VALIDATION OF SATELLITE AND RAIN-GAUGE DATA FOR PARAMETERISING A SOIL EROSION MODEL FOR SUB-SAHARAN AFRICA

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ABSTRACT

Interpolated daily and dekadal raingauge data were compared to dekadal satellite precipitation estimates. The objective of this comparison was to investigate the accuracy of these datasets and determine their advantages and limitations for parameterising a soil erosion model for sub-Saharan Africa. The raingauge network comprised of 500 GTS stations, which were interpolated using block kriging and a combination of ordinary and indicator kriging. The satellite estimates were derived from METEOSAT data using a methodology that incorporates cold cloud duration with models for orographic and warm cloud precipitation. The validation rain-gauge data consisted of 1800 stations in South Africa for the period of March 1996. The validation technique involved the interpolation of the South African network and its use as ground-truth to estimate the errors between grids on a pixel-by-pixel basis. Error criteria computed at the gauged pixels indicate that overall the three techniques perform similarly and provide good estimates for low rainfall but they all severely underestimate the larger precipitation amounts. The soil erosion model was parameterised on a daily basis using these different rainfall inputs, AVHRR NDVI to estimate vegetation cover, and other GIS data. The satellite data provide erosion estimates that are spatially more extensive and of higher magnitudes than the interpolated data, especially in those areas where the GTS network is extremely sparse. It is concluded that, in order to deal with the problem of raingauge insufficiency in developing areas, a merging technique, which combines the raingauge estimates with the satellite data, should be applied.

1 INTRODUCTION

Research on soil erosion by water has concentrated mainly on the runoff plot, the field and the catchment scale. The erosion models have been developed, calibrated, validated and used at these scales. Relatively few studies have been done at larger scales, i.e. the regional, continental and global. The problem with using and validating a model at such larger scales is the vast amounts of data required. Satellite remote sensing data can help to meet these requirements and have been used as input to such models in a GIS environment, where they can be manipulated and combined with ancillary data (e.g. Symeonakis et al, 1999).

Precipitation, which is the primary input to overland flow and soil erosion models, shows a considerable spatial variation. The variation is brought about by differences in the type and scale of development of precipitation producing processes, and is also strongly influenced by local or regional factors, such as topography and wind direction at the time of precipitation (Sumner, 1988). The problem is to try to describe the spatial variation and to make estimates of precipitation in areas where there are no monitoring stations. Resources for collecting such basic information are limited particularly in the developing world.

A quantitative evaluation of the amount and spatial distribution of precipitation is required for a number of large scale applications in hydrology and many techniques have been proposed for mapping rainfall patterns and for evaluating the mean areal rainfall by making proper use of existing data points. Methods for precipitation interpolation from ground-based point data have ranged from techniques based on Thiessen polygons and simple trend surface analysis, inverse distance weighting, multiquadratic surface fitting and Delauney triangulations through to more sophisticated statistical methods (Baily and Gatrell, 1995). So far, most of the research has focussed on interpolating precipitation over small areas and for small to regional scale applications (Barancourt and Creutin, 1992).

Because of the very considerable spatial variation of precipitation amounts and intensity, particularly for severe convectional storms, there is no guarantee that point rainfall values will in any way provide a reliable guide to the rainfall of immediate surrounding areas. Areal averages derived from raingauge observations suffer from severe limitations due to sampling but also because gauges tend to be distributed with a pronounced spatial bias toward populated areas and against areas with high elevation and/or slope (Xie and Arkin, 1995). An answer to these limitations is likely to come from satellite remote sensing, whose potential for estimating rainfall has been evident since its very earliest days. Radiances observed in many different spectral regions were found to offer a physically plausible means of deriving rainfall rates, and such applications developed quickly (Arkin and Ardanuy, 1989). However, the indirect nature of the relationship of the observations to precipitation and the fact that they require calibration using gauge data has limited the success of these remote sensing techniques.

The aim of this research is to produce precipitation estimates for the entire sub-Saharan Africa by interpolating raingauge data, to compare them to satellite estimates of the area and to examine the applicability of the two different datasets to modelling soil erosion over the continent.

