

Short title: Risk of root rots in common beans in East Africa

Full title: Assessing the risk of root rots in common beans in East Africa using simulated, estimated and observed daily rainfall data

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1 Summary

This paper seeks to establish the concept that the analysis of high temporal resolution meteorological data adds value to the investigation of the effect of climatic variability on the prevalence and severity of agricultural pests and diseases. Specifically we attempt to improve disease potential maps of root rots in common beans, based on a combination of inherent susceptibility and the risk of exposure to critical weather events. We achieve this using simulated datasets of daily rainfall to assess the probability of heavy rainfall events at particular times during the cropping season. We then validate these simulated events with observations from meteorological stations in East Africa. We also assess the utility of remotely sensed daily rainfall estimates in near real time for the purposes of updating the risks of these events over large areas and for providing warnings of potential disease outbreaks.

We find that simulated rainfall data provide the means to assess risk over large areas but there are too few datasets of observed rainfall to definitively validate the probabilities of heavy-rainfall events generated using rainfall simulations such as those generated by MarkSim. We also find that selected satellite rainfall estimates are unable to predict observed rainfall events with any power, but data from a sufficiently dense network of rain gauges is not available in the region. Despite these problems we show that remotely sensed rainfall estimates may provide a more realistic assessment of rainfall over large areas where rainfall observations are not available, and alternative satellite estimates should be explored.

2 Introduction

Pests and diseases are a major cause of low productivity in crops and livestock worldwide (Oerke et al., 1995;) and particularly in Sub Saharan Africa where there are few resources to invest in protection in the form of pesticides, vaccines etc (Williamson et al., 2008; Homewood et al, 2006; Otsyula et al., 2004).

A number of pest and disease outbreaks are triggered by climatic factors (Table 1). For some biotic stresses the general seasonal conditions are most important while for others the timing of rainfall or dry spells within a season is crucial when they coincide with susceptible periods of plant or animal growth - such as in the case of aflatoxins (*Aspergillus spp.*) in groundnuts (*Arachis hypogaea*). Risk management is an integral component of coping with the effects of natural hazards (Baez and Mason, 2008) and the use of meteorological data is among the risk management strategies available to producers to help assess the probability of events that foster the transmission or prevalence of pests and diseases. The analysis and monitoring of extreme weather events, and where possible their prediction, can help researchers, extension agents, farmers and pastoralists invest in the most appropriate risk management strategies (Cooper et al., 2008) and prepare for the effects of changes in climates (Garrett et al., 2009).

Table 1 somewhere here

In this paper we focus on one example of a disease which is triggered by particular climatic conditions. The fungal disease bean root rot complex (*Pythium spp.*, *Fusarium spp. phaseoli*, *Rhizoctonia solani*) has a major impact on bean yields throughout its range in Africa (Otsyula, 1994). Each year, the disease affects the livelihoods of millions of people who depend on beans for food security and income (Wortmann et al., 1998).

The impact of the disease varies through time. In some years, incidence is relatively low, in others entire crops are wiped out (CIAT, 1992). The distribution and severity of the disease throughout the East African region is related to the intensity of bean cultivation, the human population density, soil properties and rainfall (Otsyula and Buruchara, 2001; Wortmann et al., 1998). The disease varies widely with location; one area may be disease-free while others are hit badly (Buruchara and Rusuku, 1992). This heterogeneity obstructs adaptation of protective practices, because broad remedies become cumbersome and inefficient (Ojiem, 2006). In addition protection may penalise yield or quality; resistant or tolerant bean varieties may not be preferred (Otsyula et al., 2003), or seed producers are unable to respond to demand for resistant varieties (Otsyula et al., 2004). Cultural practices to cope with disease risk respond slowly to variations in actual risk of disease or where causality is poorly understood (Spence, 2003), which may vary significantly during a season depending on growing season rainfall (CIAT, 1992).

Maps showing the importance of root rots were produced in 1998 based on expert knowledge and some modelling of soil, human population and farming system data (Wortmann et al., 1998), but climatic factors were not considered. Root rots infestation requires free water in the root-zone of the soil since the most important pathogen (*Pythium spp.*) is water-borne (Piecarka and Abawi, 1978). Research in Rwanda over three growing seasons observed that three-day rainfall totals of at least 50mm and up to 130mm coincided with plant loss rates of up to 55% (of susceptible varieties). The one season where no 3-day rainfall events greater than 30mm were observed experienced far lower plant losses (CIAT, 1992). The timing of the events was crucial (Abawi et al., 1985) with the period between 17 and 38 days after planting being the most sensitive (Pers. Comm., Buruchara, 6th September 2005).

New datasets and tools developed since the creation of the original maps of root rot incidence allow for the more accurate representation of population and land use and for the simulation and analysis of daily weather events (Cooper et al., 2008; Jones et al., 2002).

The objectives of the research presented in this paper are twofold. The first objective is to produce disease potential maps, based on a combination of inherent susceptibility and the risk of exposure to critical weather events within a general vulnerability framework (Alwang et al., 2001). Susceptibility to root rots is determined by up to date and high resolution spatial datasets of human population density and the intensity of bean

cultivation in bean producing areas of East Africa. Risk of exposure maps show the likelihood of experiencing rainfall events during specific periods of the growing season in susceptible areas. The output of this objective allows accurate targeting of resistant cultivars or other husbandry techniques throughout the region, and quantitative insights from new models showing current and likely future incidence.

The second objective is to assess the possibility of within season monitoring of rainfall events over large areas using satellite-based rainfall estimating instruments. This would offer a flexible basis on which to improve predictive models through the continued acquisition of rainfall data especially when combined with information on the severity of root rots in any particular area.

3 Materials and Methods

This study concentrated on the East African countries most affected by root rots in beans: Rwanda, Burundi, the Democratic Republic of the Congo, Uganda, Tanzania and Kenya. Further targeting was achieved by the development of a new map of areas susceptible to root rots in beans based on population density and the intensity of bean cultivation.

The probability of experiencing heavy rainfall events in the early growing season was assessed at key locations within the susceptible areas using daily rainfall observations simulated by the MarkSim (Jones et al., 2002) software and analyzed for high intensity events using the InStat + software (University of Reading, 2008). MarkSim has been applied in the region for crop simulation modeling (Jones and Thornton, 2000) but has not been used for the analysis of disease risk. The likelihood of simulated high rainfall events were then compared with rainfall observations from meteorological stations in Kenya, Uganda and Rwanda.

Finally satellite measurements were assessed for use in further validating the risk surfaces and for their suitability for in-season monitoring of rainfall events.

3.1 Assessing the risk of root rots in East African bean producing areas

3.1.1 Areas susceptible to bean root rots

The association between root rot severity and human population density, intensity of cultivation and soil properties were based on a model derived from data collected for the atlas of common bean production in Africa (Wortmann, et al., 1998). Bean producing areas have not been captured since 1998 and we assume that production areas have not changed markedly in East Africa relative the late 1990's.

We have updated the original root rot map using more recent data on population density – the Gridded Population of the World Version 3 (Center for International Earth Science

Information Network, 2005) - and the SAGE Agricultural lands map for cropping intensity, based on the percentage of a 5 arc minute cell that is cropped (Ramankutty et al., 2008). Threshold values for crop intensity and human population density were used to further restrict the area of analysis. Values of 40% crop intensity and 200 persons per km² were chosen. These were then combined using simple map algebra in ArcMap (ESRI) software to create a map showing areas with both high human population density and high bean crop intensity (Figure 1).

