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New procedure in developing adjustment algorithm for harmonizing historical climate data sets

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ABSTRACT

Existing historical weather data in most developing countries have gaps as a result of stolen or old equipment and shortage of trained observers. This confounds analysis of climate change trends, extreme events and climate risks. In order to grapple with the problem, automatic weather stations and weather generating software have been routinely used as alternatives to fill data gaps. This study therefore seeks to analyze the statistical association between the various datasets as a way of developing adjustment algorithms in order to generate a single, fit-for-purpose climate data set. Four weather stations from Uganda's four major agro-ecological zones were purposively selected for the study; Characteristic daily weather data (1991–2013) were then obtained from the UNMA archives. Adcon telemetry automatic weather data (2010-2013) were acquired from the NARO database. Software generated datasets were attained from Weatherman and MarkSim programs. These data sets were re-arranged into suitable formats using RClimDex. Pearson's product moment correlation (r) and Simple linear regression (R-squared) were used to measure strength of linear relationship for rainfall series; Paired Samples T-test was used to make pair-wise comparisons for temperature data (at 5% significance level). There was a strong, positive, statistically significant relationship between the observed and simulated/automatic rainfall data ($r>0.7$, $p<0.05$) with about 60% of the variation explained by the fitted model. There was no significant difference in mean temperature records between generated/automated weather stations and manually observed ones ($p>0.05$). It is therefore recommended to use weather generators and automatic stations in filling out weather data gaps and harmonizing climate data.

Key words: Historical, Meteorological data-gaps, Original observations, Software generated datasets, Automatic weather data, Comparison, Correlation, Single fit-for-purpose dataset.

Abbreviations: UNMA – Uganda National Meteorological Authority, NARO – National Agricultural Research Organization.

INTRODUCTION

Accurate and reliable weather and climate information are important in many areas of society such as in government, economy, agriculture, tourism, water resources, and emergency response, to name a few. However, long-term meteorological data is largely lacking in most developing countries. The observation and analysis of meteorological data faces difficulties linked to the fragile network of weather stations and gaps in their

Table 1. Details for the four locations used in this study (E.A Meteorological Department, 1975).

Station	Latitude (^{0})	Longitude (^{0})	Altitude (ft)
Gulu	2.75	32.3333	3630
Kasese	0.1833	30.10	3600
Serere	1.5167	33.45	3738
Mbarara	-0.5833	30.5833	4900

records due to poorly equipped facilities, a lack of investment in infrastructure and personnel, and local conflict. Given these difficulties in the meteorological record, climate models have been used to provide a more useful indication of future climate trends (McSweeney *et al.,* 2007).

Climate observing stations such as rain-gauge, synoptic; managed by the National Meteorological Authorities have been used for over a century to provide temperature and precipitation information to operational weather forecasters, researchers, and the public. The climate observing stations are the backbone of climate change studies and have the advantage of long periods of record (with several providing over 100 years of data). Their data are thus well established and generally accepted as invaluable data sources in the climate community, often providing a good density of coverage. Currently, there is a growing trend of state-based automated networks that report hourly observations for a wide range of parameters. A number of these automated sites are located at agricultural research stations and provide hourly observations for atmospheric and soil parameters (Holder *et al.,* 2005).

Some global and regional climate databases do exist (NCDC, 1994; IIMI, 1997; Texas A&M Univ. Systems, 1998). Currently, however, such products are limited in one or more of the following ways: Lack of interpolation facilities, meaning that analysis can be performed only for sites where data exist; Limited number of weather variables in the database, precluding the running of certain types of models; Limited number of years of historical data database, severely restricting the inferences that can be drawn concerning temporal weather variability at the site in question; and Inappropriate temporal scale for many research applications, where scales of a month 10-d totals may be insufficient.

Thus, the objective of this study is to find out how the automated and simulated observations relate to manual station data in terms of accuracy and precision, which is a key step to be considered before filling gaps in historical weather data.

PROBLEM

Observations from manual weather stations are an important source of weather data that are used in evaluating weather and climate models for developing agricultural early warning information. However, there are data gaps alluding from these stations as a result of old equipment, system breakdown, theft and shortage of trained personnel. Increasingly, there has been the introduction of the ADCON Telemetry automated weather stations within predefined agro-ecological zones. More so, weather generating software programs such as MarkSim and Weatherman have been developed and can simulate both Grid Independent and dependent Climate Data. Assessing the compatibility of the automated and / or generated data with the original station data is an important issue in developing regional climate information and for data continuity. Therefore, it is critical to understand how the recent automated as well as simulated observations compare with the historical manual observations. Through these comparisons, this study proposes a new procedure in bridging the existing data gaps in order to produce a single fit-for-purpose data set.

