Spatial modelling of rice yield losses in Tanzania due to bacterial blight and leaf blast in a changing climate

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Abstract Rice is the most rapidly growing staple food in Africa and although rice production is steadily increasing, the consumption is still out-pacing the production. In Tanzania, two important diseases in rice production are leaf blast caused by *Magnaporthe oryzae* and bacterial blight caused by *Xanthomonas oryzae* pv. *oryzae*. The objective of this study was to quantify rice yield losses due to these two important diseases under a changing climate. We found that that bacterial blight is predicted to increase causing greater losses than leaf blast in the future, with losses due to leaf blast declining. The results of this study indicate that the effects of climate change on plant disease can not only be expected to be uneven across diseases but also across geographies, as in some geographic areas losses increase but decrease in others for the same disease.

Keywords EPIRICE · RICEPEST · Sub-Saharan Africa · *Magnaporthe oryzae* · *Xanthomonas oryzae* pv. *oryzae*

1 Introduction

Rice is the most rapidly growing staple food in Africa and although rice production is steadily increasing, the consumption is still out-pacing the production. For example, by

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2009 37 per cent of the rice consumed in Africa was imported. To reduce its reliance on imports and dependency on global markets Africa's rice production needs to increase further (Seck et al 2013). Current average yield levels in Africa range from about 1 t ha^{-1} in upland ecologies to 1.5 to 2 t ha^{-1} in rainfed lowland ecologies with the irrigated lowland ecologies having the highest yields of 3.0 to 4.0 t ha^{-1} (Diagne et al 2013). Rice yields in African farmers fields are low due to a combination of abiotic and biotic stresses that constrain them. Farmers can significantly reduce the yield gaps with improved field, water and crop management, and weed control (Saito et al 2013).

Apart from weeds, pests and diseases also are major biotic stresses that can cause significant reductions in rice yields. Two important diseases in rice are leaf blast (LB) caused by *Magnaporthe oryzae* and bacterial blight (BB) caused by *Xanthomonas oryzae* pv. *oryzae* (Verdier et al 2012). Because infectious plant disease occurs as an interaction of a favorable environment, a susceptible host and a competent pathogen (Madden et al 2007), weather conditions impact both the occurrence and gravity of plant disease. Climate change is likely to affect plant disease (Anderson et al 2004; Coakley et al 1999; Garrett et al 2006) and several others have expressed interest in changes to plant disease as a result of climate change (Chakraborty and Newton 2011; Juroszek and von Tiedemann 2011; Luck et al 2011; Pautasso et al 2010; Savary et al 2011; Sutherst et al 2011). Moreover, intensification of rice production, which was witnessed in Sub-Saharan Africa since the food crisis of 2008 (Saito et al 2013), may lead to an increased yield loss due to the blast, thus reducing the benefits that were created (Sere et al 2013). Increases in disease incidence and severity may deter farmers from investing in intensification measures because of risks related to yield losses or even total crop failure. To the authors' knowledge, the impact of climate change on leaf blast and bacterial blight diseases of rice in Africa has not yet been investigated.

Efforts to link plant disease models with a geographic information system (GIS) to assess the impact of plant diseases spatially include maps of the global number of pesticide applications necessary to control potato late blight using contemporary weather data (Hijmans et al 2000). While a meta-model to generate map estimates of changes in global potato late blight due to climate change has also been developed (Sparks et al 2014). Savary et al developed EPIRICE, a GIS–linked plant disease severity model capable of simulating several important diseases of rice, including leaf blast and bacterial blight amongst others (Savary et al 2012). Most recently, (Kim et al 2015) used a modified version of the EPIRICE model to evaluate the potential impacts of climate change on leaf blast and sheath blight in South Korean rice.

The objective of the study was to quantify the impact of climate change as forecast by the Intergovernmental Panel on Climate Change (IPCC) on rice yield loss as result of BB and LB. To carry out this study, we linked two previously unlinked, existing models, EPIRICE and RICEPEST (Willocquet et al 2000, 2002), and we applied them using spatially and temporally downscaled climate change data to generate predictions on changes in plant disease impact due to climate change in Tanzania.

The linkage of EPIRICE with RICEPEST gives two advantages. First, RICEPEST has been used to estimate yield losses due to diseases and other pest injuries in rice in varying production situations with current weather and climate conditions. However, as plant diseases are affected by weather, the linkage with EPIRICE allows us to model the effects of climate change on both the rice crop and on the diseases while using the same weather data inputs. Second, the spatial nature of EPIRICE outputs enabled us to use RICEPEST in a GIS. Until now RICEPEST yield loss estimates have not been linked to a GIS. Linking RICEPEST with a GIS allowed us to map yield losses for the whole country of Tanzania, rather than just point based predictions of yield losses.