3.1.2 Risk of exposure to heavy rainfall events

Rainfall during the first few weeks of plant development has a spatial component but is difficult to capture using conventional maps of annual or monthly rainfall totals. Averages mask the variability of rainfalls within the year or month as well as the variation between years. To obtain a better indication of risk one must analyse daily weather data and specifically daily rainfall observations during the critical period immediately after germination.

Observations from meteorological stations are often not available, incomplete or in non-susceptible locations. Sample locations were selected in areas susceptible to root rots in each bean producing area (Figure 2) and simulations of daily weather were generated for 99 years using the MarkSim Software. For each of the 24 locations the normal planting dates were identified using expert knowledge (Table 2) (pers. comm., Rubyogo 20th December 2005, Chirwa 15th December 2005).

The daily rainfall data were exported from MarkSim and imported into the Instat+ software (University of Reading, 2008). The Instat+ software has analysis capabilities designed for climatic data, specifically the identification of specific events. The rules for assessing risk of root rot were more complex than traditional rainy events but a combination of these events allowed the calculation of risk. The first step was to define a monitoring period which started approximately 1 month before the normal planting dates and identify the start of rains; a figure of 20mm over two days was used for the onset of the rainy season. The next step was to determine the absence or presence of events with over 50mm over 2 days in the period between day 17 and day 38 (after the onset of rains), a more severe test – 100mm over three days was also used. Since all locations had bimodal rainfall patterns the test was applied to both rainy seasons in the calendar year and the number of seasons where the rainfall events were experienced was recorded (Table 2). MarkSim successfully simulated daily rainfall in all but one of the locations for which the software had no climate data.

Table 2 somewhere here

These frequencies were used to produce maps of risk over large areas when the point data were interpolated to produce a risk surface (Figure 3). The frequency values were

interpolated in the ArcGIS software for all susceptible areas using inverse distance weighting with a distance decay power value of 2 and using 12 nearest neighbours.

3.2 Validation of exposure risk

Little information has been collected on the frequency of root rot incidence in beans across East Africa. Data collected in Rwanda in the early 1990's (Buruchara and Rusuku, 1992) concentrated on yield loss rather than frequency, reports from this period showed that the severity of losses was greater in some regions in Rwanda than others, which might be due to differences in rainfall patterns. However differences between neighbouring fields were also observed which serves to remind that causality of incidence is complex, with soil fertility being another important factor.

3.2.1 Comparison between observed and simulated heavy-rainfall events

Observed daily rainfall data were made available for this study in four locations in East Africa: Katumani in Eastern Province in Kenya, Kabete in Central Province in Kenya, Namulonge in Central Uganda and Kigali in Rwanda (Figure 2). The longest time series available was for Katumani, where 41 years of continuous observations between 1961 and 2001 were recorded. Daily rainfall amounts were observed for 30 years in Kabete, 32 years in Namulonge and for 11 years at Kigali.

The observations were imported into the Instat + software and the same process followed as in section 3.1.2. to determine the number of heavy rainfall events during the post germination period. Additional simulations were generated using MarkSim at the same locations as the meteorological stations. At such sites MarkSim can use observed climatic normals for rainfall, or the values built in to the software. We decided to use those built-in, to match the simulations at sites where there is no station (*cf.* Hartkamp et al., 2003).

3.3 TRMM validation of risk surfaces

Alternative sources of 'observed' daily rainfall are satellite based instruments that measure the characteristics of clouds to estimate rainfall on the ground. One of these sources – the Tropical Rainfall Measuring Mission (TRMM) – is assessed here as an alternative to ground measuring stations to validate the assessment of heavy-rainfall events and to investigate the potential of remotely sensed rainfall estimates for in-season monitoring and early warning of root rot outbreaks.

The Tropical Rainfall Monitoring Mission has five principal instruments: a precipitation radar (PR), a microwave imager (TMI), a visible and infra-red scanner (VIRS), a cloud and earth radiant energy scanner (CERES), and a lightning imaging scanner (LIS) (NASA, 2006). The principal dataset used in this section is the daily rainfall estimates

dataset derived from the 3B42 v6 algorithm which combines data from TRMM microwave and infra-red instruments (Huffman et al., 2007). The data are available from 1998 and have a spatial resolution of 0.25° x 0.25° between latitudes of 50°S and 50°N.

Given the relatively small number of years that TRMM has been providing observations the source is not suitable for validating the probability of heavy-rainfall events in a season (using MarkSim simulated daily rainfall). Instead we assessed the quality of the TRMM daily rainfall data using rainfall observations from stations in just one country in East Africa – Rwanda.

Observed rainfall data from 5 stations of the Rwandan Meteorological Service (RMS) were available and TRMM daily rainfall estimates data were extracted for the period 1998-2008 for grid cells that coincided with the RMS stations. For the purposes of monitoring conditions conducive to root rots in beans the most appropriate indicator for validating the TRMM estimates was a three-day running rainfall total during the growing seasons. Rainfall records for Kigali airport meteorological station were complete for the period 1998-2008 while there were gaps for the stations at Gisenyi and Gikongoro and serious gaps for Byumba (Table 3). Data for Kamembe airport had yet to be verified so were not analysed.

Table 3 somewhere here

We focussed the analysis on the start of the growing seasons which are between February and April inclusive and between September and November inclusive. Different rainfall amounts were chosen ranging from 100mm over three days (which is rarely encountered) to 25mm over 3 days which was almost always exceeded.

4 Results

4.1 Risk of root rots in East African bean producing areas

4.1.1 Areas susceptible to bean root rots

The areas susceptible to bean root rots are concentrated in two main regions (a) the highlands of Rwanda, Burundi and South western Uganda, and; (b) the northern shore of lake Victoria and the highlands of western Kenya. There are other smaller areas scattered in Central and Eastern provinces of Kenya and in the Kilimanjaro massif in north-eastern Tanzania. In terms of the proportion of the bean areas in each country affected in terms of area the most susceptible was Rwanda while the least susceptible was DRC (Table 4**Error! Reference source not found.**).

Table 4 somewhere here

Figure 1 somewhere here

Figure 2 somewhere here

4.1.2 Risk of exposure to heavy rainfall events

The locations with the highest risk of heavy rainfall events during the period immediately after germination are in southern Burundi, a small area in North-west Uganda, the Kakamega area of western Kenya and in Kitui in Eastern Province of Kenya. Areas with lower risk are in western Rwanda and south west Uganda. Despite a range of environments from humid to semi-arid the range of probabilities is not large, and surprisingly some of the locations with the highest probabilities of heavy-rainfall events (such as eastern Kenya and eastern Rwanda) do not have high seasonal rainfall totals.

Figure 3 somewhere here

4.2 Validation of exposure risk

4.2.1 Comparison between observed and simulated heavy-rainfall events

The differences between the numbers of seasons with heavy rainfall events in the susceptible period according to observed and simulated daily rainfall were not large and did not show consistency between locations or seasons (Table 5). For instance at Katumani there were more ‘risky’ seasons according to the simulated data using MarkSim than with the observed data, this is also true in the case of Kigali. In contrast for Kabete there were more risky seasons using observed data than the simulated daily data for the main season but this was reversed in the second season – a similar pattern to the comparison at Namulonge.