METHODOLOGY

Daily historical rainfall, minimum and maximum temperature data for the period 1991–2013 were obtained for four purposively selected weather stations from the Uganda National Meteorological Authority archives. These stations are representative of the four major agro-ecological zones in Uganda as described and shown below:

- Gulu – Northern short grasslands zone
- Kasese – Western tall grasslands zone
- Serere – Eastern high altitude zone
- Mbarara – Pastoral dry to semi-arid rangelands zone

At each location, both manual and automated weather stations are found within the same vicinity (at agricultural research stations). Table 1 shows the latitude–longitude for each selected station.

The addVANTAGE Pro software and telemetry devices work together to form the Adcon system; It was Established in 1992 and has since 2011 been a member of the OTT Hydromet Group. It has its Headquarters in Klosterneuburg - Austria (north of Vienna). Automated weather data from Adcon stations are available online (http://addvantage.adcon.at:8080). From the addVANTAGE Pro 6.4 User Guide (2013), Adcon can be defined as a system that allows you to:

1. Measure certain parameters over a predefined area
2. Send those parameters over relatively large distances

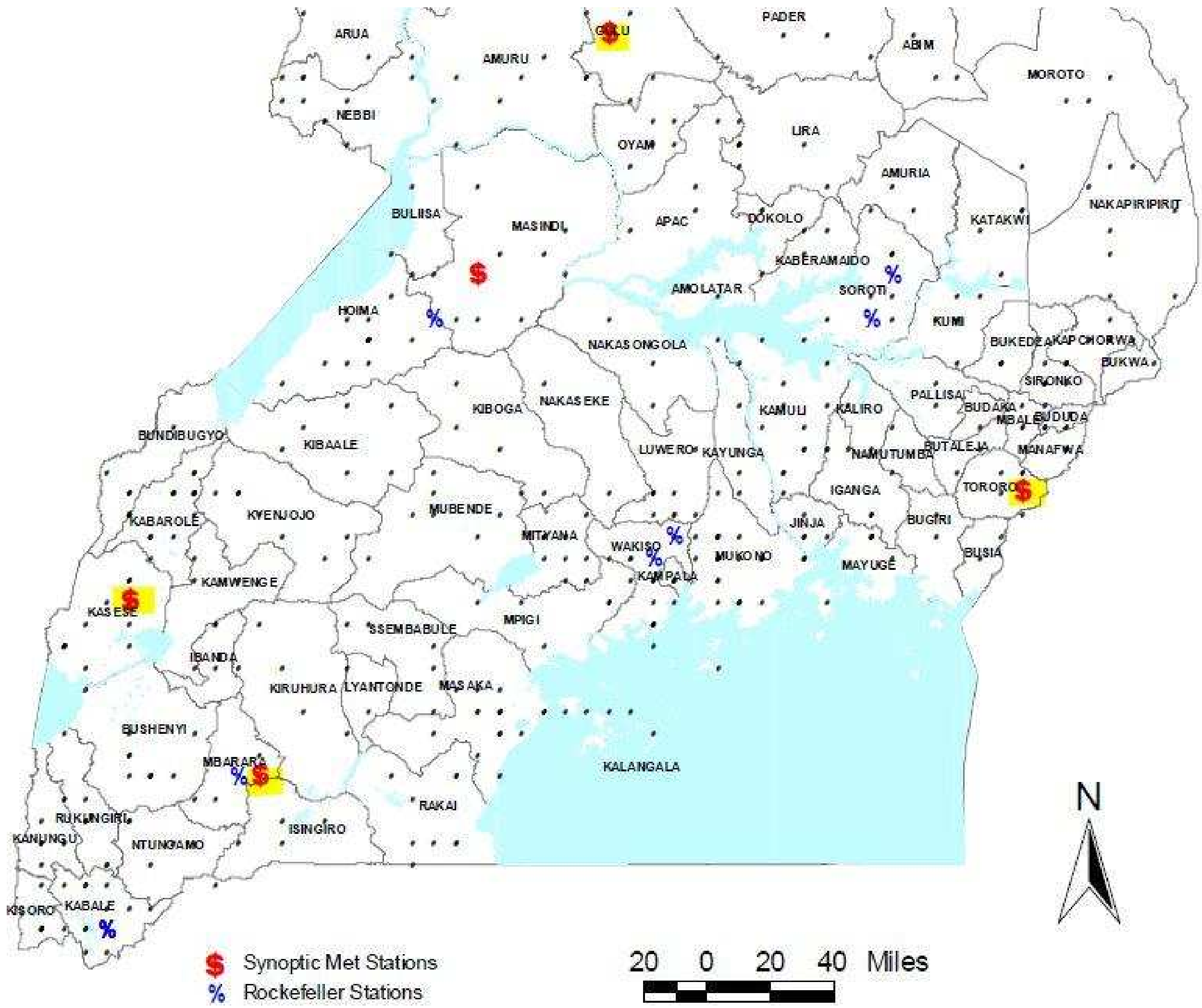


Figure 1. Locations for the weather observing stations used in the comparison study (USAID, 2013).

to a central point
3. Process the parameters as needed for various applications such as agriculture, meteorology, irrigation control, water management, and environmental analysis
Adcon telemetry automatic weather data for the period 2010-2013 for co-located stations were obtained from the National Agricultural Research Organization database. Since these data are available on hourly basis, adjustments for observation times had to be made by taking into account the official observation times analogous to the manual stations', that is 15:00 hrs (for max temperature) and 09:00 hrs (for min temperature and rainfall).

Holder *et al.,* (2005) suggest that a majority of the manual stations record observations for a particular calendar date at 0900 or 1500 rather than at midnight; that is, for example, the data recorded for a certain date would be the precipitation totals and temperature extremes for the 24-h period beginning at 0900h the previous day and ending at 0900h on the current date. Thus, the high and low temperatures that they record may not actually be for the date on which they were recorded; they can be off by a day. Such an overlap between the days is also seen in the daily rainfall totals. For morning observation times, rainfall totals can be generally improved by shifting daily rainfall