This paper will continue with a justification for the study area, followed by descriptions of the EPIRICE and RICEPEST models. We will then elaborate the framework for assessing rice yield losses under climate change that links both models. The procedure for generating daily weather inputs from the downscaled climate scenarios is outlined followed by the choice of production situations. Next the results are presented, followed by a discussion and finally conclusions.

2 Materials and Methods

2.1 The study region

Rice accounts for five percent of the total value of agricultural production in Tanzania and is the seventh most important agricultural crop with steadily increasing production over the last decade. However, rice yields in Tanzania remain significantly lower than in neighboring countries (Barreiro-Hurle 2012).

Tanzania was chosen as the study region because of its location in sub-Saharan Africa, the probable effects of climate change in the region and rice is planted widely across the country (Table 1) (Rowhani et al 2011). The bulk of the rice crop is grown from December until June of the following year during the rainy season.

According to the International Panel on Climate Change (IPCC), East Africa and especially the Great Lakes Region are among the more vulnerable regions in Africa to climate change, where the trend is towards increasing temperatures and declining rainfall according to General Circulation Model outputs (Boko et al 2007). Temperatures are predicted to increase 2°C by 2050, which in turn are predicted to negatively affect rice yields (Rowhani et al 2011).

2.2 Model descriptions

2.2.1 The EPIRICE model

EPIRICE (Savary et al 2012) is a SEIR (susceptible-exposed-infectious-removed) model (Kermack and McKendrick 1927; Madden 2006) implemented in R (R Core Team 2014) that simulates potential spatial epidemics of rice diseases including BB and LB. The model considers a $1m^2$ area of rice, which is the same area that RICEPEST considers, with maximum host susceptibility to the given disease. Model inputs are date of crop establishment and daily time-step weather data; precipitation, maximum and minimum temperature, and relative humidity. The model as originally implemented produces a single aggregated output, a map, at the end of a growing season of a measure called Area Under Disease Progress Curve (AUDPC) (Madden et al 2007). However, for this study, daily disease severity expressed as a percentage was generated for use in the RICEPEST model, which we discuss further in section 2.2.2. As the only modification made to the model was the expression of daily disease severity, we would refer the reader to (Savary et al 2012) for further information on the model structure and function.

2.2.2 The RICEPEST model

The RICEPEST model (Willocquet et al 2000, 2002) simulates rice yield losses due to several yield-reducing factors under a range of specific production situations with simulated

diseases including BB and LB. The model runs on a daily time-step with simulation starting 14 days after crop establishment for both transplanted and direct seeded rice. The model incorporates two sub-models, the first sub-model simulates the dynamics of the rice crop biomass and the second sub-model simulates the dynamics of the tiller population. The biomass sub-model accounts for the daily accumulation and partitioning of assimilates towards roots, leaves, stems, and panicles. For this study, because the damage mechanisms of the diseases of interest (BB and LB) are simulated only in the biomass sub-model, the tiller sub-model was not considered.

Bacterial blight and LB cause lesions on the leaf blades. These lesions decrease the green leaf area index (LAI), reducing the photosynthetic capacity of the plant. RICEPEST reduces the rate of growth (RG) (Formula 1) by reducing the LAI (Formula 2) by applying a damage function (Formula 3) or (4) where SLA is the specific leaf area; LEAFW is the leaf dry weight; RUE is radiation use efficiency; RAD is daily solar radiation; k is coefficient of light extinction and is defined as the proportion of light intercepted by the crop (Willocquet et al 2000), set to 0.6 (Willocquet et al 2002).

$$RG_t = RUE_t \times RAD_t \times (1 - exp(-k \times LAI_t)) \tag{1}$$

$$LAI_t = SLA_t \times LEAFW_t \tag{2}$$

The damage functions that calculate the reduction factors, BBDM (Formula 3) and LBDM (Formula 4) are the percent of leaf area covered by BB and LB respectively (Willocquet et al 2002), which were generated as raster files for use in this version of RICEPEST using the EPIRICE model as described in the previous section, 2.2.1.

$$(1 - (BBDM_t/100) \tag{3}$$

$$(1 - (LBDM_t/100)) \tag{4}$$

Thus, the complete LAI formula with the damage function for BB reducing the photosynthetic area of the leaf becomes

$$LAI_t = SLA_t \times LEAFW_t \times (1 - (BBDM_t/100)). \tag{5}$$

2.2.3 Model coupling

To facilitate coupling of EPIRICE to RICEPEST, a temporal disaggregation function was incorporated into the EPIRICE model. With this function, the modified EPIRICE model produced daily, spatially representative and non-cumulative percentage disease severity data as outputs instead of the single cumulated output, AUDPC. The time-series of daily percentage disease severity data for BB and LB produced by the modified EPIRICE model were then used as inputs for RICEPEST. Both models were linked to a geographic information system (GIS). EPIRICE is implemented in the R language using the following packages: cropsim (Hijmans et al 2009), oldweather (Hijmans et al 2009), raster (Hijmans 2014), rgdal (Bivand et al 2014), and RODBC (Ripley and Lapsley 2013), while this version of RICEPEST is implemented in Python language (Foundation 2014), using the ArcPy package, as a script in the ArcGIS platform (Institute 2011). A loose coupling approach was adopted due to the different implementation environments. This approach provided flexibility in data handling and data interoperability (Figure 1).

