Comparing Satellite Rainfall Estimates and Reanalysis Precipitation Fields with Station Data for Western Kenya[1]

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Introduction

Characterization of rainfall variation in time and space is an indispensable part of crop monitoring for food security in Africa. In order to compensate for sparse and late-reporting rain gauge stations, early warning systems often rely upon indirect estimates of precipitation. Examples are estimates derived from satellite imagery and output fields from numerical models of the atmosphere. In order to support workshop discussions, rapid and limited comparisons of two such data sets were made against available station data for a region of western Kenya. Substantially better agreement with station data was observed for the satellite rainfall estimates than was the case with atmospheric model reanalysis fields. Though limited in scope, we believe the results are indicative of the relative performance of these two classes of indirect rainfall estimators.

Study Area

Comparisons of rainfall estimates were made for a region of western Kenya lying between 1° South Latitude and 1° North Latitude, and between 34.15° and 35.55° East Longitude, an area of approximately 35,000 square kilometers. (Figure 1 depicts mean March precipitation in the study area.) The zone is roughly centered on the city of Kisumu and includes the Winam Gulf of Lake Victoria. It typifies a priority region for food security monitoring, being one of the most agriculturally productive areas of Kenya. Maize, wheat, bananas, and tea are major crops. It also includes the Nzoia river basin, a catchment that is often subject to problems of flooding that impact the local population. Though there is an extensive network of rain gauges in the region, data from them are not available in a sufficiently timely fashion to support early warning activities. Rainfall monitoring by indirect methods is therefore of keen interest.

Intra-annual rainfall in this part of Kenya is distinctly bimodal. The study focused in particular on the months of March, April, and May, the heart of the “long rains”. Convective rainfall systems are characteristic of the season in this region. The years of study were 1996, 1997, and 1998.

Data and Methods

Rainfall grids were prepared from station data for comparison with indirect estimates of precipitation. Daily accumulations from a network of 134 stations distributed throughout the study area were interpolated by Shepard’s algorithm (Shepard 1968; Willmott and Feddema, 1994, Willmott and Matsura, 1995) to assign values to a 0.1° grid, giving a

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horizontal resolution of approximately 10 kilometers. On any given day, an average of 73 stations had observations available for interpolation. The study area consisted of twenty-one rows of fourteen grid cells each, for 294 cells in all. Daily grids were summed to get grids with totals for the three dekads (WMO, 1992) of each month. A total of 27 dekadal grids were prepared – three per month, times three months per season, times three years of interest (1996, 1997, and 1998). Finally, the mean rainfall per dekad over the whole grid was calculated for all dekads, giving a series of 27 values in millimeters per dekad. These 27 values served as the reference standard for comparison with indirect estimates.

Satellite rainfall estimates (RFE) from the FEWS NET archive were processed to extract grid cell values for the study area for the 27 dekads of interest. Mean values over the grids for each dekad were calculated to get 27 values for comparison with the reference data set. The satellite rainfall estimates had been operationally produced on the same 0.1° grid as used for the present analysis. The algorithm (Herman et al., 1997) estimates convective rainfall from cloud top temperatures and orographic rainfall from topography in conjunction with numerical model fields for relative humidity and wind. Rain gauge data available daily through the WMO Global Telecommunication System (GTS) are used to remove bias. Of the approximately 400 stations on the GTS in Africa, 365 typically report on any given day. Of the population of 400 GTS stations, four fall within the study area (see Figure 2).

Daily precipitation fields from the National Center for Atmospheric Research (NCAR) reanalysis data set were extracted for the study area for the period of interest. Daily fields were summed into dekadal fields, and study area means calculated for each of the 27 dekads.

Table 1 summarizes rainfall values for the 27-dekad study period for the reference standard, satellite RFE, and NCAR reanalysis data sets.

Simple regression analysis was used to measure the degree of agreement between the reference standard and the satellite RFE, as well as between the reference standard and the NCAR reanalysis fields. Scatter plots were prepared to illustrate the results, as was a time series trace of the data in Table 1.

Results

Figure 3 illustrates the good agreement between the reference standard and the satellite RFE. Regression analysis yielded a coefficient of determination (r^2) of 0.8. Bias was on the order of 5 millimeters per dekad, or about 10% of the mean. Figure 4 shows the much weaker relationship between reanalysis precipitation fields and the reference standard, with a coefficient of determination (r^2) of only 0.2. In this case, bias was about 25 millimeters per dekad, or 50% of the mean.

Figure 5 presents a time series trace of the three data sets for the 27 dekads of interest. Note that the reanalysis performed well in 1997, but not in 1996 and 1998.