totals back one calendar day. To correct rainfall for observation time, however, hourly rainfall records are from automated stations are summed up. If, for example, a manual station records its data at 1500, hourly records for the corresponding automatic station are used to obtain the 1500 to 1500 rainfall totals. If any hour of data is missing from an automatic station, that 24-h period is not used. Therefore, the time of observation needs to be accounted for in order to ensure accurate comparison of the two datasets.

Guttman and Baker, (1996) developed one particular analysis for data from the Automated Surface Observing System (ASOS) and the Cooperative Observer Program

(COOP), both maintained by National Weather Service (NWS). They concluded that, even though differences in sensors and measurement approaches cause variability in the datasets, the most significant differences between the two datasets are caused by the distance separating the stations and from the differences in land usage and topography that are associated with the separation in the two measurements. Data in-homogeneities were found with stations separated by distances as small as 500 m, whereas consistent data was found between two particular stations that were 0.25 miles (~400 m) from each other but had similar site characteristics, such as terrain and land use. The collocated automated networks and climate observing stations are therefore ideally suited to address the issue of how similar the manual and automated data are in developing climatology for rainfall and temperature information, and hence are considered in our analysis. The collocation of the station sites also helps to reduce siting errors, which are of critical importance in assessing regional changes in these parameters (Davey and Pielke 2005).

Jones and Thornton, (2000) describe MarkSim as a software package that generates daily weather data for Latin America and Africa. The program is based on a stochastic weather generator that uses a third-order Markov process to model daily weather data. The model has been fitted to data from more than 9200 stations with long runs of daily data throughout the world. The climate normals for these stations were assembled into 664 groups using a clustering algorithm. For each of these groups, rainfall model parameters are predicted from monthly means of rainfall, air temperature, diurnal temperature range, and station elevation and latitude. The program identifies the cluster relevant to any required point using interpolated climate surfaces at a resolution of 10 min of arc (18 km^2) and evaluates the model parameters for that point. The application is still limited only to Africa and Latin America.

