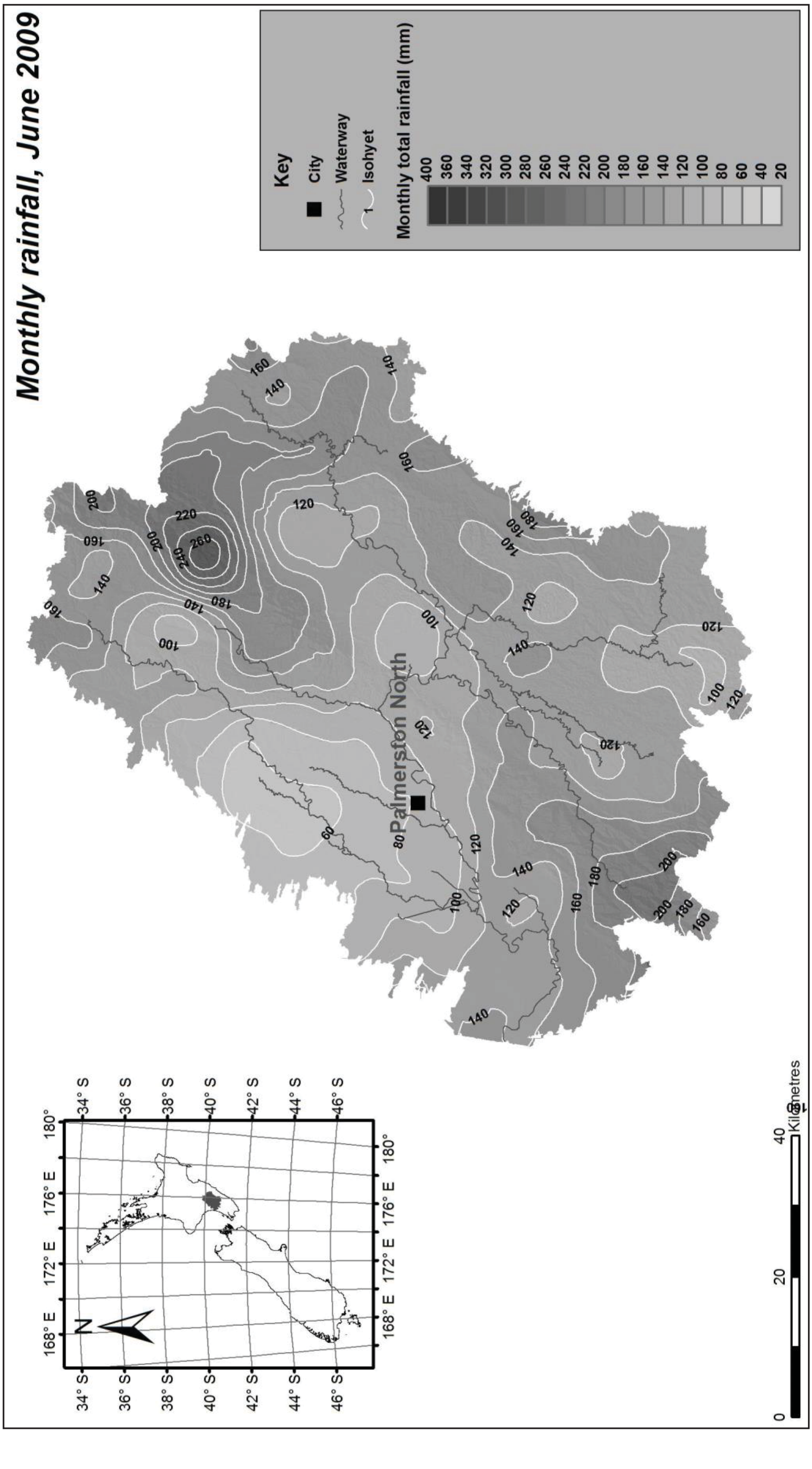
NIWA. (2013). *NIWA Taihoro Nukurangi*. Retrieved December 14, 2014, from http://www.niwa.co.nz/