2.3 Growing seasons and areas

The major planting window in Tanzania for most rain-fed ecologies in Tanzania, according to the FAO Crop Calendar database (Food and Agriculture Organization of the United Nations 2015), was October to December, with the largest area of Tanzania being planted in late November. Because the original climate data were monthly, not daily and needed to be temporally downscaled, a planting window of late November to early December was selected and ArcGIS was used to create a spatial dataset of areas with this planting window. Annual harvested rain-fed rice growing areas for Tanzania with values representing the proportion of harvested areas (in hectares) within each pixel (10,000 ha) was also obtained from MIRCA2000 (Portmann et al 2010). To select the major rice growing areas in Tanzania during this planting window, a simple raster overlay analysis was performed in ArcGIS.

2.4 Weather Data Generation

For this study, the General Circulation Model (GCM), Commonwealth Scientific and Industrial Research Organization mark 3 (CSIRO-MK3) was selected. Downscaled outputs from this GCM based on three future climate scenarios A1B, A2 and B1 as reported in the Special Report on Emission Scenarios (SRES) of the IPCC Fourth Assessment Report, for two time slices 2030s (2021-2040) and 2050s (2041-2060) were obtained. A2 is a high greenhouse gas emission scenario; A1B, a medium-emission scenario; and B1, a low-emissions scenario. The selection of the GCM and the emission scenarios were based on the availability of complete downscaled climate data to run both models. Monthly projected precipitation, minimum and maximum temperature, solar radiation and wet day frequency outputs of this GCM, spatially downscaled to approximately 10km by 10km grid resolution using a pattern scaling approach were obtained from International Center for Tropical Agriculture's (CIAT) CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) Geoportal (http://www.ccafs-climate.org) (Jones et al 2009). However, relative humidity outputs of this GCM were obtained directly from the CMIP3 dataset and spatially downscaled to 10km by 10km using statistical downscaling delta technique. Observed climate data for the period 2000s (1991-2010) was obtained from the same source and used as the baseline for this study. A parametric stochastic weather generator, MODAWEC (Liu et al 2009), which requires only monthly data (as outlined in (Geng et al 1986) and MODAWEC) was used to generate daily precipitation, maximum and minimum temperature datasets corresponding to future scenarios. This was essential in producing daily minimum and maximum temperature data that correlate with precipitation. A linear interpolation technique was, however, used in generating daily relative humidity and solar radiation from monthly data. The daily weather data generated were used as inputs in both EPIRICE and RICEPEST models.

2.5 Production situation

Rice production situations have been found to directly affect the intensity of rice yield reduction for a given injury profile. That is, the farmers' practices play a large part in determining what the diseases and injuries will occur (Savary et al 2000). For this study, production situation is defined as the combination of socioeconomic, environmental and biophysical

factors excluding pests that define the attainable yield. Temperature and solar radiation were excluded from this definition because they remain unchanged across all the possible production situations in the study area. Due to lack of reliable information about the spatial arrangement of production situations in the study area, the production situation was assumed to be homogeneous based on the most common production situation, lowland rainfed rice (Diagne et al 2013) (Table 1). We created a production situation based on PS3 from (Willocquet et al 2004). A short duration cultivar, transplanted with poor water management and medium water stress and 90kg/ha nitrogen fertilization with a modified STEMP from PS4. This modification was due to differences in temperature between Tanzania and Faizabad, Uttar Pradesh, India, the source of the original weather data for simulations in RICEPEST.

2.6 Spatial modelling of yield loss

Simulation runs of EPIRICE and RICEPEST were made separately at a spatial resolution of 10km by 10km for the growing season December to March for current climate conditions, the 2000 time slice, and for each of the three emission scenarios, A1B, A2 and B1, for both the 2030 and the 2050 time slices. These data only included precipitation and temperature changes. The effects of changes CO_2 levels on the plant host or pathogens were not considered as a part of this study.

To map and quantify the spatial distribution of rice yield loss as a result of the two diseases under current and future climate conditions, the RICEPEST model was run using daily temperature and solar radiation data and daily disease severity outputs from the EPIRICE model within the ArcGIS environment using the aforementioned Python tool in ArcGIS. Simulation runs were first made without the injury profiles to obtain the attainable yield. Maintaining the same weather data and production situation parameter values, simulation runs were then made with the treatment of injury profiles to obtain the actual yield in the presence of the two diseases separately (Figure 1). Yield loss was then modelled as the difference between attainable yield and actual yield for both BB and LB damaged crops respectively.