Discussion

There are several good reasons for the favorable performance in tropical areas by satellite RFE from the Climate Prediction Center (CPC). There are also several reasons to expect reanalysis precipitation fields to perform poorly. Satellite RFE fields *should* be reasonably accurate because they: i) are based on observations of cloud top temperatures, which in turn are related to vertical motion and convection, ii) incorporate daily station observations to correct for potential bias, leveraging the utility of sparse gauge networks, and iii) have a spatial scale (~10 km) consistent with the convective nature of tropical rainfall. Reanalysis fields, on the other hand, have several well-known problems. First and foremost, very few moisture-related observations are incorporated in the reanalysis models. These fields are therefore poorly defined, a problem exacerbated by the tendency of atmospheric moisture fields to vary fairly rapidly in space and time. This is in contrast with smoothly varying pressure and wind fields, which are generally fairly accurate. Creators of reanalysis fields fully acknowledge these facts, and caution users to regard moisture-related fields with skepticism (Kalnay et al., 1996). These problems can be exacerbated in a region like Kenya because of the complex interaction of terrain (heating, lifting and channeling the atmosphere), lake effects, and moisture advection. These processes are poorly represented by both the physics and scales used in GCM models.

These comments are not meant as a rejection of GCM precipitation fields. Our research, rather, has shown that these fields – when *constrained with gauge data* – can be surprisingly accurate. A verification of the Collaborative Historical African Rainfall Model (CHARM) dataset, which was based on reanalysis precipitation and sparse historical gauge data, revealed a coefficient of determination of 0.64 when compared with dekadal rainfall at the same Kenya study area examined here (Funk et al., 2003).

From our experience with satellite RFE from CPC (Herman et al., 1997; Xie and Arkin, 1997) and the CHARM dataset, we conclude that blending only a modest number of concurrent station observations can significantly reduce the bias in indirect estimates of precipitation. Even so, indirect estimates based on satellite observations will be more accurate than those based on reanalysis fields.

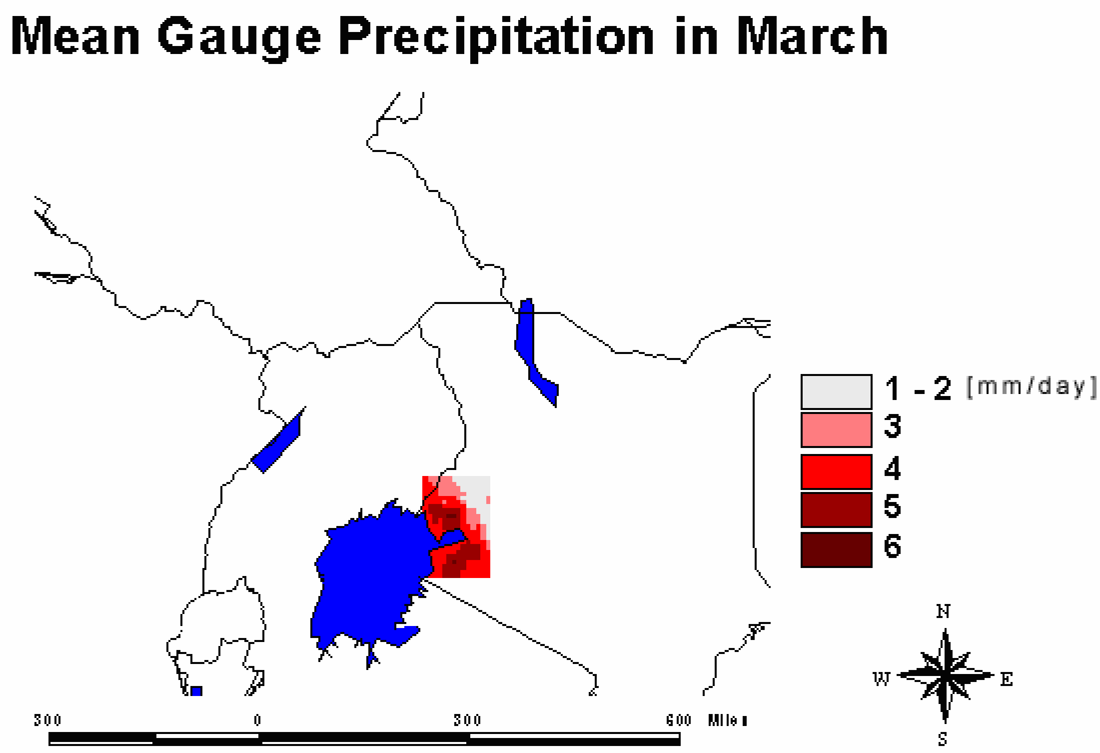

Figure 1. Mean March precipitation in millimeters per day (1961-1996) for the western Kenya study area, 1° S - 1° N latitude, 34.15° E – 35.55° E longitude.