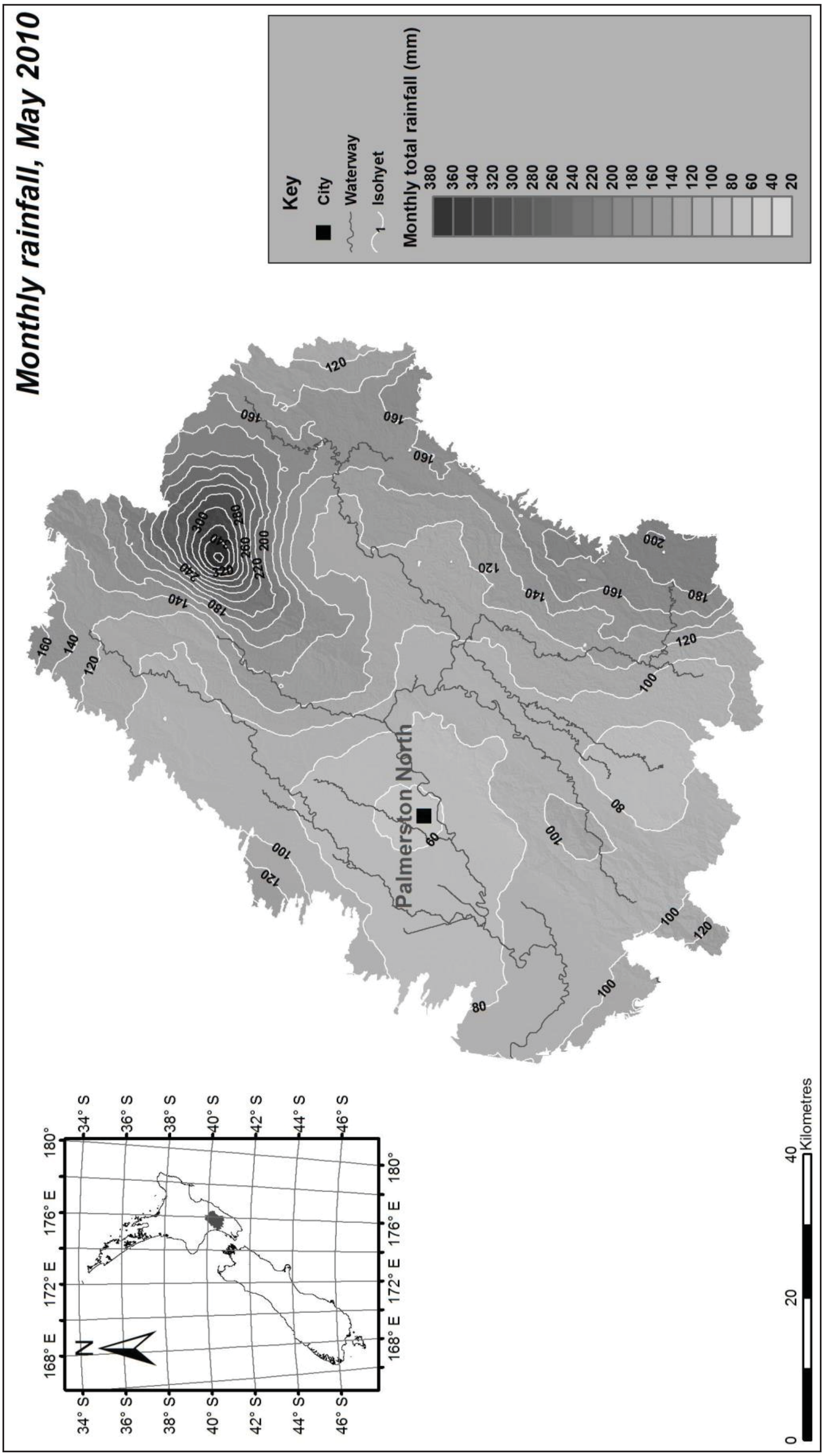
Appendix 31: Map outputs generated for all nine rainfall data sets with the most appropriate spatial estimation method Gaussian geostatistical simulation

