Spatial Interpolation of Rainfall Data Using ArcGIS: A Comparative Study

Julie Earls
Dr. Barnali Dixon
Geo-Spatial Analytics Lab
University of South Florida St. Petersburg
140 7th Ave. S., PNM 103
St. Petersburg, FL 33701
Jearls@mail.usf.edu
Bdixon@stpt.usf.edu

Abstract

Many GIS models for environmental and watershed management and planning requires rainfall as an input, in discrete or continuous format. The objective of this study was to evaluate spatial interpolation techniques for interpreting 2km OneRain data into 30m resolution using ArcGIS Spatial Analyst. The 2km data from OneRain were compared to 30m interpolated surfaces generated from the OneRain data. The interpolation methods used in this study were inverse distance weighting (variable & fixed), spline (regularized and tension) and kriging (Ordinary: spherical, circular, exponential, Gaussian, Linear and Universal: linear with linear drift and linear with quadratic drift). The drainage basin studied was Charlie Creek, Central Florida, U.S.A., a basin largely untouched by urbanization but expected to undergo rapid change in the next 10 years. This expectation has driven residents and the local water management district to be proactive in planning the use of water resources.

Introduction

Hydrologic modeling requires climatological data is an important variable. However, most of the weather data (particularly rainfall) is collected using rain gauges, hence point data in nature. However, more often than not spatially explicit rainfall data are required by the hydrologic models. The spatially explicit data are often obtained using interpolation methods. The representation of rainfall data in the digital world and its accuracy is controlled by the spatial distribution of the weather stations and the spatial interpolation methods used which may or may not reflect the reality (actual spatial pattern of rainfall). Actual patterns (intensity and duration) and spatial distribution of rainfall affects the hydrology of a watershed. In a given watershed, weather patterns can vary from low intensity-short duration or low intensity and long duration rainfall to high-intensity-short duration rainfall. Digital presentation of the variability of rainfall pattern is affected by the interpolation methods used as well as the nature of original data.

Historically, rainfall data are colleted using rain gauge stations. These site specific data were then interpolated to create continuous surface for the rainfall data. Needless to say interpolation methods more often than not fail to represent the variability of the rainfall pattern. In more recent years, the usage of Next Generation RADAR (NEXRAD) has become more widespread and gained appreciation in the hydrologic modeling community as a source of input data to hydrologic models as these dataset provide continuous spatial coverage, hence captures the rainfall variability with less uncertainty than simple point data and its derivative interpolated surfaces. Although, the temporal resolution of the NEXRAD data is very fine (every 15 minutes is available), the spatial resolution of the cells that contain rain information are generally very coarse (2km) compared to other available GIS data layers. Therefore, some issues of error propagation with hydrologic models can not be ignored. One solution to such issues is the use of Gage-Adjusted Radar Rainfall (GARR), which combines rain gage estimates at a point with the spatial distribution information from the National Weather Service NEXRAD (Hoblit & Curtis, 2005).

Spatially explicit models require that the rainfall data must be resampled to a different resolution than the source data to match the resolution of the other relevant datasets. This change in resolution of grid data also requires the use of interpolation methods; however, 'resampling' types of interpolation techniques commonly used with grid data are different from the interpolation methods commonly used with the rain gauge data to created continuous surface (eg. Theissen polygon). The overall goal of this research aims at examining the effects of different types of interpolation methods applied to the rainfall data obtained from NEXRAD. The specific objective of this study was to evaluate spatial interpolation techniques (IDW, Spline and various krigging methods) for interpreting 2km OneRain data into 30m resolution using ArcGIS Spatial Analyst. Ball & Luk (1998) discuss many of these interpolation methods, ranging from Theissen polygons to surface fitting methods to more common ones used in ArcGIS such as: spline, inverse-distance weighting (IDW) and kriging (of various types). IDW (Smith, 1993) and kriging (Kitanidis, 1997) are the most commonly used spatial interpolation methods for estimating rainfall (Keckler, 1995). In spite of the extensive work done in the field of rainfall interpolation, little is known about the factors that impact the relative performance of IDW, spline and kriging with regard to NEXRAD derived rainfall data at various resampling scales and their value/impacts in maximizing average prediction efficiency of the hydrologic models.

