MONTH-YEAR RAINFALL MAPS OF THE HAWAIIAN ISLANDS

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ABSTRACT

The Hawaiian Islands have one of the most spatially-diverse rainfall patterns on earth. Knowledge of these patterns is critical for a variety of resource management issues. In this study, month-year rainfall maps from 1920-2007 were developed for the major Hawaiian Islands. A geostatistical method comparison was performed to choose the best interpolation method. The comparison focuses on three kriging algorithms: ordinary kriging, cokriging, and kriging with an external drift. Two covariates, elevation and mean rainfall, were tested with cokriging and kriging with external drift. The combinations of methods and covariates were evaluated using cross validation statistics, where ordinary kriging produced the lowest error. To generate the final maps, the anomaly method was used to relate station data from each month with the 1978-2007 mean monthly maps. The anomalies were interpolated using ordinary kriging, and then recombined with the mean maps to produce the final maps for the major Hawaiian Islands.

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CHAPTER 1
INTRODUCTION

1.1 Context of Problem

Precipitation climatologies are very important to research in hydrology and global change. Understanding rainfall patterns is essential for water use planning applications, especially in places where water is scarce. Island communities are particularly sensitive to changes in climate, and accurate data is vital for policy decisions and resource management plans to cope with these effects. In the Hawaiian Islands, a diverse terrain, as well as varied wind patterns and a persistent trade wind inversion lead to an extremely complex rainfall pattern. Achieving an accurate representation of these patterns is a difficult task, and relies on a dense network of stations.

The recently completed "Rainfall Atlas of Hawai‘i" (Giambelluca et al. 2011) has produced mean rainfall maps for the seven major islands of Hawai‘i. Mean monthly and annual maps depict the average spatial rainfall patterns. The new maps supercede a previous Rainfall Atlas (Giambelluca et al. 1986) in which the maps were developed using subjective analysis of spatial patterns. The most recent project is more sophisticated in that it uses a Bayesian data fusion method to combine raingage data with radar rainfall estimates, mesoscale meteorological model output, PRISM (Parameter-elevation Regressions on Independent Slopes Model) (Daly et al. 1994), and vegetation-based rainfall estimates to improve the accuracy of the mean rainfall maps. These resulting maps created for the 2011 Rainfall Atlas are extremely valuable in providing more accurate depictions of mean rainfall patterns in Hawai‘i.

Because the Rainfall Atlas gives only the 30-year mean spatial patterns, it does not provide any information about year-to-year rainfall variability. To allow assessment of all types of rainfall variability, including trends, individual month-year maps are needed. However, these maps cannot be produced in the same manner as the mean maps because the predictor variables (vegetation, PRISM, MM5, and radar rainfall maps) do not exist at a monthly temporal resolution over an extended historical period. Therefore, another method needs to be developed to utilize the information available in the mean Rainfall Atlas maps and combine it with individual monthly raingage totals.

One of the best ways to incorporate climatological information with month-year data is to use the anomaly method. The anomaly method interpolates the departures from the mean (anomalies) in a given month-year, and combines the interpolated anomaly surface with the mean map to produce the final month-year map. This allows the information from the mean maps to serve as a basis for the individual months' spatial patterns. Many different geostatistical interpolation methods are available for spatially interpolating the anomalies. Few geostatistical method comparisons have been done in areas comparable to Hawai‘i, however, which makes it difficult to choose a method based on previous studies. A method comparison test is needed to test how different interpolation methods perform on rainfall anomalies in Hawai‘i, so that the best method can be chosen to produce the month-year rainfall maps.

Statement of the Problem. Currently, spatially continuous monthly maps of rainfall do not exist for the Hawaiian Islands. These are needed for the assessment of historical rainfall trends in Hawai‘i and will provide invaluable data for other hydrological studies including stream flow and groundwater recharge analysis. The existing methods for creating these maps that have been examined by previous studies are not appropriate to directly adopt for interpolating monthly rainfall across the Hawaiian Islands. A method comparison needs to be performed and will be an important addition to the geostatistical methods literature.

Objectives. The goal of this thesis was to create an 88-year dataset of month-year rainfall maps for the seven major islands of Hawai‘i from 1920-2007, and to determine the best method for interpolating the spatial patterns of rainfall for individual months. The first objective was to perform the method comparison analysis. The performance of several alternative geostatistical methods, applied to the interpolation of anomaly values, was evaluated using the cross validation statistics. The methods were compared to find the one best suited to interpolating rainfall anomalies in Hawai‘i. The next major objective of this thesis was to create the month-year maps, since only mean maps have been produced until now. Quality control was performed to ensure that the maps appeared to have realistic patterns.

1.2 Study Area: Hawaiʻi

The area under consideration is the State of Hawaiʻi, more specifically – the seven major islands Kauaʻi, Oʻahu, Molokaʻi, Lānaʻi, Maui, Kahoʻolawe and Hawaiʻi. The island of Niʻihau was not considered in this study because there were no rainfall data available. The main islands of Hawaiʻi are located in the Pacific Ocean between 18.9°N and 22.24°N latitude, and 160.25°W and 154.8°W longitude. The islands contain a total land area of 16,636.5 km² (Juvik & Juvik 1998), with Hawaiʻi Island (commonly referred to as the Big Island) being the largest.

The climate of the Hawaiian Islands is very unique and contains a great deal of diversity in a very small area. This is due to many factors including the large elevation gradient (ranging from 0 m at sea level to 4205 m at the peak of Mauna Kea) which produces a wide range of temperatures. One of the greatest factors contributing to the diverse climate, however, is the highly spatially variable rainfall distribution across the islands. The average rainfall gradients for some places in Hawaiʻi are among the steepest in the world, producing a greater range on one small island than occurs across an entire continent (Giambelluca et al. 1986). The majority of the rainfall in Hawaiʻi is produced through orographic lifting as the trade winds (ENE winds) encounter the windward slopes, producing fairly consistent rainfall patterns throughout the year at these windward mountain locations (Giambelluca et al. 2011). At high elevations, however, the growth of clouds is persistently capped by the trade wind inversion (TWI). This is a layer of air usually found around 2200 m where the air gets warmer with increased altitude, instead of a usual lapse rate situation (Cao et al. 2007). These are just some of the unique elements of Hawaiʻi's climate that make producing maps of rainfall more complicated.

1.3 Rainfall Data

1.3.1 History of Rainfall Measurement

Over 2,000 raingage stations have operated across the islands over the past 100 years (Giambelluca et al. 1986), which provides an extensive monthly rainfall database. Figure 1.1 shows the spatial distribution of stations across the islands. A great deal of work has been done to compile the data from these stations and extensive quality control has been performed to create the final dataset that was used for the Rainfall Atlas (and will be used to create the month-year maps as well). The oldest raingage in the dataset has readings from 1837. By 1890 there had been 34 stations recording rainfall data. By 1920, that number increased to 422 stations, and by 1950 there had been 1215 active raingage stations in Hawai‘i. From the data available, the number of gages still in operation as of 2007 was only 340, however. Figure 1.2 shows the number of raingages operating throughout time, and it is clear that there was a sharp decline in stations during the 1980s. Over the last 30 years, over 500 stations were discontinued.

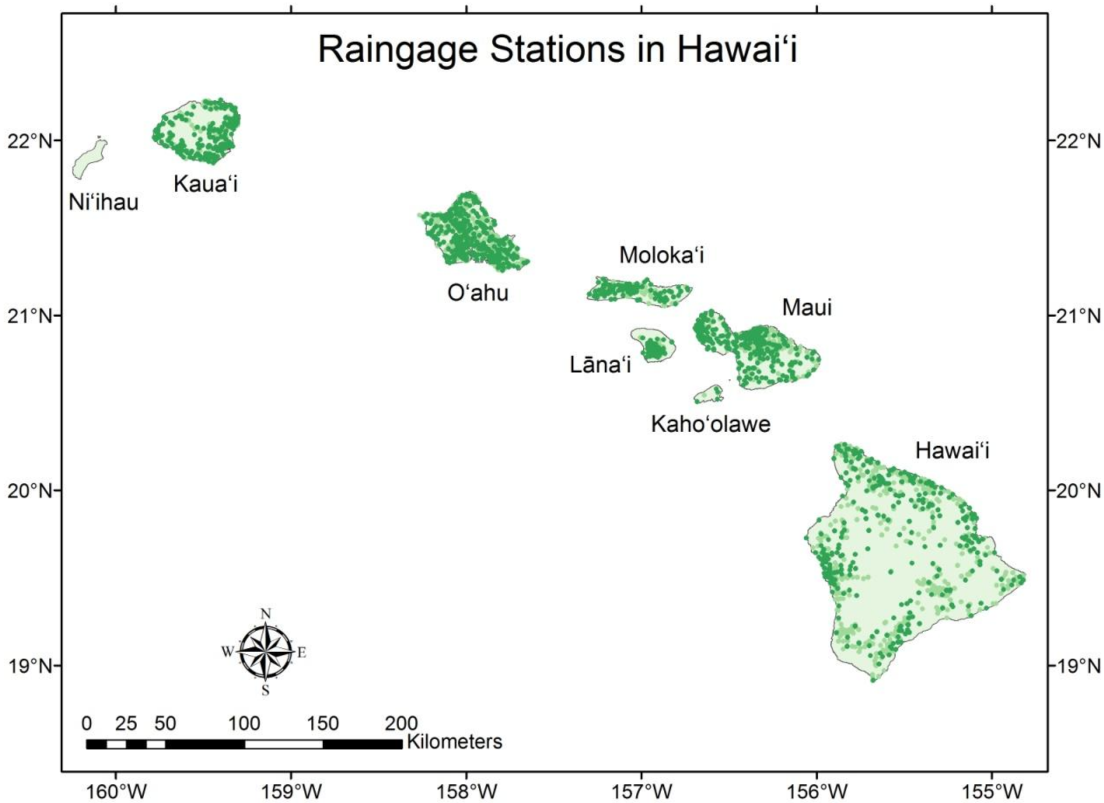


Figure 1.1. Map of the raingage stations in the State of Hawaiʻi.

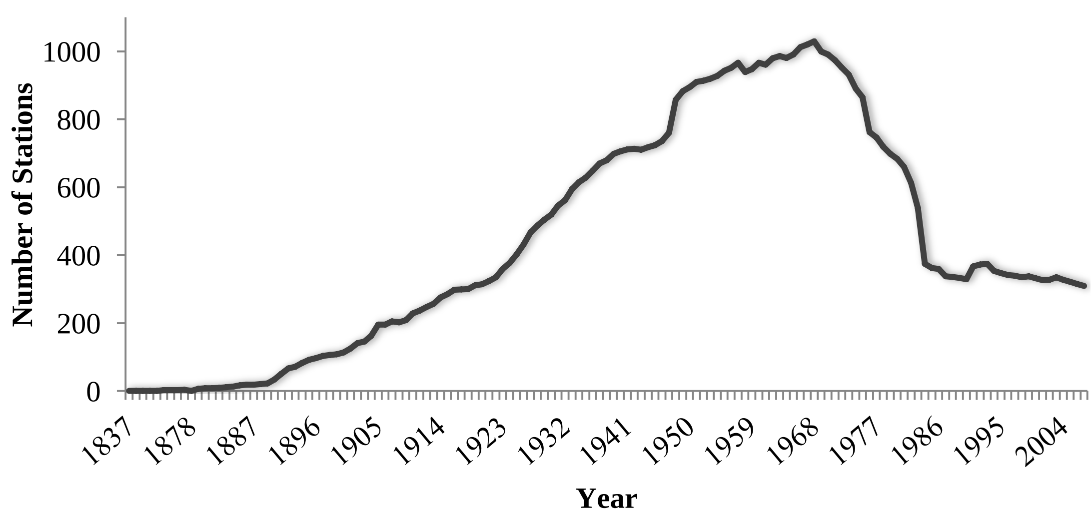


Figure 1.2. Number of stations operating in Hawaiʻi in each year.

Many of these stations, especially in the first half of the 20th century, were well maintained by the large sugarcane and pineapple plantations. Other organizations including the Honolulu Board of Water Supply, U.S. Geological Survey (USGS), the National Weather Service (NWS), and even private citizens also had interests in water availability in Hawaiʻi and helped to create the large network of raingages operated in the state (Giambelluca et al. 1986). Most of these gages were manually read, and it was not until the latter part of the 20th century that more automatic gages began to replace some of these manual gages. Automatic gages allowed for more reliable data in remote areas, since the data collection did not require someone to regularly travel to areas that are difficult to access.

1.3.2 Data Sources

The majority of the raingage data, especially from the long-term stations, are maintained by the State of Hawaiʻi. The observer ideally records daily rainfall values by hand, and mails the carbon copies of the record to the office of the State Climatologist and to the National Climatic Data Center (NCDC). Therefore, one would expect these two sources of rainfall data to match. However, due to errors with data entry, there were many discrepancies found between the State dataset and the NCDC dataset which had to be resolved.

Aside from these two major sources of data, smaller networks of raingages are operated and maintained by private groups and contribute extremely valuable data. The final dataset merged data from the state and NCDC datasets, as well as from USGS (U.S. Geological Survey), HaleNet, Hydronet, SCAN (Soil Climate Analysis Network), and RAWS (Remote Automated Weather Stations) networks. The proportions of data in the final database from each source break down as follows: approximately 59% of the data are from the state dataset alone; 28% are from state and NCDC (overlapping); 8% are from the NCDC monthly dataset; 3% are from Hydronet; 1% for USGS; 1% for RAWS; and less than 1% from the other small networks.

1.3.3 Mean Maps

As previously mentioned, the newly released Rainfall Atlas project used this database to produce mean rainfall maps for Hawai‘i (Giambelluca et al. 2011). The means of the raingage stations over the most recent 30-year period (1978-2007) were used along with a new Bayesian data fusion method to incorporate radar estimates, MM5 model output, the PRISM dataset (Daly et al. 1994) and vegetation data to produce the final mean maps. The output is 13 maps: one for each month and one annual map. The maps have a spatial resolution of 250 m, with an annual range of 10,000 mm (about 400 inches). These mean maps along with the rainfall database will serve as the two major inputs for creating the month-year maps using the anomaly method.

1.4 Interpolation Methods

1.4.1 Anomaly Method

Many methods can be used to develop month-year rainfall maps. To go from a finite number of irregularly spaced points (raingage sites) to a continuous surface (rainfall map), some form of interpolation is required, either by the direct interpolation method—interpolating point data directly, or by the anomaly interpolation method—interpolating anomaly values and combining them with the mean map (Dawdy & Langbein 1960; Peck & Brown 1962). When interpolating a complex surface, even from a relatively large number of data points, a myriad of different results could be obtained, which makes the choice of the method of interpolation critical. It has been shown in many studies that the anomaly interpolation method outperforms the direct interpolation method (New et al. 2000; Chen et al. 2002). The anomaly method is also appealing for this study because it can incorporate the mean maps created for the Rainfall Atlas, and therefore the supplementary information they contain.

1.4.2 Kriging Methods

Many gaps still exist in the literature about which methods are best to use to interpolate monthly rainfall anomaly values in complex terrain regions. One of the most widely used geostatistical interpolation schemes is kriging, which assumes spatial correlation between stations, assigning more weight to stations nearby, assuming they are more alike than stations that are farther apart (Webster & Oliver 2007). Kriging provides an uncertainty estimate, and it is able to easily incorporate secondary variables such as elevation (Goovaerts 2000; Mair & Fares 2011), radar rainfall estimates (Seo et al. 1990; Haberlandt 2007), and atmospheric variables such as cold cloud duration (CCD) remotely sensed data (Moges et al. 2007), wind speed and humidity (Kyriakidis et al. 2001). Under the kriging approach there are many method variations, creating a huge number of combinations when one considers all of the possible covariates combined with the different kriging algorithms.

Previous method evaluations have looked at many of these combinations, but most of them differed in scope or terrain type in comparison with Hawaiʻi. Some of the case studies only dealt with small networks of stations and were not necessarily in areas with as much terrain variation as Hawaiʻi (Goovaerts 2000; Vicente-Serrano et al. 2003; Moral 2009), which is an important distinciton because landscape heterogeneity has a significant impact on precipitation patterns, and the density of the station network also influences how well the interpolation performs. Some studies dealt with interpolation on a global scale (New et al. 2000; Chen et al. 2002), which is generally done at a relatively coarse spatial resolution. Many of the projects considered other climate variables besides rainfall such as temperature and soil variables. (Bourennane & King 2003; Hengl et al. 2007), while another common group of case study results were shown only for daily or hourly rainfall data (Haberlandt 2007; Yatagai et al. 2008; Haylock et al. 2008). None of these results are directly indicative of which methods will be most successful for interpolating monthly rainfall anomaly data in an area like Hawaiʻi.

For uniformity, only one interpolation method will be chosen to produce the anomaly maps for all islands. If there is sufficient evidence to support the choice of a second method, such as a method performing significantly better on one island and poorly on the rest of the islands, then a second method will be considered. Due to the heterogeneity in the data throughout time and space, it is expected that the best-performing method will differ at every time step. However, the goal is to strive for consistency across the state by selecting only one method that performs the best overall.

1.5 Layout of the Thesis

Following this introductory chapter, Chapter 2 describes the methods used in this study. Details about the anomaly method and different kriging methods are explained, as well as the procedure for completing the method comparison and generating the final maps. The results are described in Chapter 3, including examples of the final month-year maps and the cross validation statistics. The final chapter contains the discussion and conclusions, with suggestions for further steps and a summary of findings.

CHAPTER 2
METHODS

2.1 Research Strategy

The objectives of this thesis were to perform a geostatistical method comparison to determine the best interpolation method to use for Hawaiʻi, and to produce month-year rainfall maps of the seven major islands from 1920-2007 using the newly developed rainfall database. Specifically, three different kriging methods were compared (with two different covariates) using cross validation statistics for assessment. The interpolation method chosen as the best method was used to interpolate the relative anomaly values, creating anomaly maps. The anomaly maps were then multiplied by the mean maps to generate the final rainfall maps. Both the anomaly maps and final month-year maps will be made available for analysis purposes.

2.2 Database Development

2.2.1 Gap Filling

The number of raingage stations in operation at any given time varied greatly, which reduced the spatial and temporal resolution of the dataset. To address these temporal gaps in the dataset, a gap-filling procedure was used on stations with at least 20 years of original data (Eischeid et al. 2000) to create a serially complete dataset. This procedure uses five different statistical methods to fill gaps in the monthly data using data from nearby stations. Any stations with less than 20 years of data could not establish robust regressions and were filled using a simpler Normal Ratio Method (Paulhus & Kohler 1952). The missing monthly values were filled in as much as possible from 1920 to 2007. The filled data were rigorously tested to ensure that these new values were reasonable and maintained the statistical characteristics of each station (Giambelluca et al. 2011). Whenever the filled values did not pass these tests, the values were removed from the dataset, leaving blank values for some stations. Creating this serially complete dataset helped to reduce interpolation error in the final maps since the spatial extent of the station coverage is much greater in any given month using the filled data than it is using the original, unfilled data. It also allows for better comparison between stations since they almost all have data in every period.

2.2.2 Quality Control

Other than compiling and filling the dataset, the majority of the work done on the dataset was done to quality check the values and coordinates. With the coordinates, the datum and locations had to be adjusted for many of the stations. Most raingage coordinates were given in the Old Hawaiian Datum, and had to be converted to NAD83. Some stations were plotted in the ocean, whereas others disagreed on the location when multiple datasets were compared (mostly due to lack of precision). These were resolved using a report entitled "Climatologic Stations in Hawaiʻi", Report R42, a book of all the station locations published in 1973 by DLNR, as well as elevation analysis and in some cases contacting the particular station's observer.

For the data values, data homogeneity testing was performed using standardized reference series (Wang et al. 2007; Wang 2008) in order to identify inhomogeneities in the data. Any stations that were marked in the station metadata as "accumulated", i.e., read at a frequency of less than once per day with the multi-day total recorded, were identified and any totals accumulated over more than one month were removed from the dataset manually. Any extreme outliers and negative values were also removed. Some of the automatic gages with missing daily values were prorated so as not to introduce a negative bias by assuming all missing days were zero, and a cutoff was set to determine how many missing days constituted a missing monthly value. A few stations were found to have overlapping data values, or the same year entered twice with different values. Issues like these relating to data values were checked against the original paper records whenever possible and corrected as appropriate.

2.3 Develop Anomalies

The anomaly method (Jones 1994; New et al. 2000) first interpolates the monthly departures from the reference period mean, and then combines that surface with the mean map to create the final monthly rainfall map. This method produces better results than interpolating the raw rainfall totals at a regional scale (Chen et al. 2002), and has been used in a number of studies (Dawdy & Langebein 1960; Peck & Brown 1962; de Montmollin et al. 1980; Bradley et al. 1987; Dai et al. 1997; Brown & Comrie 2002; Mitchell & Jones 2005; Haylock et al. 2008). It can recreate the climatological pattern even when some of the data are missing for a particular month (Yatagai et al. 2008) since monthly anomalies are more likely to be a product of large-scale circulation (New et al. 1999). Some studies use standardization due to the skewed nature of precipitation distributions, and approaches include calculating the anomalies in standard deviation terms (Jones & Hulme 1996), or using some type of distribution (e.g., gamma distribution, Diaz et al. 1989). Most studies, however, tend to use the absolute anomaly (individual value minus the mean) or relative anomaly (individual value divided by the mean). For precipitation, relative anomalies are preferred to absolute anomalies because the percentage better preserves the variance relationship between the value and the mean (New et al. 2000).