Table 5 somewhere here

The comparison between the observed and simulated rainfall events is between two binomial distributions, where each season either experiences a heavy rainfall event or not. Our hypothesis was that the probability of the heavy rainfall event was the same for each distribution. This hypothesis was only rejected at the 5% confidence level for the second season at Katumani (Table 5).

4.3 TRMM validation of risk surfaces

Results are organised for each of the four stations in Rwanda: Kigali, Gisenyi, Gikongoro and Byumba. Greatest attention was paid to the results obtained from Kigali since it had the longest and best quality weather data available.

A plot of the 3-day running totals (calculated daily) from the TRMM and observed rainfall data at Kigali showed a lack of a clear relationship between the totals from TRMM and from meteorological stations ($R^2=0.204$). The TRMM data give slightly higher 3-day totals although there are more extreme rainfall events (e.g. $> 100\text{mm}$) in the observed dataset.

Graphs were also produced for individual years, with a range of predictive capacities of the observed cumulative rainfall using just TRMM estimates between $R^2=0.05$ in 2008 and 0.64 in 2002.

These predictive models investigate the relationship between the TRMM wet events and the observed wet events on a daily basis, but they do not show the differences in the experience of at least one heavy rainfall event during the growing season. An alternative approach is to analyse threshold values of 3-day rainfall events in any particular growing season (i.e. the same as that used to examine the rainy events in the analysis of the TRMM data conducted previously by the authors).

The summary of the presence of different events (Table 6) shows that the amount of trigger events is broadly similar between the observed and the TRMM rainfall data. When the individual years are analysed separately the coincidence between the two datasets is not as strong, especially for the 50mm trigger rainfall events where the trigger rainfall amount is estimated correctly in only 55% of the 3 monthly periods. Observed data for Byumba station were only available for 2007 and 2008 limiting the power of the comparison with the TRMM data. More data were available for the station at Gisenyi but the number of matches is low compared to Kigali, with the number of false negatives very large. There are gaps in the observed rainfall data for Gikongoro, with only 2008, 2003, 1999 and all but the first week of 1998 complete. All the other years have some months missing and only the second season in 2004 was complete. As with Gisenyi the number of false absences in Gikongoro is far greater than the false presences of heavy rainfall events. The seasonal totals of the observed rainfall were also greater than the TRMM estimates.

The TRMM therefore provides little power for predicting these three-day rainfall events at the meteorological stations.

Table 6 somewhere here

5 Discussion

The research presented in this paper outlines a new use of simulations of daily rainfall, and specifically a new use of the MarkSim software. The value of these simulated data is increased when they are combined with climatic statistical and spatial tools and they demonstrate the use of such data for targeting both strategic research and specific interventions to tackle crop pests and diseases. This research is particularly pertinent in the face of potential changes in rainfall patterns over the coming decades (van de Steeg et al., 2009).

Although no ‘ground truthing’ was possible in this study, the map of the probability of root rots appears consistent with the previous map of root rot severity (Wortmann, et al., 1998). Nevertheless the revised map can be improved by using MarkSim simulations of daily rainfall over all the susceptible areas rather than interpolating between the 24 locations that were sampled in this study as well as alternative interpolation methods such as kriging (e.g. Grimes et al., 1999). This will require a more automated procedure for the identification of heavy rainfall events. The variation in risk of heavy rainfall events shown here does not show a simple correlation with annual or seasonal rainfall averages and thus provides a novel tool for targeting the promotion of root rot resistant bean varieties and other cultural practices for modifying the soil structure and improving soil fertility. This tool can be modified for other pests and diseases and for other crops or agricultural technologies. Nevertheless the research here has shown that the spatial scale at which pests and diseases are manifest will limit the usefulness of the tool since MarkSim currently has a spatial resolution of 18km. Differences in root rot incidence and severity within and between plots are due mainly to the build up of pathogens in the soil – which is linked to the soil fertility status and the cultivation history of a particular plot – and whether a variety is resistant to root rots.

Plant breeding for resistance to root rots has been ongoing within the Pan African Bean Research Alliance (PABRA), but there is often a trade-off between traits. In addition the resources destined for crop improvement need to be targeted to those areas where particular constraints are most severe, both now and in the future. It is currently difficult to link the rainfall event probability map to actual incidence and severity of root rots in the region, due to a lack of routine monitoring of outbreaks of the disease. If monitoring were carried out it would allow for better calibration of the model and also an even better understanding of the risk. This understanding will be vital for modeling the incidence of root rots in beans under future climates, especially for areas where the disease is currently uncommon.

The validation of the MarkSim heavy rainfall events with rainfall observations from four stations shows that the differences between the two sources were in most cases not statistically significant. Access to a longer series of observed rainfall data would be needed to comprehensively assess the simulated dataset in those areas where the differences between the observed and simulated datasets are large. We are unable to reject the hypothesis that the distributions of risky rainfall events are the same between the observed and simulated daily rainfall datasets. We therefore tentatively conclude that

simulated daily rainfall can be used for producing these kinds of risk assessments, but that the validation could be improved by increasing the sample of meteorological stations.

The rainfall amounts over the two and three day time steps used in this analysis are derived from a combination of the probability of rain days as well as the amount of rain falling on a rainy day. The first of these is derived from the analysis of the daily data for the meteorological station used to define the climate type, while the amounts of rainfall depend on the monthly mean rainfall values. Within MarkSim there is the possibility of updating the monthly mean rainfall amounts for specific locations and further research could consider the use of summaries of observed data (climate normals) instead of the interpolated means which are in the MarkSim database. The thresholds for heavy-rainfall events are based on trials carried out in Rwanda and the results of the risk model are dependent on the rainfall threshold as well as the planting date. Further research should therefore assess the sensitivity of the model to both of these factors as well as the size of rainfall events simulated by the MarkSim software (e.g. Dixit et al., this issue). Specifically research is required on the effect of the gamma curves which are an essential characteristic of each type of climate within MarkSim and which define the probabilities of rainfall events.

The biggest problem for the comparison is the relatively short duration of the observed rainfall records, especially in Kigali which showed the largest differences between the two datasets. The other problem is the very small number of cases in the analysis which was restricted due to the lack of meteorological stations with available observed daily rainfall. Access to a larger set of meteorological observations would allow for a better assessment of the relationship.

Our study of four stations in Rwanda shows that rainfall estimates from TRMM satellite instruments are poor predictors of rainfall observations, coinciding with the findings of Dinku et al. (2008). The most complete set of rainfall observations were available for the Kigali Airport station. Of the six different trigger values the worst comparison was the 50mm value, which was incorrectly estimated for 10 of the 22 seasons – either positively estimated when there was no event observed or not estimated when the ground station recorded the event. As the trigger value decreased the number of seasons when the value was estimated also increased, which is not surprising due to the frequent occurrence of these less intense rainfall events.