The third-order Markov rainfall model fits individual station data very well (Jones and Thornton, 1993), for comprehensive testing of the model for three sites in the tropics. However, the interpolation system is only as good as the inter-polated surface. One type of problem occurs where the interpolated surface is plainly wrong. This may be because of errors or gaps in the data and in the interpolation method. A mapping of the sites from the calibration data set of more than 9200 stations reveals significant gaps where sufficiently complete and long-term data are not readily available. Currently, it is difficult to gain access to data for Sudan, Uganda, Zaire, Angola, Nigeria, Venezuela, and a significant list of other countries. Some countries are represented by very few stations. For large countries, this can vastly underestimate the climatic diversity present. Although much effort has been spent on preparing the surfaces to be free of data error, in practice this is extremely difficult to achieve. Such errors can be corrected over time. Other errors may occur in situations where the underlying digital elevation model is inadequate, and estimates are produced using incorrect elevation data.

Daily weather data commonly used in simulation models of agricultural or ecological systems are sometimes incomplete, frequently contain errors, and are often in an inconvenient format. The WeatherMan is a user-oriented software package designed to assist in preparing daily weather data for use with simulation models. The software can import or export daily weather files and convert the data to desirable units. Data are checked and flagged for possible errors on import. Several techniques are available for filling in missing values and erroneous data on export. WeatherMan also contains two methods (WGEN and SIMMETEO) for stochastically generating sequences of daily weather data. Both methods can be parameterized from the daily data and the second method uses monthly means from any secondary data source. Summary statistics of raw and generated data can be graphed or presented in tables (Pickering *et al.,* 1994).

However, stochastic weather generators used most frequently with agricultural and ecological simulation models tend to under predict inter-annual variability of generated sequences of precipitation (Gregory *et al.,* 1993; Jones and Thornton, 1993; Katz and Parlange, 1998; Wilks, 1999) and other variables (Mearns *et al.,* 1996; Semenov *et al.,* 1998; Mavromatis and Hansen, 2001). The use of generated sequences of weather data generally results in under prediction of variability, and sometimes biased prediction of the mean values, of output of agricultural or hydrological simulation models (Richardson, 1985; Jones and Thornton, 1993; Semenov and Porter, 1995; Mearns *et al.,* 1996; Mavromatis and Jones, 1998).

Once the data corrections and quality control checks are performed, data points from corresponding days are compared using mean error (ME), mean absolute error (MAE) and root-mean square error (see Wu *et al.,* 2005), as well as Pearson product–moment correlation (*R*).
Software generated datasets were obtained from Weatherman and MarkSim programs. These data sets were then re-arranged into suitable formats using RClimDex. Monthly summaries of all the data sets were then obtained, that is: monthly total rainfall and mean monthly temperature (max and min). Pearson's product moment correlation (r) and Simple linear regression (R-squared) were used to measure the strength of the linear relationship between monthly summaries of rainfall data; Paired samples t-test on the other hand was used to make pair-wise comparisons for monthly mean temperature data. The comparison was done in two phases; one between generated (Weatherman and MarkSim) and actual (station) data, the other between automatic station data and manual station data. All comparisons were assessed at 95% confidence level using SPSS 18.

Assuming normality of observed series, the simple linear model fitted for rainfall observations was: $y = a + bx + e$; where y = simulated or automated, x = manual station, e = error, b = slope (change in y as a unit change