The data values at every raingage station were converted into relative anomalies by dividing the station value by the mean monthly value at that location (e.g., a January data value was divided by the January mean value). These anomaly values are dimensionless, i.e., the units are inches per inch. The mean monthly values were extracted from the Rainfall Atlas of Hawaiʻi mean monthly maps (Giambelluca et al. 2011) using ArcGIS™ 10 (ESRI, Redlands, CA, USA). All station data were used, including short-term stations that were not able to be gap filled. These relative anomalies were interpolated using the method chosen by the method comparison test, and those interpolated anomaly surfaces will then be multiplied back by the mean maps

2.4 Kriging

2.4.1 Kriging Theory

As for choosing the best interpolation scheme for the anomalies, a method comparison was completed to test the performances of different combinations of kriging algorithms with different covariates. Kriging refers to a subset of geostatistical methods that rely on the spatial structure of the data, assuming data points that are closer together are more alike than points that are further apart. Kriging is an unbiased and optimal estimator, which means that the weights used for the points must sum to one, and the goal of the estimator is to minimize the estimation variance (Goovaerts 1997). Kriging uses a semivariogram to assess the dissimilarity between points in a search neighborhood (or covariance to measure the similarity between points). For known values z(x_1), z(x_2), … , z(x_N), at points x_1, x_2 , … , x_N for a variable Z, the experimental semivariogram $\hat{\gamma}(h)$ at lag h is shown in Equation 2.1:

$$\hat{\gamma}\,(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{z(x_i) - \mathrm{z}(x_i + h)\}^2 \qquad [2.1]$$

where $N(h)$ is the number of pairs of data points a vector h apart. The spherical variogram model used in this study is characterized by linear behavior at the origin, and curves gradually toward the sill (Goovaerts 2000). The spherical model is the most widely used model as it is usually the best fit in one, two and three-dimensions. The equation for the spherical model is shown in Equation 2.2:

$$\gamma(h) = \begin{cases} c\left\{\dfrac{3h}{2a} - \dfrac{1}{2}\left(\dfrac{h}{a}\right)^3\right\} & for\ h \le a \\ c & for\ h > a \end{cases} \qquad [2.2]$$

where c is the sill variance and a is the range (Webster & Oliver 2007).

2.4.2 Method Choices

Ordinary kriging (OK) is the most frequently used and robust type of kriging. OK interpolates the point data alone (without secondary variables), and is used in most method comparison studies as a base method against which to compare other methods (Goovaerts 2000; Kyriakidis et al. 2001; Moges et al. 2007; Moral 2009; Mair & Fares 2011). In most of these studies, methods that incorporate a secondary variable proved to outperform OK. However, Mair & Fares found in their study on west Oʻahu island, Hawaiʻi, that OK consistently performed the best.

Many interpolation methods incorporate a secondary variable. A common method used to incorporate a covariate is ordinary cokriging (OCK). OCK capitalizes on the cross-semivariance between the primary and secondary variables, and incorporates that information into the kriging matrix, which makes this method more computationally expensive and complex than OK. Another way to include secondary information is in the form of an external drift, as in the kriging with external drift method (KED). This method has been shown to outperform OK and OCK (Goovaerts 2000; Kyriakidis et al. 2001; Moral 2009). Appendix A contains complete equations for these methods.

2.4.3 Secondary Variables

In many studies, a secondary variable is shown to greatly improve interpolation results (Goovaerts, 2000; Kyriakidis et al. 2001; Moges et al. 2007; Moral 2009). A densely sampled or spatially continuous secondary variable can improve the measurement of the primary variable that may be less densely sampled, since it draws from existing patterns rather than the stations alone. The first variable considered as a covariate for this project was elevation. Elevation has been used by many to help interpolate rainfall because of the strong orographic influences on precipitation (Daly et al. 1994). However, other studies have shown that when compared to atmospheric variables, elevation is not very well correlated with rainfall data (Kyriakidis et al. 2001). Because it is one of the most commonly used covariates, elevation was included to test how well it works in Hawaiʻi's complex terrain. A 30 m resolution digital elevation model (DEM) was used for the State, with values ranging from 0 m to 4200 m.

Another variable that seemed like an appropriate candidate for a secondary variable was mean monthly rainfall from the 2011 Rainfall Atlas maps. On a month-year time scale, Daly et al. 2004 found that mean monthly rainfall maps were much better predictors than elevation. The mean maps contain additional information about the complex rainfall patterns through the incorporation of additional predictor datasets. The Rainfall Atlas mean maps are at 250 m resolution, with mean annual rainfall ranging from 204 mm to 10,271 mm (8 inches to 404 inches). The values from both sets of maps were extracted at every station point using ArcGIS™ 10 (ESRI, Redlands, CA, USA).

2.5 Method Comparison

For the complete method comparison, all 12 months were tested on every island for a 30-year period. The period of 1940-1969 was chosen for the comparison because the middle part of the century had the largest amount of original data compared to the beginning or end of the century (where more of the data were gap-filled). For the method comparison and mapping, Kahoʻolawe, with only five stations, was combined with Maui. The other five islands were analyzed independently.

2.5.1 ArcGIS

ArcGIS™ 10 (ESRI, Redlands, CA, USA) was the main software package that was used to complete the method comparison. The ordinary kriging (OK) and ordinary cokriging (OCK) methods were available in this program, and since ArcGIS™ gave the option to auto-fit variogram parameters and has a more powerful user interface to visualize and prepare final maps (Hengl et al. 2007), this was used as the primary program for producing OK and OCK maps, as well as processing the output for the final maps. The relative anomaly values were imported into file geodatabases so that null values could be supported, given that there were many station records (despite gap filling) that did not have data in every month and year. The secondary variables, elevation and the 2011 Rainfall Atlas monthly means, were already in raster format to be used for cokriging.

To create the maps, an OK (or OCK) geostatistical layer was created in the ArcGIS 10™ Geostatistical Wizard once per island, setting a lag and neighborhood size. That example layer was saved as a template, and using Python command line code, the remaining month-years for each island were created by taking the template and updating the data source to reflect the month-year, and auto-fitting the nugget, range, and sill values. The cross validation tool was then used (via Python commands) to extract the mean error statistics needed for the method comparison. This was performed for OK, OCK with elevation, and OCK with the 2011 Rainfall Atlas from 1940-1969 for all months and islands.

2.5.2 GSLIB

Since kriging with external drift (KED) was not available in ArcGIS™ 10, a different geostatistical software package was used: GSLIB (Deutsch & Journel 1998). Unlike ArcGIS™ 10, GSLIB requires the user to model variograms manually and purchase a separate interface. This program handles spatial data using grids instead of coordinates, which meant that all the station anomaly data and raster information from the secondary variables had to be converted to a simple grid (using rows and columns instead of coordinates) for each island. The station anomaly data also had to be reformatted to a style specific to GSLIB.

Once all the data was correctly formatted, the variograms were computed for each month and year. To visualize the data and test the model parameters, the variogram output was imported into Microsoft Excel and the spherical model was plotted. The parameters were adjusted manually, and re-plotted in GSLIB once parameters were set. Then the KED was run, and the cross validation output was saved. This procedure was completed for KED with elevation and KED with the 2011 Rainfall Atlas monthly mean maps from 1940-1969 for all months and islands.

2.5.3 Assessment of Cross Validation Statistics

The kriging methods were assessed by comparing the cross validation statistics for the different methods, as these are more bias-free than the error map produced directly by the kriging interpolation. Although there are still weaknesses with the cross validation method (Jeffrey et al. 2001), it is the most widely used way to complete method intercomparisons. The two error statistics that were used to analyze the results were the mean absolute error (MAE) and the root mean square error (RMSE), as these are considered the "best" measures of overall performance (Willmott 1982). MAE is a natural measure of average error, and expresses the errors in the same units as the rainfall. RMSE is a measure of random error, and is a very commonly used statistic due to its sensitivity to outliers. The MAE and RMSE equations are shown in Equations 2.3 and 2.4:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|p_i - o_i| \qquad [2.3]$$

$$\text{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(p_i - o_i)^2\right]^{1/2} \qquad [2.4]$$

where n is the count of stations, p_i are the predicted values at each station, and o_i are the observed values. The error $(p_i - o_i)$ gives an idea of the bias of the interpolation (positive or negative), whereas RMSE is a measure of scatter. The MAE and RMSE values of the stations were computed for every island-month and year for all five methods: OK, OCK with elevation, OCK with mean rainfall, KED with elevation, and KED with mean rainfall. This was done by using Microsoft Excel VBA code to compile the data from the software's cross validation outputs.

With the cross validation statistics organized, there were four different ways to choose the "best" method for a given island-month:

- Category 1: The minimum of the average 30 years of MAE values
- Category 2: The highest percent of years (out of 30) where a method had the minimum MAE value
- Category 3: The minimum of the average 30 years of RMSE values

- Category 4: The highest percent of years (out of 30) where a method had the minimum RMSE value

A ranking system was developed to choose one best method for every island-month, to incorporate how well the methods performed in each category. In each of the four categories, the methods were ranked 1 to 5 (best to worst), and the method with the lowest average rank across the four categories was deemed the best method (Hofstra et al. 2008). Table 2.1 shows an example of the ranking scheme, where ordinary kriging achieves the lowest average rank and would be chosen as the best method for this island-month. Since only one method would be used to produce the final maps, single factor ANOVA (Analysis of Variance) testing was used to compare the mean statistics for different methods to see if they were significantly different from each other. Methods were defined as having a statistically significantly different means if the F value was greater than the critical F value, and if the p-value was less than alpha (the alpha value used for this testing was 0.05).

Table 2.1. Example of the ranking procedure for the method comparison assessment for a sample island-month. Units for categories 1 and 3 are the same as the relative anomalies: dimensionless (inches per inch).

	OK	**OCK_EL**	**OCK_RF**	**KED_EL**	**KED_RF**
Category 1: Min Avg MAE	0.00830	0.00833	0.01515	0.00873	0.02309
Rank 1	*1*	*2*	*4*	*3*	*5*
Category 2: Max % Years with lowest MAE	0.2	0.2	0.333	0.167	0.1
Rank 2	*2*	*2*	*1*	*4*	*5*
Category 3: Min Avg RMSE	0.76966	0.82541	0.82252	0.86421	0.86593
Rank 3	*1*	*3*	*2*	*4*	*5*
Category 4: Max % Years with lowest RMSE	0.533	0.067	0.3	0	0.1
Rank 4	*1*	*4*	*2*	*5*	*3*
Average Rank	**1.25**	**2.75**	**2.25**	**4**	**4.5**

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

2.4.4 Pilot Study

A preliminary test was performed for a five year period in two months, January and July 1996-2000, for the island of Kaua'i to test the three methods, and determine whether the methods performed differently in the summer and winter seasons. The three algorithms chosen (OK, OCK, and KED) were used with the two covariates. However, the 2011 Rainfall Atlas maps were not completed at the time of this preliminary study, so the 1986 Rainfall Atlas mean maps were used in their place. The cross validation results (error and root mean square error, RMSE) for January are shown in Table 2.2, and the results for July are shown in Table 2.3, with average values shown in Table 2.4. In all tables, the method with the lowest average absolute statistic (last column) is shown in bold (indicating that it performed the best over that period).

Table 2.2. January cross validation results – Kaua'i sample period, 1996-2000. Units for error and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

		Jan 1996	**Jan 1997**	**Jan 1998**	**Jan 1999**	**Jan 2000**	**Avg Jan**
Error	OK	-0.00252	-0.00694	0.00005	0.00088	-0.00025	-0.00175
	OCK_EL	-0.00174	-0.00604	0.00028	0.00138	-0.00051	**-0.00133**
	OCK_RF	-0.00208	-0.00605	0.00008	0.00088	-0.00061	-0.00155
	KED_EL	0.01003	0.01776	-0.00481	0.01049	0.00012	0.00672
	KED_RF	0.00515	0.01030	-0.00442	0.00472	-0.00311	0.00253
RMSE	OK	0.33020	0.34310	0.17180	0.16870	0.21190	0.24514
	OCK_EL	0.33040	0.34180	0.17150	0.16950	0.20980	0.24460
	OCK_RF	0.32980	0.34160	0.17140	0.16870	0.20920	**0.24414**
	KED_EL	0.34636	0.37035	0.19103	0.18934	0.24091	0.26760
	KED_RF	0.33802	0.35929	0.21647	0.19176	0.24851	0.27081

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. RMSE is root mean square error.

Table 2.3. July cross validation results – Kaua'i sample period, 1996-2000. Units for error and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

		Jul 1996	**Jul 1997**	**Jul 1998**	**Jul 1999**	**Jul 2000**	**Avg Jul**
Error	OK	-0.00913	-0.01244	-0.00223	-0.01284	-0.00417	-0.00816
	OCK_EL	-0.01148	-0.01462	-0.00226	-0.01685	-0.01110	-0.01126
	OCK_RF	-0.01156	-0.01463	-0.00243	-0.01770	-0.01145	-0.01155
	KED_EL	0.00905	-0.00589	0.00018	-0.00803	0.01007	**0.00107**
	KED_RF	-0.00759	0.00016	-0.00332	-0.01700	0.01724	-0.00210
RMSE	OK	0.43860	0.89140	0.21580	0.98700	0.52340	0.61124
	OCK_EL	0.45290	0.89900	0.21750	1.00500	0.54200	0.62328
	OCK_RF	0.45400	0.90010	0.21710	1.01300	0.54270	0.62538
	KED_EL	0.46495	0.95492	0.22443	1.23257	0.59965	0.69530
	KED_RF	0.39730	0.87037	0.21354	1.05819	0.51403	**0.61068**

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. RMSE is root mean square error.

Table 2.4. Average cross validation results – Kaua'i sample period, 1996-2000. Units for error and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

		Avg Jan	**Avg Jul**	**Avg All**
Error	OK	-0.00175	-0.00816	-0.00496
	OCK_EL	-0.00133	-0.01126	-0.00629
	OCK_RF	-0.00155	-0.01155	-0.00655
	KED_EL	0.00672	0.00107	0.00390
	KED_RF	0.00253	-0.00210	**0.00021**
RMSE	OK	0.24514	0.61124	**0.42819**
	OCK_EL	0.24460	0.62328	0.43394
	OCK_RF	0.24414	0.62538	0.43476
	KED_EL	0.26760	0.69530	0.48145
	KED_RF	0.27081	0.61068	0.44075

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. RMSE is root mean square error.

Comparing three methods and two different covariates, it was difficult to determine which method performed the best overall. Both KED methods showed a slight positive bias (positive error values), while all three ordinary kriging methods showed a slight negative bias. Ordinary cokriging (OCK) performed better in January, kriging with external drift (KED) performed better in July, and ordinary kriging (OK) had the best average RMSE statistics. Therefore, more tests were needed to determine the best methods to use to make the final maps. Figure 2.1 shows the output from OCK with elevation (OCK_EL) for January 1996-2000 (the method with the lowest overall error value in January). The pilot study showed that all methods performed well, but results from only five years in two different months were not conclusive enough to choose a method for the test island, which is why a more complete, 30-year test was performed for all months and islands.

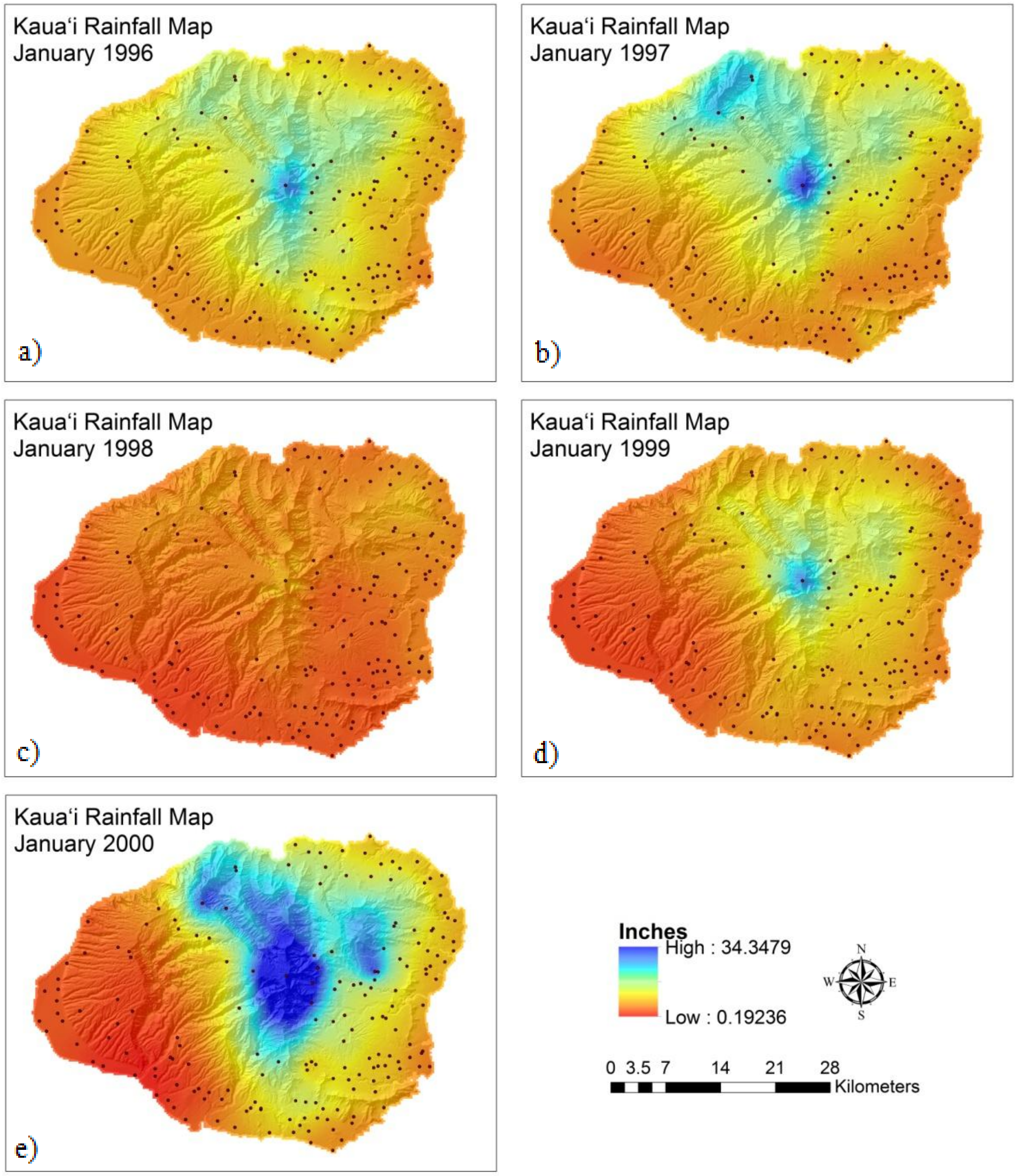


Figure 2.1. Pilot study results for January, Kauaʻi using ordinary cokriging with elevation (with the points representing the raingage stations used for that map). a) January 1996; b) January 1997; c) January 1998; d) January 1999; e) January 2000.

2.6 Final Maps

2.6.1 Anomaly Maps

With an interpolation method chosen, the final month-year maps could then be produced. The first step was to generate anomaly maps by interpolating the relative anomalies at the raingage stations for the remaining month-years that were not already completed in the method comparison step. This was done by following the same procedure used in the method comparison, including the generation of cross validation statistics to compare the results for all 88 years with the 30-year sample. To ensure that the auto-fit variogram parameters had produced reasonable patterns, the geostatistical layers were all examined manually. Also, for a better transition from geostatistical layer to raster, a smooth neighborhood setting was used (with a 0.3 smoothing factor) for all maps. These anomaly maps will also be part of the output, as they are useful for many analyses. The maps were masked by the coastline using ArcGIS™ 10 (ESRI, Redlands, CA, USA) and saved as raster layers with the same extent and 250 m spatial resolution as the mean maps so that the pixels would match.

2.6.2 Generating Monthly Rainfall Maps

Once the anomaly maps were completed, they needed to be converted back into a rainfall map. Since the anomaly values were generated by dividing the rainfall value at the station by the Rainfall Atlas mean, the anomaly maps had to be multiplied by the Rainfall Atlas mean maps to produce the final month-year rainfall maps. The anomaly maps were multiplied by the mean maps using ArcGIS (e.g., January anomalies were multiplied by the January mean map). All 12 monthly maps in each year were then summed together to produce annual maps for each year. These final maps were also converted from inches to millimeters by multiplying the maps by a factor of 25.4.

