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ASSESSING THE RISK OF ROOT ROTS IN COMMON BEANS IN EAST AFRICA USING SIMULATED, ESTIMATED AND OBSERVED DAILY RAINFALL DATA

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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 are 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.

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. (Homewood *et al.*, 2006; Otsyula *et al.*, 2004; Williamson *et al.*, 2008).

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

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

Target	Pest/disease	Climate favouring outbreak
Cattle	Rift valley fever	Moist conditions
Groundnut (*Arachis*)	Aflatoxin	Dry spell during pod filling
Potato (*Solanum tuberosum*)	Late blight (*Phytophthora infestans*)	Moist conditions
Maize (*Zea mays*)	Maize streak virus	Moist conditions
Cassava (*Manihot eculenta*)	Cassava mosaic virus	Moist conditions
Sorghum (*Sorghum bicolor*)	Mould/smut (*Fusarium moniliforme*)	Dryer conditions
Sorghum	Charcoal rot (*Macrophomina phaseolina*)	Soil moisture stress
Cattle	Sleeping sickness (trypanosomiasis)	Rainfall and temperature
Common bean (*Phaseolus vulgaris*)	Root rots (*Pythium* spp.)	Free water in soil post-germination
Chickpea (*Cicer arietinum*)	Stem rot (*Sclerotinia sclerotiorum*)	Cool and wet conditions
Banana (*Musa* spp.)	Black sigatoka (*Mycosphaerella fijiensis*)	High relative humidity and water on leaves
Pearl millet (*Pennisetum glancum*)	Smut (*Tolyposporium pennicillariae*)	Warm temperature, moderate humidity and low windspeed
Pearl millet	Ergot (*Claviceps fusiformis*)	Moderate minimum temperatures and water on leaves

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

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).

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 solani subsp. 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 penalize yield or quality; resistant or tolerant bean varieties may not be preferred (Otsyula *et al.*, 2003), and seed producers may be 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 rot infestation requires free water in the root-zone of the soil since the most important pathogen (*Pythium* spp.) is water-borne (Pieczarka and Abawi, 1978). Research in Rwanda over three growing seasons showed that three-day rainfall totals of at least 50 mm and up to 130 mm coincided with plant loss rates of up to 55% (of susceptible varieties). In the one season where no three-day rainfall events greater than 30 mm were observed, there were 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.

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.

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 analysed for high intensity events using the InStat+ software (University of Reading, 2008). (For further details see Supplementary Online Appendix at http://journals.cambridge.org/EAG). MarkSim has been applied in the region for crop simulation modelling (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.

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

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 to the late 1990s.

We have updated the original root rot map using more recent data on population density – the Gridded Population of the World Version 3 (CIESIN, 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 km^2 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).

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 rainfall 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) (personal communications, Rubyogo, December 2005, Chirwa, 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 that started approximately one month before the normal planting dates and identify the start of rains; a figure of 20 mm 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 50 mm over two days in the period between day 17 and day 38 (after the onset of rains); a more severe test – 100 mm 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.

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.

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 1990s (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.

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 described above (*Risk of exposure to heavy rainfall events*) 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).

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

MarkSim ID	Country	Latitude	Longitude	Main season: Start	Main season: Day number for monitoring start of season	Main season: 50 mm over 2 days	Main season: 100 mm over 3 days	Other season: Start	Other season: Day number for monitoring start of season	Other season: 50 mm over 2 days	Other season: 100 mm over 3 days	Average: 50 mm over 2 days	Average: 100 mm 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
(i)	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

†Sample locations are indicated on Figure 2.

Table 3. Rwanda Meteorological Service stations 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

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 TRMM has five principal instruments: a precipitation radar, a microwave imager, a visible and infra-red scanner, a cloud and earth radiant energy scanner and a lightning imaging scanner (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 $0.25° \times 0.25°$ 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 five 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.

We focused 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 100 mm over three days (which is rarely encountered) to 25 mm over three days which was almost always exceeded.