2 METHODOLOGY

2.1 The Raingauge Data

The only readily available rainfall data for the African continent on a daily basis are those of the World Meteorological Organisation (WMO), which consist of daily records from about 760 Global Telecommunications System (GTS) stations. Around 463 of these GTS stations are within sub-Saharan Africa, and are the ones used for the estimation of interpolated areal rainfall, described in the next section.

2.2 Interpolation Of The GTS Rain-Gauge Data

Two different interpolation schemes were applied and compared: ordinary block kriging (BK), and a combination of block kriging and indicator kriging, which we will refer to as the ‘combined kriging’ (CK) technique. Indicator kriging (IK) has been proven to be a good estimator of the occurrence of precipitation (Barancourt et al, 1992). It is a non-linear form of ordinary kriging in which the original data are transformed from continuous to binary, with ones representing rain occurrence and zeros the absence ($I(r) = 0$ for $r = 0$ and $I(r) = 1$ for $r > 0$). By applying BK to the GTS data in conjunction with its indicator counterpart, a more efficient delineation of the dry areas was intended. The validation and comparison of the different precipitation estimates was carried out for the period of March 1996. For that month, both interpolation schemes were applied to the 3 dekadal datasets, produced by summing the daily sets on a dekadal basis to match the temporal resolution of the satellite estimates.

The semi-variogram is a statistical way of quantifying the spatial variation of the data. The semi-variance is estimated by the sample semi-variogram the value of which, for a station separation-distance of h is the average squared difference in the amount of rainfall between pairs of stations separated by h:

$$\gamma(h) = 1/(2n) \sum\{p(x_i) - p(x_i + h)\}^2 \quad (1)$$

The variograms were fairly well behaved following the same kind of shape (Figure 1):

- For relatively short distances the semi-variances are low, increasing rapidly with distance until approximately the first 100km.
- A first sill is then reached and the semi-variance becomes constant until about the first 1000km. This can be attributed to the fact that for distances that contribute to this sill, the stations are close enough to belong to a homogenous rainfall regime.
- Between distances of 2000km and 3000km the semi-variances increase rapidly again. This signifies the decrease in spatial dependence between stations separated by such distances.
- This ‘hump’ vanishes at distances

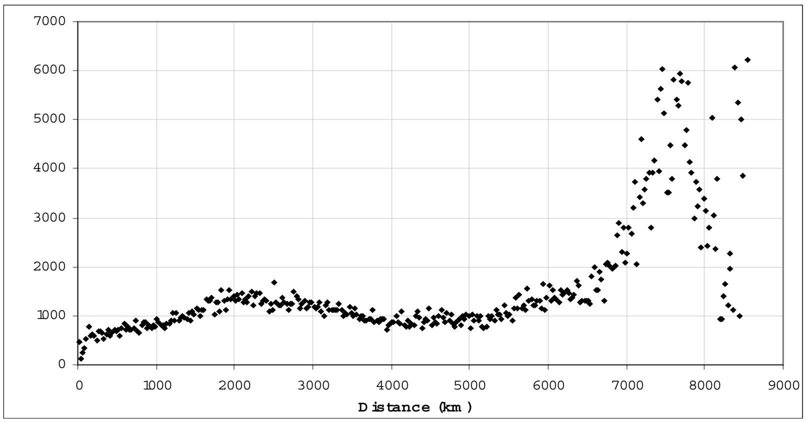

Figure 1: Experimental semi-variogram, 2nd dekad March 1996

between stations of approximately 4500-5000km, where the semi-variances have about the same magnitude as the variances of the first sill (i.e. first 1000km), and finally

- From distances of 6500km and over the semi-variances increase dramatically and continuously: a clear sign of a complete lack of spatial dependence, something expected from a phenomenon such as precipitation.

Three different techniques of fitting spherical and exponential theoretical models to the experimental points were utilised, in order to choose the most appropriate model (i.e. the one that minimises the error of the interpolation): (a) visual fit**,** (b) fit by generalised least squares (GLS)**,** and (c) fit by maximum likelihood (ML). After applying all three different fitting techniques, leave-one-out cross validation was applied, in order to select the optimal model. Leave-one-out cross validation works by leaving each sample point in turn out of the dataset and predicting its value from the rest of the data, using a particular variogram model. This results in an observed set of prediction errors between the predicted and true values at each sample site. For each combination of model type, range, sill and nugget, the following summary statistics were estimated: the bias, RMSE, normalised RMSE and the stabilised geometric mean cR (Kitanidis, 1997). Ideally, for a perfect estimate, $bias_d$ = 0, $bias_r$ and $RMSE_{norm}$ = 1, and RMSE and cR are minimised. The optimal theoretical model paremeters that were chosen for the interpolation were consistent in the type (exponential for all three dekads), but the ranges varyied from 100 to 180km, the sills from 100 to 950mm^2 and the nuggets from 40 to 450mm^2.