Comparisons at the other stations were less revealing because the numbers of complete seasons of observed rainfall were fewer than at Kigali. Both the stations in Gikongoro and Gisenyi were at the edge of the 25km x 25km TRMM cell, and given the small size of tropical thunderstorms it is possible that rainfall associated with cloud recorded by the TRMM sensor was not recorded at the meteorological station. Indeed, given the large decay in correlation of rainfall over relatively small distances in the tropics (Lebel et al., 1992), especially over short periods the utility of a single rain gauge to represent a large area (such as those covered by TRMM pixels) is limited, and the TRMM may give a better estimate of areal rainfall. While the spatial variation in rainfall has been shown

over different time periods (Grimes and Pardo-Igúzquiza, 2010) there is no research on the spatial variation of these heavy rainfall events over short distances such as could be used to explain the differences between the TRMM areal estimates and the meteorological stations. The AGRHYMET cluster of rainfall gauges (Lebel et al., 1992) or the rain gauges managed by the Ethiopian National Meteorological Agency (Grimes and Pardo-Igúzquiza, 2010) offer such an opportunity to study the local differences in the frequency of heavy-rainfall events.

TRMM rainfall data are particularly suited to in-season rainfall monitoring due to the short time between data capture and publication. Typically the data are available the next day when using the TRMM Online Visualisation and Analysis System (TOVAS)⁴. The time period can be set so that cumulative seasonal totals are displayed (Figure 4**Error! Reference source not found.**) or for shorter periods to monitor within season events. These values would still need to be validated using observations although the time between observation, verification and publication would need to be improved. Alternative rainfall estimates from satellite exist, such as NASA's Prediction Of World Energy Resources POWER⁵, but this has a considerable delay between capture and publishing and is thus currently not suited to in-season monitoring of rainfall. Other rainfall products estimated using satellite instruments include the Tropical Applications of Meteorological Satellites (TAMSAT) method applied to thermal infra-red imagery from the Meteosat platform (Thorne et al., 2001). The algorithm used in the TAMSAT method is locally calibrated and has performed well in Africa in comparison with more complex algorithms like those used to produce the TRMM rainfall estimates (Teo and Grimes, 2007). The TAMSAT group provides routine products at 10-day, monthly and seasonal timescales; the dekadal and monthly products are available from the EUMETSAT portal. The TAMSAT estimates thus offer some promise for in-season monitoring for root rots but would imply access to daily rainfall estimates.

Figure 4 somewhere here.

To conclude, in this paper we have shown the value of long-term meteorological rainfall observations for assessing the risk of outbreaks of pests and diseases. We have also shown that where data are sparse simulations may be able to provide an acceptable alternative. More rainfall observations from meteorological stations are needed to check the validity of the results from the simulated data and hence to improve the confidence in the results from the simulations. The methods used have shown that these data enable maps of areas susceptible to root rot in beans to be produced, by showing the long term probability of heavy rainfall events during a critical period after germination. These, in turn, can help assess long term risks or can be used for early-warning within a particular season.

⁴ <http://disc2.nascom.nasa.gov/Giovanni/tovas/>

⁵ <http://earth-www.larc.nasa.gov/power/>

6 References

- Abawi, G.S., Crosier, D.C. and Cobb, A.C., 1985. Root Rot of Snap Beans in New York. *New York's Food and Life Sciences Bulletin*, 110: 2-7.
- Alwang, J., Siegel, P.B. and Jorgensen, S.L., 2001. *Vulnerability: A View from Different Disciplines*. 0115, World Bank, Washington, D.C.
- Baez, J. E. and Mason, A., 2008. *Dealing with Climate Change: Household Risk Management and Adaptation in Latin America*. SSRN eLibrary. Available at <http://ssrn.com/paper=1320666>
- Buruchara, R.A., and Rusuku, G., 1992. Root Rots Research in the Great Lakes Region. In Buruchara, R.A., and Scheidegger, U.C., (eds.), 1992. *Proceedings of the Pan-Africa Bean Pathology Working Group Meeting*. Centro Internacional de Agricultura Tropical, Thika, Kenya, 26th – 30th May 1992.
- Center for International Earth Science Information Network (CIESIN), Columbia University; and Centro Internacional de Agricultura Tropical (CIAT). 2005. *Gridded Population of the World Version 3 (GPWv3): Population Density Grids*. Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University. Available at <http://sedac.ciesin.columbia.edu/gpw>. (Accessed 17/03/2006).
- CIAT, 1992. Pathology in Africa. In: CIAT (ed.) *Bean Programme Annual Report*. Cali, Colombia, Centro Internacional de Agricultura Tropical. December 1992.
- Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B. and Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? *Agriculture, Ecosystems & Environment*, 126: 24-35.
- Dinku, T., Chidzambwa, S., Ceccato, P., Connor, S.J., and Ropelewski, C.F., 2008. Validation of high-resolution satellite rainfall products over complex terrain. *International Journal of Remote Sensing*, 29 (14): 4097-4110
- Dixit, P.N., Cooper, P.J.M., Rao, K.P., and Dimes, J., this issue. Adding value to field-based agronomic research through climate risk assessment: A case study of maize production in Kitale, Kenya.
- Ford, J., and Leggate B.M., 1961. The geographical and climatic distribution of trypanosome infection rates in *G. morsitans* group of tsetse-flies (*Glossina* WIED. DIPTERA). *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 55 (4): 383-397
- Fry, W.E., and Goodwin, S.B., 1997. Resurgence of the Irish Potato Famine Fungus. *BioScience*, 47 (6): 363-371

Garrett K., Forbes, G., Pande, S., Savary, S., Sparks, A., Valdivia, C., Vera Cruz, C., and Willocquet, L., 2009. Anticipating and responding to biological complexity in the effects of climate change on agriculture. *IOP Conf. Series: Earth and Environmental Science* 6 372007. doi:10.1088/1755-1307/6/7/372007

Grimes, D.I.F., and Pardo-Igúzquiza, E., 2010. Geostatistical Analysis of Rainfall. *Geographical Analysis*, 42: 136-160.

Grimes, D.I.F., Pardo-Igúzquiza, E. and Bonifacio, R., 1999. Optimal areal rainfall estimation using raingauges and satellite data. *Journal of Hydrology*, 222: 93-108.

Hartkamp, A.D., White, J.W. and Hoogenboom, G., 2003. Comparison of three weather generators for crop modeling: a case study for subtropical environments. *Agricultural Systems*, 76, 539-560.

Haware, M.P., 1990. Fusarium wilt and other important diseases of chickpea in the Mediterranean area. In Saxena M.C., Cubero J.I., and Wery J. (eds.), *Present status and future prospects of chickpea crop production and improvement in the Mediterranean countries*. Zaragoza : CIHEAM-IAMZ. p. 61-64

Homewood, K., Trench, P., Randall, S., Lynen, G. and Bishop, B., 2006. Livestock health and socio-economic impacts of a veterinary intervention in Maasailand: Infection-and-treatment vaccine against East Coast fever. *Agricultural Systems*, 89: 248-271.