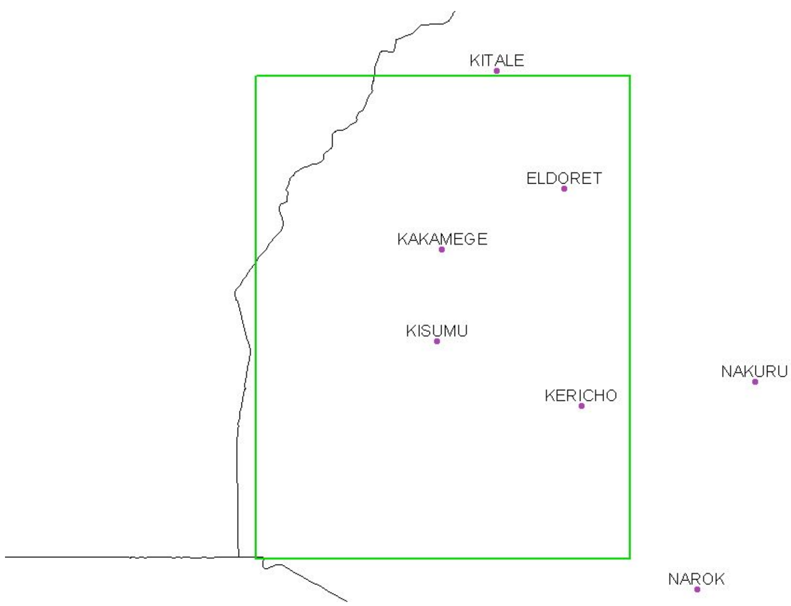

Figure 2. Locations of GTS stations in and around the study area, as defined by the green box.

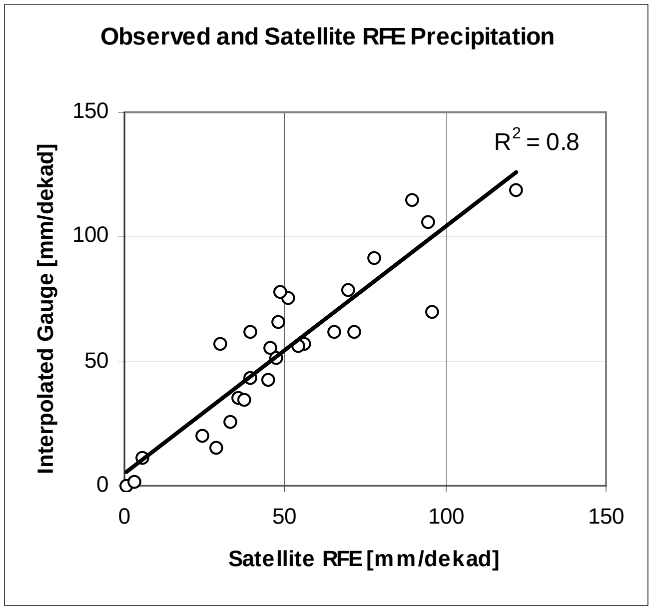

Figure 3. Scatter plot of reference standard (interpolated gauge) precipitation versus satellite RFE, in millimeters per dekad, with coefficient of determination of 0.8.

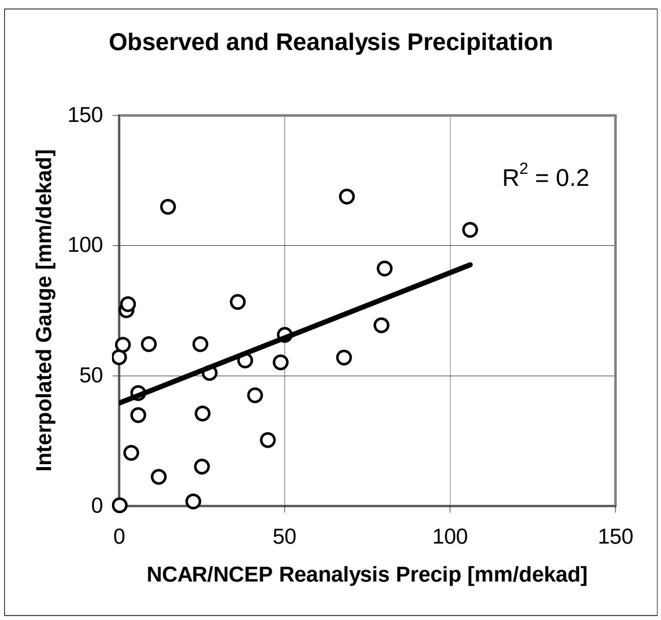

Figure 4. Scatter plot of reference standard (interpolated gauge) precipitation versus NCAR reanalysis, in millimeters per dekad, with coefficient of determination of 0.2.