The next step was to apply ordinary kriging to the daily and the dekadal GTS datasets using the model parameters that the cross-validation procedure indicated as most appropriate. A search radius of 1000km and a minimum number of eight participating neighbouring stations was used. Examples of the output of ordinary kriging and the estimated kriging errors for the first dekad of March 1996 are shown in figures 2a and 2b respectively. For that dekad the vast majority of the continent was dry or received relatively small amounts of rainfall. More specifically, 33% of the 463 stations reported zero precipitation and 53% less than 10mm. The kriging RMS errors are lower for those areas surrounding the locations of the GTS stations, but even for those small areas, in most of the cases the kriging errors represent a large relative uncertainty in the estimation of precipitation (up to 50%). Areas which receive significant amounts of daily rain, e.g. Madagascar in figure 2a, which received 100 to 180mm on the first dekad, are substantially more accurate with errors of less than 10%. The total lack of stations in a very large part of the continent (figure 2a), especially in Angola, the Democratic Republic of Congo, Somalia and Sudan, and the problem of missing observations, are the main sources of the big errors in these areas (darker tones of gray in figure 2b). Parts of Angola for example, with an estimated amount of dekadal precipitation of 20-50 mm, are producing errors of as high as 100% and the tip of Somalia with an estimated amount of less than 10mm and an error of as high as 300%.

Kriging assigns zero values only by rounding or if the entire set of neighbouring data points within the range is

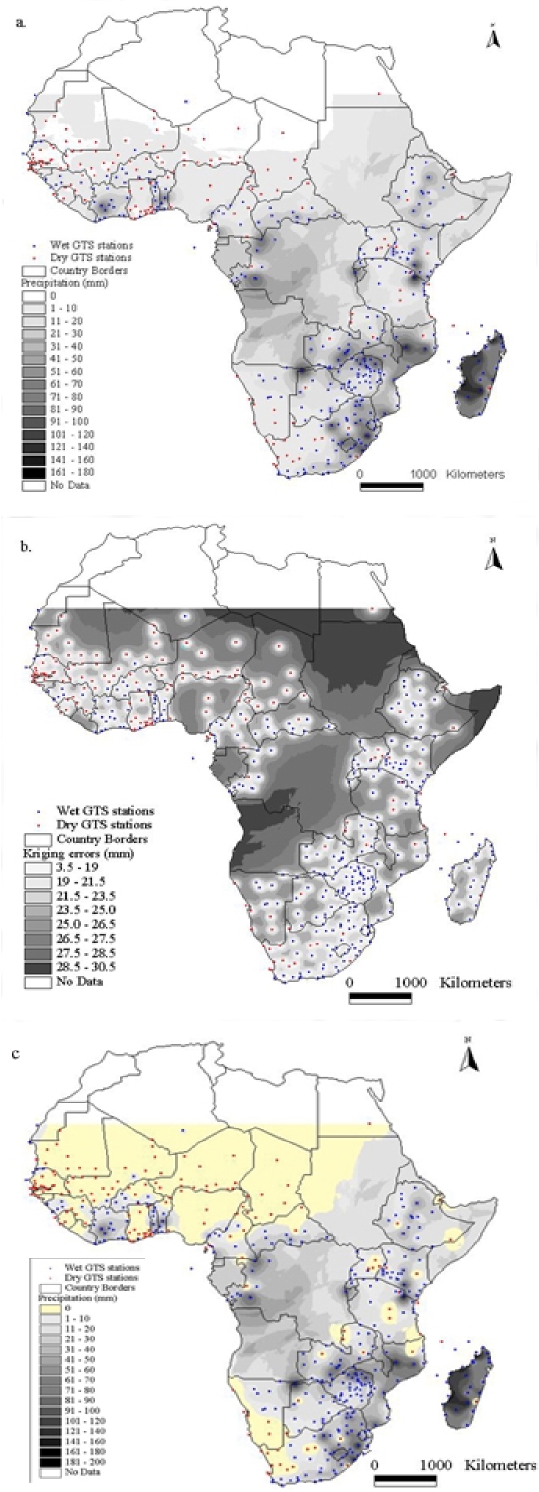

Figure 2: (a) Ordinary kriging output (b) respective kriging errors and (c) combined kriging output, 1st dekad March 1996. Blue dots are wet stations and red the dry ones.