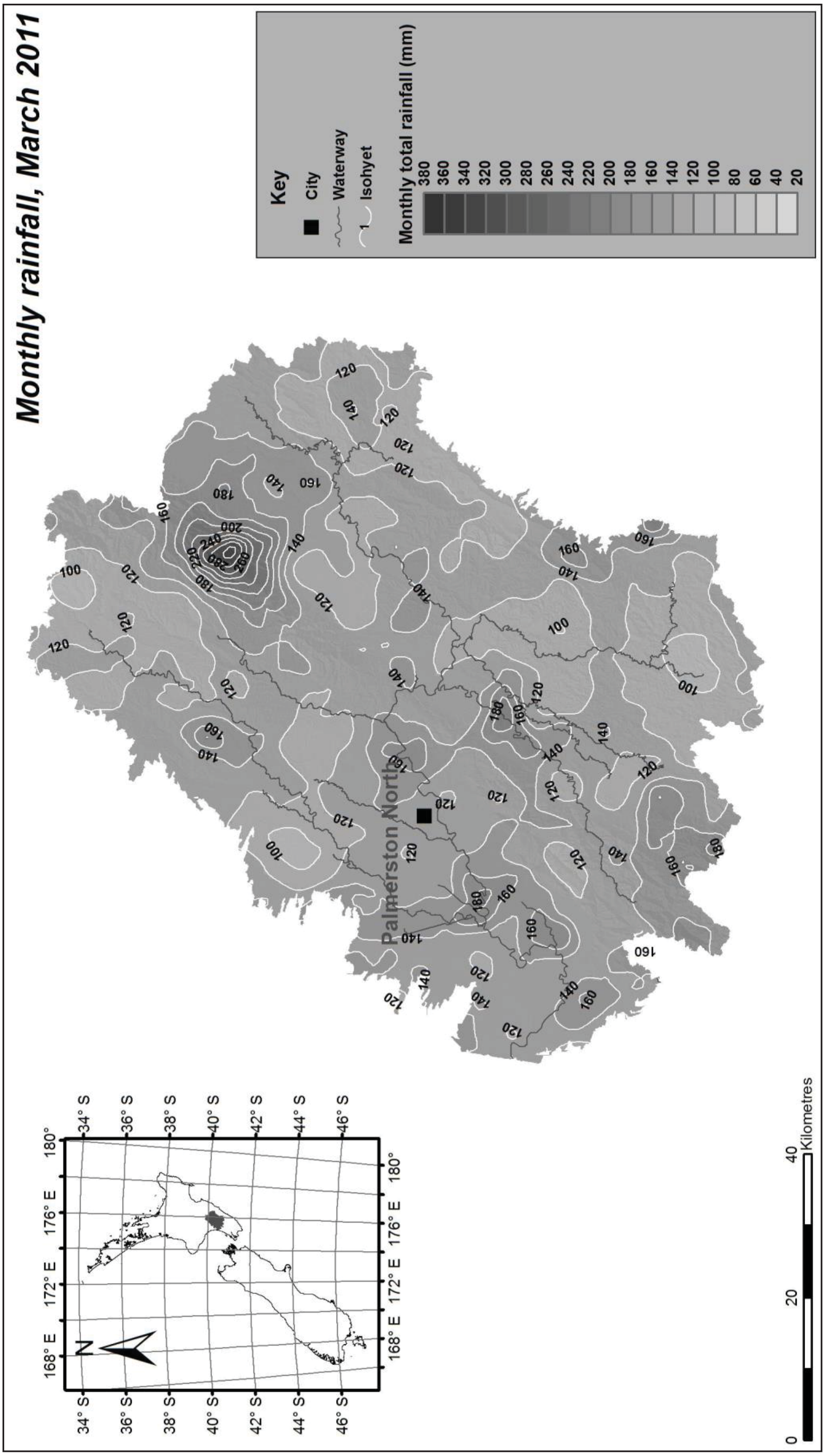


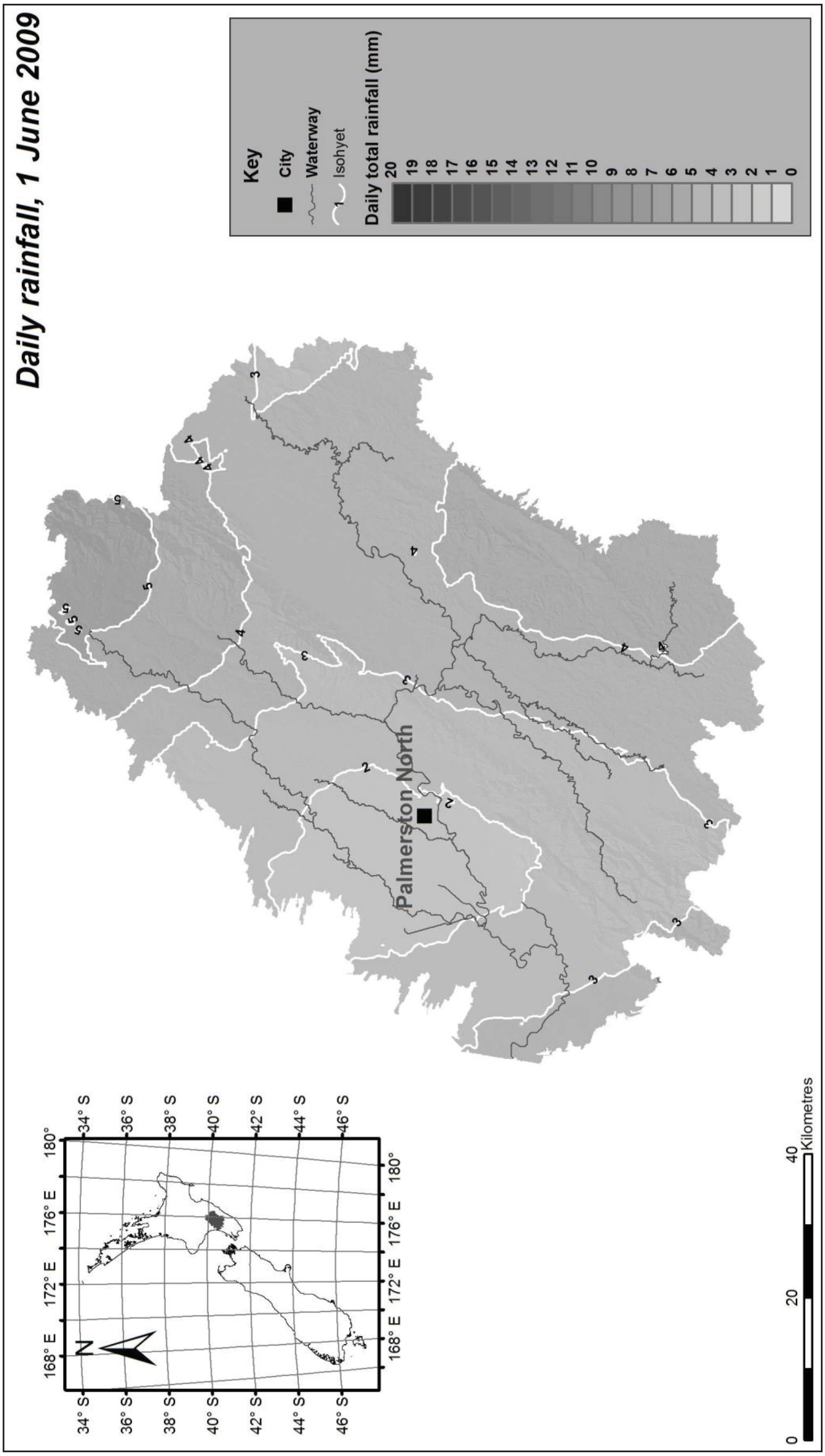

Yearly rainfall, 2010
Key
City
Waterway
Isohyet
Yearly total rainfall (mm)
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
Palmerston North
Kilometres
0
20
40
168° E
172° E
176° E
180°
34° S
36° S
38° S
40° S
42° S
44° S
46° S
N