3 Results and discussion

3.1 Changes in temperature

The average base temperature for Tanzania used in this data was 22.69 °C, with all succeeding time slices increasing in average temperature (Table 1). The average increase in future time slices due to climate change was 1.17 °C (Table 1).

3.2 Potential disease epidemics (EPIRICE model output)

Predicted leaf blast epidemics were not sever for the entire country. Severity of the disease was predicted to be less than 2.5 percent across Tanzania for all time slices and emission scenarios (Figure 2). Disease peaks halfway through the season, which is characteristic of this disease that tends to occur during vegetative growth stages before the crop reaches reproductive stages and final maturity.

Table 1 Average temperature and change in temperatures for Tanzania from the base 2000 time slice for IPCC A1B, A2 and B1 scenarios for 2030 and 2050 time slices for the months of November through February. The 2000 time slice represents 1991-2010, 2030 time slice represents 2021-2040, the 2050 time slices represents 2041-2060.

Scenario and Time Slice	Average Temperature (°C)	Change in Temperature (°C)
Base 2000	22.69	-
A2 2030	23.88	1.19
A2 2050	24.38	1.68
A1B 2030	23.73	1.04
A1B 2050	23.95	1.25
B1 2030	23.48	0.79
B1 2050	23.73	1.04

Bacterial blight epidemics exhibited normal progress curves for the disease with a much greater severity in all time slices than that of LB. Under all time slices and scenarios the predicted epidemic started rapidly increasing around day 50 and increased up until day 100, when it began decreasing at crop maturity (Figure 3), which is normal for this disease. The three different emission scenarios resulted in differing AUDPC responses for bacterial blight across the time slices. The A2 scenario resulting in the highest predicted disease levels, the B1 scenario was the lowest.

3.3 Predicted yields and yield losses (RICEPEST model output)

3.3.1 Attainable yields

RICEPEST predicted the mean attainable yields under the current conditions, in the absence of yield reducing factors, to be 3.88 t ha^{-1} for the current rice growing areas of Tanzania for the base climate (Figure 4). Future conditions were all predicted to have higher mean attainable yields. All simulated time-slices exhibited a minimal amount of values that were reported as zero t ha^{-1}.

3.3.2 Yield losses due to leaf blast

Differences due to leaf blast between all time slices and scenarios were negligible (Figure 5). The base had the highest average yield loss values due to leaf blast, 0.12 t ha^{-1}. However, the B1 2050 scenario exhibited the lowest average yield losses of any scenario and time slice combination, but the highest values at 0.13 t ha^{-1} lost.

3.3.3 Yield losses due to bacterial blight

Bacterial blight was predicted to cause much greater losses than leaf blast (Figure 6). The overall trend in losses due to bacterial blight was up for all three climate scenarios, from the Base 2000. The A2 2050 and AB 2050 scenario and time slices had the highest average predicted values with 0.73 t ha^{-1} lost due to bacterial blight. The A2 2030 scenario and time slice registered the single highest losses, 1.44 t ha^{-1}.

4 Conclusions and discussions

The loose coupling approach that we adopted for this research has proven to be useful. It allows for us to examine patterns and trends that previously we were unable to easily examine. This approach should prove useful for further work where spatial modelling of rice yield loss is desired for both current conditions and future predictions.

Some initial difficulties in selecting the proper production situation for an area outside the original application domain of the model were experienced. Because the original PS3 was based in Faizabad, Uttar Pradesh, India, the temperatures and duration of the rice were too long to be consistent with Tanzania. Because of this, we elected to modify the model using currently available information in the model itself based on our determinations of what best matched the situation on the ground. The results of the modified RICEPEST model seem to better represent possible scenarios than the original unmodified model was able to.

The RICEPEST model is a simple empirical crop growth model that does not account for CO_2 concentration changes and increases yield as temperature increases, though the temperature to maturity is reached sooner, which reduces net biomass accumulation. A next logical step for climate change studies could be to link EPIRICE output with a more advanced model such as ORYZA (Bouman et al 2001), although such a linkage will be more difficult due to the added complexity of the ORYZA model.

Despite the predictions of climate change to reduce rice crop yields, this study predicted that the attainable yield would increase with an increase in temperatures. Since the average temperatures were below 24 °C, it is likely that this would be the case as temperatures below 20 °C can cause yield losses, so the increased temperatures are more optimal for tropical rice (Yoshida 1981).

Thornton et al (2009) found that climate change effects are likely to be unequal across East Africa when they examined maize and bean crops. Localised adaptations to climate change will be necessary. This seems to be the case when examining the maps of change in yield losses due to BB (Figure 7). Some areas appear to lose more than another half ton per hectare to BB than they previously have, while others appear to actually lose less to BB, gaining 0.75 t ha[-1] potential yield due to the reduction in the severity of BB.