Table 4. Percentage of bean growing areas in East and Central 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

DRC: Democratic Republic of the Congo.

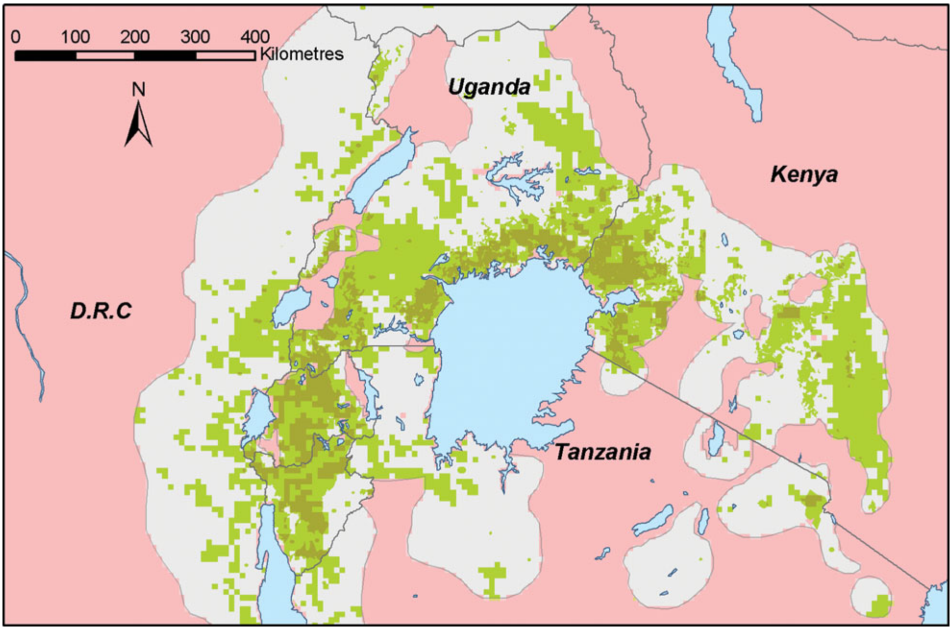

Figure 1. Combination of crop intensity and population density to focus on bean areas susceptible to root rots. Pink signifies non-bean areas; grey areas excluded according to two criteria; light green areas are excluded by one criterion; dark green areas satisfy both criteria. DRC: Democratic Republic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

RESULTS

Risk of root rots in East African bean producing areas

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 the most susceptible was Rwanda while the least susceptible was the Democratic Republic of the Congo (Table 4).