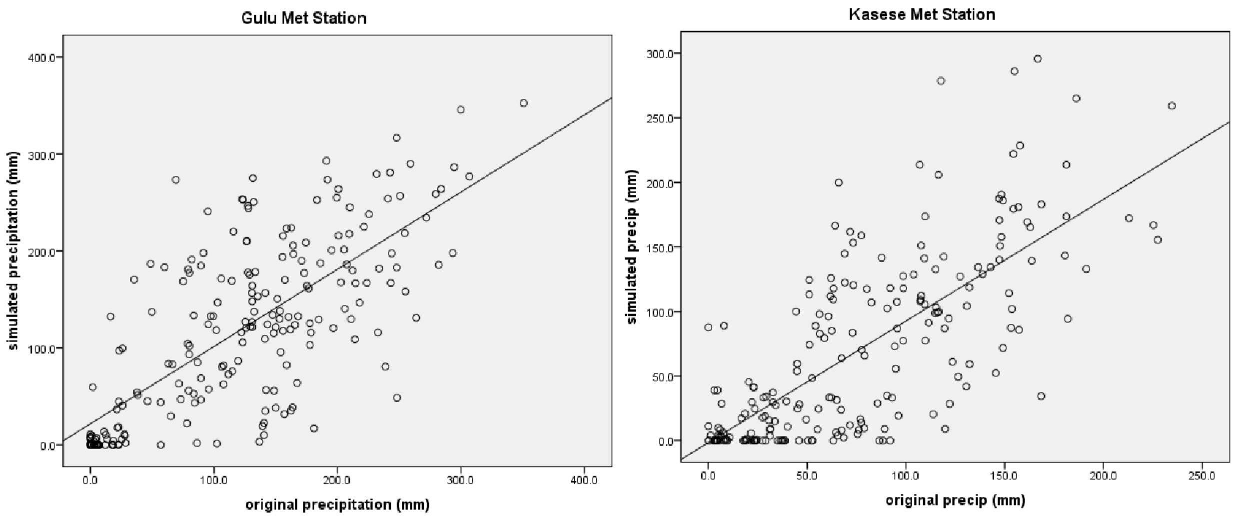


Figure 2. Comparison between original and simulated monthly rainfall data sets (MarkSim).

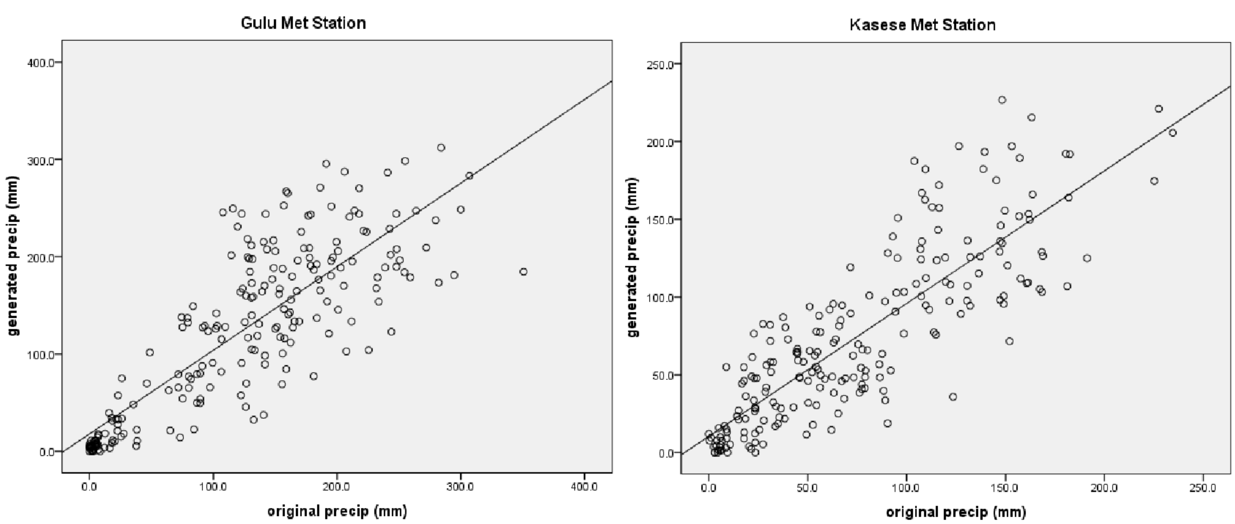


Figure 3. Comparison between original and generated monthly rainfall data sets (WeatherMan).

in x). R-squared is the amount of variation explained by model.

DISCUSSION OF FINDINGS

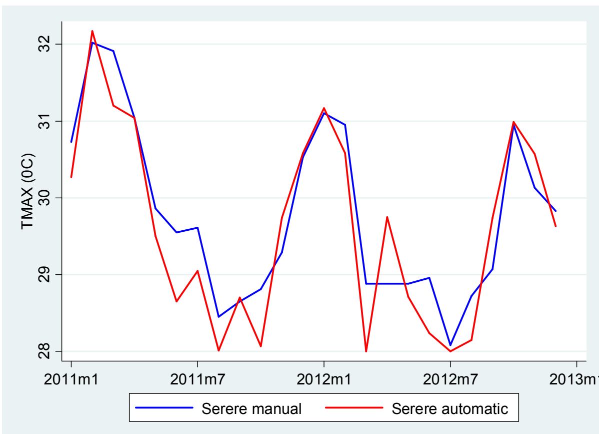
For both stations, a positive relationship was exhibited between the manually recorded monthly rainfall data and the generated monthly rainfall.