This research was performed testing spatial interpolation these methods for the Charlie Creek watershed (Figure 1) in central Florida, U.S.A. against the 2km GARR data provided by OneRain© to create the best 30m representation of the rain data. The study time period was January 2004 to January 2006.

Figure 1. Study area.

Methodology

Data Setup

The University of South Florida St. Petersburg (USFSP) was provided with a Charlie Creek polygon shapefile for the drainage basin of the study by USGS and a point shapefile provided by USGS, which extended roughly 2-3 km outside the boundary of the watershed. This was to ensure that the spatial interpolation was catching any clusters of rainfall that might be occurring close to the extent of the basin and correctly interpolating them. Next, the point shapefile was spatially "joined" to the desired rainfall data (provided as monthly *.txt files). The common field (required to accomplish this) was, in this case, "pixel." Now, the data was able to be visualized and analyzed in ESRI ArcGIS using the Spatial Analyst extension.

Plotting the data by individual date and examining the spatial distribution without any interpolation was a useful tool. This allowed researchers to develop a baseline of what was actually in the original OneRain© data and something to use for comparison once data is interpolated. To accomplish this, the 2km polygon shapefile of each "pixel" (clipped to the study area including the buffer) was spatially joined to the date in question and then the original (uninterpolated by USFSP) data displayed. The next step was selecting an interpolation method.

The spatial interpolation methods were each applied to 4 different dates with varying amounts of rain to determine the best statistical representation of the data. The dates selected for initial analysis were: 12/16/1999 (Figure 2), 12/24/2004 (Figure 3), 5/4/2005 (Figure 4) and 6/1/2005 (Figure 5). These dates cover a range of very little rainfall to large amounts of rainfall and were merely used to test the appropriateness of the methods.

Statistical

ArcGIS Statistical Analyst has the capability to apply many types of spatial interpolation to input point data. Depending on the spatial variability, some types are not necessary or appropriate. Part of this study was to determine the most appropriate interpolation method for the data provided. The data presented for analysis has already been normalized to a 2km grid, for example, so some surface interpolation methods may not truly come into play. Rarely in science is there a truly homogeneous surface like the study data (which is only thus because it has already been interpreted from rain gauges and RADAR).

For this project, the initial interpolation methods used were: inverse distance weighting (IDW), spline and kriging. The 2 types of kriging used in this study were ordinary and universal. The ordinary kriging includes spherical, circular, exponential, Gaussian and linear methods of interpolation (McBratney and Webster, 1986).

For the analysis in this study, all criteria were left to defaults on all interpolation methods except the output cell size, which was changed to 30m.

Results and Discussion

The first 2 methods, IDW and spline, are part of a method of interpolation called "deterministic" interpolation as they allocate interpolated values to locations as a result of surrounding measured values and mathematical formulas to create a surface from point data. Kriging, however, falls into a category of geostatistical methods, which adds the ability to determine some evaluation of accuracy of the resulting predicted surface. The kriging method assumes the variation in the z value is statistically homogenous throughout all locations in the surface. The user can look at the semivariogram to obtain an estimate of the spatial variation. If the data is considered to have local trends, then universal kriging may be used effectively, as it incorporates the component of drift.

In comparing the methods of interpolation, while several of the techniques represent large trends well, there are only a couple that represent smaller (1 or 2 pixels at 2km original resolution) trends at all. These two methods that stand out are IDW with variable search radius (b in the Figures) and ordinary kriging with exponential semivariogram and variable search radius. The lightest ran day tested, 5-4-2005, had the most trouble with interpolation for any of the methods, most over-predicting greatly the small amounts of rain (<0.25 in most places). In general, kriging methods produced better results than IDW and spline. In some cases, selection of one method over the other may require use of cross-validation statistics and analyses of range of spatial correlation.