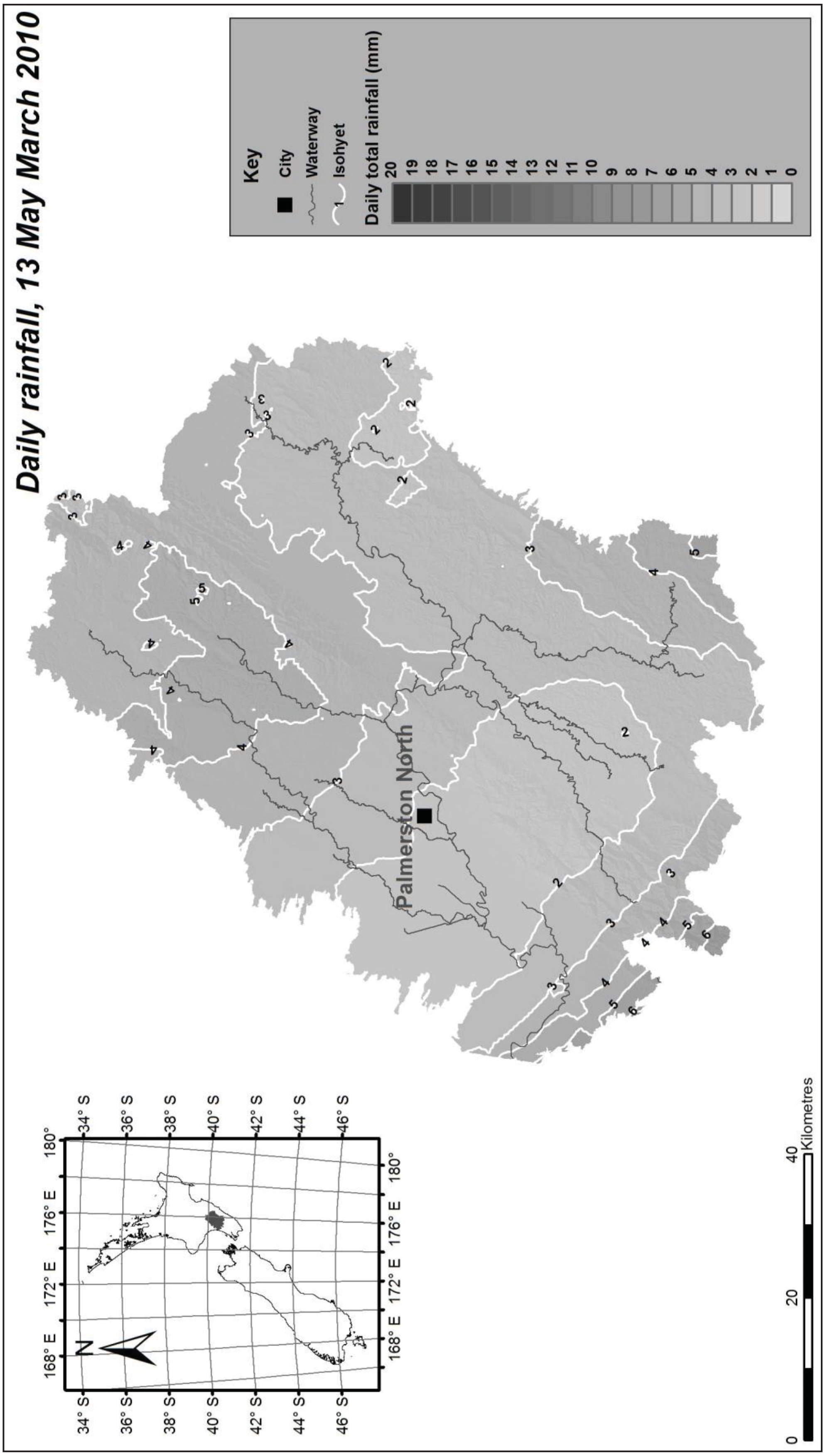

Yearly rainfall, 2011
Key
City
Waterway
Isohyet
Yearly total rainfall (mm)
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
Palmerston North
0
20
40
Kilometres
N
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°