Huffman, G.J., Adler, R.F., Bolvin, D.T., Gu, G., Nelkin, E.J., Bowman, K.P., Hong, Y., Stocker, E.F., and Wolff, D.B., 2007. The TRMM multi-satellite precipitation analysis: quasi-global, multi-year, combined-sensor precipitation estimates at fine scale. *Journal of Hydrometeorology*, 8 (1): 38–55
See also: <http://trmm.gsfc.nasa.gov/3b42.html>

Jésus W.C., Valadares, R., Cecilio, R.A., Moraes, W.B., Vale, F.X.R., Alves, F.R., and Paul, P.A., 2008. Worldwide geographical distribution of black sigatoka for banana: predictions based on climate change models. *Scientia Agricola*, 65: 40-53.

Jones, P. G. and Thornton, P. K., 2000. MarkSim: Software to Generate Daily Weather Data for Latin America and Africa. *Agronomy Journal*, 92: 445-453.

Jones, P.G., Thornton, P.K., Diaz, W., and Wilkens, P.W., 2002. MarkSim, Version 1. A computer tool that generates simulated weather data for crop modeling and risk assessment. CIAT CD-ROM series, CIAT, Cali, Colombia.

Kousik, C. S., Thakur, R. P. and Subba Rao, K. V., 1988. Influence of environmental factors on production and dispersal of *Tolyposporium penicillariae* sporidia. *Indian Journal of Aerobiology*, 1: 85-91.

Lebel, T., Sauvageot, H., Hoepffner, M., Desbois, M., Guillot, B., and Hubert, P., 1992. Rainfall estimation in the Sahel: the EPSAT-NIGER experiment. *Hydrological Sciences Journal*, 37, (3): 201-215.

Morton, J. F., 2007. The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the National Academy of Sciences*, 104: 19680.

Mouliom Pefora, A., 1991. Effect of climatic factors on the development of *Mycosphaerella fijiensis* (black sigatoka disease) in banana (AAA) in Moungo, Cameroon (1987-1989). In, Wolf, J.N. (ed.) 1991, Proceedings of IFS/CTA Regional Seminar Influence of the climate on the production of tropical crops, Ouagadougou, Burkina Faso. Stockholm/Ede

NASA, 2006. *NASA Facts: TRMM Instruments*. Last access: February 2010. http://trmm.gsfc.nasa.gov/overview_dir/instrumentfacts.html

Nene, Y.L. 1979. *Proceedings of the Consultants' Group Discussion on the Resistance to Soil-borne Diseases of Legumes*. Patancheru, India, International Crops Research Institute for the Semi-Arid Tropics, (ICRISAT), 8th - 11th January 1979.

Nyvall, R., 1999. *Field Crop Diseases Handbook*, Iowa State University, Ames, USA.

Oerke, E.C., Dehne, H.W., Schohnbeck, F., and Weber, A., 1995. *Crop Production and Crop Protection: Estimated Losses in Major Food and Cash Crops*. Elsevier. Amsterdam and New York. 830 pp.

Ojiem, J.O., 2006. *Exploring socio-ecological niches for legumes in western Kenya smallholder farming systems*. PhD thesis, Wageningen University, Netherlands.

Otsyula, R.M., 1994. Development of an Integrated Bean Root Rot Control Strategy for Western Kenya. In Gridley (ed.), *Proceedings of a Working Group Meeting of Bean Breeders in the Eastern Africa Region*. Kampala, Uganda, Centro Internacional de Agricultura Tropical, 30th May – 2nd June 1994.

Otsyula, R., Rubaihayo, P. and Buruchara, R., 2003. Inheritance of Resistance to *Pythium* Root Rot in Beans (*Phaseolus vulgaris*) genotypes. *African Crop Science Conference Proceedings*, 6: 295-298

Otsyula, R., Rachier, G., Ambitsi, N., Juma, R., Ndiya, C., Buruchara, R.A., and Sperling, L. 2004. The use of informal seed producer groups for diffusing root-rot resistant varieties during periods of acute stress. In: Sperling, L.; Remington, T.; Haugen, J.M.; Nagoda, S. (eds.). *Addressing seed security in disaster response: Linking relief with development*. International Center for Tropical Agriculture (CIAT), Cali, CO. p. 69-89.

Otsyula R.M. and Buruchara R., 2001. Research on Bean Root Rot in Kenya. In *Proceedings of the PABRA Millennium Workshop*. Arusha, Tanzania, 28th May – 1st June 2001, pp 159-166

Pieczarka, D.J. and Abawi, G.S., 1978. Influence of Soil Water Potential and Temperature on Severity of Pythium Root Rot of Snap Beans. *Ecology and Epidemiology*, 68: 766-772.

Ramankutty, N., Evan, A.T., Monfreda, C., and Foley, J.A., 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, 22 (1): 1-19

Reddy T.Y., and Sulochanamma, B.N., 2008. Effect of minimal amount of supplemental irrigation during drought stress on yield and quality of groundnut. *Legume Research - An International Journal*, 31 (2).

Rogers, D.J., Hay, S.I., and Packer, M.J., 1996. Predicting the distribution of tsetse flies in West Africa using temporal Fourier processed meteorological satellite data. *Annals of Tropical Medicine and Parasitology*, 90 (3): 225-241

Spence, N., 2003. Characterisation and epidemiology of root rot diseases caused by *Fusarium* and *Pythium* spp. in beans in Uganda. Final Technical Report. Horticulture Research International, Wellesbourne, Warwick

van de Steeg, J.A., Herrero, M., Kinyangi, J., Thornton, P.K., Rao, K.P.C., Stern, R., and Cooper, P., 2009. *The influence of climate variability and climate change on the agricultural sector in East and Central Africa—Sensitizing the ASARECA strategic plan to climate change*. Research report 22. ILRI (International Livestock Research Institute), Nairobi, Kenya, ICRISAT (International Crop Research Institute for the Semi-Arid Tropics), Nairobi, Kenya, and ASARECA (Association for Strengthening Agricultural Research in Eastern and Central Africa), Entebbe, Uganda.

Teo, C.-K. and Grimes, D.I.F., 2007. Stochastic modelling of rainfall from satellite data. *Journal of Hydrology*, 346 (1-2): 33-50

Thakur, R.P., Rao, V.P., and King, S.B., 1991. Influence of temperature and wetness duration on infection of pearl millet by *Claviceps fusiformis*. *Phytopathology*, 81: 835-838.

Thorne, V., Coakeley, P., Grimes, D. and Dugdale, G., 2001. Comparison of TAMSAT and CPC rainfall estimates with raingauges, for southern Africa. *International Journal of Remote Sensing*, 22: 1951 - 1974.

University of Reading, 2008. *Instat+™ – an interactive statistical package*. Statistical Services Centre, University of Reading, UK.

Williamson, S., Ball, A. and Pretty, J., 2008. Trends in pesticide use and drivers for safer pest management in four African countries. *Crop Protection*, 27: 1327-1334.

Wortmann, C.S., Kirkby, R.A., Eledu, C.A. and Allen, D.J., 1998. *Atlas of common bean (Phaseolus vulgaris L.) production in Africa*, Cali, Colombia, CIAT.

7 Acknowledgements

The authors would like to acknowledge the African Development Bank who provided funds through the Association for Strengthening Agricultural Research in East and Central Africa (ASARECA) to support the project '*Managing Uncertainty: Innovation systems for coping with climate variability and change*' which were used, in part to support this study. The authors are also grateful to the Swiss Agency for Development and Cooperation (SDC) and the Canadian International Development Agency (CIDA) for continuing to support the Pan African Bean Research Alliance (PABRA) which provided additional support to this study. We offer our thanks for the comments and advice of two reviewers which greatly improved the manuscript, and for the commitment and enthusiasm of Peter Cooper.