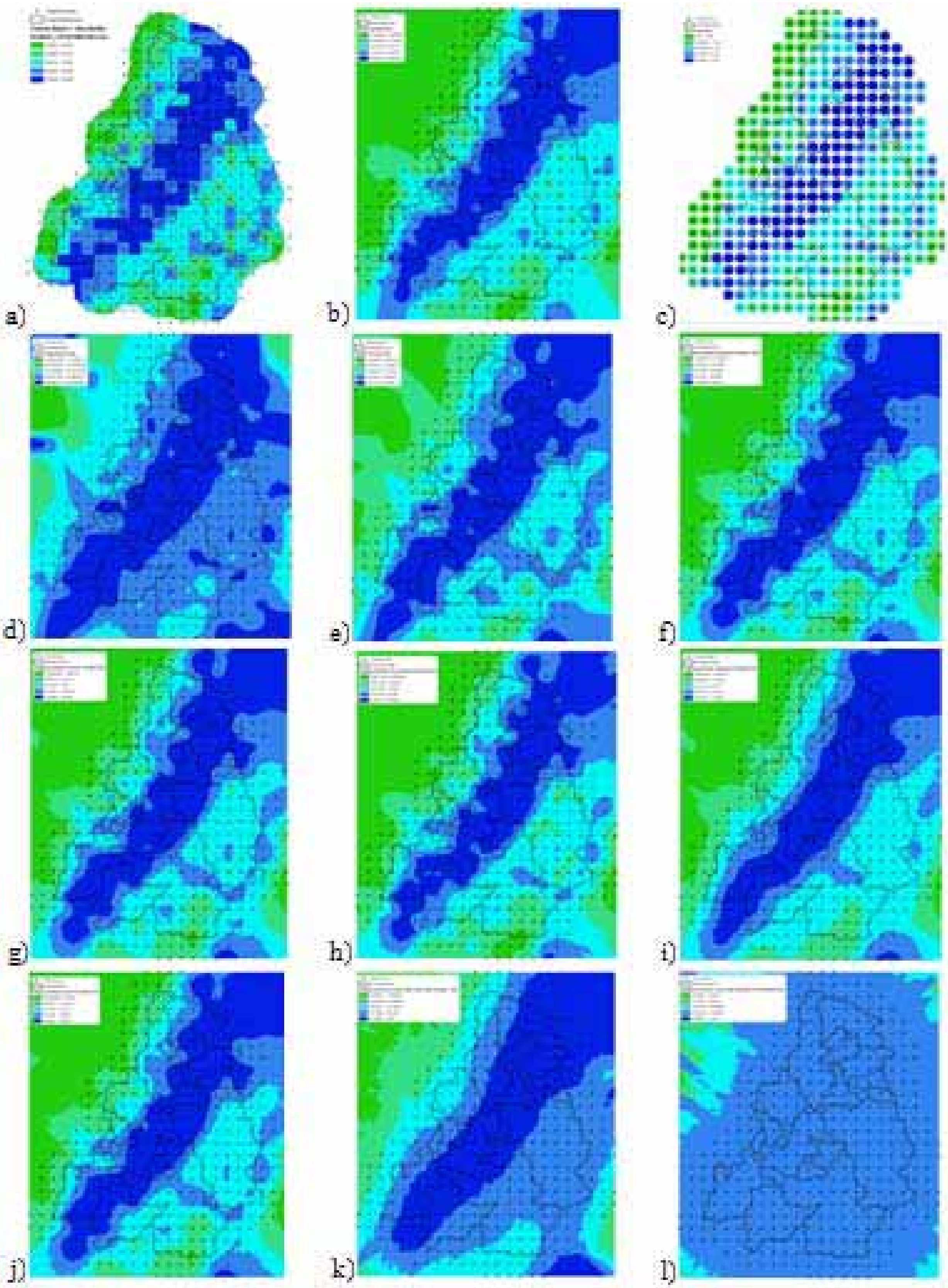

Figure 2. Results of interpolation for 12-16-1999. A) uninterpolated, b) IDW – Variable search radius, c) IDW – Fixed search radius, d) Spline – Regularized, e) Spline – Tension, f) Kriging – Ordinary – Spherical – Variable, g) Kriging – Ordinary – Circular – Variable, h) Kriging – Ordinary – Exponential – Variable, i) Kriging – Ordinary – Gaussian – Variable, j) Kriging – Ordinary – Linear – Variable, k) Kriging – Universal – Linear with Linear Drift – Variable, l) Kriging – Universal – Linear with Quadratic Drift – Variable.00