Nnaji, (1999) identified key primary climate controls in developing statistical models for precipitation forecast. The input consisted of time series of ocean-atmospheric variables with thirty four years of data namely, sea surface temperature, sea level pressure, oscillation index, temperature and historic rainfall. Using synoptic stations, Comparisons were made for observations of maximum temperature, minimum temperature and total rainfall amounts at monthly periods for four different collocated weather stations. Manually observed monthly rainfall data recorded at both Gulu and Kasese stations were found to relate positively to the simulated monthly rainfall.

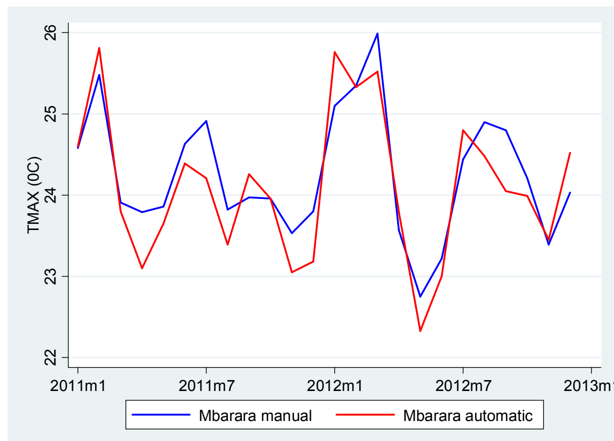
fluctuation in rainfall was determined and the resultant trend modeled by least square multiple regression. By means of Pearson's product moment correlation, while testing for significance of correlation coefficients at different rainfall lags, an analysis of association between the identified climate forcing agents and rainfall indicated that different combinations of climate agents actually force rainfall. By employing identified climate agents in rainfall forecast, seasonal and monthly models can be

Table 2. Correlation between actual and generated monthly precipitation.

		OBSERVED (STATION)					
		GULU			KASESE		
	Pairs (N)	Corr. (r)	Sign. (p)	R sqr (%)	Corr. (r)	Sign. (p)	R sqr (%)
MARKSIM	214	0.729	0.000	53.1	0.736	0.000	54.2
WEATHERMAN	214	0.829	0.000	68.7	0.841	0.000	70.7
		MANUAL (STATION)					
		SERERE			**MBARARA**		
	Pairs (N)	**Corr. (r)**	**Sign. (p)**	**R sqr (%)**	**Corr. (r)**	**Sign. (p)**	**R sqr (%)**
AUTOMATIC	24	0.860	0.000	74.0	0.872	0.000	76.0



Max temperature at Serere station



Max temperature at Mbarara station

Figures 4. Relationship between manually observed and automatic station Maximum temperature records.

derived. In particular, standardized seasonal model yields the least error component. It was shown that the standardized seasonal model successfully improved forecast by about sixty six percent.

For this study, analysis goes beyond rainfall prediction. It highlights how temperature data can be forecast using stochastic weather generators or automatic weather station data. This is achieved by testing for significant deviations in averages from manually observed temperatures. The T-test used here is deemed most appropriate for this task.

In validating Met&Roll-1, a surface weather generator which may stochastically generate daily series of four weather characteristics, tests were done to examine its ability to reproduce the stochastic structure of daily weather series. In other words, the statistics including means, variances, frequency of occurrence of extremes, correlations and lag-correlations between variables derived from the synthetic data were tested to check whether they statistically insignificantly differed from those derived from the observed data. Sufficiently long (30 years for testing variability of monthly and annual means) synthetic time series were generated for the tests to be well resolute. It was found that the generator well preserves some features of the stochastic structure of the series (Dubrovsky, 1997).

The added advantage of this study is the validation of one other source of climate data. Not only does is look at stochastic weather generators (MarkSim and WeatherMan) but also assesses the accuracy of automatic Weather Stations (AWS) through statistical comparisons while using more than one test statistic.

Statistical Comparison

MarkSim: There was a strong, positive, statistically significant relationship between manual station and simulated monthly rainfall data at both Gulu and Kasese stations ($r > 0.7$, $p < 0.05$). In other words, an increase in rainfall amounts recorded at the manual stations implied an increase in the corresponding simulated rainfall. More so, at both stations, slightly more than a half of the variation in the simulated data was explained by the model (R-squared > 50%).