CHAPTER 3
RESULTS

3.1 Method Comparison

The performance of each interpolation method is summarized in Table 3.1**,** which shows the average error statistics and ranks for each island. Based on the ranking procedure described previously, ordinary kriging (OK) was chosen as the best method to use for interpolating rainfall anomalies in Hawai‘i. Overall, OK showed the smallest cross validation errors (had the least bias and scatter) compared to the other four methods. This result was unequivocal in three of the islands (Kaua‘i, O‘ahu, and Hawai‘i islands), while for the other islands OK was selected for about half of the months. Table 3.2 shows the best interpolation methods chosen by each island-month based on the MAE and RMSE values using the ranking scheme described in the previous chapter. The differences between the top methods were small, however. A visual example comparing the five methods is shown for May 1964 for O‘ahu in Figure 3.1, where rainfall for all five maps is shown on the same scale. The scatterplots of all 30 years for May on O‘ahu are shown for the five methods in Figure 3.2. The r^2 results are very similar for all methods in this month, but OK shows the highest correlation of all the methods. The details regarding which method was chosen by each of the four categories in every island-month can be found in Appendix B.

Table 3.1. Summary of the four categories of error statistics and the final rank score from the cross validation test for all islands, averaged over all months. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

		Avg MAE	Avg Rnk	Avg % Yrs Min MAE	Avg Rnk	Avg RMSE	Avg Rnk	Avg % Yrs Min RMSE	Avg Rnk	Avg All Ranks
Ka	OK	0.00118	1.42	0.703	1.00	0.32559	1.00	0.806	1.00	1.10
	OCK_EL	0.00242	2.33	0.089	3.08	0.34871	3.08	0.053	2.83	2.83
	OCK_RF	0.00280	2.92	0.081	3.17	0.34617	2.42	0.056	2.67	2.79
	KED_EL	0.00924	4.25	0.061	3.42	0.55001	5.00	0.006	3.92	4.15
	KED_RF	0.00624	4.08	0.067	3.33	0.35913	3.50	0.081	2.92	3.46
Oa	OK	0.00057	1.50	0.589	1.00	0.31999	1.00	0.806	1.00	1.13
	OCK_EL	0.00224	3.33	0.075	3.83	0.34869	4.08	0.011	3.58	3.71
	OCK_RF	0.00132	2.42	0.139	2.83	0.33903	2.58	0.061	2.75	2.65
	KED_EL	0.00261	3.83	0.097	3.33	0.35562	4.67	0.006	3.83	3.92
	KED_RF	0.00295	3.92	0.100	3.33	0.33743	2.67	0.117	2.33	3.06
Mo	OK	0.00447	2.83	0.244	2.25	0.54863	1.42	0.367	1.50	2.00
	OCK_EL	0.00395	2.33	0.197	2.58	0.58013	3.83	0.089	3.75	3.13
	OCK_RF	0.00409	2.42	0.347	1.25	0.56777	2.17	0.322	1.75	1.90
	KED_EL	0.00814	3.75	0.111	4.17	0.58706	4.33	0.067	4.33	4.15
	KED_RF	0.00829	3.67	0.100	4.25	0.57984	3.25	0.156	3.00	3.54
La	OK	0.00902	2.50	0.289	2.00	0.33618	2.17	0.200	2.67	2.33
	OCK_EL	0.01194	3.67	0.131	3.58	0.34000	3.42	0.153	3.50	3.54
	OCK_RF	0.00972	2.42	0.192	2.75	0.33399	1.83	0.208	2.50	2.38
	KED_EL	0.01806	4.00	0.114	4.17	0.39878	5.00	0.089	4.33	4.38
	KED_RF	0.01055	2.42	0.275	1.92	0.33428	2.58	0.350	1.25	2.04
Ma	OK	0.00309	2.33	0.286	1.75	0.56646	1.42	0.433	1.33	1.71
	OCK_EL	0.00394	3.00	0.119	3.92	0.58017	3.33	0.067	4.00	3.56
	OCK_RF	0.00304	2.00	0.333	1.58	0.57111	2.33	0.322	1.83	1.94
	KED_EL	0.01301	3.58	0.183	2.75	0.53275	4.25	0.072	3.67	3.56
	KED_RF	0.01628	4.08	0.078	4.42	0.54533	3.67	0.106	3.75	3.98
Ha	OK	0.00086	1.58	0.417	1.00	0.43304	1.00	0.631	1.00	1.15
	OCK_EL	0.00304	3.08	0.125	3.58	0.45664	3.58	0.047	4.00	3.56
	OCK_RF	0.00158	2.17	0.244	2.25	0.44589	2.33	0.181	2.25	2.25
	KED_EL	0.00405	3.92	0.117	3.67	0.46507	4.67	0.056	3.58	3.96
	KED_RF	0.00513	4.25	0.097	3.92	0.46254	3.42	0.086	3.33	3.73

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.
Ka is Kauaʻi, Oa is Oʻahu, Mo is Molokaʻi, La is Lānaʻi, Ma is Maui, and Ha is Hawaiʻi Island.

Table 3.2. Best interpolation method for each island-month based on the cross validation test, 1940-1969.

	Hawai‘i	Kaua‘i	Lāna‘i	Maui	Moloka‘i	O‘ahu
Jan	OK	OK	OK	OCK_RF	OK	OK
Feb	OK	OK	OK	OCK_RF	OCK_RF	OK
Mar	OK	OK	KED_RF	OK	OCK_RF	OK
Apr	OK	OK	KED_RF	OK	OCK_RF	OK
May	OK	OK	OK	OK	OCK_RF	OK
Jun	OK	OK	KED_RF	OCK_RF	OK	OK
Jul	OK	OK	OCK_RF	OK	OCK_RF	OK
Aug	OK	OK	OK	OK	OK	OK
Sep	OK	OK	OK	OK	OK	OK
Oct	OK	OK	OK	OK	OK	OK
Nov	OK	OK	OCK_RF	OK	OCK_RF	OK
Dec	OK	OK	KED_RF	OCK_RF	OCK_RF	OK

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall.

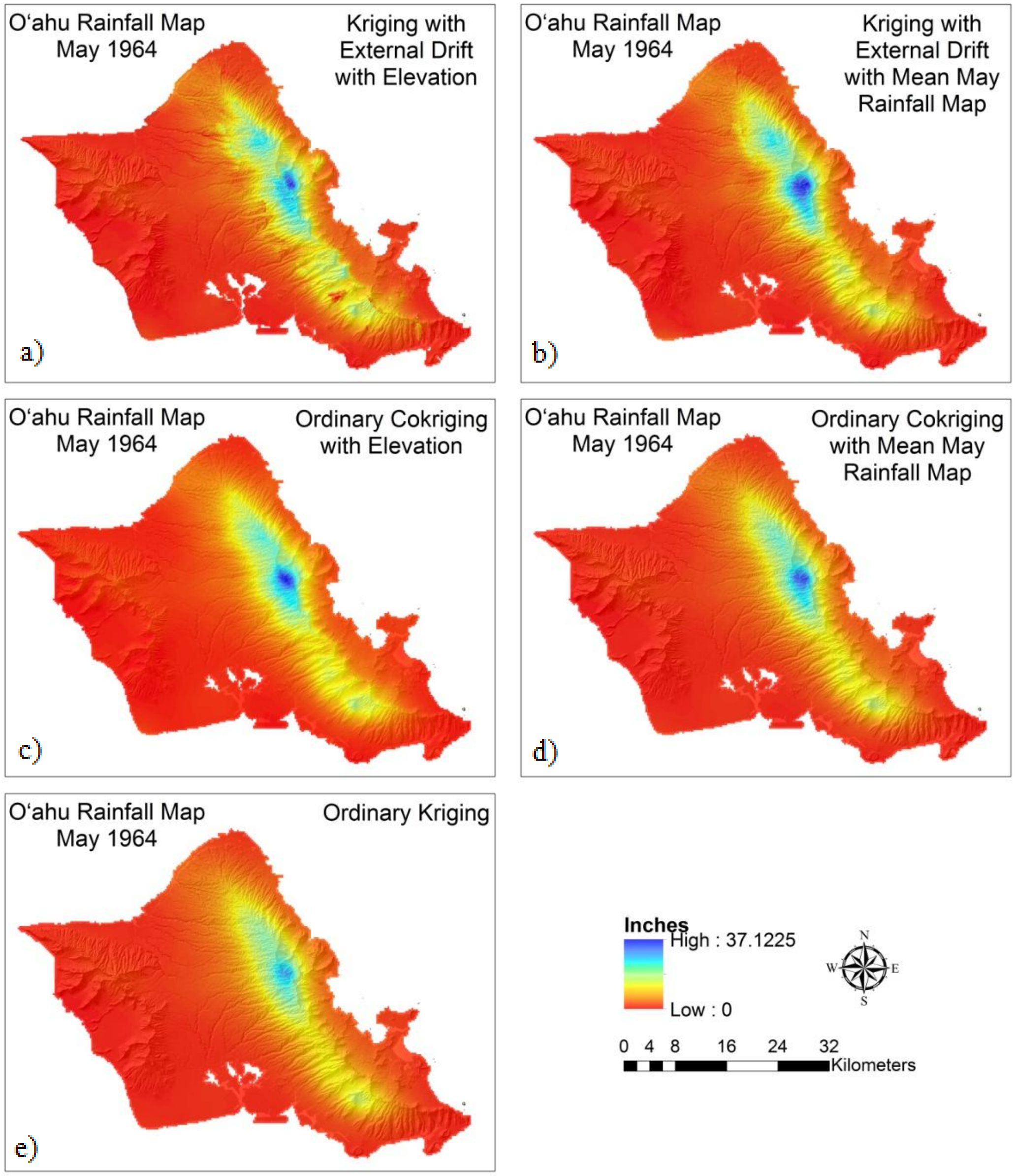


Figure 3.1. Example of the rainfall output from five different interpolation methods for O‘ahu May 1964. a) O‘ahu rainfall map, May 1964, created by kriging with external drift with elevation; b) O‘ahu rainfall map, May 1964, created by kriging with external drift with mean rainfall; c) O‘ahu rainfall map, May 1964, created by ordinary cokriging with elevation; d) O‘ahu rainfall map, May 1964, created by ordinary cokriging with mean rainfall; e) O‘ahu rainfall map, May 1964, created by ordinary kriging.

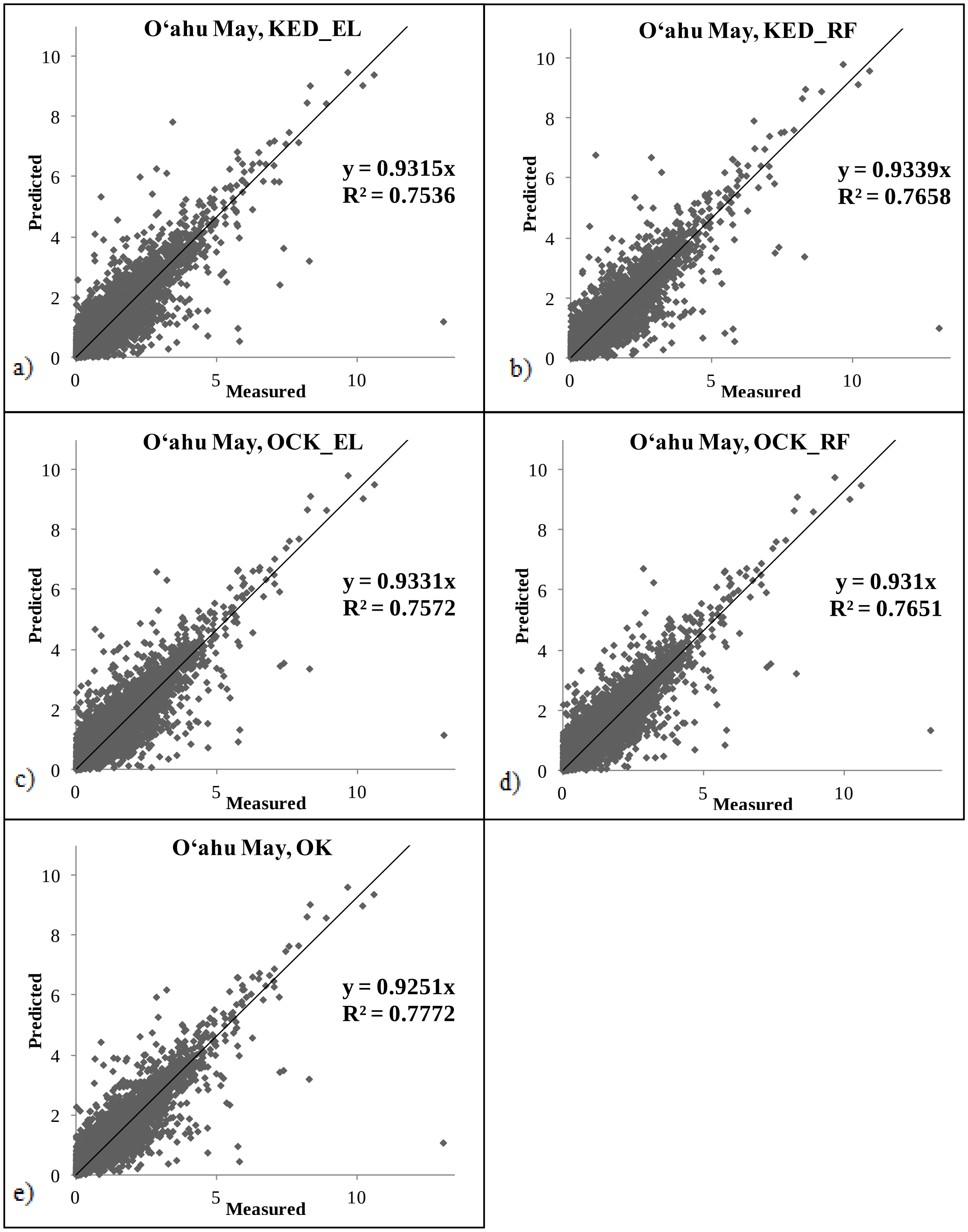


Figure 3.2. Example scatterplots of measured versus predicted rainfall for all 30 years of O‘ahu May (1940-1969) with R^2 values for each of the five methods. a) O‘ahu May scatterplot of kriging with external drift with elevation results; b) O‘ahu May scatterplot of kriging with external drift with mean rainfall results; c) O‘ahu May scatterplot of ordinary cokriging with elevation results; d) O‘ahu May scatterplot of ordinary cokriging with mean rainfall results; e) O‘ahu May scatterplot of ordinary kriging results.

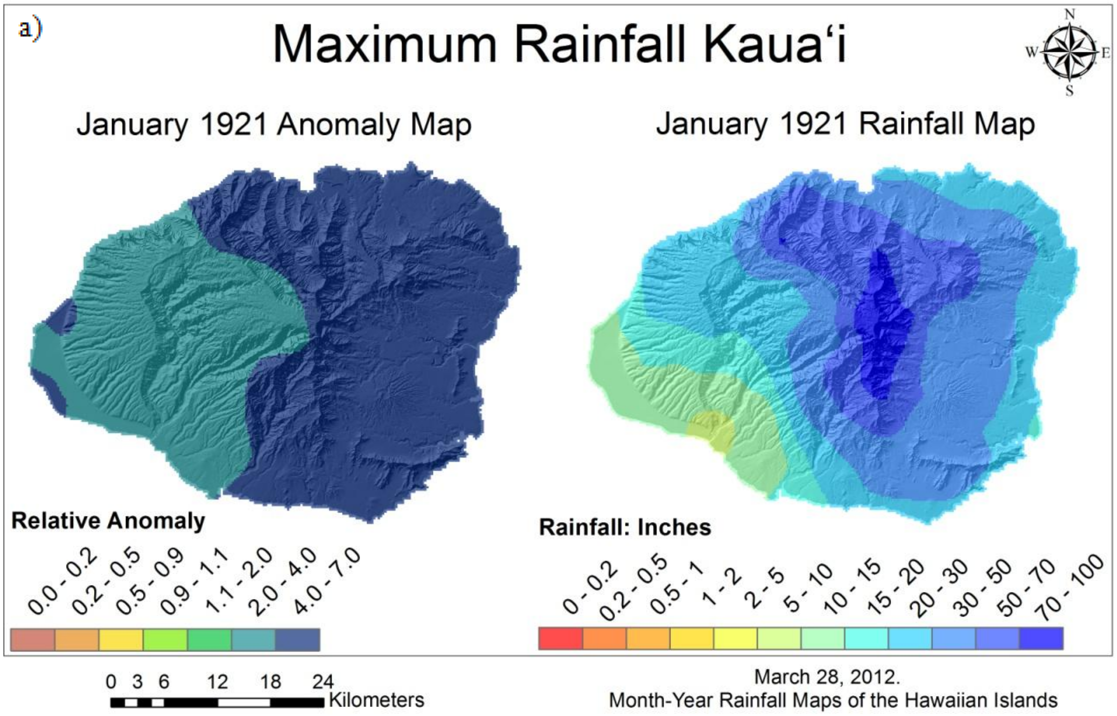
OK was the method chosen for the majority of months (55 island-months out of a possible 72). For the 17 months where OK was not chosen as the best method, the means of the methods were compared to see if there were large differences in method performance. The ANOVA results (Table 3.3) indicated that the OK method was not significantly different from the method chosen as the best. Since OK still performed well in these island-months despite not having the best ranked statistics, it was decided that OK would be selected as the method used to interpolate the anomalies for all island-months.

Table 3.3. ANOVA results for the island-months where ordinary kriging was not chosen as the best method.

	Error			RMSE		
	F	**P-value**	**F crit**	**F**	**P-value**	**F crit**
Lānaʻi Mar	0.33794	0.85202	2.43407	0.18890	0.94388	2.43407
Lānaʻi Apr	0.71862	0.58051	2.43407	0.42949	0.78715	2.43407
Lānaʻi Jun	0.12099	0.88619	3.10130	0.41472	0.79783	2.43407
Lānaʻi Jul	1.36288	0.26133	3.10130	0.72400	0.57688	2.43407
Lānaʻi Nov	0.86487	0.48670	2.43407	0.34703	0.84575	2.43407
Lānaʻi Dec	0.58011	0.67752	2.43407	0.48070	0.74987	2.43407
Maui Jan	1.12104	0.34894	2.43407	1.24611	0.29411	2.43407
Maui Feb	2.24789	0.06675	2.43407	0.15678	0.95967	2.43407
Maui Jun	0.79959	0.52731	2.43407	0.16566	0.95549	2.43407
Maui Dec	2.16775	0.07552	2.43407	0.05624	0.99406	2.43407
Molokaʻi Feb	1.79455	0.13306	2.43407	0.22155	0.92605	2.43407
Molokaʻi Mar	0.62418	0.64599	2.43407	0.08605	0.98664	2.43407
Molokaʻi Apr	0.23396	0.91886	2.43407	0.04113	0.99676	2.43407
Molokaʻi May	1.81085	0.12985	2.43407	0.07979	0.98842	2.43407
Molokaʻi Jul	0.64382	0.63211	2.43407	0.05801	0.99370	2.43407
Molokaʻi Nov	1.18044	0.32192	2.43407	0.12313	0.97398	2.43407
Molokaʻi Dec	0.54007	0.58465	3.10130	0.10599	0.98027	2.43407

3.2 Final Maps

A total of 6,336 anomaly maps and 6,864 rainfall maps were created (anomaly maps were not used to produce the annual maps). An additional 6,864 rainfall maps were generated in millimeters, which gives a total of 20,064 maps. Figures 3.3 – 3.8 contain the maps with the maximum and minimum rainfall for each island over the entire 88-year period paired next to the anomaly map for that month. The rainfall values are scaled the same for each island set, as are the anomaly values. The extreme range in values over this 88-year period is apparent, with the maximum Maui map showing values from less than one inch to over 200 inches in a single month on this one island. More sample maps of the most recent 15 years of October on Moloka‘i are shown in Figure 3.9, where the scale for all maps is the same for comparison. The complete set of month-year maps is available as raster GIS layers and can be downloaded from the Rainfall Atlas website by December 2012: http://rainfall.geography.hawaii.edu/downloads.html.



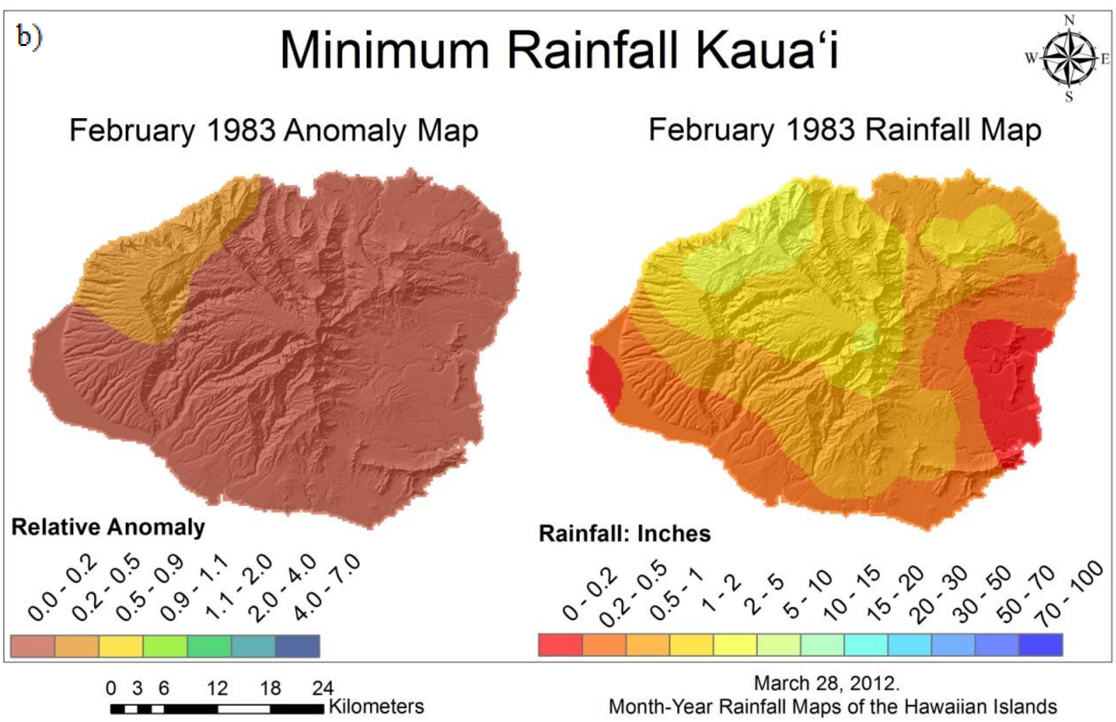


Figure 3.3. a) Maximum rainfall map and corresponding anomaly map for Kaua'i (January 1921); b) Minimum rainfall map and corresponding anomaly map for Kaua'i (February 1983). Relative anomalies are percentages of the mean.