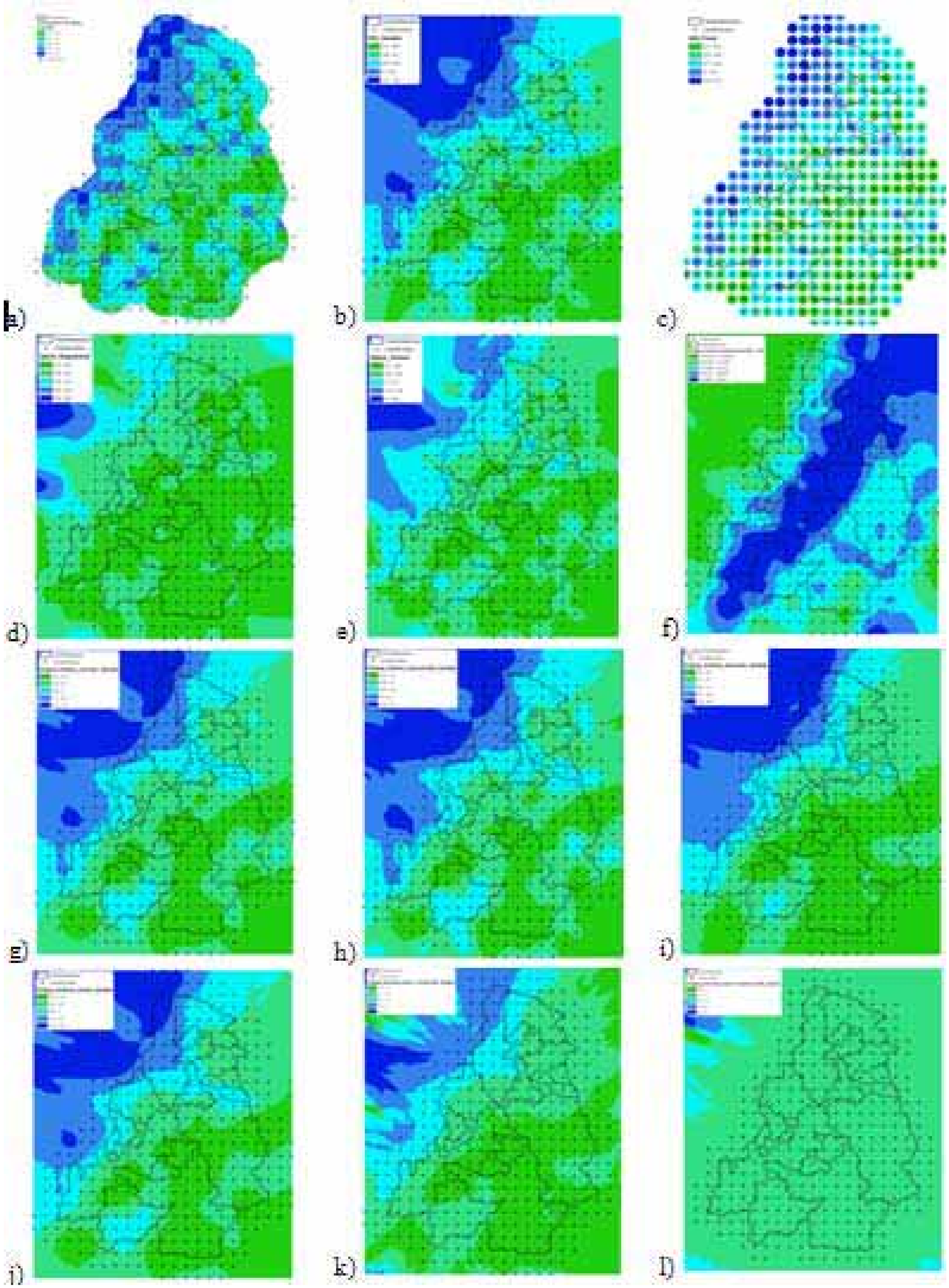

Figure 3. Results of interpolation for 12-25-2004. A) uninterpolated, b) IDW – Variable search radius, c) IDW – Fixed search radius, d) Spline – Regularized, e) Spline – Tension, f) Kriging – Ordinary – Spherical – Variable, g) Kriging – Ordinary – Circular – Variable, h) Kriging – Ordinary – Exponential – Variable, i) Kriging – Ordinary – Gaussian – Variable, j) Kriging – Ordinary – Linear – Variable, k) Kriging – Universal – Linear with Linear Drift – Variable, l) Kriging – Universal – Linear with Quadratic Drift – Variable.