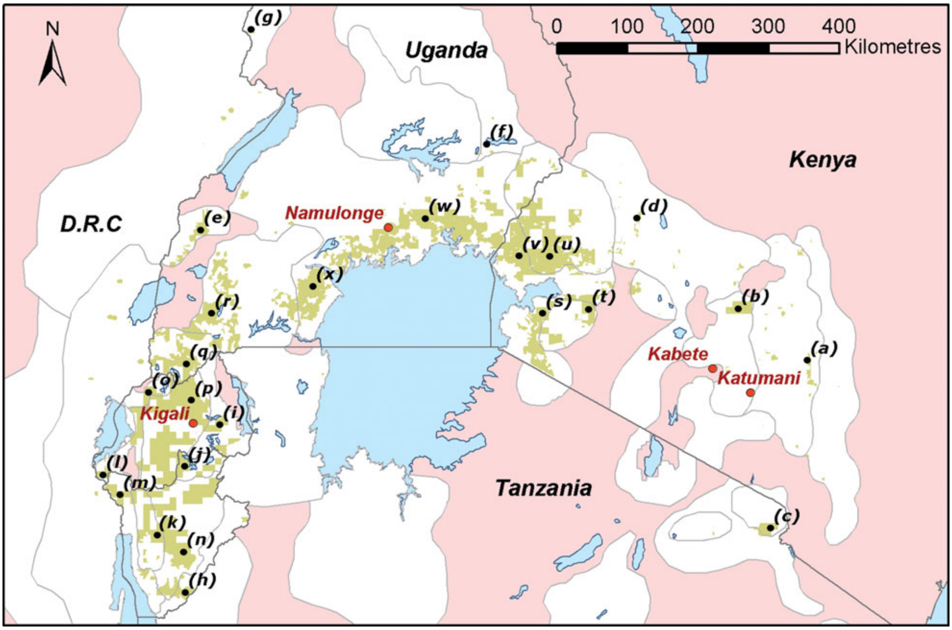

Figure 2. Locations of MarkSim simulations in bean areas susceptible to root rots. Meteorological stations shown as red circle, MarkSim simulation locations shown as black circles (sample locations given in Table 2 are identified by letters in parentheses). Pink signifies non-bean areas; white areas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

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 northwest Uganda, the Kakamega area of western Kenya and in Kitui in Eastern Province of Kenya. Areas with lower risk are in western Rwanda and southwest 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.

Validation of exposure risk

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.

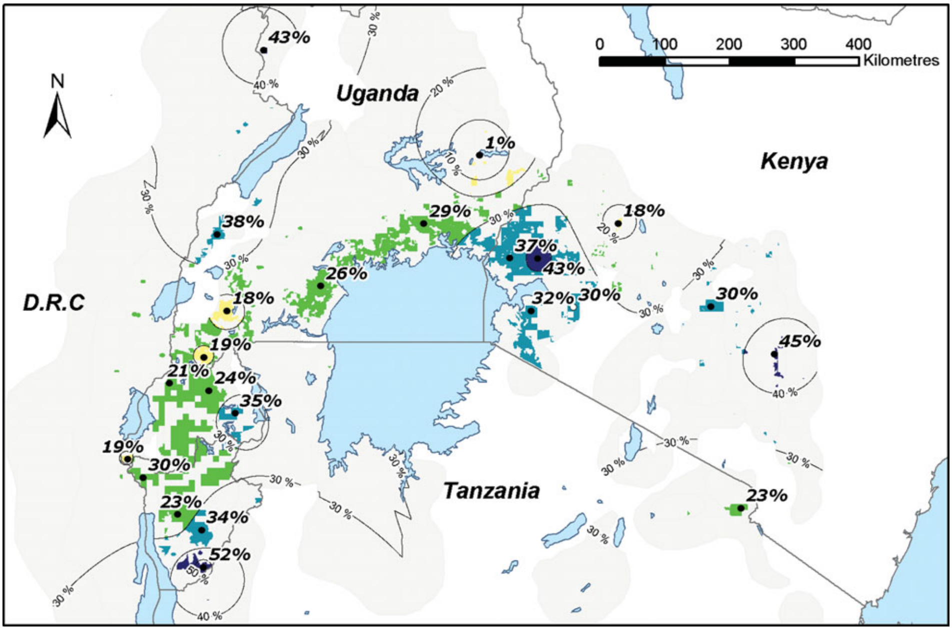

Figure 3. Probability of rainfall events exceeding 50 mm in 3 week post-germination susceptible period. MarkSim simulation locations shown as black circles. White = non-bean areas; grey = excluded according to one or two criteria; yellow = <20%; green = 20–30%; blue = 30–40%; dark blue = >40%. DRC: Democratic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

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).

TRMM validation of risk surfaces

Results are organized 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 three-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 three-day totals although there are more extreme rainfall events (e.g. > 100 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

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 main seasons with		% of other seasons with	
	No. of years	50 mm over 2 days	100 mm over 3 days	50 mm over 2 days	100 mm over 3 days
Katumani, Eastern Kenya (a)					
Observed	41	22	5	27	5
Simulated	99	35	13	45	14
p-value**		0.12	0.15	0.04	0.12
Kabete, Central Kenya (b)					
Observed	30	47	20	17	3
Simulated	99	39	11	22	7
p-value**		0.48	0.21	0.51	0.46
Namulonge, Uganda (c)					
Observed†	32	19	3	19	3
Simulated	99	25	7	13	1
p-value**		0.45	0.42	0.43	0.40
Kigali, Rwanda (d)					
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-September–early October.