also zero and thus spreads low rainfall values over dry areas. By applying combined kriging to the GTS data a more efficient delineation of the dry areas is possible. The combined kriging scheme consisted of three individual stages:

(a) the calculation of the indicator field (I(r) = 0 for r = 0, I(r) = 1 for r > 0) and the application of IK to the transformed binary data. The output of IK is valued between 0 and 1 and it equates to the probability of rainfall.

(b) the thresholding of the indicator kriging output to produce the rainfall occurrence field. The optimal thresholds were selected using statistical scores, namely the hit rate (HR), the false alarm rate (FAR), the accuracy of the forecasts (ACC), the probability of detection (POD) and the Kuipers skill score (KS). Ideally, for a perfect match between estimated and observed occurrence / absence of rainfall, ACC, POD, HR and KS should be 1 and the FAR zero (Stanski et al, 1989).

(c) the multiplicative combination of the binary rain/no-rain masks with the interpolated rainfall images created by block kriging. The CK output for the 1st dekad is shown in figure 2c, below the BK product (Figure 2a), where the effect of kriging to produce some rainfall amount over areas covered only by 'dry' stations can be seen. CK masks out these areas, shown in yellow in the figure 2c.

2.3 The FEWS Estimates

The alternative precipitation dataset used and compared to the interpolated GTS gauge data, was the satellite derived estimates. Work on producing these is performed for the United States Agency for International Development (USAID), Famine Early Warning System (FEWS) to assist in drought monitoring efforts for the African continent. The estimates - from now on referred to as the *FEWS estimates*- are freely available on the Internet via the United States Geological Survey (USGS) EROS Data Center, Climate Prediction Centre (CPC) which is a component of the National Centers for Environmental Prediction (NCEP) (Herman et al., 1997). The production of the estimates is based on Meteosat 5 satellite data, GTS rain gauge reports, model analyses of wind and relative humidity, and orography for the computation of accumulated rainfall. Meteosat 5 thermal infrared (IR) data at 5km pixel resolution is accessed every 30 minutes and then reformatted and converted to a geographical grid with a 0.1° spatial resolution. The spatial resolution of 0.1° was chosen for the estimate computations to correspond with the absolute positioning error of the satellite of approximately 10km. A preliminary estimate of accumulated precipitation is made based on the GOES Precipitation Index (GPI), an algorithm developed by Arkin and Meisner (1987). The GPI uses the duration of cold cloud tops over a region for the determination of accumulated precipitation by assigning 3mm of precipitation for each hour that cloud top temperatures are measured to be less than 235°K. The GPI estimate is corrected using a bias field that is calculated by incorporating the GTS observational data and fitting the biases to a grid using optimal interpolation, thus producing an estimate of convective precipitation. For the regions over which precipitation is due to orographic lifting and the clouds are relatively warm (top temperatures between 275°-235°K), the rainfall rate is estimated using a process which combines the relative humidity, wind direction and the terrain slope. Therefore, the combined technique incorporates rainfall from both the convective and stratiform cloud types producing a final estimate of total accumulated precipitation (Herman et al, 1997).