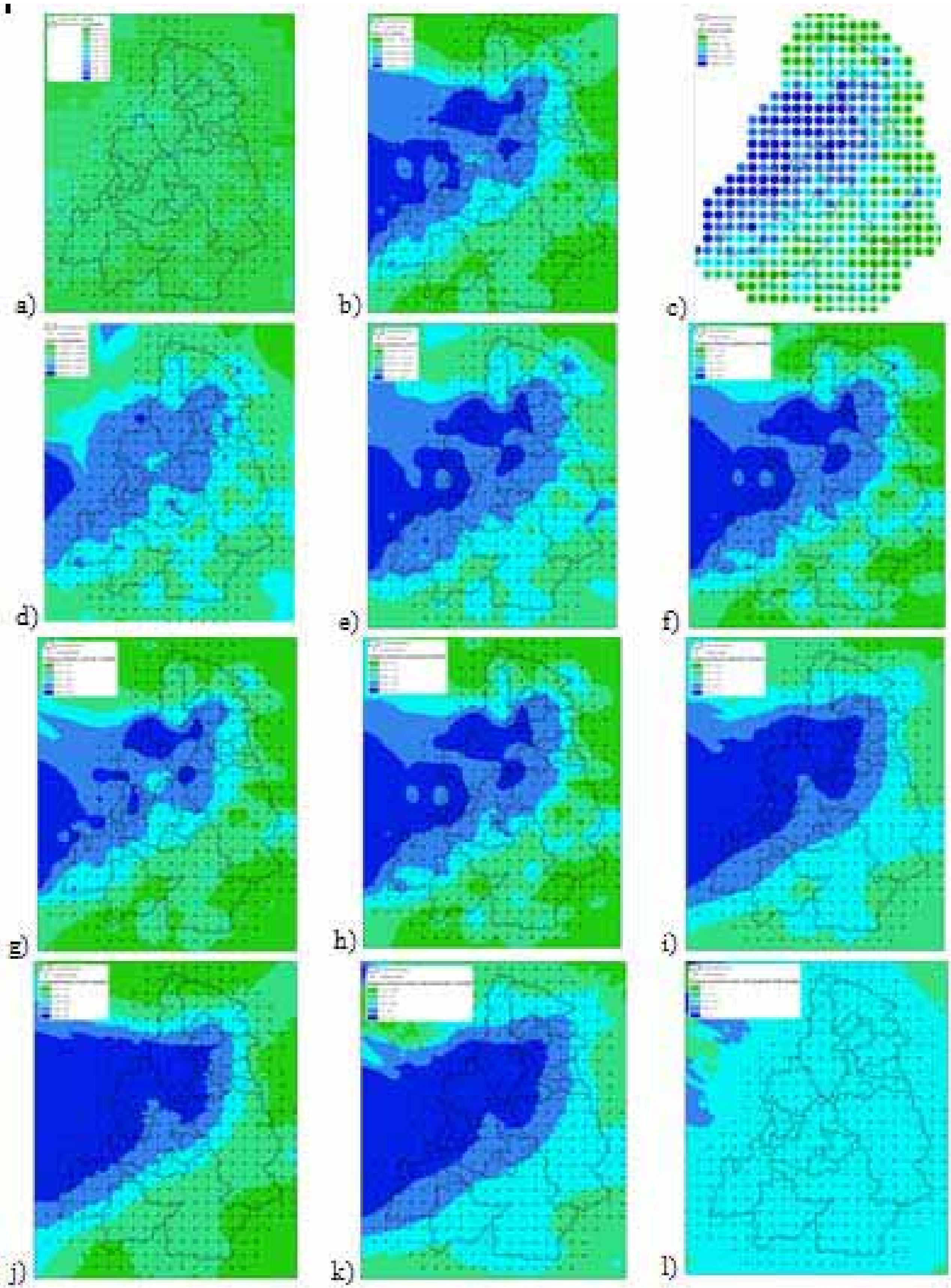
a) b) c) d) e) f) g) h) i) j) k) l)