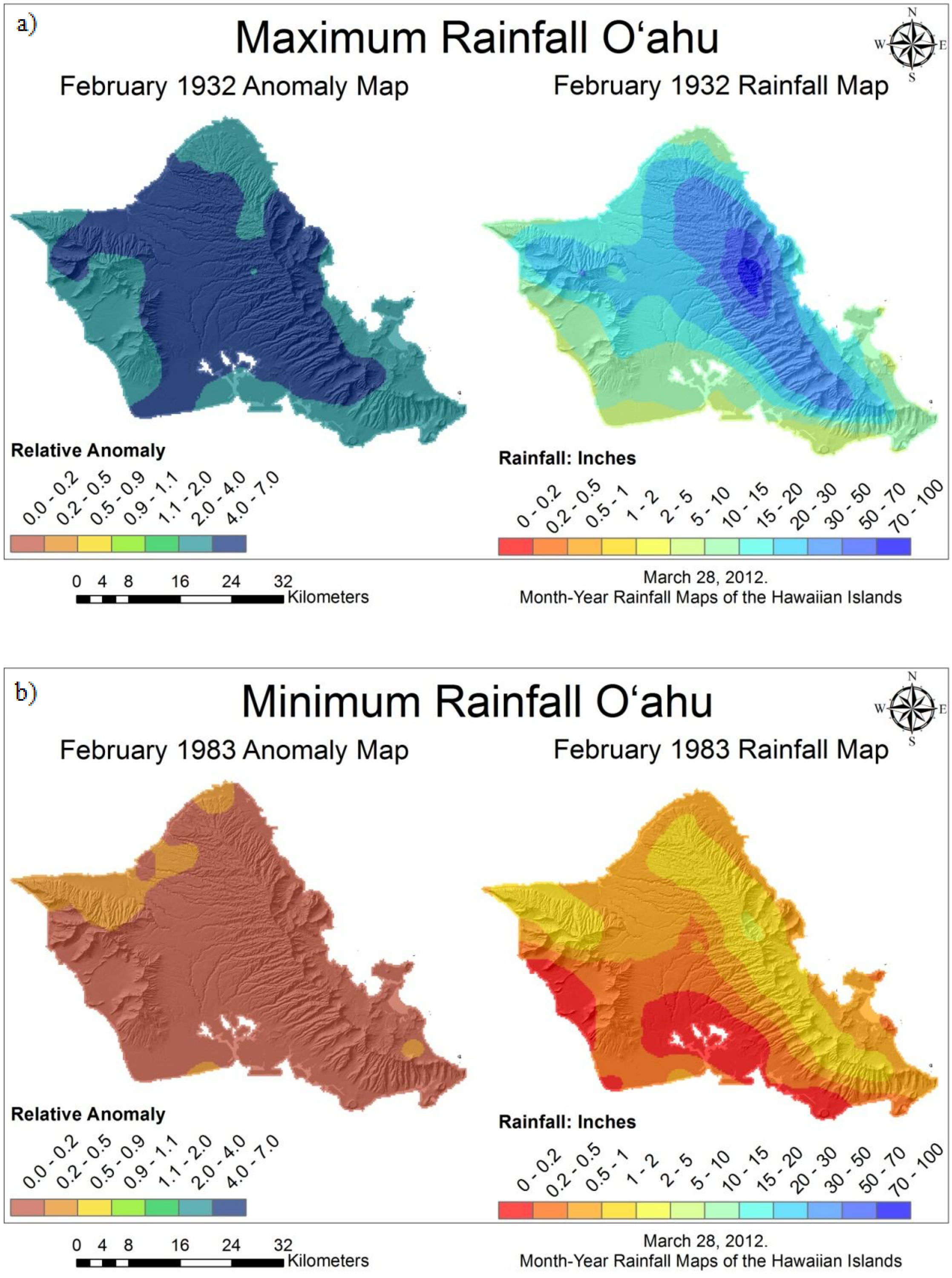
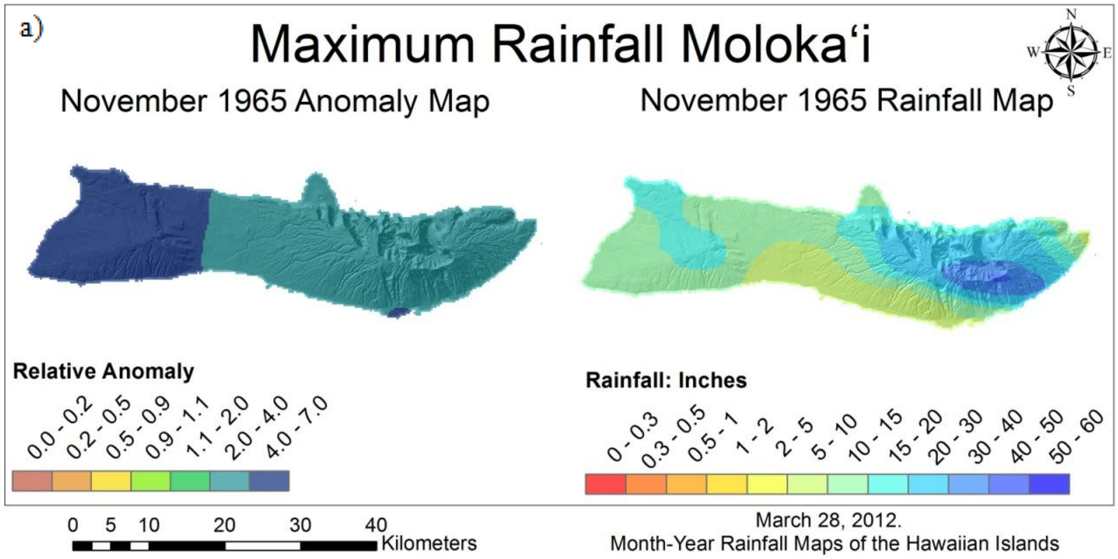


Figure 3.4. a) Maximum rainfall map and corresponding anomaly map for O‘ahu (February 1932); b) Minimum rainfall map and corresponding anomaly map for O‘ahu (February 1983). Relative anomalies are percentages of the mean.



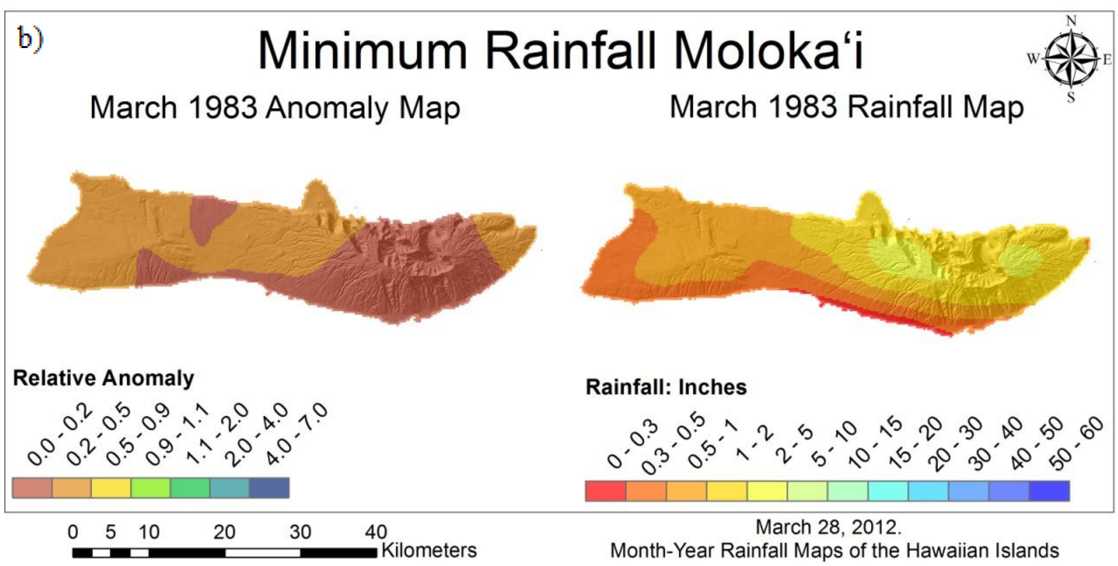


Figure 3.5. a) Maximum rainfall map and corresponding anomaly map for Moloka‘i (November 1965); b) Minimum rainfall map and corresponding anomaly map for Moloka‘i (March 1983). Relative anomalies are percentages of the mean.

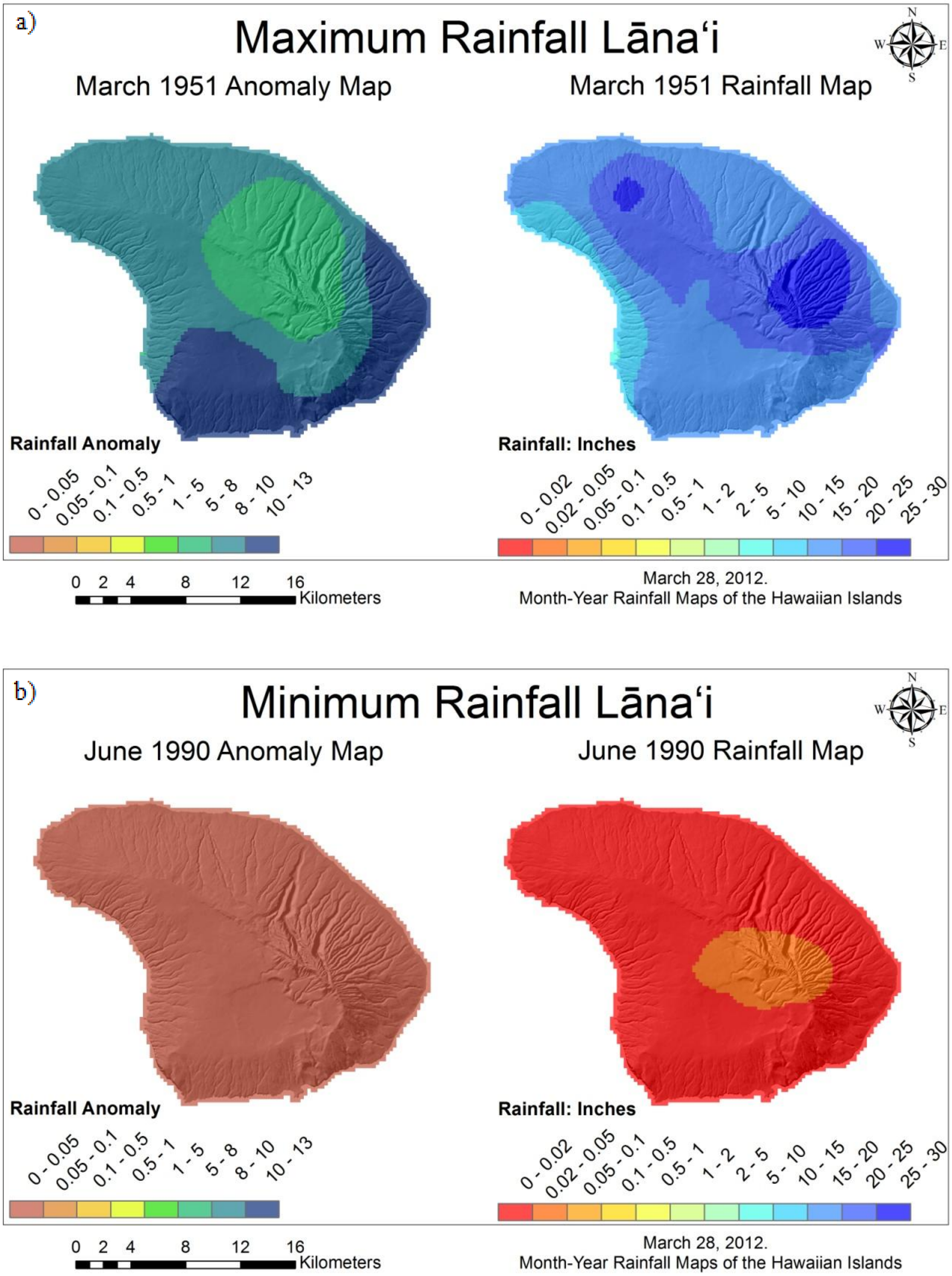


Figure 3.6. a) Maximum rainfall map and corresponding anomaly map for Lānaʻi (March 1951); b) Minimum rainfall map and corresponding anomaly map for Lānaʻi (June 1990). Relative anomalies are percentages of the mean.

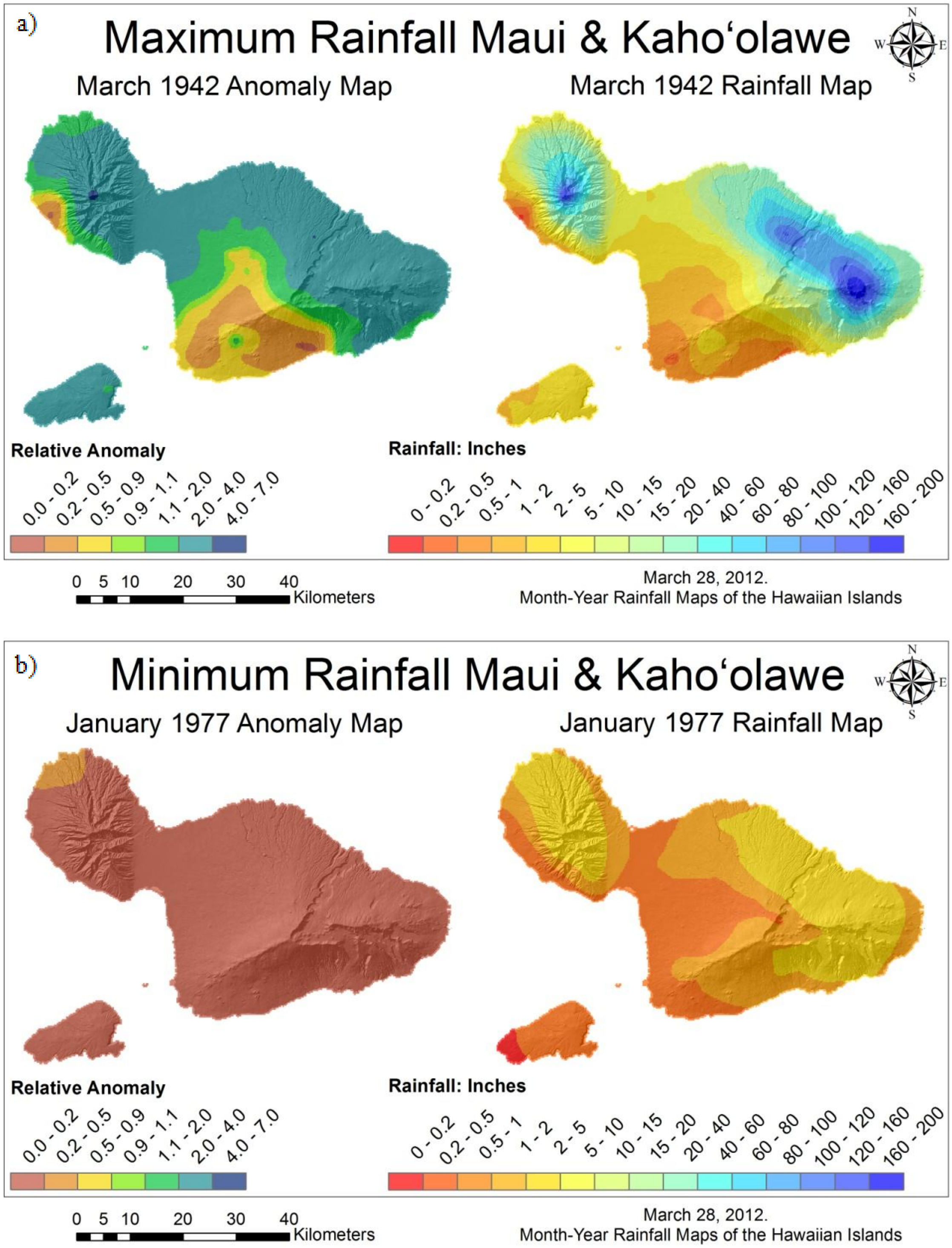


Figure 3.7. a) Maximum rainfall map and corresponding anomaly map for Maui and Kahoʻolawe (March 1942); b) Minimum rainfall map and corresponding anomaly map for Maui and Kahoʻolawe (January 1977). Relative anomalies are percentages of the mean.

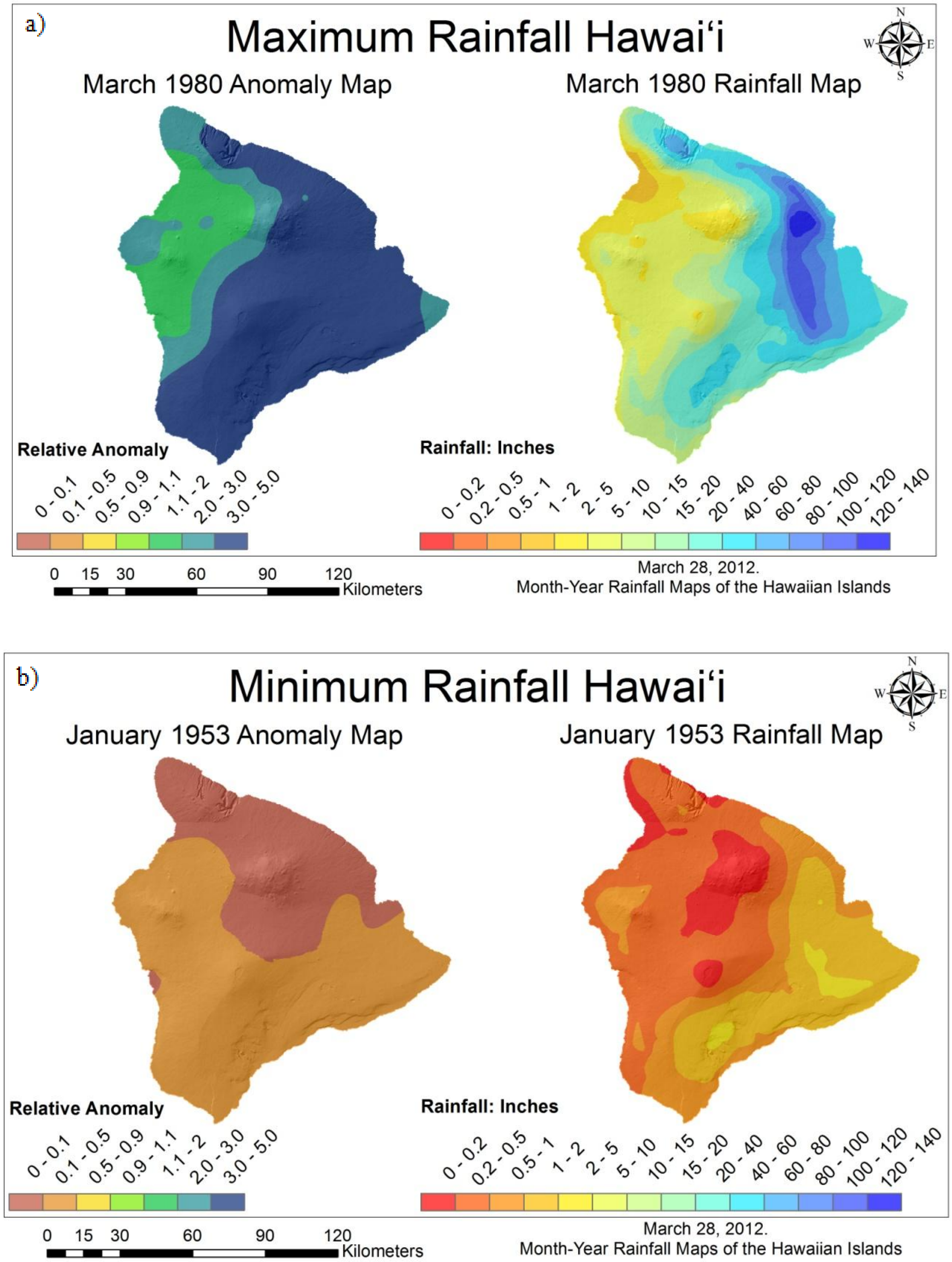


Figure 3.8. a) Maximum rainfall map and corresponding anomaly map for Hawai'i (March 1980); b) Minimum rainfall map and corresponding anomaly map for Hawai'i (January 1953). Relative anomalies are percentages of the mean.