The FEWS estimate for the second dekad March 1996 is shown in figure 4b along with the interpolated one, derived from the GTS data with the combined kriging method (Figure 4a). The different datasets appear to have some qualitative similarities and some differences. In all three dekads, the two datasets seem to agree in both the amount and the spatial distribution of rainfall over certain areas, such as Madagascar and South Africa, and generally over areas where the gauge network is dense enough for kriging to produce reasonable results. The FEWS estimates of all the dekads give higher rainfall rates than those produced by kriging. Especially in central Africa, over parts of the

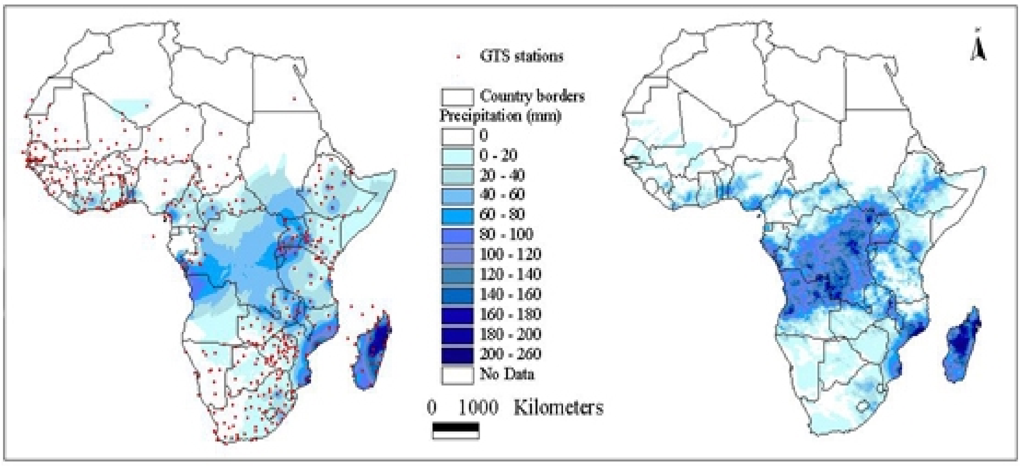

Figure 3: (a) Interpolated GTS data using combined kriging and (b) FEWS estimate, 2nd dekad March 1996

Democratic Republic of Congo, and Angola, rainfall estimated by FEWS is very high (i.e. around 200mm/dekad) in contrast to that estimated by kriging (i.e. around 60mm/dekad).

2.4 Comparison and Results

The different precipitation sets that were used for the comparison were the three dekadal interpolated GTS data and the three dekadal FEWS satellite estimates for March 1996. The comparison was carried out using a validation set of gauges, independent of those of the GTS network. It consisted of a very dense network of about 1800 stations in South Africa. Due to the high density of the validation gauge network, in most of the cases, a number of stations fell within the same 0.1° by 0.1° pixel of the areal estimates and as Lebel et al. (1987) point out, it is often more useful for a hydrologist to evaluate the error involved in areal rather than in point rainfall estimation. Therefore, areal 'ground truth' images were created from the validation sets in order to calculate a number of statistical parameters on a pixel-by-pixel basis. The daily South African data were summed to form the three dekads and interpolated using the combined technique of ordinary and indicator kriging. The experimental variograms were produced using a lag distance of 5km.The theoretical models were fitted to them visually. Cross validation was used to choose the appropriate models and CK was applied using a minimum number of 20 neighbouring stations. Kriging errors were low for the wet areas in the east of the country where for example, for precipitation amounts up to 140mm in the first dekad, RMSEs were less than 14mm or less than 10% of the estimated amount.

From the validation images, only those pixels that contained validation gauges were selected for the comparison of the interpolated GTS and the FEWS data. These were 1624 pixels in total. The following statistical parameters were estimated to measure the strength of the statistical relationship between the estimated values and the reference values: the bias, the linear correlation coefficient r (where r measures the confluctuation between estimated and measured value, and therefore it is not sensitive to a bias), the RMSE, the Nash Index or non-dimensional skill score i (where i is equal to 1 for a perfect estimate and equal to 0 for the best constant estimate, Murphy, 1995, Obled et al, 1994), and the scaled RMSE (the contribution of small observed precipitation values P_i to s-RMSE would be very large and therefore s-RMSE was computed only for P_i larger than 10mm, which was chosen so that a sufficient number of observed values could be used for the calculation of s-RMSE, Laurent et al, 1998).