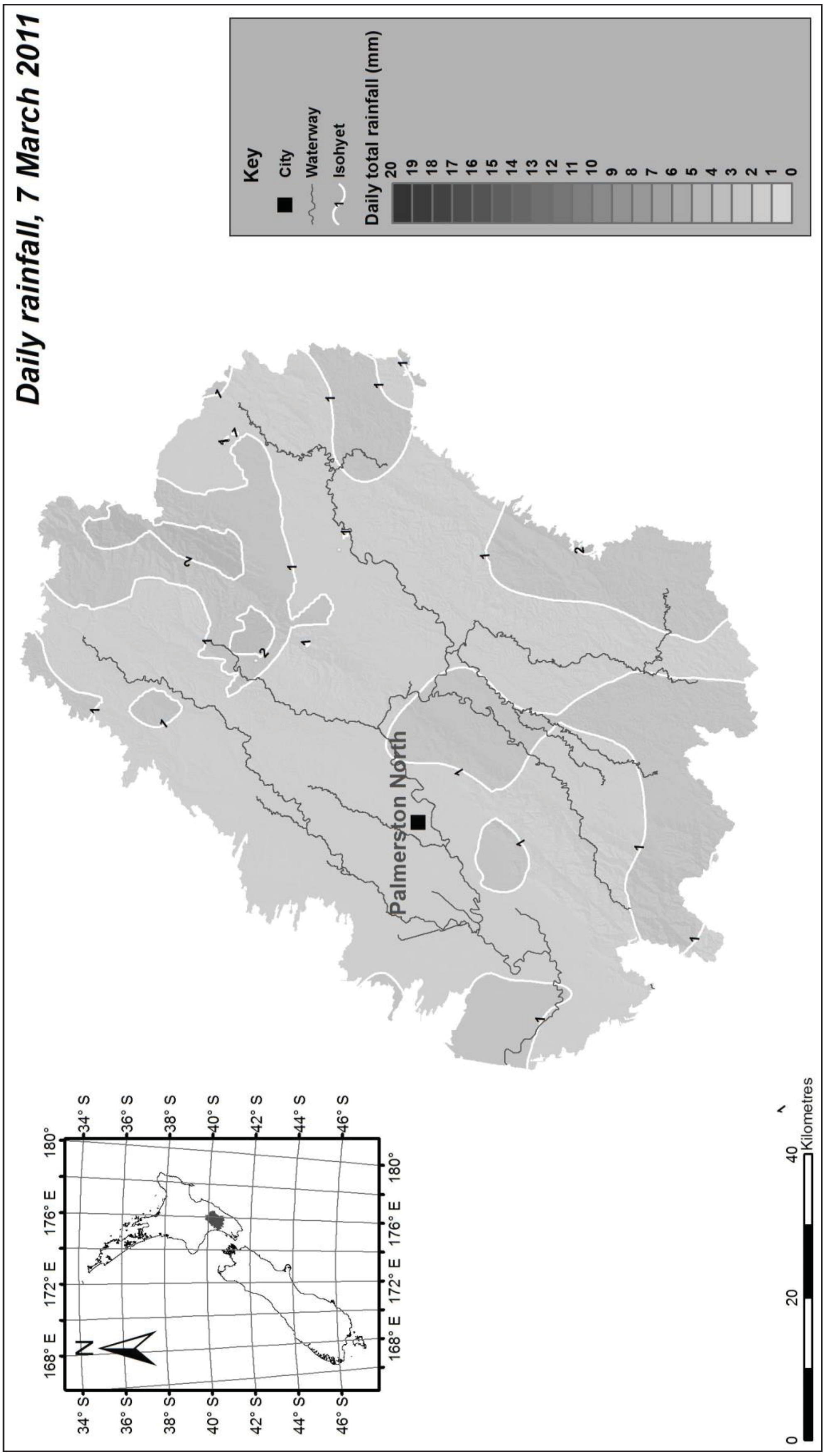

Monthly rainfall, June 2009
Key
City
Waterway
Isohyet
Monthly total rainfall (mm)
400
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Palmerston North
0
20
40
Kilometres
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°
N


Monthly rainfall, May 2010
Key
City
Waterway
Isohyet
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Palmerston North
0
20
40
Kilometres
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°


Monthly rainfall, March 2011
Key
City
Waterway
Isohyet
Monthly total rainfall (mm)
380
360
340
320
300
280
260
240
220
200
180
160
140
120
100
80
60
40
20
Palmerston North
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°
N
0
20
40
Kilometres


Daily rainfall, 1 June 2009
Key
City
Waterway
Isohyet
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Palmerston North
0
20
40
Kilometres
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°
N


Daily rainfall, 13 May March 2010
Key
City
Waterway
Isohyet
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Palmerston North
0
20
40
Kilometres
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°
N


Daily rainfall, 7 March 2011
Key
City
Waterway
Isohyet
Daily total rainfall (mm)
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
Palmerston North
0
20
40
Kilometres
34° S
36° S
38° S
40° S
42° S
44° S
46° S
168° E
172° E
176° E
180°
N

Glossary

Anisotropic variation: Is a variation that tends to display change one direction more than another.

Cross validation: A technique for comparing the performance of spatial estimation methods by removing in turn, each sample point from the whole data set and using the rest of the data to estimate its value. The accuracy of the estimation is determined by comparing the estimated value with the measured value.

Diagnostic statistic: A statistic (for example root mean square) that is determined with the estimation error. The statistic is a measure of the performance of the estimation method.

Estimation: The process of forming an approximation determined with observed data and a model with its parameters.

Geostatistics: A science about generating sampling designs, designing statistical models, estimating values at unvisited locations, extracting spatiotemporal pattern in data, and determining and analysing the uncertainty associated in the estimation.