The results of this study indicate that the effects of climate change on plant disease can be expected to be uneven as the environment becomes less favourable for some diseases such as LB, it becomes more favorable for others like BB. One thing that the results fail to capture is the variation in weather. Because this exercise is based on time-slice averages, what is captured here is the most likely to occur in a given year based on the climate. Weather patterns have great influence on plant diseases. However, these results should be instructive for breeders and policy makers. We should not ignore leaf blast, however these results indicate that in the future bacterial blight will be more of an issue for rice growers in Tanzania than leaf blast. This information can be useful for breeders and policy makers so breeding efforts for resistance and other mitigation methods can be put into place with this outcome in mind.

5 Software, data and supplementary file availability

All code used for analysis and data used in this dataset are available from figshare, http://figshare.com/articles/MICORDEA/1408501, and can also be cloned from GitHub, https://github.com/adamhsparks/MICORDEA. A Stella language version of the original, complete version of the RICEPEST model by the original authors, L. Willocquet and S.

Savary, is available for download from The American Phytopathological Society Education Center,
https://www.apsnet.org/edcenter/advanced/topics/BotanicalEpidemiology/Pages/default.aspx.

KML files of the change in yield losses due to bacterial blight (Figure 7) and attainable yields (Figure 4) are also available in the figshare data and GitHub repository in the "KML" folder for further exploration and the ability to interactively explore the changes across time-slices using GoogleEarth.

6 Author attributions

- – Inputs preparation (CD, AS)
- – Model coupling and processing (CD, AS)
- – Data analysis (CD, AS, SZ)
- – Manuscript preparation (CD, AS, SZ)

References

Anderson PK, Cunningham AA, Patel NG, Morales FJ, Epstein PR, Daszak P (2004) Emerging infectious diseases of plants: pathogen pollution, climate change and agrotechnology drivers. Trends in Ecology & Evolution 19(10):535–544, DOI http://dx.doi.org/10.1016/j.tree.2004.07.021, URL http://www.sciencedirect.com/science/article/pii/S0169534704002186

Barreiro-Hurle J (2012) Analysis of incentives and disincentives for rice in the united republic of tanzania. Technical note series, MAFAP, FAO, Rome

Bivand R, Keitt T, Rowlingson B (2014) rgdal: Bindings for the Geospatial Data Abstraction Library. URL http://CRAN.R-project.org/package=rgdal, R package version 0.8-16

Boko M, Niang I, Nyong A, Vogel C, Githeko A, Medany M, Osman-Elasha B, Tabo R, Yanda P (2007) Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, chap Africa, pp 433–467

Bouman B, Kropff M, Tuong T, Woperies M, ten Berge H, van Laar H (2001) ORYZA2000: modeling lowland rice. International Rice Research Institute, and Wageningen: Wageningen University and Research Center, Suite 1009, Pacific Bank Building, 6776 Ayala Avenue, Makati City, Philippines

Chakraborty S, Newton AC (2011) Climate change, plant diseases and food security: an overview. Plant Pathology 60(1):2–14, DOI 10.1111/j.1365-3059.2010.02411.x, URL http://dx.doi.org/10.1111/j.1365-3059.2010.02411.x

Coakley SM, Scherm H, Chakraborty S (1999) Climate change and plant disease management. Annual Review of Phytopathology 37(1):399–426, DOI 10.1146/annurev.phyto.37.1.399, URL http://dx.doi.org/10.1146/annurev.phyto.37.1.399, pMID: 11701829, http://dx.doi.org/10.1146/annurev.phyto.37.1.399

Diagne A, Amovin-Assagba E, Futakuchi K, Wopereis M (2013) Realizing Africa's rice promise, CABI, Nosworthy Way, Wallingford, Oxfordshire OX10 8DE, UK, chap Estimation of cultivated area, number of farming households and yield for major rice-growing environments in Africa, pp 35–45

Food and Agriculture Organization of the United Nations (2015) CROPCALENDAR. Crop calendar (Database). Webpage, URL http://data.fao.org/ref/2ca1cadd-9ee2-42ee-84d4-34473f2508fa.html?version=1.0

Foundation PS (2014) The Python Language Reference. Python Software Foundation, URL https://docs.python.org/2/

Garrett KA, Dendy SP, Frank EE, Rouse MN, Travers SE (2006) Climate change effects on plant disease: Genomes to ecosystems. Annual Review of Phytopathology 44(1):489–509, DOI 10.1146/annurev.phyto.44.070505.143420, URL http://dx.doi.org/10.1146/annurev.phyto.44.070505.143420, pMID: 16722808, http://dx.doi.org/10.1146/annurev.phyto.44.070505.143420

Geng S, de Vries FWP, Supit I (1986) A simple method for generating daily rainfall data. Agricultural and Forest Meteorology 36(4):363–376, DOI http://dx.doi.org/10.1016/0168-1923(86)90014-6, URL http://www.sciencedirect.com/science/article/pii/0168192386900146