Table 1 gives the error criteria for the three dekads of March 1996. The best score in each column is depicted in red. All techniques performed similarly. The most significant dekad with respect to precipitation totals in the validation area of South Africa is the first one since there is a much larger number of stations that received relatively high rainfall amounts (between 45 and 130mm per dekad and an average of 28.94mm per dekad, Figure 4). In this dekad, CK scored better in four of the five criteria and FEWS in the fifth. In the second dekad (mean = 13.92mm), CK had the best correlation coefficient, RMSE and scaled RMSE and FEWS the best bias and Nash index. Finally, in the 3rd, least rainy dekad (mean = 7.07mm), FEWS scored the highest correlation, the smallest bias and RMSE and CK the best scaled RMSE and Nash index.

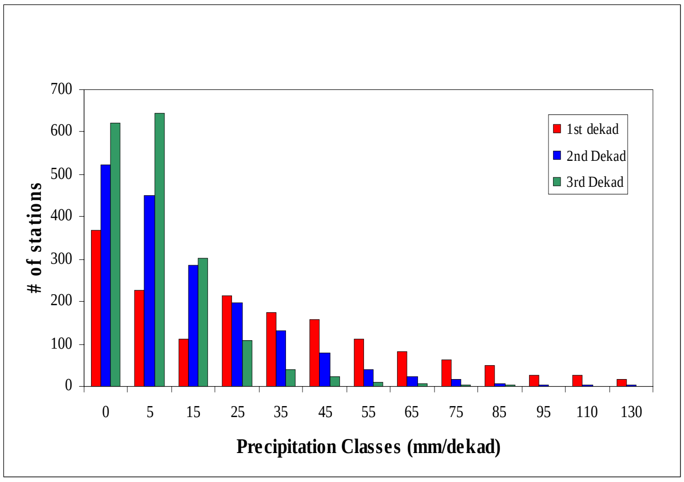

Figure 4: Frequency distribution of precipitation measured at the South African validation gauges

		Mean (mm)	Stdev (mm)	cor coef	bias	RMSE (mm)	s-RMSE	Nash Index
1 DEKAD	**SAF valid**	28.94	26.46					
	BK	30.08	22.00	0.78	0.04	21.16	0.52	0.07
	CK	29.41	22.72	**0.79**	**0.02**	21.16	**0.50**	**0.13**
	FEWS	33.27	21.74	0.75	0.15	**20.57**	0.67	0.10
2 DEKAD	**SAF valid**	13.92	15.49					
	BK	12.06	12.66	0.76	-0.13	10.98	0.52	0.27
	CK	11.74	12.91	**0.77**	-0.16	**10.80**	**0.51**	0.28
	FEWS	13.48	14.70	0.74	**-0.03**	11.31	0.63	**0.41**
3 DEKAD	**SAF valid**	7.07	8.63					
	BK	8.69	5.83	0.45	0.23	10.24	0.51	-2.09
	CK	8.49	6.05	0.46	0.20	10.24	**0.50**	**-1.87**
	FEWS	7.79	7.99	**0.55**	**0.10**	**8.54**	0.59	-0.14

Table 1: Error criteria estimated at the South African gauged pixels for the three dekads of March 1996. 'SAF valid' is the South African validation data and BK and CK are the block kriged and the combined kriged estimates, respectively.

In figure 5 measured precipitation is plotted against the dekadal estimated amounts for the three different estimates (BK, CK, FEWS). The numbers of the participating pixels per rainfall class are shown in red. All methods severely underestimate the larger amounts of precipitation. BK and CK perform similarly to FEWS only in the estimation of the smaller amounts of precipitation where there is very little difference between all techniques, but FEWS is better in the higher amounts where kriging appears to be insensitive to spatial rainfall variations. This can be explained by the inability of the semi-variances to represent the high spatial variability in the actual rainfall due to the insufficiency of the GTS network (Symeonakis et al, 1999). In general, the area selected for the validation is one where a significant number of GTS stations exist (n = 80) and the kriging errors are relatively low. In other parts of the continent however, the GTS network is very sparse and the number of station inadequate (e.g. in Angola, Sudan, etc) and as previously mentioned the kriging errors are very high. Therefore, a merging of the kriged with the satellite estimates appears as the most reasonable solution.