Grid: An array of equally sized cells arrange in rows and columns and each cell has an attribute value and location coordinates. Another word for grid is a raster.

H-index: This index is determined by the number of publications of an author and the number of citations per publication of the same author, which distinguish authors with only a small number of highly-cited papers and authors with a sustained, long lasting record of good academic performance.

Isohyet: Is represented by a line on a map that joins points with an equal quantity of rainfall.

Isotropic variation: Is a variation that does not show any directional effect.

New Zealand Map Grid: A map projection uses a geometric projection with a minimal distortion. The projection is unique to New Zealand, but it can be difficult to apply in computer software. The New Zealand Map Grid is based on New Zealand Geodetic Datum 1949, which was the official geodetic datum for New Zealand before the New Zealand Geodetic Datum 2000 was introduced in 1998.

New Zealand Transverse Mercator: A map projection uses a Transverse Mercator projection and is based on the New Zealand Geodetic Datum 2000 datum using the GRS80 reference ellipsoid.

Semivariogram: A graph that portrayed autocorrelation of the measured sample points (rain gauge values).

Spatial estimation: A spatial calculation that uses measured sample points to determine estimated values at other locations. Spatial estimation implies interpolation (estimation based on surrounding known points) and extrapolation (estimation based on not enough surround known points).

Spatial estimation method: A specific calculation with its own variables that used measured sample points to determine estimated values at other locations. Ordinary kriging, inverse distance weighting, nearest neighbours and regression models are examples of a spatial estimation method.

Validation: A technique for comparing the performance of spatial estimation methods by dividing sample points into two sample data sets or having two different data sets from the start of the estimation. Using one sample data set for the estimation and the other sample data set for testing the accuracy of the estimation.