a)

b)

c)

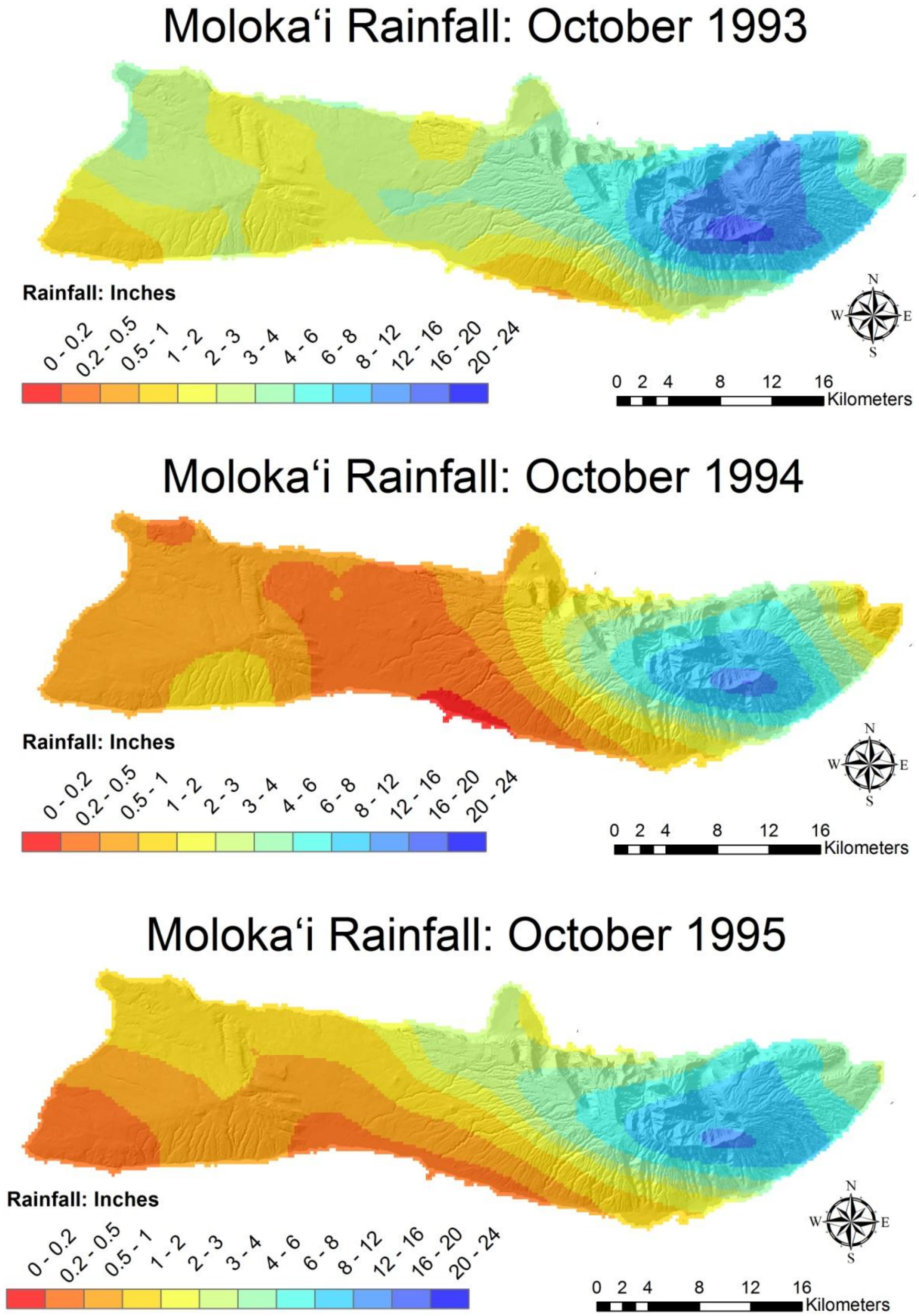
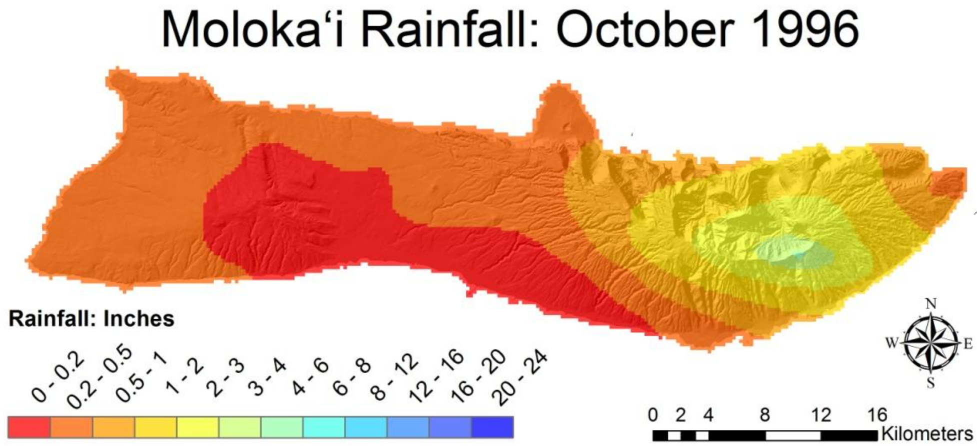


Figure 3.9. Examples of the last 15 years of October rainfall maps for Moloka‘i. a) October 1993; b) October 1994; c) October 1995; d) October 1996; e) October 1997; f) October 1998; g) October 1999; h) October 2000; i) October 2001; j) October 2002; k) October 2003; l) October 2004; m) October 2005; n) October 2006; o) October 2007.

d)



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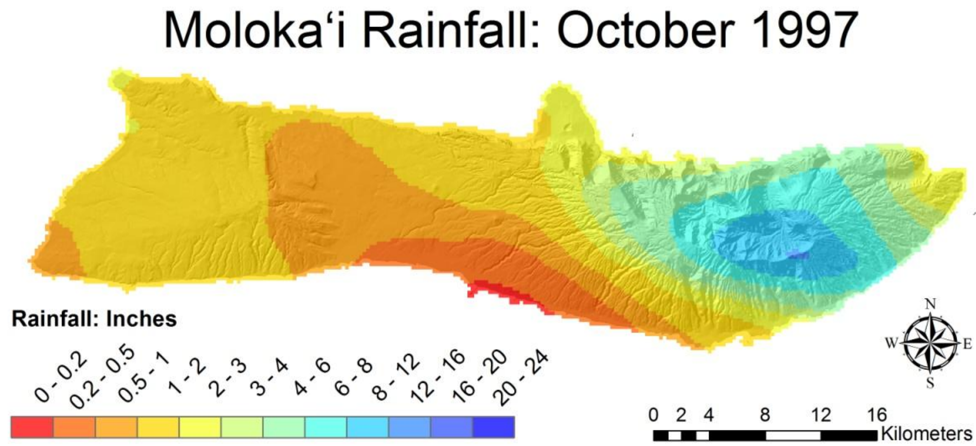

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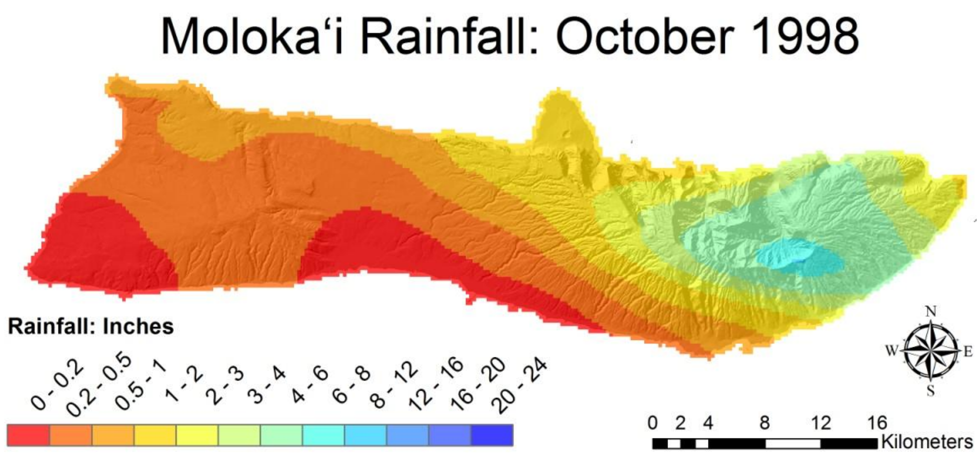
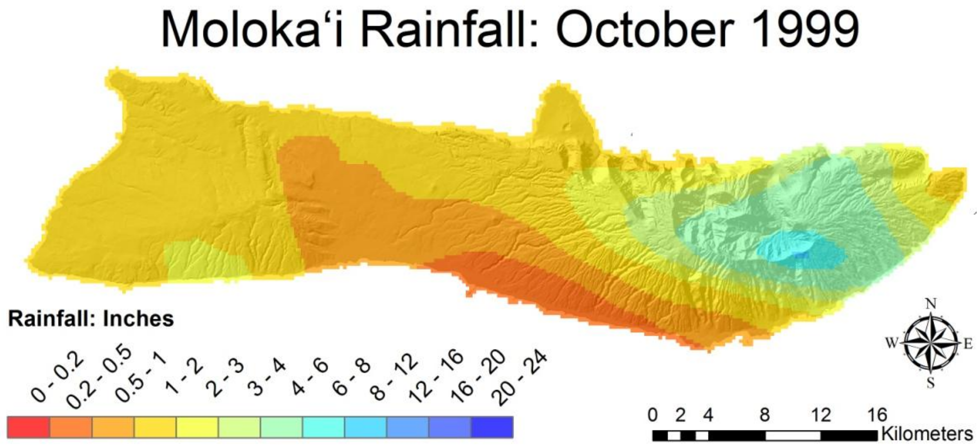
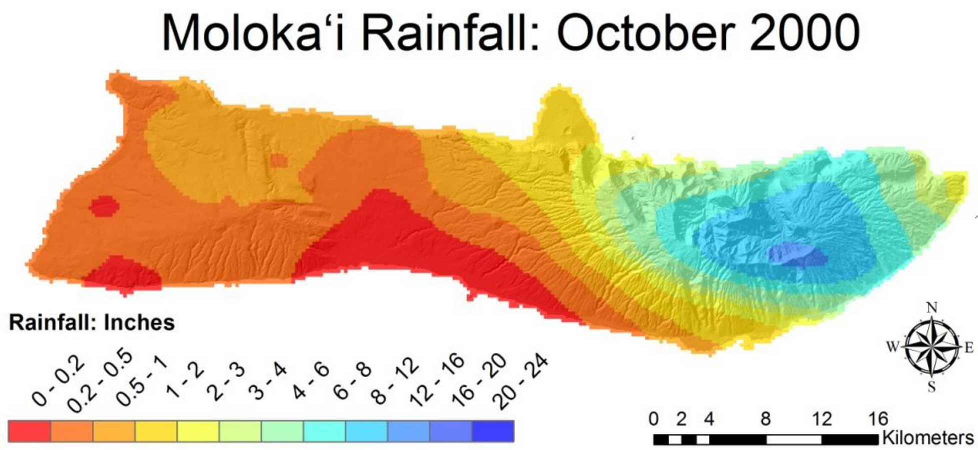


Figure 3.9. (Continued) Examples of the last 15 years of October rainfall maps for Moloka‘i.

g)



h)



i)

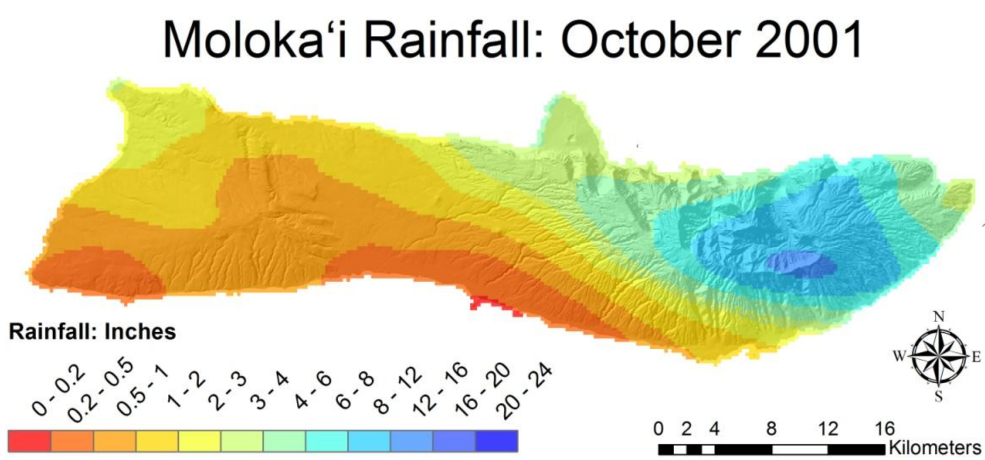
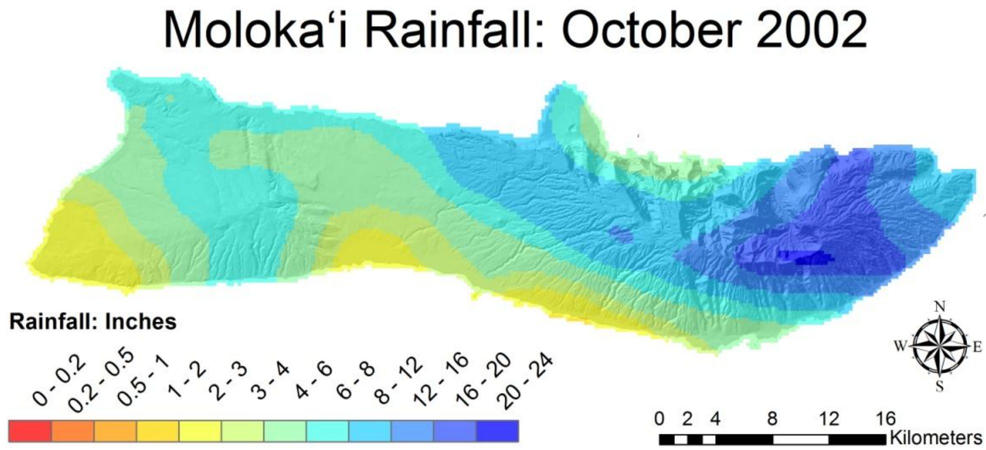
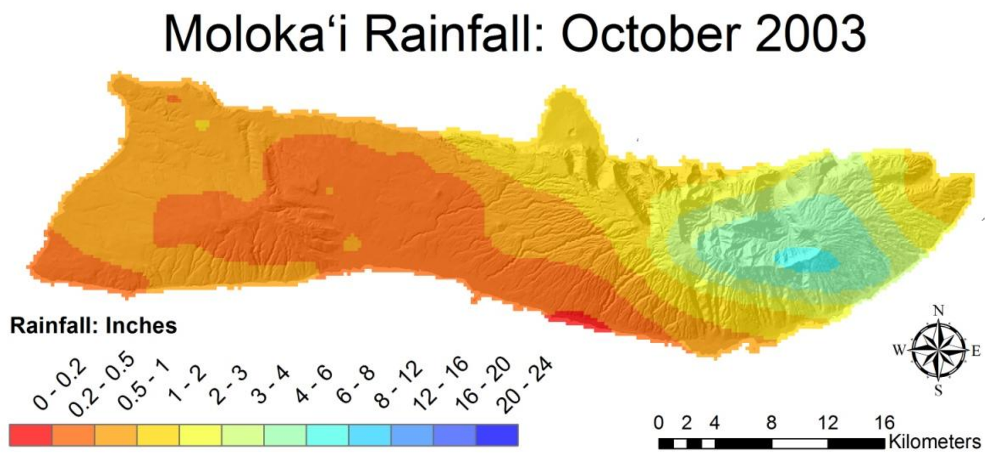


Figure 3.9. (Continued) Examples of the last 15 years of October rainfall maps for Moloka‘i.

j)



k)



l)

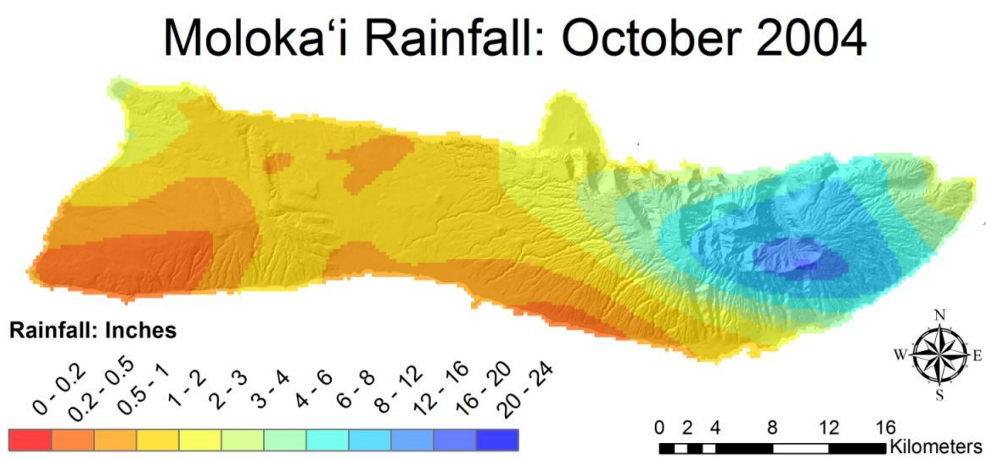
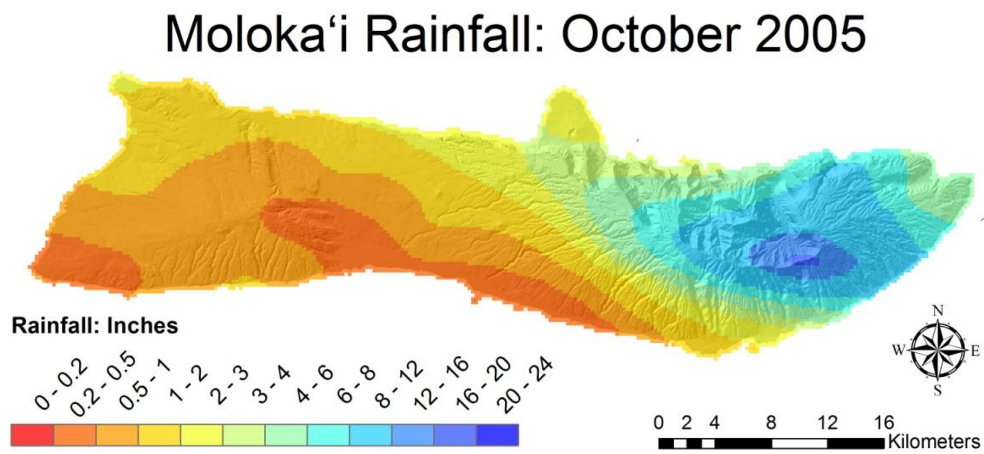
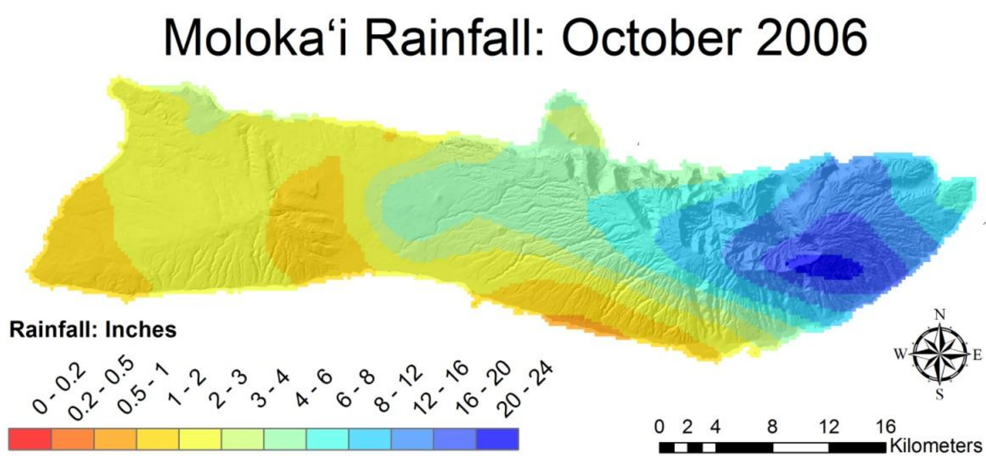


Figure 3.9. (Continued) Examples of the last 15 years of October rainfall maps for Moloka‘i.

m)



n)



o)

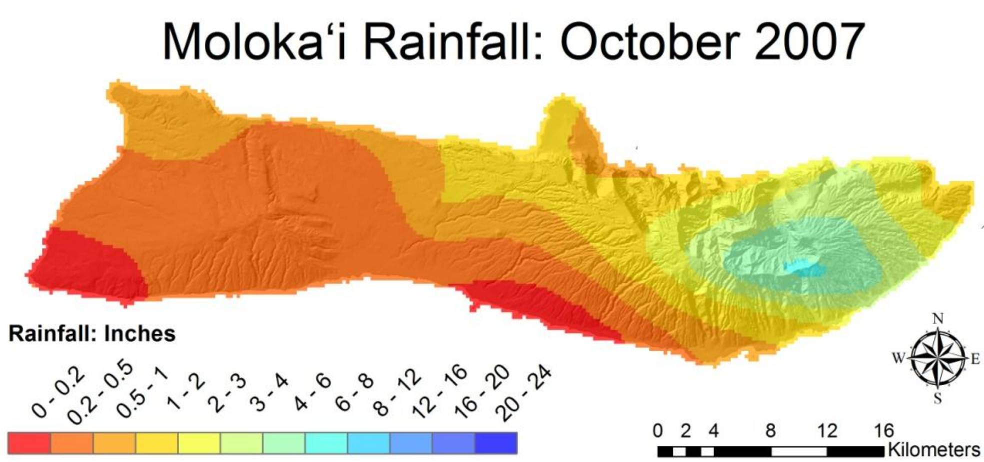


Figure 3.9. (Continued) Examples of the last 15 years of October rainfall maps for Moloka‘i.