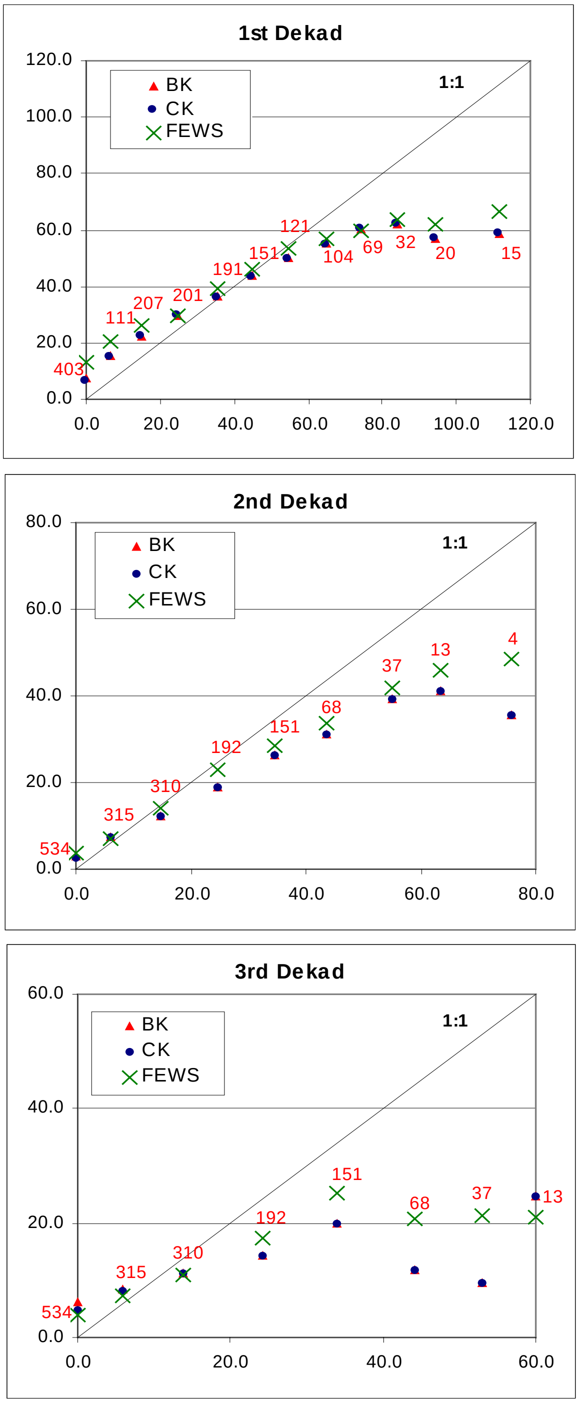

Figure 5: Measured against estimated precipitation at the S.African locations

2.5 Erosion Model Implementation

Using the two different rainfall datasets, dekadal erosion was estimated for the three dekads of March 1996. The erosion model used was the following (Drake et al., 1999a, Drake et al, 1999b):

$$E = k\, s^{1.67}\, of^{2}\, e^{-0.07\, vc} \qquad (2)$$

where: *E* is erosion (mm/dekad), *k* the soil erodibility coefficient, *of* is the overland flow (mm/dekad), *s* is slope and *vc* the vegetation cover. For the estimation of the soil erodibility coefficient, overland flow and the slope, see Drake *et al.*, (this volume). Vegetation cover was estimated using the NDVI images available from the Africa Data Dissemination Service (ADDS) on the Internet (http:// edcintl.cr.usgs.gov/ bin/ satform/ a=ndvi/ b=af). The NDVI is derived from data collected by the National Oceanic and Atmospheric Administration (NOAA) satellites, and processed by the Global Inventory Monitoring and Modelling Studies (GIMMS) at the National Aeronautics and Space Administration (NASA). The spatial resolution of the NDVI data is approximately 7.6km. The raw NDVI data contained numerous blank areas where there was cloud cover for the whole of the 10 day period. These areas were filled with the average values for the preceding and following dekads. Most of the images needed no ‘gap filling’ or just one averaging step, but a few needed up to three in order to become ‘cloud free’. Finally, a scaled NDVI (N^*) was used to estimate vegetation cover (Choudhury *et al.*, 1994), which is defined as:

$$N^* = (NDVI - NDVI_o) / (NDVI_s - NDVI_o) \qquad (3)$$

where $NDVI_s$ is the value of NDVI at 100% vegetation cover ($N^* = 1.0$) and $NDVI_o$ is that value for bare soil ($N^* = 0$). The index N^* has the advantage of being relatively insensitive to viewing angle, sensor drift, and uncertainties in atmospheric correction.