8 Appendix

The process in the Instat+ software is as follows:

- In Excel run the INSTAT macro to get the MarkSim output in a format suitable for the Instat+ software.
- Import excel file into the Instat+ software (noting the MarkSim value for 9998 for February 29 which should be *** in the Instat+ software).
- Find the start of the rains in the main season – given a start date find days where the cumulative rainfall total over two days is equal or above 20mm.
- Get germination date – assume 10 days after onset of rains for planting, and a further 7 days for germination, therefore add 17 days to start of rains.
- Get end of risk period – assume period of maximum risk 3 weeks after germination; therefore add 21 days to the germination date.
- Seek events – in the Instat+ software it is easier to search for events using the start of the rains procedure, we simply change the threshold value from 20mm over 2 days to 50mm over 2 days or 100mm over three days.
- Record number of events – every event is logged; we sum the log of events and see how many years out of 99 are risky.⁶

⁶ Get the start of the rains, 20mm over 2 days after 60 days : RUN X1-X99;RANge 0.85;SUM 2 20;FIRst 60;DAYs X100

Check that the start of the rains is in the first season: X101 = -(X100<=180)

Get the start of the risky period : X102 = (X100+17) * X101

Get the end of the risky period: X103 = (X102+21) * X101

Get the first day that experiences 100mm (over this and the previous 2 days) : RUN X1-X99;RANge 0.85;SUM 3 100;FIRst X102;DAYs X104

Get the first day that experiences 50mm (over this and the previous day): RUN X1-X99;RANge 0.85;SUM 2 50;FIRst X102;DAYs X105

If the day when 100mm was recorded over 3 days is in the risky period then give the value 1 (where FALSE = 0 and TRUE = -1 in INSTAT) : X106 = -(X104<=X103)+(X104=0)

If the day when 50mm was recorded over 2 days is in the risky period then give the value 1 (where FALSE = 0 and TRUE = -1 in INSTAT): $X107 = -(X105 \leq X103) + (X105 = 0)$

The sum of 100mm events over 99 years : $K1 = \text{SUM}(X106)$

The sum of 50mm events over 99 years: $K2 = \text{SUM}(X107)$

Tables and Figures

Table 1. Examples of crop pests and diseases associated with specific climatic conditions

<i>Target</i>	<i>Pest/disease</i>	<i>Climate favouring outbreak</i>
Cattle	Rift valley fever	Moist conditions
Groundnut (<i>Arachis</i>)	Aflatoxin	Dry spell during pod filling
Potato (<i>Solanum tuberosum</i> L.)	Late Blight (<i>Phytophthora infestans</i>)	Moist conditions
Maize (<i>Zea mays</i>)	Maize streak Virus	Moist conditions
Cassava (<i>Manihot esculenta</i>)	Cassava Mosaic Virus	Moist conditions
Sorghum (<i>Sorghum bicolor</i> (L.) Moench)	Mould/smud (<i>Fusarium moniliforme</i> J. Sheld)	Dryer conditions
Sorghum	Charcoal rot (<i>Macrophomina phaseolina</i>)	Soil moisture stress
Cattle	Sleeping sickness (<i>Tripanosomiasis</i>)	Rainfall and temperature
Common Bean (<i>Phaseolus vulgaris</i>)	Root rots (<i>Pythium spp</i>)	Free water in soil post-germination
Chick-pea (<i>Cicer arietinum</i>)	Stem rot (<i>Sclerotinia sclerotiorum</i> (Lib.) de Bary.)	Cool and wet conditions
Banana (<i>Musa spp.</i>)	Black Sigatoka (<i>Mycosphaerella fijiensis</i> Morelet)	High relative humidity and water on leaves
Pearl Millet (<i>Pennisetum glaucum</i>)	Smut (<i>Tolyposporium pennicillariae</i>)	Warm temperature, moderate humidity and low windspeed
Pearl Millet	Ergot (<i>Claviceps fusiformis</i>)	Moderate minimum temperatures and water on leaves

Morton, 2007; Reddy and Sulochanamma, 2008; Fry and Goodwin, 1997; Nene, 1979; Ford and Leggate, 1961; Rogers et al., 1996; Jésus et al., 2008; Mouliom Pefora, 1991; Kousik et al., 1988; Thakur et al., 1991; Haware, 1990

Table 2. Sample locations with number of years with heavy-rainfall events (simulated by MarkSim) per 99 years

MarkSim ID	Country	Latitude	Longitude	Start	Main Season			Start	Other Season			Average	
					Day number for monitoring start of season	50mm over 2 days	100mm over 3 days		Day number for monitoring start of season	50mm over 2 days	100mm over 3 days	50mm over 2 days	100mm over 3 days
(a)	Central Kenya	-1.168	37.949	March	32	36	22	September	213	53	34	45	28
(b)	Central Kenya	-0.514	37.069	March	32	36	17	September	213	24	6	30	12
(c)	Tanzania	-3.310	37.485	March	32	37	9	September	213	9	1	23	5
(d)	Western Kenya	0.640	35.783	Feb - April	32	20	4	Aug-Oct	213	15	0	18	2
(e)	Uganda	0.490	30.223	March	32	36	10	September	213	39	5	38	8
(f)	Uganda	1.585	33.865	March	32	1	0	September	213	0	0	1	0
(g)	Uganda	3.049	30.865	March	32	37	7	September	213	48	13	43	10
(h)	Burundi	-4.130	30.032	March - April	60	67	17	Sept - Oct	244	36	12	52	15
(j)	Rwanda	-1.992	30.470	March - April	60	38	6	Sept - Oct	244	32	5	35	6
(j)	Burundi	-2.522	30.024	March - April	60	No Data	No Data	Sept - Oct	244	No Data	No Data		
(k)	Burundi	-3.397	29.671	March - April	60	29	2	Sept - Oct	244	17	3	23	3
(l)	Rwanda	-2.631	28.981	March - April	60	20	0	Sept - Oct	244	18	1	19	1
(m)	Burundi	-2.884	29.199	March - April	60	33	4	Sept - Oct	244	27	8	30	6
(n)	Burundi	-3.616	30.007	March - April	60	45	8	Sept - Oct	244	23	2	34	5
(o)	Rwanda	-1.575	29.561	March - April	60	28	3	Sept - Oct	244	14	1	21	2
(p)	Rwanda	-1.676	30.108	March - April	60	31	3	Sept - Oct	244	16	1	24	2
(q)	Uganda	-1.214	30.041	March	32	19	4	September	213	19	3	19	4
(r)	Uganda	-0.574	30.361	March	32	22	0	September	213	14	1	18	1
(s)	Western Kenya	-0.574	34.576	Feb - April	32	34	6	Aug-Oct	213	29	8	32	7
(t)	Western Kenya	-0.524	35.165	Feb - April	32	37	8	Aug-Oct	213	23	2	30	5
(u)	Western Kenya	0.149	34.669	Feb - April	32	41	7	Aug-Oct	213	44	16	43	12
(v)	Western Kenya	0.157	34.282	Feb - April	32	29	4	Aug-Oct	213	45	3	37	4
(w)	Uganda	0.637	33.087	March	32	28	2	September	213	29	2	29	2
(x)	Uganda	-0.229	31.656	March	32	24	7	September	213	28	0	26	4