The monthly mean rainfall statistics are shown in Figure 3.10 for each island, where the characteristic annual cycle of rainfall in Hawai‘i can be seen immediately. February is typically lower than January and March, which tend to be some of the highest rainfall months, with the summer months showing the lowest rainfall. The minimum, maximum, and mean statistics for each island and month, including the anomaly maps and annual maps are shown in Appendix C. These statistics for the annual maps are shown in Table 3.4, where one location on Maui had an annual value of over 600 inches (a location on Kaua‘i had 576 inches in that same year, 1982). Table 3.5 documents the minimum, maximum, and average number of raingage stations used on each island. The number of gages varied throughout time as the station network evolved, with the highest numbers of stations seen during the 1950s and 1960s.

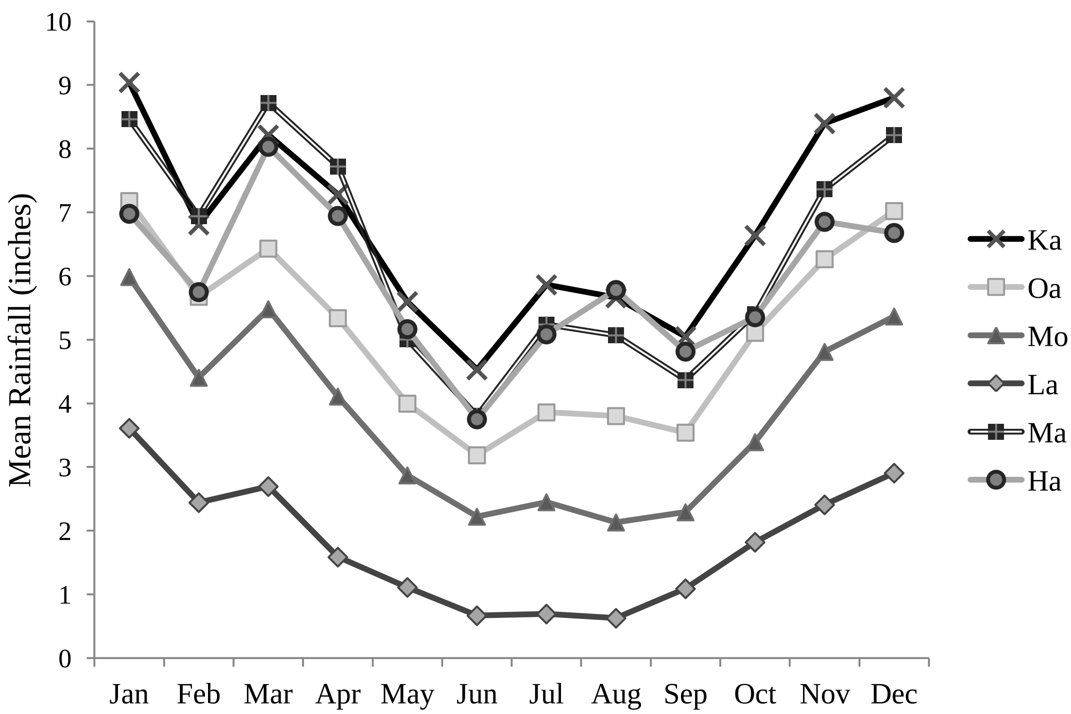


Figure 3.10. Mean monthly rainfall statistics derived from the month-year maps, averaged over all 88 years (in inches) for each island-month. Ka is Kaua‘i, Oa is O‘ahu, Mo is Moloka‘i, La is Lāna‘i, Ma is Maui, and Ha is Hawai‘i Island.

Table 3.4. Statistics for the annual maps for all islands (in inches), over all 88 years.

	Minimum	Maximum	Mean
Kauaʻi	6.193	576.683	81.920
Oʻahu	5.837	428.052	61.413
Molokaʻi	2.731	269.969	45.513
Lānaʻi	2.427	83.443	21.653
Maui & Kahoʻolawe	1.720	608.403	76.326
Hawaiʻi	2.497	453.255	71.198

Table 3.5. Minimum, maximum and mean statistics for the number of raingage stations used to make the maps for each island, averaged over all months.

	Minimum	Maximum	Mean
Kauaʻi	167	211	179
Oʻahu	274	356	312
Molokaʻi	62	87	72
Lānaʻi	40	50	44
Maui & Kahoʻolawe	208	250	232
Hawaiʻi	275	348	304

3.3 Cross Validation Comparison

The means of the cross validation statistics (MAE and RMSE) for the final maps were compared with the cross validation statistics from the method comparison test to determine whether the results from the method comparison were representative of the final outcome. The final maps spanned an 88-year period from 1920-2007, while the method comparison test statistics only covered a 30-year period from 1940-1969. When the statistics were tested together, the final statistics were comparable in every island-month. Table 3.6 shows the average of the monthly results of comparing the average MAE and average RMSE for all years between the five methods tested in the 30-year method comparison with the OK results from all 88 years, and the full results by month are found in Appendix D.

The new results could only be compared with the results from the 30-year test for ranking categories 1 and 3: minimum average MAE and RMSE. Since categories 2 and 4 relied on testing the minimum value in each year, the OK results from all 88 years would be virtually the same as the 30-year OK results since only the 1940-1969 period can be used (the other methods do not have information for the full 88-year period). The OK results from all 88 years were ranked with the five methods from the 30-year test from 1 to 6 (best to worst), using only categories 1 and 3. The averages of these ranks over all months are shown in Table 3.6 for each island, with complete monthly results shown in Appendix D.

Table 3.6. Average MAE and average RMSE results for all islands with the average rank value for 30-year cross validation results (5 methods) and 88-year cross validation results (1 method). Units for MAE (mean absolute error) and RMSE (root mean square error) are the same as the relative anomalies: dimensionless (inches per inch).

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Ka	Avg MAE	0.00118	0.00242	0.00280	0.00924	0.00624	0.00046
	Avg RMSE	0.32559	0.34871	0.34617	0.55001	0.35913	0.34169
	Avg Rank	1.88	3.42	3.42	5.63	4.58	2.08
Oa	Avg MAE	0.00057	0.00224	0.00132	0.00261	0.00295	0.00112
	Avg RMSE	0.31999	0.34869	0.33903	0.35562	0.33743	0.36790
	Avg Rank	1.33	4.29	2.88	4.71	3.88	3.92
Mo	Avg MAE	0.00447	0.00395	0.00409	0.00814	0.00829	0.00292
	Avg RMSE	0.54863	0.58013	0.56777	0.58706	0.57984	0.58662
	Avg Rank	2.63	3.63	2.83	4.71	4.13	3.08
La	Avg MAE	0.00902	0.01194	0.00972	0.01806	0.01055	0.00487
	Avg RMSE	0.33618	0.34000	0.33399	0.39878	0.33428	0.38043
	Avg Rank	2.88	4.13	2.63	5.25	2.83	3.29
Ma	Avg MAE	0.00309	0.00394	0.00304	0.01301	0.01628	0.00123
	Avg RMSE	0.56646	0.58017	0.57111	0.53275	0.54533	0.51113
	Avg Rank	2.29	3.79	2.5	4.46	4.46	3.5
Ha	Avg MAE	0.00086	0.00304	0.00158	0.00405	0.00513	0.00084
	Avg RMSE	0.43304	0.45664	0.44589	0.46507	0.46254	0.45125
	Avg Rank	1.67	4.08	2.83	5.17	4.63	2.63

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall.
Ka is Kaua‘i, Oa is O‘ahu, Mo is Moloka‘i, La is Lāna‘i, Ma is Maui, and Ha is Hawai‘i island.

CHAPTER 4

DISCUSSION AND CONCLUSIONS

Month-year rainfall maps of the major Hawaiian Islands were produced from 1920 – 2007 using ordinary kriging of the relative rainfall anomalies. A geostatistical method comparison was successfully completed between ordinary kriging, kriging with an external drift, and ordinary cokriging using elevation and monthly mean rainfall maps as covariates. The interpolation methods were evaluated using cross validation statistics, specifically: mean absolute error (MAE) and root mean square error (RMSE). Methods were ranked based on these error statistics, and the best ranked method, ordinary kriging, was chosen to create the month-year rainfall maps.

The differences between the methods' performances were fairly small in most cases. Many times, greater differences were seen between months within a method than between methods. All methods seemed to perform better in winter months than in the summer, but seasonality did not seem to favor one method over another – the rank order remained fairly steady throughout the year. The ANOVA testing showed how truly similar these mean error values were, allowing for the conclusion that ordinary kriging was the best method to use for the interpolation of the month-year anomalies for all months and islands.

Based on the numerous geostatistical method comparison studies that have been performed globally, it was not expected that ordinary kriging would be a better predictor of rainfall than more complex methods that incorporate a secondary variable. However, none of the other studies were performed on a surface comparable to Hawai‘i, or on the same time scale or variable with a similar station network density, which is why the comparison was performed here. The only previous study that corroborates these results is that of Mair and Fares (2011) who found that over a small area on western O‘ahu, ordinary kriging produced more accurate rainfall predictions than simple kriging with varying local means (SKlm) using elevation and distance to a regional rainfall maximum as the two secondary variables. SKlm has been shown to produce similar results to KED (Goovaerts 2000). Based on this evidence, using a secondary variable does not seem to provide a better prediction when interpolating the rainfall surface in Hawai‘i.

It was unsure whether the 30-year period chosen for the method comparison test would be representative of the entire 88-year period. The years 1940-1969 were chosen for the large active station network during this time and therefore the high percentage of original station data available. The 5-year, 2-month pilot study performed for Kaua‘i produced inconclusive results, prompting the choice of a longer study period for all islands. Not only were the results of the 30-year comparison test conclusive, but the cross validation statistics from the 88-year period showed that the 30-year results were representative of the entire period. When the MAE and RMSE results from the 88-year period using OK were compared with the 30-year results for the five methods used in the comparison test (looking only at the minimum average MAE and RMSE, ranking categories 1 and 3), the 88-year OK results were among the top ranked methods in almost every month-year across the across the islands (Appendix D).

While performing the visual quality checks (QC) on the final maps, many of the map surfaces appeared to show a smooth pattern. However, in a few instances the pattern of the rainfall map was not smooth, even when the anomaly surface was fairly smooth. This problem appeared to be more severe in months where the rainfall values were relatively low, perhaps causing more detail to be visible than would be if the values were higher. It is unclear how a month-year rainfall map should look, and how smooth it should be. Maps of this temporal scale have not been produced in Hawai‘i before, and it is not known whether an irregular surface is realistic. The non-exact nature of the kriging interpolator will have the effect of over-smoothing peaks and troughs to produce a more even surface. The extent of this over-smoothing has yet to be explored with these month-year maps.

Assessing the uncertainty in the map estimates is an important step for providing users with an idea of the accuracy of the product. The cross validation statistics give an idea of how accurate the interpolation is, and calculating trends and performing spatial trend analysis will be an important way to compare the map values with the data that has already been assessed. Another test that can be done right away is to aggregate the month-year maps into mean values and compare them with existing mean maps, which are accepted as having appropriate rainfall values. Table 4.1 compares the mean annual values from the month-year maps (the average of the most recent 30 year period, 1978-2007) with the mean climatology values from the 2011 Rainfall Atlas (average of the 1978-2007 rainfall) and the 1971-2000 PRISM map values (Daly et al. 2006). When the means were compared, the month-year annual estimate showed an underestimation of the mean for most islands. Four out of the six islands had month-year means below the Rainfall Atlas and PRISM, with Kauaʻi and Oʻahu showing the largest discrepancies (with month-year maps averaging about 6 inches lower). Though the mean annual values from the month-year maps are within a similar range as the other climatologies, this underestimation could be caused by excess smoothing of rainfall peak areas.

Table 4.1. Comparison of mean values between the 2011 Rainfall Atlas, PRISM maps, and the 30-year mean values from the month-year maps (1978-2007), in inches.

	2011 Rainfall Atlas	**PRISM**	**Annual Month-Year Maps (30-yr mean)**
Kauaʻi	84.26	86.74	79.04
Oʻahu	64.10	67.14	59.35
Molokaʻi	48.58	43.83	46.47
Lānaʻi	22.04	24.22	20.92
Maui & Kahoʻolawe	77.36	74.36	75.64
Hawaiʻi	72.75	72.65	70.16

One important item that this study can provide is a template for generating current maps. New data can be entered into the rainfall database and turned into a map using the same procedure as these historical month-year maps. The only difference will be the database used. The serially complete database helped to fill in the gaps caused by the declining raingage station network in Hawaiʻi. If new data are imported into the database without this filling procedure, a sharp discontinuity may be seen between the 2007 and the 2008 maps because of the abrupt change in the number of stations available for analysis. Therefore, this filling procedure should be applied to any data used for future map updates to take advantage of the rich information provided by historical stations.

The ideal solution to the decline in the network would be to install more raingages across the state, however, Hawaiʻi will probably never see a network as dense as it was in the 1960s (with over 1,000 stations operating at once). With regard to the spatial distribution of the station network, Table 3.5 shows the obvious bias in station placement. The island of Oʻahu has more raingage stations than the island of Hawaiʻi, which is more than six times the size of Oʻahu. Installation of any new raingages in the State should take into account the locations of current stations, and where the largest spatial gaps are occurring.

In summary, month-year rainfall maps from 1920-2007 have been generated for Hawaiʻi, with accompanying anomaly maps relative to the 1978-2007 mean. These maps may slightly underestimate peak rainfall on some islands, but more analysis is required. Based on cross validation results, it was concluded that ordinary kriging outperformed ordinary cokriging and kriging with an external drift using elevation and mean rainfall as secondary variables. The final maps were created by using ordinary kriging to interpolate the anomaly values, and this procedure can be used in the future to produce current month-year maps as the data become available.

APPENDIX A

(Adapted from Webster & Oliver 2007; Deutsch & Journel 1998; and Goovaerts 1997)

Ordinary kriging is the most common and robust type of kriging; it is a weighted linear combination of data values. Kriging will estimate values of a variable Z given known values z(x_1), z(x_2), … , z(x_N), at points x_1, x_2 , … , x_N. Equation A.1 shows how to estimate Z at a point x_0 :

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i z(x_i) \qquad [A.1]$$

where λ_i are the weights. Kriging is an unbiased estimator, so the weights must sum to one (Equation A.2). The weights are not just a function of the distance between the known data points and the prediction points, but also based on the spatial structure of the points (spatial autocorrelation) – quantified by the semivariance.

$$\sum_{i=1}^{N} \lambda_i = 1 \qquad [A.2]$$

With every estimate there is an accompanying kriging variance, expressed by $\sigma^2(x_0)$. The variance is defined in Equation A.3:

$$\sigma^2(x_0) = 2\sum_{i=1}^{N} \lambda_i \gamma(x_i, x_0) - \sum_{i=1}^{N}\sum_{i=1}^{N} \lambda_i \lambda_j \gamma(x_i, x_j) \qquad [A.3]$$

where $\gamma(x_i, x_0)$ is the semivariance of Z between the *i*th data point and the estimated point x_0, and $\gamma(x_i, x_j)$ is the semivariance between the two data points x_i and x_j.

Since kriging is also an optimal estimator, its goal is to minimize variance. To solve for the kriged estimate, the next step is to find the weights that accomplish this goal of minimizing the kriging variance. A Lagrange multiplier method is used to ensure minimized variance under unbiased conditions. This creates N+1 equations with N+1 unknowns for ordinary kriging (including the Lagrange multiplier, ψ), as seen in Equation A.4:

$$\sum_{i=1}^{N} \lambda_i \gamma(x_i, x_j) + \psi(x_0) = \gamma(x_j, x_0) \qquad \forall j \qquad [\mathrm{A.4}]$$

In matrix form, the kriging equations are shown in Equation A.5:

$$\boldsymbol{A\lambda} = \boldsymbol{b} \qquad [\mathrm{A.5}]$$

where:

$$\boldsymbol{A} = \begin{bmatrix} \gamma(x_1, x_1) & \gamma(x_1, x_2) & \dots & \gamma(x_1, x_N) & 1 \\ \gamma(x_2, x_1) & \gamma(x_2, x_2) & \dots & \gamma(x_2, x_N) & 1 \\ . & . & & . & . \\ . & . & \dots & . & . \\ . & . & & . & . \\ \gamma(x_N, x_1) & \gamma(x_N, x_2) & \dots & \gamma(x_N, x_N) & 1 \\ 1 & 1 & \dots & 1 & 0 \end{bmatrix}$$

$$\boldsymbol{\lambda} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ . \\ . \\ . \\ \lambda_N \\ \psi(x_0) \end{bmatrix} \qquad \boldsymbol{b} = \begin{bmatrix} \gamma(x_1, x_0) \\ \gamma(x_2, x_0) \\ . \\ . \\ . \\ \gamma(x_N, x_0) \\ 1 \end{bmatrix}$$

Therefore, to solve for the weights, the matrix $\boldsymbol{A}$ needs to be inverted, as in Equation A.6 (since the interpolation is only working with a subset of data most of the time, the matrices are smaller and it is relatively computationally rapid):

$$\boldsymbol{\lambda} = \boldsymbol{A}^{-1}\boldsymbol{b} \qquad [\mathrm{A.6}]$$

The mean of the surface does not need to be known (as in Simple Kriging), and instead is re-estimated at every location (therefore using moving-window neighborhoods). Ordinary kriging also assumes a stationary mean instead of a drift present, as in Universal Kriging (UK). In UK the trend is modeled as a function of coordinates. The drift may also be defined by one or more external variables, which is the case in Kriging with External Drift (KED). KED with one external variable uses N+2 equations, accounting for the 2 constraints on the weights (add one constraint per external drift variable included). The trend, $u(x)$, is modeled as a linear function of the external drift variable $y(x)$, seen in Equation A.7:

$$u(x) = a_0 + a_1 y(x) \qquad [A.7]$$

where a_0 and a_1 are regression coefficients estimated by the kriging system at each search neighborhood. KED can account for changes in correlation across the study area because the relationship between the external variable and the rainfall is assessed locally (Goovaerts, 2000). The KED estimator is shown in Equation A.8:

$$\hat{Z}_{\mathrm{KED}}(x_0) = \sum_{i=1}^{N} \lambda_i^{KED} \mathrm{z}(x_i) \qquad [A.8]$$

The weights (λ_i^{KED}) are obtained by the solution of the system of N+2 equations in Equation A.9:

$$\begin{cases} \sum_{i=1}^{N} \lambda_i^{KED}\, \gamma(x_i, x_j) + \psi_0 + \sum_{i=1}^{N} \psi_k\, y_k(x_j) = \gamma(x_0, x_j) & \forall\, j, j = 1, 2, \dots, N, \\ \sum_{i=1}^{N} \lambda_i^{KED} = 1, & \\ \sum_{i=1}^{N} \lambda_i^{KED}\, y_k(x_i) = y_k(x_0) & for\ k = 1, 2, \dots, K \end{cases} \qquad [A.9]$$

A limitation of KED is that the secondary variable needs to be known for all target points and at all primary data points. When using a secondary variable that does not meet these criteria, the cokriging method is often used. Cokriging takes advantage of the cross-semivariance between the primary and secondary variables to add information that the primary variable is missing. For one secondary variable (y), the ordinary cokriging (OCK) estimator is shown in Equation A.10:

$$\hat{Z}(x_0) = \sum_{i_1=1}^{N_1} \lambda_{i_1}\, \mathrm{z}(x_{i_1}) + \sum_{i_2=1}^{N_2} \lambda_{i_2}{}'\, \mathrm{y}(x'_{i_2}) \qquad [\text{A}.10]$$

where the weights (λ_{i_1}) are for the N_1 z samples, and the weights $(\lambda_{i_2}{}')$ are for the N_2 y samples. The traditional constraints on the weights are that the sum of the weights for the primary variable (λ_{i_1}) must equal one, and the weights for the secondary variable $(\lambda_{i_2}{}')$ must sum to zero. In matrix form, $\mathbf{\Gamma_{zy}}$ represents a matrix of semivariances between sampling points, shown in Equation A.11, and has order $N_1 \times N_2$:

$$\mathbf{\Gamma_{zy}} = \begin{bmatrix} \gamma_{zy}(x_1, x_1) & \gamma_{zy}(x_1, x_2) & \dots & \gamma_{zy}(x_1, x_{N_2}) \\ \gamma_{zy}(x_2, x_1) & \gamma_{zy}(x_2, x_2) & \dots & \gamma_{zy}(x_2, x_{N_2}) \\ . & . & & . \\ . & . & \dots & . \\ . & . & & . \\ \gamma_{zy}(x_{N_1}, x_1) & \gamma_{zy}(x_{N_1}, x_2) & \dots & \gamma_{zy}(x_{N_1}, x_{N_2}) \end{bmatrix} \qquad [\text{A}.11]$$