Figure 6 shows erosion estimated with the two different rainfall inputs for the second dekad of March 1996. Erosion estimated with the use of the satellite estimate (Figure 6b) is spatially more extensive than that estimated with the GTS data (Figure 6a). This can be attributed to the fact that in those areas the GTS network is very sparse, especially in Zaire and Angola. In most areas, the amounts of erosion estimated with the FEWS data are higher. This is expected, since rainfall is also higher: maximum rainfall for this specific dekad estimated by FEWS is 250mm, whereas with kriging it is 191mm. That leads to estimated maximum amounts of overland flow and erosion of 136mm/dekad and 147mm/dekad, which are about three times higher than those estimated with the kriged images (53mm/dekad and 57mm/dekad, respectively).

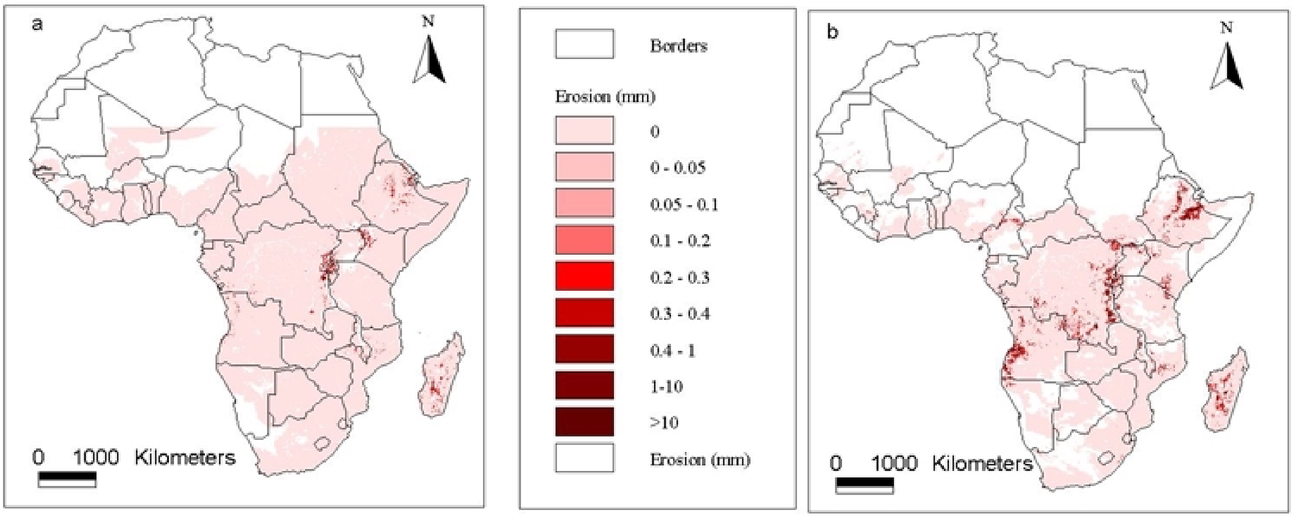

Figure6: Erosion for the 2nd dekad March 1996, estimated with (a) the GTS CK interpolation scheme and (b) FEWS

2.6 Conclusions

FEWS estimates are similar or slightly worse than the interpolated gauge data when the GTS network is dense and better when it is sparse, especially in the estimation of the higher amounts of rainfall, which play an important role in soil erosion. They are also a freely-available, ready-to-use product, involving no pre-processing. Hence, it is concluded that they are an attractive datsaset to use for the operational modelling of processes such as erosion, and especially in the developing areas, such as sub-Saharan Africa, where resources are scarce. The erosion model used is highly sensitive to the precipitation input and ideally, a combination of the best aspects of both satellite and interpolation methods in a single method should provide the solution to accurate precipitation estimation. Huffman et al. (1997) combine satellite and ground-based techniques in the production of the global precipitation climatology project (GCCP) and Grimes et al. (1999) merged METEOSAT estimates with kriged estimates obtained from rain-gauges, a process which yielded more reliable results both for the mean areal rainfall and its spatial distribution. Therefore, the two techniques should not be viewed as alternatives, since using each in isolation discards potentially useful information in the other.

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