Table 3. RMS stations in Rwanda with available rainfall data

Station	Start date	Finish date	Years with at least 1 month missing
Kigali	January 1998	December 2008	0
Gisenyi	March 2002	December 2008	0
Gikongoro	January 1998	December 2008	7
Byumba	January 2007	December 2008	0
Kamembe	January 2004	May 2009	0

Table 4. Percentage of bean growing areas in East Africa susceptible to root rots

Country	Total Bean Growing Areas (Ha)	Susceptible (Ha)	%
Burundi	2,648,000	841,000	32
DRC	17,304,000	32,000	0
Kenya	13,655,000	1,248,000	9
Rwanda	2,197,000	929,000	42
Tanzania	10,825,000	45,000	0
Uganda	16,310,000	2,136,000	13

Table 5 Comparison of number of seasons with heavy-rainfall events using observed and simulated (MarkSim) daily rainfall data for four locations in East Africa

	# of years	% of main seasons with		% of other seasons with	
		50mm over 2 days	100mm over 3 days	50mm over 2 days	100mm over 3 days
<i>Katumani Eastern Kenya</i>					
Observed	41	22	5	27	5
Simulated	99	35	13	45	14
p-value**		0.12	0.15	0.04	0.12
<i>Kabete Central Kenya</i>					
Observed	30	47	20	17	3
Simulated	99	39	11	22	7
p-value**		0.48	0.21	0.51	0.46
<i>Namulonge Uganda</i>					
Observed*	32	19	3	19	3
Simulated	99	25	7	13	1
p-value**		0.45	0.42	0.43	0.40
<i>Kigali Rwanda</i>					
Observed	11	36	0	18	0
Simulated	99	36	6	22	5
p-value**		1.00	0.40	0.76	0.45

Main season: a, b,c = March; d = Mid-March early April. Other season: a, b,c = September; d = Mid-Sept-early Oct.

* 1991 main season observations not available but other season (September-November) observations were available

** The p-value is the significance level for the test that the two proportions are equal.

Table 6. Comparison of total number of seasons with rainfall events and season by season comparison of absence/presence of events 1998-2008 at Kigali

Rainfall event	# of seasons		Percentage of seasons		Match	False Presence	False Absence
	TRMM	Observed	TRMM	Observed			
100mm in 3 days	0	0	0	0	22	0	0
50mm in 3 days	12	12	55	55	12	5	5
40mm in 3 days	16	17	73	77	17	2	3
35mm in 3 days	17	19	77	87	16	2	4
30mm in 3 days	19	21	86	95	18	1	3
25mm in 3 days	20	21	91	95	19	1	2
n = 22							

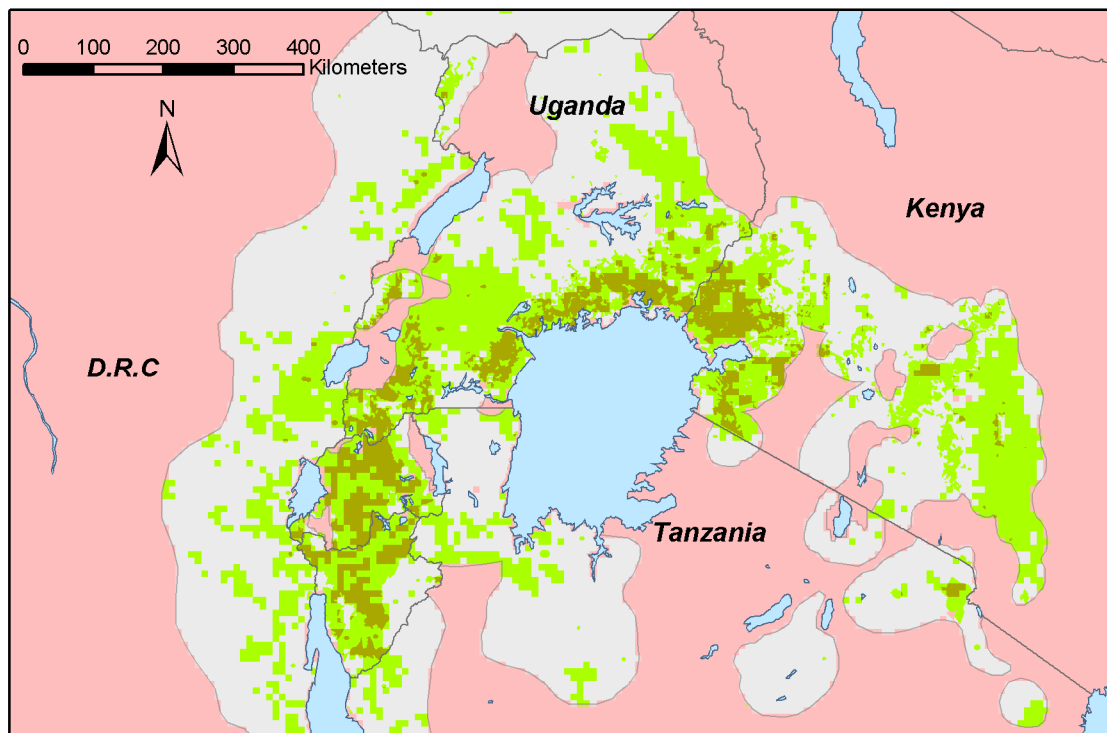


Figure 1. Combination of crop intensity and population density to focus on bean areas susceptible to root rots. Pink signifies non-bean areas; grey areas excluded according to two criteria; light green areas are excluded by one criterion; dark green areas satisfy both criteria.