WeatherMan: For both stations, a very strong, positive, statistically significant relationship was exhibited between actual and generated monthly rainfall data ($r > 0.8$, $p < 0.05$). In other words, an increase in rainfall recordings at

Table 3. T-test for differences in monthly average **max** temperature.

			Statistic			Tests for differences			
	Station	**Comparison**	**Pairs (N)**	**Mean (°C)**	**StdDev**	**difference in means (d)**	**t**	**df**	**p-value**
MARKSIM	Gulu	Simulated	216	28.9905	1.74184	-0.79710	-3.782	215	0.016
		Original	216	29.7876	1.31525				
	Kasese	Simulated	216	29.9023	1.29409	-0.69850	-4.068	215	0.025
		Original	216	30.6008	1.07199				
WEATHERMAN	Gulu	Generated	216	29.6137	1.89839	-0.17385	-1.348	215	0.079
		Original	216	29.7876	1.31525				
	Kasese	Generated	216	30.4064	0.85988	-0.19443	-2.253	215	0.065
		Original	216	30.6008	1.07199				
AUTOMATED	Serere	Manual	24	29.8262	1.13482	0.22830	2.500	23	0.082
		Automatic	24	29.5979	1.27518				
	Mbarara	Manual	24	24.2487	0.78115	0.14748	1.819	23	0.094
		Automatic	24	24.1012	0.90925				

***StdDev** stands for standard deviation; **df** stands for degrees of freedom.*

the manual stations implied an increase in the generated rainfall as well. Furthermore, at both stations, most of the variation in the generated data was explained by the fitted model (R-squared > 70%).

Automated stations: A very strong, positive, statistically significant relationship was found between manually and automatically observed monthly rainfall data at both Mbarara and Serere stations ($r > 0.8$, $p < 0.05$). In other words, an increase in the manually recorded rainfall at these stations implies an increase in the automatically recorded rainfall. In addition, at both stations, most of the variation in automatic station data was explained by the model (R-squared > 70%).

Maximum Temperature

From the line graphs above, the monthly maximum temperature records obtained from automated stations were found to closely approximate those from manual observation stations.

MarkSim: There was a significant difference ($|d| > 0.6°C$, $p < 0.05$) between the simulated mean monthly maximum temperature and the manually observed one at both Gulu and Kasese stations, implying that max temperature simulated by MarkSim was not a good estimate of the actual max temperature.

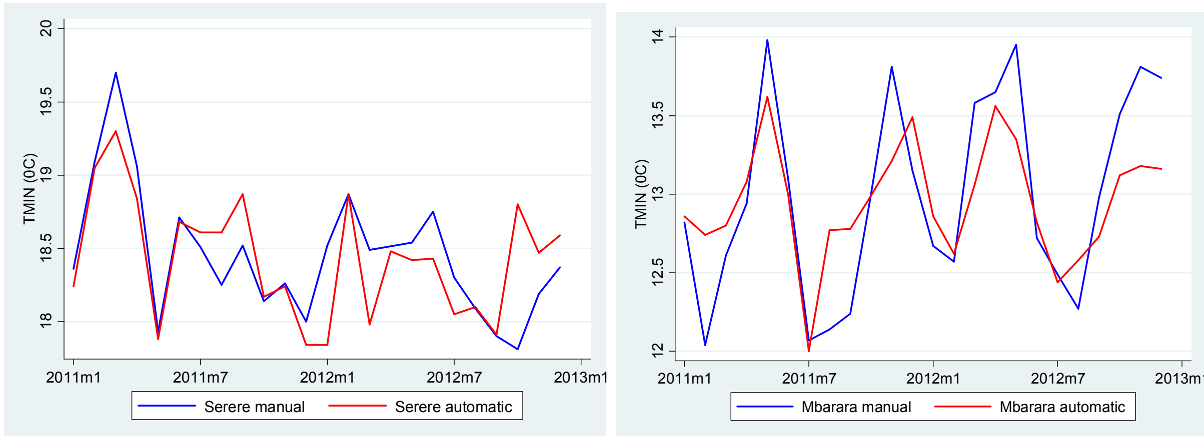
Weatherman: The generated mean monthly maximum temperature at both Gulu and Kasese stations did not significantly differ from the manually recorded one ($|d| < 0.2°C$, $p > 0.05$). In other words, max temperature generated by WeatherMan was indeed a good estimate of the manually observed one.