The $\boldsymbol{\lambda}$ matrix includes the two Lagrange parameters (accounting for the two bias constraints on the weights), and the $\boldsymbol{b}$ matrix (Equation A.12) includes vectors of autosemivariance for the primary variable z, and cross-semivariances with the secondary variable y:

$$\boldsymbol{b_{zz}} = \begin{bmatrix} \gamma_{zz}(x_1, x_0) \\ \gamma_{zz}(x_2, x_0) \\ . \\ . \\ . \\ \gamma_{zz}(x_{N_1}, x_0) \end{bmatrix} \qquad \boldsymbol{b_{zy}} = \begin{bmatrix} \gamma_{zy}(x_1, x_0) \\ \gamma_{zy}(x_2, x_0) \\ . \\ . \\ . \\ \gamma_{zy}(x_{N_2}, x_0) \end{bmatrix} \qquad [\text{A}.12]$$

The matrix equation, $\mathbf{\Gamma}\boldsymbol{\lambda} = \boldsymbol{b}$, for ordinary cokriging is shown in Equation A.13:

$$
\begin{bmatrix}
 & & & & & & & & 1 & 0 \\
 & & & & & & & & 1 & 0 \\
 & \boldsymbol{\Gamma}_{\mathbf{zz}} & & & & \boldsymbol{\Gamma}_{\mathbf{zy}} & & & \vdots & \vdots \\
 & & & & & & & & 1 & 0 \\
 & & & & & & & & 0 & 1 \\
 & & & & & & & & 0 & 1 \\
 & \boldsymbol{\Gamma}_{\mathbf{yz}} & & & & \boldsymbol{\Gamma}_{\mathbf{yy}} & & & \vdots & \vdots \\
 & & & & & & & & 0 & 1 \\
1\;1 & \dots & 1 & 0\;0 & & \dots & 0 & & 0 & 0 \\
0\;0 & \dots & 0 & 1\;1 & & \dots & 1 & & 0 & 0
\end{bmatrix}
\cdot
\begin{bmatrix}
\lambda_{1z} \\ \lambda_{2z} \\ \vdots \\ \lambda_{N_1 z} \\ \lambda_{1y} \\ \lambda_{2y} \\ \vdots \\ \lambda_{N_2 y} \\ \psi_z \\ \psi_y
\end{bmatrix}
=
\begin{bmatrix}
\\ \\ \boldsymbol{b}_{zz} \\ \\ \\ \\ \boldsymbol{b}_{zy} \\ \\ 1 \\ 0
\end{bmatrix}
\qquad [A.13]
$$

The three methods detailed in this appendix, ordinary kriging, kriging with an external drift, and ordinary cokriging, will be the methods compared in this study.

APPENDIX B

Table B.1. Method comparison: cross validation results for Kauaʻi. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	**Category 2: Max % Years with lowest MAE**	**Category 3: Min Avg RMSE**	**Category 4: Max % Years with lowest RMSE**	**Best Rank**
Jan	OK	OK	OK	OK	OK
Feb	OK	OK	OK	OK	OK
Mar	KED_EL	OK	OK	OK	OK
Apr	OK	OK	OK	OK	OK
May	OK	OK	OK	OK	OK
Jun	OK	OK	OK	OK	OK
Jul	OK	OK	OK	OK	OK
Aug	KED_RF	OK	OK	OK	OK
Sep	OK	OK	OK	OK	OK
Oct	OCK_EL	OK	OK	OK	OK
Nov	OK	OK	OK	OK	OK
Dec	OK	OK	OK	OK	OK

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

Table B.2. Method comparison: cross validation results for O‘ahu. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	Category 2: Max % Years with lowest MAE	Category 3: Min Avg RMSE	Category 4: Max % Years with lowest RMSE	Best Rank
Jan	OK	OK	OK	OK	OK
Feb	OK	OK	OK	OK	OK
Mar	OK	OK	OK	OK	OK
Apr	OK	OK	OK	OK	OK
May	OCK_RF	OK	OK	OK	OK
Jun	KED_RF	OK	OK	OK	OK
Jul	OK	OK	OK	OK	OK
Aug	KED_EL	OK	OK	OK	OK
Sep	OCK_RF	OK	OK	OK	OK
Oct	OCK_RF	OK	OK	OK	OK
Nov	OK	OK	OK	OK	OK
Dec	OK	OK	OK	OK	OK

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

Table B.3. Method comparison: cross validation results for Molokaʻi. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	**Category 2: Max % Years with lowest MAE**	**Category 3: Min Avg RMSE**	**Category 4: Max % Years with lowest RMSE**	**Best Rank**
Jan	OK	OCK_EL	KED_RF	KED_RF	OK
Feb	OCK_EL	OCK_RF	OCK_RF	OCK_RF	OCK_RF
Mar	OK	OCK_RF	OCK_RF	OCK_RF	OCK_RF
Apr	OCK_RF	OCK_RF	OK	OK	OCK_RF
May	KED_RF	OCK_RF	OK	OK	OCK_RF
Jun	OK	OCK_RF	OK	OK	OK
Jul	KED_EL	OCK_RF	OK	OK	OCK_RF
Aug	KED_RF	OK	OK	OK	OK
Sep	OCK_EL	OCK_RF	OK	OK	OK
Oct	OCK_EL	OCK_RF	OK	OK	OK
Nov	OCK_RF	OK	OCK_RF	OCK_RF	OCK_RF
Dec	OCK_EL	OCK_RF	OCK_RF	OCK_RF	OCK_RF

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

Table B.4. Method comparison: cross validation results for Lānaʻi. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	**Category 2: Max % Years with lowest MAE**	**Category 3: Min Avg RMSE**	**Category 4: Max % Years with lowest RMSE**	**Best Rank**
Jan	OK	OK	KED_RF	KED_RF	OK
Feb	KED_EL	KED_RF	OK	OK	OK
Mar	KED_RF	KED_RF	KED_RF	KED_RF	KED_RF
Apr	KED_RF	KED_RF	KED_RF	KED_RF	KED_RF
May	OK	OK	OCK_RF	KED_RF	OK
Jun	KED_RF	KED_RF	OCK_RF	OCK_RF	KED_RF
Jul	OCK_RF	OCK_EL	KED_RF	KED_RF	OCK_RF
Aug	KED_RF	OK	OCK_EL	KED_RF	OK
Sep	OK	OK	OK	KED_RF	OK
Oct	OK	OK	OK	KED_RF	OK
Nov	KED_RF	OCK_RF	OCK_RF	OK	OCK_RF
Dec	KED_RF	OK	OK	KED_RF	KED_RF

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

Table B.5. Method comparison: cross validation results for Maui & Kaho'olawe. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	Category 2: Max % Years with lowest MAE	Category 3: Min Avg RMSE	Category 4: Max % Years with lowest RMSE	Best Rank
Jan	KED_EL	OCK_RF	OCK_RF	OCK_RF	OCK_RF
Feb	OCK_RF	OCK_RF	OCK_RF	OCK_RF	OCK_RF
Mar	OK	OK	OK	OK	OK
Apr	OK	OK	OK	OK	OK
May	OCK_RF	OK	OK	OK	OK
Jun	OCK_EL	OCK_RF	KED_EL	OK	OCK_RF
Jul	OCK_EL	OCK_RF	OK	OK	OK
Aug	OCK_EL	OCK_RF	OK	OCK_RF	OK
Sep	OK	OCK_RF	OK	OK	OK
Oct	OCK_RF	OCK_RF	OK	OK	OK
Nov	KED_RF	KED_EL	OK	OK	OK
Dec	OCK_RF	OCK_RF	OK	OK	OCK_RF

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

Table B.6. Method comparison: cross validation results for Hawai‘i. Best method chosen by each of the four ranking categories in each month.

	Category 1: Min Avg MAE	**Category 2: Max % Years with lowest MAE**	**Category 3: Min Avg RMSE**	**Category 4: Max % Years with lowest RMSE**	**Best Rank**
Jan	OK	OK	OK	OK	OK
Feb	OK	OK	OK	OK	OK
Mar	OCK_RF	OK	OK	OK	OK
Apr	OK	OK	OK	OK	OK
May	OCK_RF	OK	OK	OK	OK
Jun	OK	OK	OK	OK	OK
Jul	OK	OK	OK	OK	OK
Aug	OCK_EL	OK	OK	OK	OK
Sep	OCK_EL	OK	OK	OK	OK
Oct	KED_EL	OK	OK	OK	OK
Nov	OK	OK	OK	OK	OK
Dec	OK	OK	OK	OK	OK

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error.

APPENDIX C

Table C.1. Monthly statistics for the Kaua‘i anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0027	7.7695	1.1739
	Feb	0.0032	5.8405	1.0298
	Mar	0.0043	12.4897	1.0229
	Apr	0.0013	13.1452	1.1851
	May	0.0005	8.0554	1.0129
	Jun	0.0001	22.2439	0.9861
	Jul	0.0012	10.8148	1.0676
	Aug	0.0018	17.0010	1.0738
	Sep	0.0029	6.8185	0.9468
	Oct	0.0055	5.9967	0.9433
	Nov	0.0013	4.2945	0.9174
	Dec	0.0017	6.0187	1.0444
RF	Jan	0.0094	111.6923	9.0419
	Feb	0.0113	89.3922	6.8064
	Mar	0.0079	108.3324	8.2155
	Apr	0.0011	90.8546	7.2834
	May	0.0007	87.6665	5.5981
	Jun	0.0000	59.7252	4.5289
	Jul	0.0005	75.9853	5.8631
	Aug	0.0008	65.3431	5.6608
	Sep	0.0022	64.4539	5.0487
	Oct	0.0128	62.1177	6.6385
	Nov	0.0033	95.5403	8.3970
	Dec	0.0064	76.9851	8.8024
	Annual	6.1934	576.6827	81.9195

Table C.2. Monthly statistics for the O‘ahu anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0033	6.2178	1.0541
	Feb	0.0021	6.4196	1.0533
	Mar	0.0035	9.5895	1.0407
	Apr	0.0020	10.7687	1.1231
	May	0.0005	10.7422	0.9801
	Jun	0.0006	12.6595	0.8890
	Jul	0.0105	7.1306	0.9126
	Aug	0.0011	8.9807	0.8943
	Sep	0.0067	14.6868	0.8380
	Oct	0.0020	9.6290	0.8945
	Nov	0.0028	7.7845	0.9300
	Dec	0.0152	8.8511	1.0339
RF	Jan	0.0122	71.7901	7.1796
	Feb	0.0045	86.2780	5.6759
	Mar	0.0071	70.5138	6.4331
	Apr	0.0025	72.1082	5.3400
	May	0.0004	55.4634	3.9971
	Jun	0.0002	35.2287	3.1856
	Jul	0.0036	42.3023	3.8593
	Aug	0.0018	56.2262	3.8023
	Sep	0.0108	43.1215	3.5419
	Oct	0.0044	43.6860	5.1105
	Nov	0.0071	68.3767	6.2655
	Dec	0.0467	62.7786	7.0224
	Annual	5.8368	428.0517	61.4130

Table C.3. Monthly statistics for the Moloka‘i anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0066	8.3108	0.9939
	Feb	0.0186	5.3488	0.9482
	Mar	0.0057	8.5690	1.0718
	Apr	0.0031	9.3781	0.9935
	May	0.0001	5.8088	0.8360
	Jun	0.0001	14.5270	0.9168
	Jul	0.0002	7.3343	0.8877
	Aug	0.0114	13.4869	0.8682
	Sep	0.0094	19.3348	1.4470
	Oct	0.0010	8.6369	0.9368
	Nov	0.0116	9.4739	0.9604
	Dec	0.0022	6.1675	0.9628
RF	Jan	0.0166	58.0474	5.9864
	Feb	0.0383	50.6888	4.4041
	Mar	0.0089	47.2679	5.4809
	Apr	0.0044	41.2873	4.1086
	May	0.0001	33.1243	2.8704
	Jun	0.0000	41.1062	2.2219
	Jul	0.0002	33.3209	2.4493
	Aug	0.0036	29.8986	2.1312
	Sep	0.0003	28.3881	2.2908
	Oct	0.0019	34.6517	3.3924
	Nov	0.0220	58.7871	4.8105
	Dec	0.0046	38.8711	5.3665
	Annual	2.7310	269.9688	45.5131

Table C.4. Monthly statistics for the Lānaʻi anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0011	5.9586	1.0646
	Feb	0.0057	4.7561	0.9019
	Mar	0.0034	13.3311	1.2430
	Apr	0.0031	12.0740	1.0888
	May	0.0020	12.7245	1.0542
	Jun	0.0012	7.1600	0.7820
	Jul	0.0016	14.0240	0.9941
	Aug	0.0077	12.0166	1.0559
	Sep	0.0002	8.1794	0.9778
	Oct	0.0056	4.7291	1.0014
	Nov	0.0005	6.1179	0.8855
	Dec	0.0005	3.9869	0.9107
RF	Jan	0.0035	19.6763	3.6104
	Feb	0.0103	15.2980	2.4421
	Mar	0.0046	30.4772	2.6948
	Apr	0.0040	19.0975	1.5859
	May	0.0012	19.1357	1.1103
	Jun	0.0008	9.3533	0.6656
	Jul	0.0010	10.3351	0.6926
	Aug	0.0010	6.9222	0.6259
	Sep	0.0001	11.8103	1.0891
	Oct	0.0084	11.1385	1.8201
	Nov	0.0013	19.8558	2.4077
	Dec	0.0016	17.1304	2.9056
	Annual	2.4271	83.4425	21.6531

Table C.5. Monthly statistics for the Maui & Kahoʻolawe anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0004	7.9592	1.0313
	Feb	0.0014	7.8959	1.0789
	Mar	0.0000	12.7831	1.1039
	Apr	0.0010	15.5440	1.2551
	May	0.0016	10.0302	0.9563
	Jun	0.0001	28.8155	0.8637
	Jul	0.0002	25.1266	1.1432
	Aug	0.0008	26.4126	1.1774
	Sep	0.0009	17.5191	1.0750
	Oct	0.0004	13.9177	1.1340
	Nov	0.0001	8.9170	0.9176
	Dec	0.0002	7.2607	0.9966
RF	Jan	0.0013	107.8208	8.4644
	Feb	0.0022	111.1893	6.9407
	Mar	0.0000	206.2669	8.7223
	Apr	0.0004	125.2418	7.7223
	May	0.0007	67.1540	5.0056
	Jun	0.0000	102.6735	3.8044
	Jul	0.0000	82.9018	5.2414
	Aug	0.0001	90.7815	5.0698
	Sep	0.0001	83.6842	4.3691
	Oct	0.0001	144.3712	5.4064
	Nov	0.0002	103.5891	7.3643
	Dec	0.0005	111.9078	8.2151
	Annual	1.7195	608.4033	76.3258

Table C.6. Monthly statistics for the Hawai'i anomaly (anom) and rainfall (RF) maps (in inches), over all 88 years.

		Minimum	Maximum	Mean
Anom	Jan	0.0034	7.2278	1.0551
	Feb	0.0169	11.2081	1.0801
	Mar	0.0023	8.6382	0.9564
	Apr	0.0049	7.8969	1.0381
	May	0.0132	8.0732	1.0246
	Jun	0.0110	7.9032	0.9196
	Jul	0.0104	6.3835	0.8981
	Aug	0.0063	8.0529	1.0738
	Sep	0.0241	7.1609	0.9689
	Oct	0.0009	7.0263	1.0722
	Nov	0.0030	13.5376	0.9215
	Dec	0.0000	7.3319	1.0288
RF	Jan	0.0074	98.7022	6.9801
	Feb	0.0160	92.8080	5.7495
	Mar	0.0025	139.2772	8.0323
	Apr	0.0035	104.1811	6.9460
	May	0.0309	68.0857	5.1669
	Jun	0.0073	56.1794	3.7521
	Jul	0.0034	76.3046	5.0859
	Aug	0.0085	74.2489	5.7828
	Sep	0.0233	57.2755	4.8151
	Oct	0.0010	59.2960	5.3554
	Nov	0.0027	106.8192	6.8533
	Dec	0.0001	87.5853	6.6785
	Annual	2.4973	453.2547	71.1978

APPENDIX D

Table D.1. Kaua‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00124	0.00222	0.00281	0.00352	0.00319	0.00073
	Rank MAE	2	3	4	6	5	1
	Avg RMSE	0.29654	0.32184	0.32014	0.41814	0.34959	0.29414
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	2	3.5	3.5	6	5	1
Feb	Avg MAE	0.00183	0.00292	0.00367	0.01412	0.00487	0.00022
	Rank MAE	2	3	4	6	5	1
	Avg RMSE	0.30934	0.33693	0.33377	0.47260	0.34959	0.30019
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	2	3.5	3.5	6	5	1
Mar	Avg MAE	0.00043	0.00342	0.00113	0.00010	0.00583	0.00007
	Rank MAE	3	5	4	2	6	1
	Avg RMSE	0.31777	0.36617	0.36003	0.43763	0.35919	0.30712
	Rank RMSE	2	5	4	6	3	1
	Avg Rank	2.5	5	4	4	4.5	1
Apr	Avg MAE	0.00375	0.00647	0.00833	0.00948	0.01330	0.00148
	Rank MAE	2	3	4	5	6	1
	Avg RMSE	0.34019	0.34906	0.34850	0.65957	0.37216	0.35842
	Rank RMSE	1	3	2	6	5	4
	Avg Rank	1.5	3	3	5.5	5.5	2.5
May	Avg MAE	0.00141	0.00259	0.00280	0.00148	0.00998	0.00059
	Rank MAE	2	4	5	3	6	1
	Avg RMSE	0.33811	0.35220	0.34791	0.50988	0.37682	0.33901
	Rank RMSE	1	4	3	6	5	2
	Avg Rank	1.5	4	4	4.5	5.5	1.5
Jun	Avg MAE	0.00131	0.00313	0.00401	0.01214	0.00472	0.00064
	Rank MAE	2	3	4	6	5	1
	Avg RMSE	0.38526	0.40394	0.40490	0.81653	0.39836	0.45026
	Rank RMSE	1	3	4	6	2	5
	Avg Rank	1.5	3	4	6	3.5	3
Jul	Avg MAE	0.00076	0.00100	0.00081	0.03071	0.00887	0.00066
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.39879	0.41803	0.41854	0.82416	0.44026	0.43464
	Rank RMSE	1	2	3	6	5	4
	Avg Rank	1.5	3	3	6	5	2.5

Table D.1. (Continued) Kaua'i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK_ALL
Aug	Avg MAE	0.00060	0.00009	0.00116	0.00253	0.00006	0.00021
	Rank MAE	4	2	5	6	1	3
	Avg RMSE	0.43930	0.46039	0.45605	0.90978	0.45432	0.40861
	Rank RMSE	2	5	4	6	3	1
	Avg Rank	3	3.5	4.5	6	2	2
Sep	Avg MAE	0.00051	0.00113	0.00202	0.01177	0.00463	0.00013
	Rank MAE	2	3	4	6	5	1
	Avg RMSE	0.29938	0.32219	0.32008	0.47779	0.32781	0.35541
	Rank RMSE	1	3	2	6	4	5
	Avg Rank	1.5	3	3	6	4.5	3
Oct	Avg MAE	0.00050	0.00015	0.00048	0.00691	0.00803	0.00009
	Rank MAE	4	2	3	5	6	1
	Avg RMSE	0.23602	0.25476	0.25157	0.33304	0.27449	0.27675
	Rank RMSE	1	3	2	6	4	5
	Avg Rank	2.5	2.5	2.5	5.5	5	3
Nov	Avg MAE	0.00090	0.00292	0.00358	0.01211	0.00599	0.00050
	Rank MAE	2	3	4	6	5	1
	Avg RMSE	0.23974	0.26403	0.26357	0.35449	0.26469	0.26761
	Rank RMSE	1	3	2	6	4	5
	Avg Rank	1.5	3	3	6	4.5	3
Dec	Avg MAE	0.00096	0.00300	0.00282	0.00601	0.00547	0.00025
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.30668	0.33501	0.32894	0.38658	0.34230	0.30814
	Rank RMSE	1	4	3	6	5	2
	Avg Rank	1.5	4	3	6	5	1.5