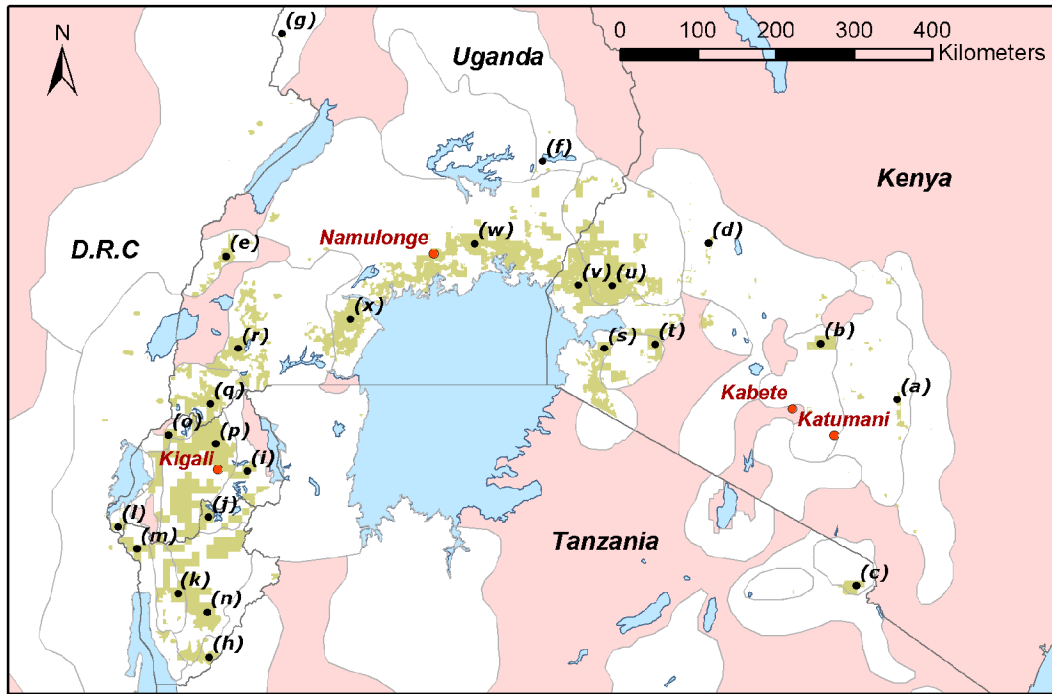


Figure 2. Locations of MarkSim simulations in bean areas susceptible to root rots. Meteorological stations shown as red circle, MarkSim simulation locations shown as black circles (sample locations given in Table 2 are identified by letters in parenthesis). Pink signifies non-bean areas; white areas excluded according to one or two criteria; olive green areas satisfy both criteria.

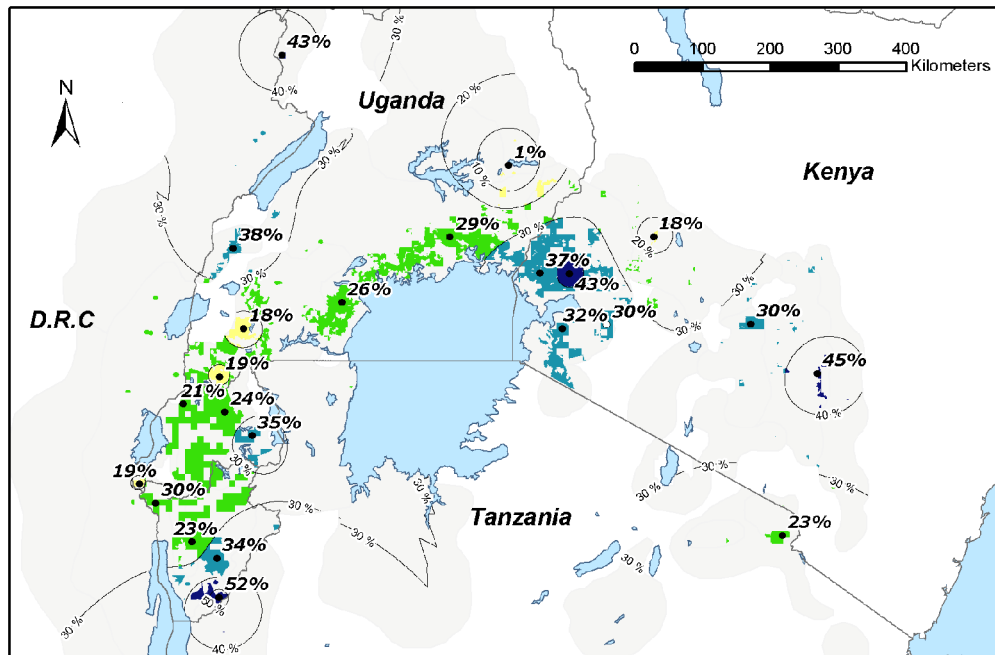


Figure 3. Probability of rainfall events exceeding 50mm in 3 week post-germination susceptible period. MarkSim simulation locations shown as black circles. White = non-bean areas; grey = excluded according to one or two criteria; yellow = < 20%; green = 20-30%; blue = 30 – 40%; dark blue = > 40%

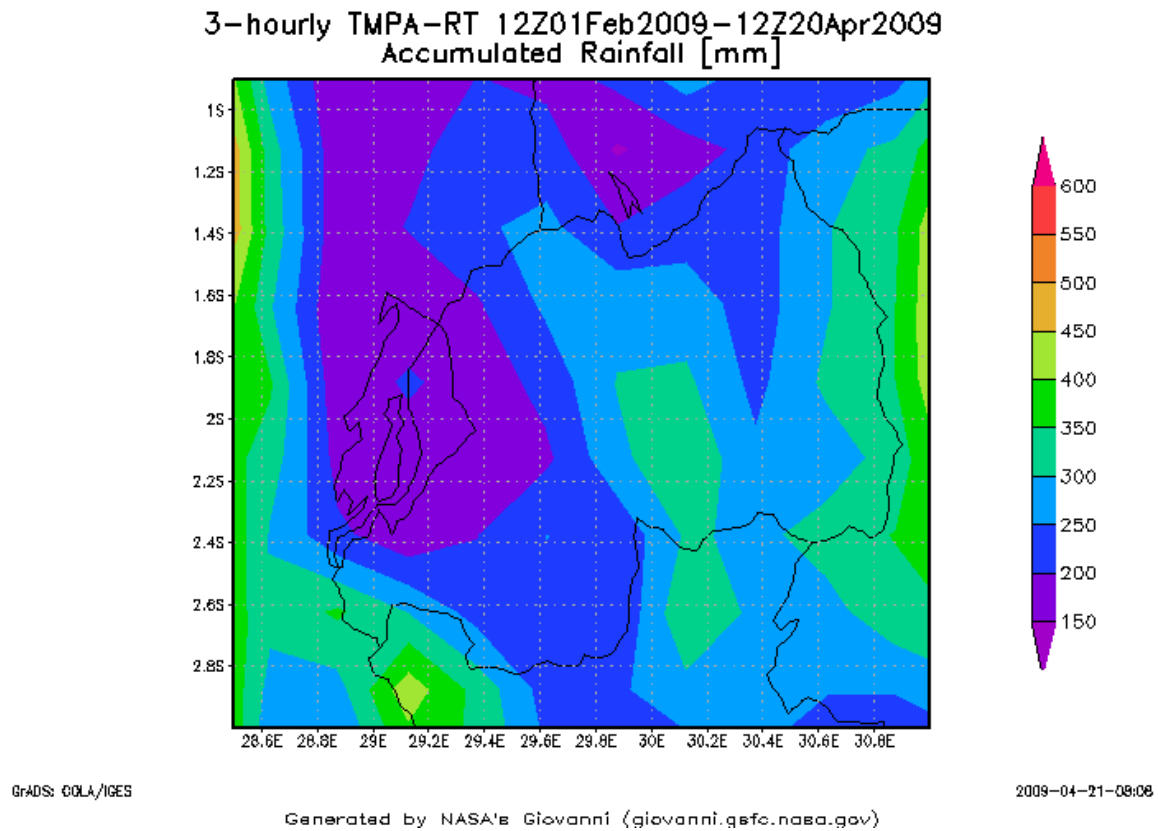


Figure 4. TRMM rainfall total for Rwanda: February-April 2009⁷

⁷ "The images and data used in this study were acquired using the GES-DISC Interactive Online Visualization AND aNalysis Infrastructure (Giovanni) as part of the NASA's Goddard Earth Sciences (GES) Data and Information Services Center (DISC)."