Hijmans RJ (2014) raster: raster: Geographic data analysis and modeling. URL http://CRAN.R-project.org/package=raster, R package version 2.2-31

Hijmans RJ, Forbes GA, Walker TS (2000) Estimating the global severity of potato late blight with gis-linked disease forecast models. Plant Pathology 49(6):697–705, DOI 10.1046/j.1365-3059.2000.00511.x, URL http://dx.doi.org/10.1046/j.1365-3059.2000.00511.x

Hijmans RJ, Savary S, Pangga R, Aunario J (2009) cropsim: Simulation modeling of crops and their diseases. R package version 0.2.0-5

Institute ESR (2011) ArcGIS Desktop: Release 10. Environmental Systems Research Institute, Redlands, CA

Jones P, Thornton P, Heinke J (2009) Generating characteristic daily weather data using downscaled climate model data from the ipcc's fourth assessment report

Juroszek P, von Tiedemann A (2011) Potential strategies and future requirements for plant disease management under a changing climate. Plant Pathology 60(1):100–112, DOI 10.1111/j.1365-3059.2010.02410.x, URL http://dx.doi.org/10.1111/j.1365-3059.2010.02410.x

Kermack W, McKendrick A (1927) A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London 115:700–721

Kim KH, Cho J, Lee YH, Lee WS (2015) Predicting potential epidemics of rice leaf blast and sheath blight in south korea under the {RCP} 4.5 and {RCP} 8.5 climate change scenarios using a rice disease epidemiology model, {EPIRICE}. Agricultural and Forest Meteorology 203(0):191–207, DOI http://dx.doi.org/10.1016/j.agrformet.2015.01.011, URL http://www.sciencedirect.com/science/article/pii/S016819231500012X

Liu J, Williams JR, Wang X, Yang H (2009) Using MODAWEC to generate daily weather data for the EPIC model. Environmental Modelling & Software 24(5):655–664, DOI http://dx.doi.org/10.1016/j.envsoft.2008.10.008, URL http://www.sciencedirect.com/science/article/pii/S1364815208001904

Luck J, Spackman M, Freeman A, Trebicki P, Griffiths W, Finlay K, Chakraborty S (2011) Climate change and diseases of food crops. Plant Pathology 60(1):113–121, DOI 10.1111/j.1365-3059.2010.02414.x, URL http://dx.doi.org/10.1111/j.1365-3059.2010.02414.x

Madden L, Hughes G, van den Bosch F (2007) The study of plant disease epidemics. The American Phytopathological Society, APS Press, St. Paul, Minnesota

Madden LV (2006) Botanical epidemiology: some key advances and its continuing role in disease management. European Journal of Plant Pathology 115(1):3–23, DOI 10.1007/s10658-005-1229-5, URL http://dx.doi.org/10.1007/s10658-005-1229-5

Pautasso M, Dehnen-Schmutz K, Holdenrieder O, Pietravalle S, Salama N, Jeger MJ, Lange E, Hehl-Lange S (2010) Plant health and global change – some implications for landscape management. Biological Reviews 85(4):729–755, DOI 10.1111/j.1469-185X.2010.00123.x, URL http://dx.doi.org/10.1111/j.1469-185X.2010.00123.x

Portmann FT, Siebert S, Döll P (2010) Mirca2000—global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles 24(1), DOI 10.1029/2008GB003435, URL http://dx.doi.org/10.1029/2008GB003435

R Core Team (2014) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL http://www.R-project.org/

Ripley B, Lapsley M (2013) RODBC: ODBC Database Access. URL http://CRAN.R-project.org/package=RODBC, R package version 1.3-10

Rowhani P, Lobell DB, Linderman M, Ramankutty N (2011) Climate variability and crop production in tanzania. Agricultural and Forest Meteorology 151(4):449–460, DOI http://dx.doi.org/10.1016/j.agrformet.2010.12.002, URL http://www.sciencedirect.com/science/article/pii/S0168192310003357

Saito K, Nelson A, Zwart S, Niang A, Sow A, Yoshida H, Wopereis M (2013) Realizing Africa's rice promise, CABI, Nosworthy Way, Wallingford, Oxfordshire OX10 8DE, UK, chap Towards a better understanding of biophysical determinants of yield gaps and potential expansion of rice area in Africa, pp 188–203

Savary S, Willocquet L, Elazegui FA, Teng PS, Van Du P, Zhu D, Tang Q, Huang S, Lin X, Singh HM, Srivastava RK (2000) Rice pest constraints in tropical asia: Characterization of injury profiles in relation to production situations. Plant Disease 84(3):341–356, DOI 10.1094/PDIS.2000.84.3.341, URL http://dx.doi.org/10.1094/PDIS.2000.84.3.341