†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.

in the experience of at least one heavy rainfall event during the growing season. An alternative approach is to analyse threshold values of three-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 50 mm trigger rainfall events where the trigger rainfall amount is estimated correctly in only 55% of the three-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.

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.

	No. of seasons ($n = 22$)		Percentage of seasons				
Rainfall event	TRMM	Observed	TRMM	Observed	Match	False presence	False absence
100 mm in 3 days	0	0	0	0	22	0	0
50 mm in 3 days	12	12	55	55	12	5	5
40 mm in 3 days	16	17	73	77	17	2	3
35 mm in 3 days	17	19	77	87	16	2	4
30 mm in 3 days	19	21	86	95	18	1	3
25 mm in 3 days	20	21	91	95	19	1	2

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

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 18 km. 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, 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 modelling 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.*, 2011). 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 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 50 mm 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 25 km × 25 km 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 Visualization and Analysis System (TOVAS) (http://disc2.nascom.nasa.gov/Giovanni/tovas/). The time period can be set so that cumulative seasonal totals are displayed (Figure 4) 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 (http://earth-www.larc.nasa.gov/power/), 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 infrared 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 decadal 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.

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

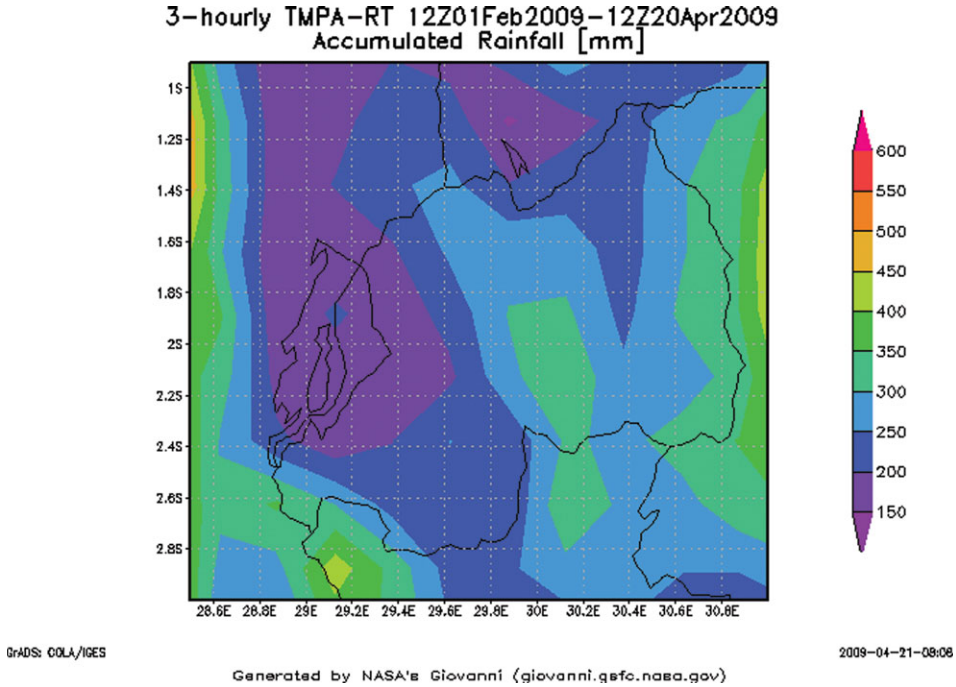

Figure 4. TRMM rainfall total for Rwanda: February–April 2009. The images and data used in this study were acquired using the GES-DISC Interactive Online Visualization ANd aNalysis Infrastructure (Giovanni) as part of the NASA's Goddard Earth Sciences Data and Information Services Center.

also shown that where data are sparse simulations may be are 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.

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