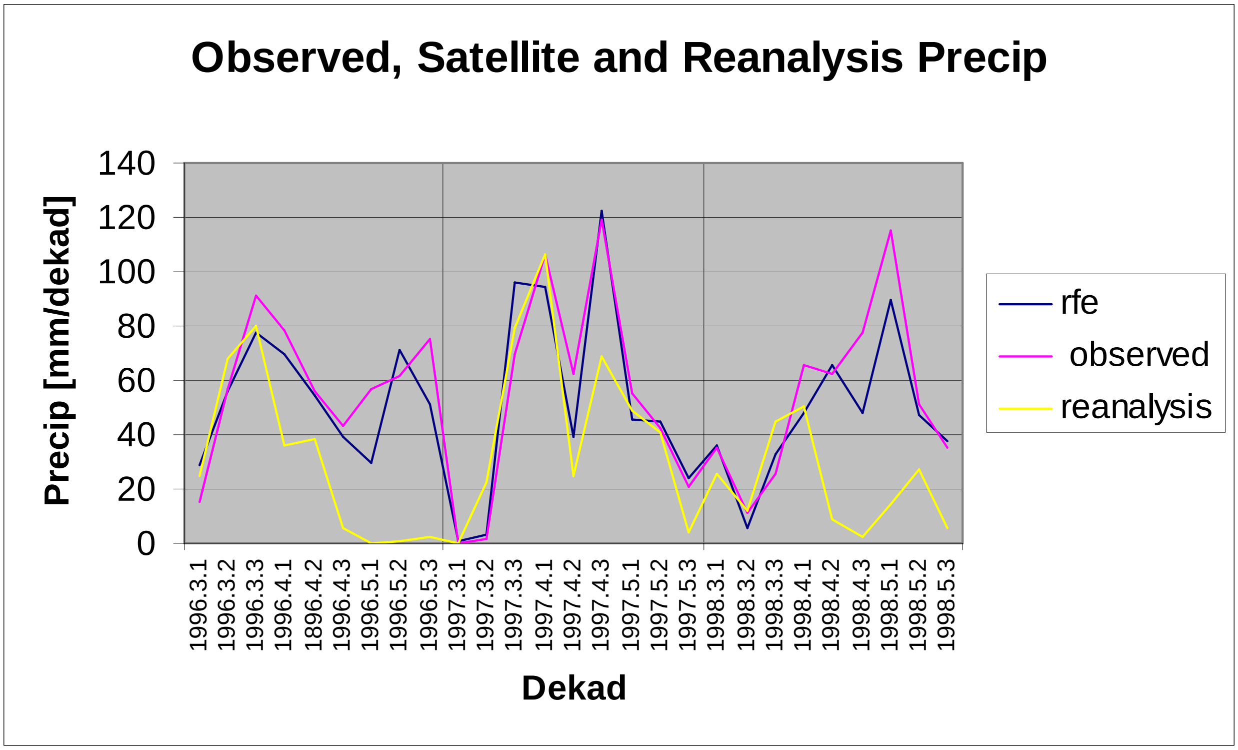

Figure 5. Time series traces of mean study area precipitation (millimeters per dekad) for the 27 dekads of interest for the reference standard (observed), satellite RFE, and NCAR reanalysis.

Dekad	**Reference Standard**	**Satellite RFE**	**NCAR Reanalysis**
1996.3.1	15.1	28.8	25.0
1996.3.2	57.0	55.9	68.0
1996.3.3	91.2	77.6	80.2
1996.4.1	78.4	69.5	35.9
1896.4.2	55.9	54.3	38.1
1996.4.3	43.4	39.0	5.8
1996.5.1	57.1	29.6	0.0
1996.5.2	61.9	71.3	1.1
1996.5.3	75.1	51.1	2.2
1997.3.1	0.2	0.4	0.2
1997.3.2	1.7	2.9	22.4
1997.3.3	69.4	95.8	79.3
1997.4.1	106.0	94.7	106.1
1997.4.2	62.1	38.9	24.6
1997.4.3	118.8	122.2	68.8
1997.5.1	55.1	45.3	48.8
1997.5.2	42.5	45.1	41.1
1997.5.3	20.4	24.0	3.7
1998.3.1	35.5	35.7	25.3
1998.3.2	11.2	5.7	12.0
1998.3.3	25.3	32.9	45.0
1998.4.1	65.8	47.8	50.1
1998.4.2	62.1	65.6	9.0
1998.4.3	77.5	48.3	2.7
1998.5.1	114.8	89.8	14.8
1998.5.2	51.1	47.4	27.4
1998.5.3	34.8	37.5	5.8
	55.2	**50.3**	**31.2**

Table 1. Mean dekadal rainfall over the study area from gridded stations (reference standard), satellite RFE, and NCAR reanalysis fields (in millimeters per dekad).

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