Figure 4 . Results of interpolation for 5-4-2005. A) uninterpolated, b) IDW – Variable search radius, c) IDW – Fixed search radius, d) Spline – Regularized, e) Spline – Tension, f) Kriging – Ordinary – Spherical – Variable, g) Kriging – Ordinary – Circular – Variable, h) Kriging – Ordinary – Exponential – Variable, i) Kriging – Ordinary – Gaussian – Variable, j) Kriging – Ordinary – Linear – Variable, k) Kriging – Universal – Linear with Linear Drift – Variable, l) Kriging – Universal – Linear with Quadratic Drift – Variable.

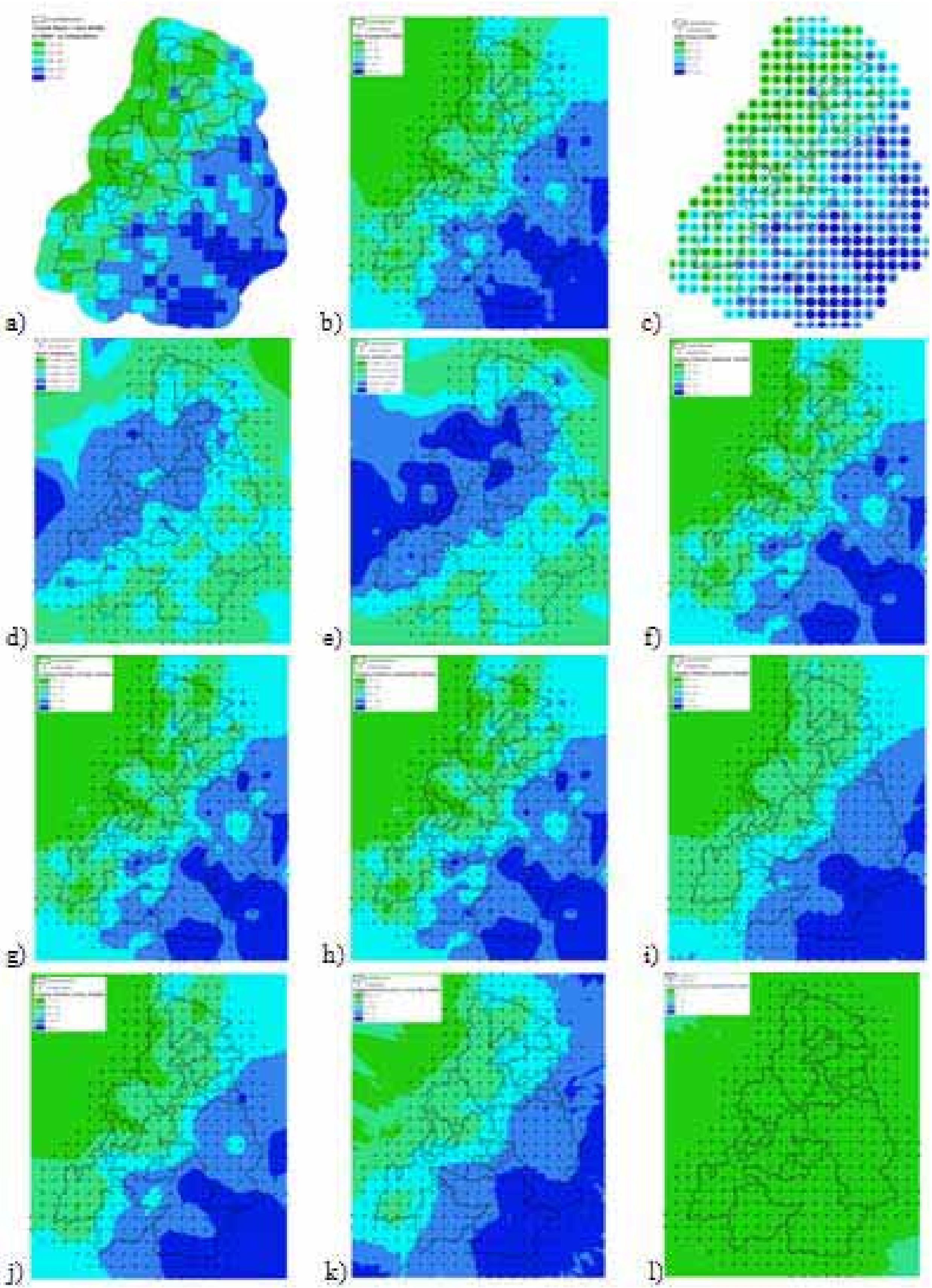

Figure 5. Results of interpolation for 6-1-2005. A) uninterpolated, b) IDW – Variable search radius, c) IDW – Fixed search radius, d) Spline – Regularized, e) Spline – Tension, f) Kriging – Ordinary – Spherical – Variable, g) Kriging – Ordinary – Circular – Variable, h) Kriging – Ordinary – Exponential – Variable, i) Kriging – Ordinary – Gaussian – Variable, j) Kriging – Ordinary – Linear – Variable, k) Kriging – Universal – Linear with Linear Drift – Variable, l) Kriging – Universal – Linear with Quadratic Drift – Variable.

Conclusions

From this research, it appears that the ordinary kriging using exponential semivariogram and variable search radius (h in Figures 2-5) is the best approach to depict the unique variation within the dataset with IDW – Variable search radius as a viable alternative. This may be a function of the distribution and intensity of the Florida rainfall and minimal elevation within the watershed, or perhaps because the kriging method is the product of weighted estimates of the actual data, therefore the contours follow a more agreeable trend and don't lose the small (viz., one 2km pixel) of rain as with some of the other methods. In general, kriging methods produced better results than IDW and spline and an added benefit is that the kriging gives you the resultant errors in the calculation as well. However, IDW