Savary S, Nelson A, Sparks AH, Willocquet L, Duveiller E, Mahuku G, Forbes G, Garrett KA, Hodson D, Padgham J, Pande S, Sharma M, Yuen J, Djurle A (2011) International agricultural research tackling the effects of global and climate changes on plant diseases in the developing world. Plant Disease 95(10):1204–1216, DOI 10.1094/PDIS-04-11-0316, URL http://dx.doi.org/10.1094/PDIS-04-11-0316

Savary S, Nelson A, Willocquet L, Pangga I, Aunario J (2012) Modeling and mapping potential epidemics of rice diseases globally. Crop Protection 34(0):6–17, DOI http://dx.doi.org/10.1016/j.cropro.2011.11.009,

URL http://www.sciencedirect.com/science/article/pii/S0261219411003656

Seck P, Toure A, Coulibaly J, Diagne A, Wopereis M (2013) Realizing Africa's rice promise, CABI, Nosworthy Way, Wallingford, Oxfordshire OX10 8DE, UK, chap Africa's rice economy before and after the 2008 rice crisis, pp 24–34

Sere Y, Fargette D, Abo M, Wydra K, Bimerew M, Onasanya A, Akator S (2013) Realizing Africa's rice promise, CABI, Nosworthy Way, Wallingford, Oxfordshire OX10 8DE, UK, chap Managing the major diseases of rice in Africa, pp 213–228

Sparks AH, Forbes GA, Hijmans RJ, Garrett KA (2014) Climate change may have limited effect on global risk of potato late blight. Global Change Biology 20(12):3621–3631, DOI 10.1111/gcb.12587, URL http://dx.doi.org/10.1111/gcb.12587

Sutherst RW, Constable F, Finlay KJ, Harrington R, Luck J, Zalucki MP (2011) Adapting to crop pest and pathogen risks under a changing climate. Wiley Interdisciplinary Reviews: Climate Change 2(2):220–237, DOI 10.1002/wcc.102, URL http://dx.doi.org/10.1002/wcc.102

Thornton PK, Jones PG, Alagarswamy G, Andresen J (2009) Spatial variation of crop yield response to climate change in east africa. Global Environmental Change 19(1):54–65, DOI http://dx.doi.org/10.1016/j.gloenvcha.2008.08.005, URL http://www.sciencedirect.com/science/article/pii/S0959378008000812

Verdier V, Cruz CV, Leach JE (2012) Controlling rice bacterial blight in africa: Needs and prospects. Journal of Biotechnology 159(4):320–328, DOI http://dx.doi.org/10.1016/j.jbiotec.2011.09.020, URL http://www.sciencedirect.com/science/article/pii/S0168165611005578

Willocquet L, Savary S, Fernandez L, Elazegui F, Teng P (2000) Development and evaluation of a multiple-pest, production situation specific model to simulate yield losses of rice in tropical asia. Ecological Modelling 131(2 − 3):133–159, DOI http://dx.doi.org/10.1016/S0304-3800(00)00271-4, URL http://www.sciencedirect.com/science/article/pii/S0304380000002714

Willocquet L, Savary S, Fernandez L, Elazegui F, Castilla N, Zhu D, Tang Q, Huang S, Lin X, Singh H, Srivastava R (2002) Structure and validation of ricepest, a production situation-driven, crop growth model simulating rice yield response to multiple pest injuries for tropical asia. Ecological Modelling 153(3):247–268, DOI http://dx.doi.org/10.1016/S0304-3800(02)00014-5, URL http://www.sciencedirect.com/science/article/pii/S0304380002000145

Willocquet L, Elizegui FA, Castilla N, Fernandez L, , Fischer KS, Peng S, Ten PS, Srivastava RK, Singh HM, Zhu D, Savary S (2004) Research priorities for rice management in tropical asia: A simulation analysis of yield losses and management efficiencies. Phytopathology 94:672–682

Yoshida S (1981) Fundamentals of Rice Science. The International Rice Research Institute, PO Box 933, Metro Manila, Philippines