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

Table D.2. Oʻahu cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00091	0.00178	0.00156	0.00464	0.00319	0.00080
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.28012	0.30503	0.29995	0.30908	0.33616	0.31802
	Rank RMSE	1	3	2	4	6	5
	Avg Rank	1.5	3.5	2.5	5	5.5	3
Feb	Avg MAE	0.00032	0.00076	0.00045	0.00147	0.00531	0.00156
	Rank MAE	1	3	2	4	6	5
	Avg RMSE	0.31808	0.35356	0.33402	0.35011	0.33616	0.34248
	Rank RMSE	1	6	2	5	3	4
	Avg Rank	1	4.5	2	4.5	4.5	4.5
Mar	Avg MAE	0.00018	0.00135	0.00182	0.00357	0.00302	0.00081
	Rank MAE	1	3	4	6	5	2
	Avg RMSE	0.33315	0.36933	0.35840	0.37998	0.34234	0.33958
	Rank RMSE	1	5	4	6	3	2
	Avg Rank	1	4	4	6	4	2
Apr	Avg MAE	0.00086	0.00304	0.00136	0.00126	0.00716	0.00260
	Rank MAE	1	5	3	2	6	4
	Avg RMSE	0.34364	0.36495	0.36026	0.38711	0.36806	0.42270
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	1	4	2.5	3.5	5	5
May	Avg MAE	0.00036	0.00141	0.00002	0.00077	0.00387	0.00144
	Rank MAE	2	4	1	3	6	5
	Avg RMSE	0.38287	0.41719	0.39531	0.41698	0.39944	0.42474
	Rank RMSE	1	5	2	4	3	6
	Avg Rank	1.5	4.5	1.5	3.5	4.5	5.5
Jun	Avg MAE	0.00044	0.00512	0.00168	0.00107	0.00022	0.00049
	Rank MAE	2	6	5	4	1	3
	Avg RMSE	0.33513	0.36379	0.35680	0.36573	0.34757	0.42918
	Rank RMSE	1	4	3	5	2	6
	Avg Rank	1.5	5	4	4.5	1.5	4.5
Jul	Avg MAE	0.00008	0.00576	0.00272	0.00591	0.00173	0.00138
	Rank MAE	1	5	4	6	3	2
	Avg RMSE	0.36457	0.39455	0.38137	0.39804	0.37387	0.40683
	Rank RMSE	1	4	3	5	2	6
	Avg Rank	1	4.5	3.5	5.5	2.5	4

Table D.2. (Continued) O‘ahu cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Aug	Avg MAE	0.00250	0.00182	0.00393	0.00172	0.00361	0.00177
	Rank MAE	4	3	6	1	5	2
	Avg RMSE	0.36808	0.39757	0.38879	0.42119	0.39094	0.38420
	Rank RMSE	1	5	3	6	4	2
	Avg Rank	2.5	4	4.5	3.5	4.5	2
Sep	Avg MAE	0.00021	0.00184	0.00016	0.00269	0.00233	0.00042
	Rank MAE	2	4	1	6	5	3
	Avg RMSE	0.31402	0.33639	0.33210	0.35330	0.32265	0.40595
	Rank RMSE	1	4	3	5	2	6
	Avg Rank	1.5	4	2	5.5	3.5	4.5
Oct	Avg MAE	0.00038	0.00072	0.00036	0.00115	0.00074	0.00067
	Rank MAE	2	4	1	6	5	3
	Avg RMSE	0.25467	0.27856	0.27544	0.28360	0.26419	0.32790
	Rank RMSE	1	4	3	5	2	6
	Avg Rank	1.5	4	2	5.5	3.5	4.5
Nov	Avg MAE	0.00010	0.00141	0.00083	0.00140	0.00159	0.00062
	Rank MAE	1	5	3	4	6	2
	Avg RMSE	0.26300	0.28811	0.28102	0.29183	0.27561	0.29924
	Rank RMSE	1	4	3	5	2	6
	Avg Rank	1	4.5	3	4.5	4	4
Dec	Avg MAE	0.00050	0.00184	0.00098	0.00571	0.00261	0.00084
	Rank MAE	1	4	3	6	5	2
	Avg RMSE	0.28260	0.31525	0.30492	0.31055	0.29219	0.31398
	Rank RMSE	1	6	3	4	2	5
	Avg Rank	1	5	3	5	3.5	3.5

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

Table D.3. Moloka‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00050	0.00100	0.00122	0.00212	0.00208	0.00115
	Rank MAE	1	2	4	6	5	3
	Avg RMSE	0.39795	0.41986	0.40018	0.41449	0.36474	0.37960
	Rank RMSE	3	6	4	5	1	2
	Avg Rank	2	4	4	5.5	3	2.5
Feb	Avg MAE	0.00389	0.00108	0.00343	0.00279	0.00395	0.00324
	Rank MAE	5	1	4	2	6	3
	Avg RMSE	0.34462	0.36842	0.34349	0.37147	0.36474	0.38408
	Rank RMSE	2	4	1	5	3	6
	Avg Rank	3.5	2.5	2.5	3.5	4.5	4.5
Mar	Avg MAE	0.00004	0.00117	0.00126	0.00591	0.00564	0.00116
	Rank MAE	1	3	4	6	5	2
	Avg RMSE	0.48917	0.51676	0.48625	0.52388	0.50539	0.45863
	Rank RMSE	3	5	2	6	4	1
	Avg Rank	2	4	3	6	4.5	1.5
Apr	Avg MAE	0.00238	0.00202	0.00151	0.00271	0.00210	0.00107
	Rank MAE	5	3	2	6	4	1
	Avg RMSE	0.46061	0.48644	0.46631	0.49104	0.47134	0.49624
	Rank RMSE	1	4	2	5	3	6
	Avg Rank	3	3.5	2	5.5	3.5	3.5
May	Avg MAE	0.00560	0.00400	0.00115	0.00388	0.00070	0.00193
	Rank MAE	6	5	2	4	1	3
	Avg RMSE	0.49638	0.52028	0.50799	0.53290	0.52059	0.48030
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	4	4.5	2.5	5	3	2
Jun	Avg MAE	0.00830	0.00833	0.01515	0.00873	0.02309	0.00296
	Rank MAE	2	3	5	4	6	1
	Avg RMSE	0.76966	0.82541	0.82252	0.86421	0.86593	0.85332
	Rank RMSE	1	3	2	5	6	4
	Avg Rank	1.5	3	3.5	4.5	6	2.5
Jul	Avg MAE	0.01557	0.01311	0.00851	0.00792	0.00964	0.00974
	Rank MAE	6	5	2	1	3	4
	Avg RMSE	0.65232	0.69095	0.68552	0.68659	0.68399	0.62638
	Rank RMSE	2	6	4	5	3	1
	Avg Rank	4	5.5	3	3	3	2.5

Table D.3. (Continued) Moloka‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Aug	Avg MAE	0.00513	0.01206	0.00653	0.02332	0.00140	0.00205
	Rank MAE	3	5	4	6	1	2
	Avg RMSE	0.64606	0.70529	0.66719	0.68348	0.67744	0.60992
	Rank RMSE	2	6	3	5	4	1
	Avg Rank	2.5	5.5	3.5	5.5	2.5	1.5
Sep	Avg MAE	0.00288	0.00007	0.00601	0.02315	0.02650	0.00303
	Rank MAE	2	1	4	5	6	3
	Avg RMSE	1.08065	1.12349	1.16657	1.15021	1.10386	1.38267
	Rank RMSE	1	3	5	4	2	6
	Avg Rank	1.5	2	4.5	4.5	4	4.5
Oct	Avg MAE	0.00353	0.00060	0.00114	0.00676	0.01361	0.00367
	Rank MAE	3	1	2	5	6	4
	Avg RMSE	0.45210	0.46562	0.47803	0.48971	0.55180	0.49598
	Rank RMSE	1	2	3	4	6	5
	Avg Rank	2	1.5	2.5	4.5	6	4.5
Nov	Avg MAE	0.00189	0.00247	0.00159	0.00195	0.00818	0.00349
	Rank MAE	2	4	1	3	6	5
	Avg RMSE	0.41987	0.43888	0.41799	0.44450	0.46109	0.48526
	Rank RMSE	2	3	1	4	5	6
	Avg Rank	2	3.5	1	3.5	5.5	5.5
Dec	Avg MAE	0.00394	0.00148	0.00162	0.00838	0.00257	0.00148
	Rank MAE	5	2	3	6	4	1
	Avg RMSE	0.37424	0.40018	0.37120	0.39227	0.38711	0.38702
	Rank RMSE	2	6	1	5	4	3
	Avg Rank	3.5	4	2	5.5	4	2

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

Table D.4. Lānaʻi cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00328	0.00830	0.00645	0.01041	0.00873	0.00276
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.22024	0.23088	0.22213	0.27719	0.21115	0.22968
	Rank RMSE	2	5	3	6	1	4
	Avg Rank	2	4.5	3	6	3	2.5
Feb	Avg MAE	0.00313	0.00394	0.00166	0.00019	0.00153	0.00206
	Rank MAE	5	6	3	1	2	4
	Avg RMSE	0.20531	0.20789	0.20618	0.23818	0.21115	0.22461
	Rank RMSE	1	3	2	6	4	5
	Avg Rank	3	4.5	2.5	3.5	3	4.5
Mar	Avg MAE	0.00803	0.00555	0.00521	0.00422	0.00078	0.00315
	Rank MAE	6	5	4	3	1	2
	Avg RMSE	0.37860	0.37413	0.36195	0.40727	0.33162	0.38163
	Rank RMSE	4	3	2	6	1	5
	Avg Rank	5	4	3	4.5	1	3.5
Apr	Avg MAE	0.01197	0.01684	0.01180	0.00725	0.00356	0.00525
	Rank MAE	5	6	4	3	1	2
	Avg RMSE	0.32744	0.33129	0.32669	0.40375	0.32384	0.40589
	Rank RMSE	3	4	2	5	1	6
	Avg Rank	4	5	3	4	1	4
May	Avg MAE	0.01032	0.01655	0.01432	0.01562	0.02006	0.00655
	Rank MAE	2	5	3	4	6	1
	Avg RMSE	0.48725	0.49508	0.48362	0.57252	0.49009	0.47027
	Rank RMSE	3	5	2	6	4	1
	Avg Rank	2.5	5	2.5	5	5	1
Jun	Avg MAE	0.00521	0.00881	0.00650	0.02463	0.00402	0.00456
	Rank MAE	3	5	4	6	1	2
	Avg RMSE	0.32438	0.32949	0.32031	0.40259	0.32718	0.44555
	Rank RMSE	2	4	1	5	3	6
	Avg Rank	2.5	4.5	2.5	5.5	2	4
Jul	Avg MAE	0.01949	0.02072	0.01892	0.05701	0.03112	0.00800
	Rank MAE	3	4	2	6	5	1
	Avg RMSE	0.46132	0.45955	0.45738	0.56151	0.45211	0.48032
	Rank RMSE	4	3	2	6	1	5
	Avg Rank	3.5	3.5	2	6	3	3

Table D.4. (Continued) Lāna‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Aug	Avg MAE	0.01466	0.01772	0.01872	0.02617	0.01178	0.00538
	Rank MAE	3	4	5	6	2	1
	Avg RMSE	0.55601	0.55382	0.55418	0.65229	0.57152	0.57306
	Rank RMSE	3	1	2	6	4	5
	Avg Rank	3	2.5	3.5	6	3	3
Sep	Avg MAE	0.01518	0.02384	0.01606	0.03464	0.02695	0.01076
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.40403	0.41347	0.40549	0.44154	0.41081	0.49506
	Rank RMSE	1	4	2	5	3	6
	Avg Rank	1.5	4	2.5	5.5	4	3.5
Oct	Avg MAE	0.00683	0.00871	0.00863	0.01917	0.01180	0.00422
	Rank MAE	2	4	3	6	5	1
	Avg RMSE	0.28000	0.28405	0.28060	0.34694	0.28350	0.40000
	Rank RMSE	1	4	2	5	3	6
	Avg Rank	1.5	4	2.5	5.5	4	3.5
Nov	Avg MAE	0.00415	0.00349	0.00251	0.00833	0.00157	0.00249
	Rank MAE	5	4	3	6	1	2
	Avg RMSE	0.21716	0.22124	0.21623	0.26763	0.21796	0.23818
	Rank RMSE	2	4	1	6	3	5
	Avg Rank	3.5	4	2	6	2	3.5
Dec	Avg MAE	0.00600	0.00882	0.00581	0.00906	0.00475	0.00331
	Rank MAE	4	5	3	6	2	1
	Avg RMSE	0.17249	0.17913	0.17314	0.21393	0.18043	0.22089
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	2.5	4	2.5	5.5	3	3.5

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

Table D.5. Maui & Kaho‘olawe cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00127	0.00218	0.00099	0.00006	0.00067	0.00119
	Rank MAE	5	6	3	1	2	4
	Avg RMSE	0.28591	0.30590	0.28299	0.29997	0.35973	0.32663
	Rank RMSE	2	4	1	3	6	5
	Avg Rank	3.5	5	2	2	4	4.5
Feb	Avg MAE	0.00090	0.00032	0.00028	0.00399	0.00325	0.00047
	Rank MAE	4	2	1	6	5	3
	Avg RMSE	0.33204	0.34622	0.33173	0.34840	0.35973	0.34394
	Rank RMSE	2	4	1	5	6	3
	Avg Rank	3	3	1	5.5	5.5	3
Mar	Avg MAE	0.00209	0.00443	0.00338	0.00452	0.00977	0.00212
	Rank MAE	1	4	3	5	6	2
	Avg RMSE	0.36453	0.37281	0.36794	0.38056	0.37707	0.39546
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	1	3.5	2.5	5	5	4
Apr	Avg MAE	0.00035	0.00191	0.00134	0.01336	0.01659	0.00188
	Rank MAE	1	4	2	5	6	3
	Avg RMSE	0.46336	0.47283	0.47245	0.49930	0.47637	0.57289
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	1	3.5	2	5	5	4.5
May	Avg MAE	0.00214	0.00549	0.00161	0.00530	0.00778	0.00166
	Rank MAE	3	5	1	4	6	2
	Avg RMSE	0.45846	0.46874	0.47410	0.47929	0.46999	0.48760
	Rank RMSE	1	2	4	5	3	6
	Avg Rank	2	3.5	2.5	4.5	4.5	4
Jun	Avg MAE	0.01516	0.01302	0.01483	0.07409	0.09424	0.00138
	Rank MAE	4	2	3	5	6	1
	Avg RMSE	1.69805	1.70324	1.68373	1.04881	1.19777	0.67616
	Rank RMSE	5	6	4	2	3	1
	Avg Rank	4.5	4	3.5	3.5	4.5	1
Jul	Avg MAE	0.00460	0.00298	0.00477	0.01844	0.01795	0.00045
	Rank MAE	3	2	4	6	5	1
	Avg RMSE	0.85299	0.87589	0.85427	0.89286	0.88154	0.75784
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	2.5	3	3.5	6	5	1

Table D.5. (Continued) Maui & Kahoʻolawe cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Aug	Avg MAE	0.00394	0.00262	0.00443	0.01187	0.02197	0.00009
	Rank MAE	3	2	4	5	6	1
	Avg RMSE	0.69168	0.71544	0.70412	0.72615	0.71493	0.69198
	Rank RMSE	1	5	3	6	4	2
	Avg Rank	2	3.5	3.5	5.5	5	1.5
Sep	Avg MAE	0.00036	0.00359	0.00238	0.01326	0.01138	0.00045
	Rank MAE	1	4	3	6	5	2
	Avg RMSE	0.57985	0.59420	0.59646	0.59262	0.58748	0.70664
	Rank RMSE	1	4	5	3	2	6
	Avg Rank	1	4	4	4.5	3.5	4
Oct	Avg MAE	0.00324	0.00395	0.00024	0.01011	0.01070	0.00199
	Rank MAE	3	4	1	5	6	2
	Avg RMSE	0.46732	0.48018	0.47448	0.48976	0.48960	0.51393
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	2	3.5	1.5	5	5	4
Nov	Avg MAE	0.00243	0.00439	0.00191	0.00077	0.00040	0.00225
	Rank MAE	5	6	3	2	1	4
	Avg RMSE	0.29421	0.30660	0.29600	0.31083	0.30713	0.32570
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	3	4.5	2.5	3.5	2.5	5
Dec	Avg MAE	0.00063	0.00246	0.00028	0.00037	0.00070	0.00077
	Rank MAE	3	6	1	2	4	5
	Avg RMSE	0.30909	0.31996	0.31511	0.32449	0.32265	0.33484
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	2	4.5	1.5	3.5	4	5.5

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

Table D.6. Hawai‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Jan	Avg MAE	0.00088	0.00369	0.00147	0.00174	0.00558	0.00098
	Rank MAE	1	5	3	4	6	2
	Avg RMSE	0.33584	0.35872	0.34279	0.35820	0.44867	0.41048
	Rank RMSE	1	4	2	3	6	5
	Avg Rank	1	4.5	2.5	3.5	6	3.5
Feb	Avg MAE	0.00061	0.00279	0.00188	0.00618	0.00740	0.00052
	Rank MAE	2	4	3	5	6	1
	Avg RMSE	0.42510	0.44491	0.43610	0.46067	0.44867	0.44742
	Rank RMSE	1	3	2	6	5	4
	Avg Rank	1.5	3.5	2.5	5.5	5.5	2.5
Mar	Avg MAE	0.00009	0.00291	0.00004	0.00432	0.00337	0.00059
	Rank MAE	2	4	1	6	5	3
	Avg RMSE	0.39937	0.42170	0.40638	0.43010	0.41815	0.40787
	Rank RMSE	1	5	2	6	4	3
	Avg Rank	1.5	4.5	1.5	6	4.5	3
Apr	Avg MAE	0.00008	0.00334	0.00043	0.00225	0.00018	0.00081
	Rank MAE	1	6	3	5	2	4
	Avg RMSE	0.44329	0.47027	0.46551	0.47225	0.46845	0.47135
	Rank RMSE	1	4	2	6	3	5
	Avg Rank	1	5	2.5	5.5	2.5	4.5
May	Avg MAE	0.00196	0.00371	0.00123	0.00691	0.00668	0.00217
	Rank MAE	2	4	1	6	5	3
	Avg RMSE	0.48344	0.51455	0.49287	0.51266	0.50468	0.47320
	Rank RMSE	2	6	3	5	4	1
	Avg Rank	2	5	2	5.5	4.5	2
Jun	Avg MAE	0.00183	0.00537	0.00230	0.00745	0.01159	0.00109
	Rank MAE	2	4	3	5	6	1
	Avg RMSE	0.50608	0.53074	0.51031	0.56195	0.53320	0.49332
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	2	4	3	5.5	5.5	1
Jul	Avg MAE	0.00098	0.00287	0.00106	0.00426	0.00490	0.00168
	Rank MAE	1	4	2	5	6	3
	Avg RMSE	0.40736	0.42687	0.41788	0.43714	0.43079	0.43835
	Rank RMSE	1	3	2	5	4	6
	Avg Rank	1	3.5	2	5	5	4.5

Table D.6. (Continued) Hawai‘i cross validation statistics: compare all years (OK) with the 30-year test for 5 methods.

		30-Year Cross Validation Results					88-Year Final Results
		OK	OCK_EL	OCK_RF	KED_EL	KED_RF	OK
Aug	Avg MAE	0.00139	0.00084	0.00090	0.00399	0.00298	0.00039
	Rank MAE	4	2	3	6	5	1
	Avg RMSE	0.49975	0.52879	0.51654	0.54317	0.53090	0.49041
	Rank RMSE	2	4	3	6	5	1
	Avg Rank	3	3	3	6	5	1
Sep	Avg MAE	0.00042	0.00025	0.00333	0.00068	0.00442	0.00053
	Rank MAE	2	1	5	4	6	3
	Avg RMSE	0.38538	0.40840	0.40350	0.40767	0.40606	0.45776
	Rank RMSE	1	5	2	4	3	6
	Avg Rank	1.5	3	3.5	4	4.5	4.5
Oct	Avg MAE	0.00119	0.00207	0.00075	0.00069	0.00820	0.00017
	Rank MAE	4	5	3	2	6	1
	Avg RMSE	0.46418	0.48034	0.48579	0.48670	0.48061	0.48002
	Rank RMSE	1	3	5	6	4	2
	Avg Rank	2.5	4	4	4	5	1.5
Nov	Avg MAE	0.00056	0.00386	0.00337	0.00449	0.00490	0.00038
	Rank MAE	2	4	3	5	6	1
	Avg RMSE	0.40306	0.42122	0.42164	0.42517	0.41714	0.41819
	Rank RMSE	1	4	5	6	2	3
	Avg Rank	1.5	4	4	5.5	4	2
Dec	Avg MAE	0.00038	0.00478	0.00222	0.00567	0.00132	0.00079
	Rank MAE	1	5	4	6	3	2
	Avg RMSE	0.44360	0.47322	0.45140	0.48519	0.46318	0.42661
	Rank RMSE	2	5	3	6	4	1
	Avg Rank	1.5	5	3.5	6	3.5	1.5

Note: OK is ordinary kriging, OCK_EL is ordinary cokriging with elevation, OCK_RF is ordinary cokriging with mean rainfall, KED_EL is kriging with external drift with elevation, and KED_RF is kriging with external drift with mean rainfall. MAE is mean absolute error; RMSE is root mean square error. Units for MAE and RMSE are the same as the relative anomalies: dimensionless (inches per inch).

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