interpolation is a smoothing technique by definition that leads to practical calculations without results exceeding the range of meaningful values. But, for the sampling of dates examined, the spatial interpolation that appeared to be the best representation of the GARR OneRain© meteorological dataset was the ordinary kriging using exponential semivariogram and variable search radius.

References

Ball, J. E. and Luk, K. C. "Modeling Spatial Variability of Rainfall Over a Catchment". Journal of Hydrological Engineering, American Society of Civil Engineers, Vol. 3, No. 2, April 1998.

Burrough, P.A. "Principles of Geographical Information Systems for Land Resources Assessment". New York: Oxford University Press. 1986.

ESRI, ArcGIS 9.1 Help.

Heine, G.W. "A Controlled Study of Some Two-Dimensional Interpolation Methods". COGS Computer Contributions 3 (no. 2): 60-72. 1986.

Hoblit, B. C. and D. C. Curtis. "Radar Estimates + Gauge Data: A Perfect Union". Southwest Hydrology, May/June 2005:22-24.

Keckler, P. K. Surfer for Windows, Golden Software, Inc., Golden, CO, 1995.

Kitanidis, P. K. Introduction to Geostatistics, Cambrsidge University Press, 1997.

McBratney, A.B., and R. Webster. "Choosing Functions for Semi-variograms of Soil Properties and Fitting Them to Sampling Estimates". Journal of Soil Science 37: 617-639. 1986.

Oliver, M.A. "Kriging: A Method of Interpolation for Geographical Information Systems". International Journal of Geographic Information Systems 4: 313-332. 1990.

Press, W.H., S.A. Teukolsky, W.T. Vetterling, and B.P. Flannery. "Numerical Recipes in C, The Art of Scientific Computing". New York: Cambridge University Press. 1988.

Royle, A.G., F.L. Clausen, and P. Frederiksen. "Practical Universal Kriging and Automatic Contouring". Geoprocessing 1: 377-394. 1981.

Smith, J. A. Precipitation, Handbook of Hydrology, David R. Maidment, ed. McGraw-Hill, Inc., pp. 3-20, 1993.