Automated stations: The automatically recorded mean monthly maximum temperature at both Serere and Mbarara stations did not exhibit a significant difference from the manually obtained one ($|d| < 0.25°C$, $p > 0.05$); thus making the automatically recorded max temperature a good estimate of the observed max temperature.

Minimum Temperature

From the line graphs above, the monthly minimum temperature recorded by automated stations was found to be a close approximation of similar observations from manual stations. This was indicated by a similar pattern depicted by both series over time at both stations.

MarkSim: At both Gulu and Kasese stations, a significant difference ($|d| > 0.9°C$, $p < 0.05$) was observed between the simulated mean monthly minimum temperature and



Min temperature at Serere station *Min temperature at Mbarara station*

Figure 5. Relationship between manually observed and automatic station Minimum temperature records.

Table 4. T-test for differences in monthly average **min** temperature.

			Statistic			**Tests for differences**			
	Station	**Comparison**	**Pairs (N)**	**Mean (°C)**	**StdDev**	**difference in means (d)**	**t**	**df**	**p-value**
MARKSIM	Gulu	Simulated	216	16.9348	1.35281	-0.90170	-10.97	215	0.000
		Original	216	17.8365	0.71875				
	Kasese	Simulated	216	16.9166	1.28360	-0.98420	-4.936	215	0.000
		Original	216	17.9008	0.80530				
WEATHERMAN	Gulu	Generated	216	17.7009	0.93956	-0.13562	-1.685	215	0.094
		Original	216	17.8365	0.71875				
	Kasese	Generated	216	17.7139	1.04666	-0.18688	-2.034	215	0.072
		Original	216	17.9008	0.80530				
AUTOMATED	Serere	Manual	24	18.4722	0.38943	0.17736	1.591	23	0.090
		Automatic	24	18.2949	0.43480				
	Mbarara	Manual	24	12.9927	0.63360	0.04202	0.524	23	0.126
		Automatic	24	12.9507	0.36777				

***StdDev** stands for standard deviation; **df** stands for degrees of freedom.*

the manually recorded one, implying that the min temperature simulated by MarkSim was not a good approximation of the actual min temperature.

Weatherman: At both stations, the generated mean monthly minimum temperature was not significantly different from the manually observed one (|d| < 0.2°C, p > 0.05); thus making the min temperature generated by WeatherMan a good approximation of the actual min temperature.

Automated stations: Similarly, at both Serere and

Mbarara stations, the automatically recorded mean monthly minimum temperature did not significantly differ from the manually obtained one ($|d| < 0.2^oC$, $p > 0.05$). This implied that the automatically recorded min temperature was indeed a good approximation of the manually observed one.

CONCLUSIONS

Automated Weather Stations (AWS) as well as Weather generators present a significant augmentation to the already established Manual Observation Stations (MOS), and many fields of meteorology can benefit from their integration. This creates a denser network of data and provides valuable hourly data to supplement daily data. However, data from the identified sources can only be integrated after appropriate quality checks. Adjustments for differences in data observation time and location need to be taken into consideration to account for inherent system biases. More so, statistical comparisons need to be made to assess validity of data sources

Pearson's correlation coefficient and Paired t-test are used to determine if there are significant relationships and differences in total rainfall and mean temperature respectively, between observed data and automated-generated data. Results show that rainfall data from AWS relates strongest ($r>0.8$, $p<0.05$) to the one originally recorded at MOS as compared to data simulated by weather generating programs. However, in regard to the stochastic weather generators, WeatherMan ($r>0.8$) generated better observed rainfall series than MarkSim ($r>0.7$). Both minimum and maximum temperature differences were insignificant for AWS ($d<0.25$, $p>0.05$). More so, the differences between simulated and observed temperature records were also lesser for WeatherMan ($d<0.2$, $p>0.05$) as compared to MarkSim ($d>0.6$, $p<0.05$). This study therefore concludes that with simple corrections, comparisons between manual and automated-generated data should be embraced as a necessary procedure in validating several sources of climate data and in developing a single fit-for-purpose harmonized climate data set.

It is recommended that for bridging gaps in historical weather data, records from already installed automatic stations should be given priority. In case these are unavailable, weather generating programs particularly WeatherMan can be used as a substitute in order to develop a continuous climate data set. It is from this input that climate risk analysis, scenarios and crop modeling can be derived for enhancing Climate Change Adaptation and Food Security Analysis.

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