Fig. 1 Flowchart illustrating the loose coupling between EPIRICE, used to simulate unmanaged disease epidemics as affected by weather conditions, and RICEPEST, used to estimate yield losses due to leaf blast and bacterial blight severity. Three time slices, 2000, 2030 and 2050 were examined for four climate scenarios, current or base, IPCC A1B, IPCC A2 and IPCC B1.
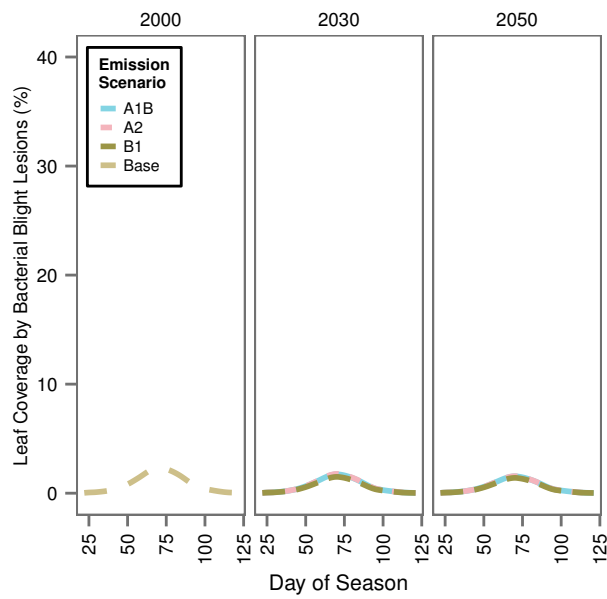
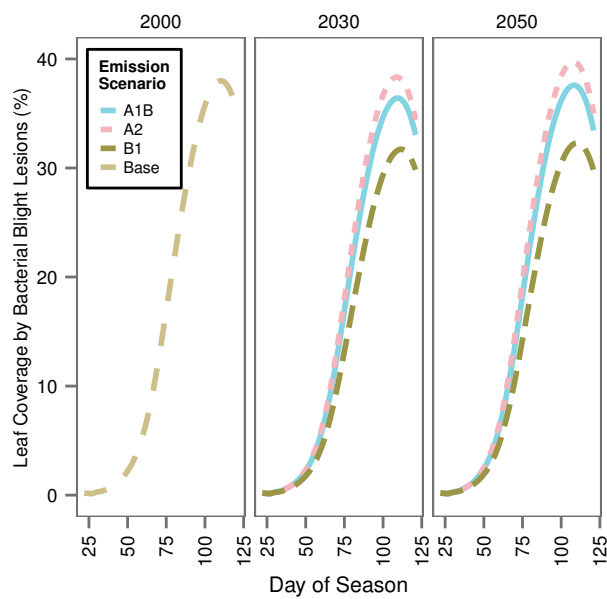**Fig. 2** Leaf blast disease severity curves as predicted by the EPIRICE model averaged for Tanzania.

Fig. 3 Bacterial leaf blight disease severity curves as predicted by the EPIRICE model using observed and future, modelled weather data for three climate change scenarios, A1B; A2 and B1 and three time slices, 2010; 2030 and 2050.
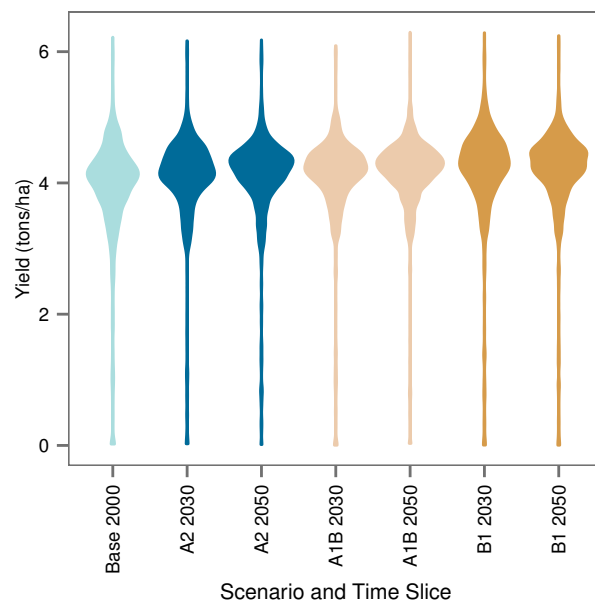
Fig. 4 RICEPEST predicted attainable yield (i.e., the yield in the absence of yield reducing factors) in t ha[-1] for all time slices and emission scenarios.
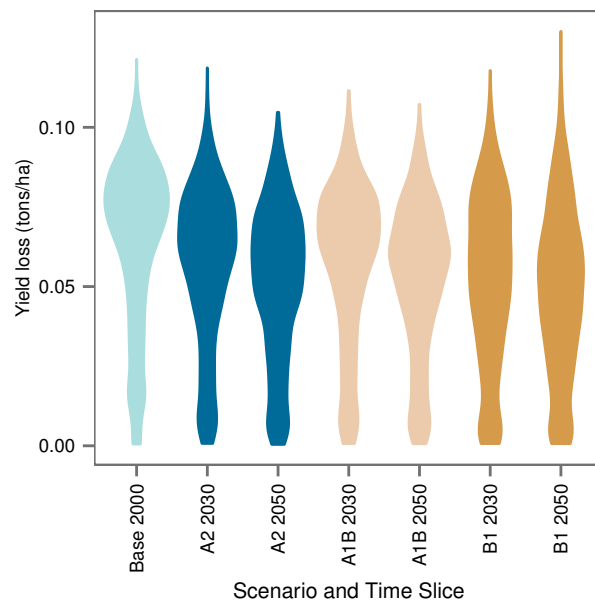

Fig. 5 Yield losses in t ha[-1] due to leaf blast as predicted by the EPIRICE and RICEPEST model three time slices and three IPCC climate emission scenarios.
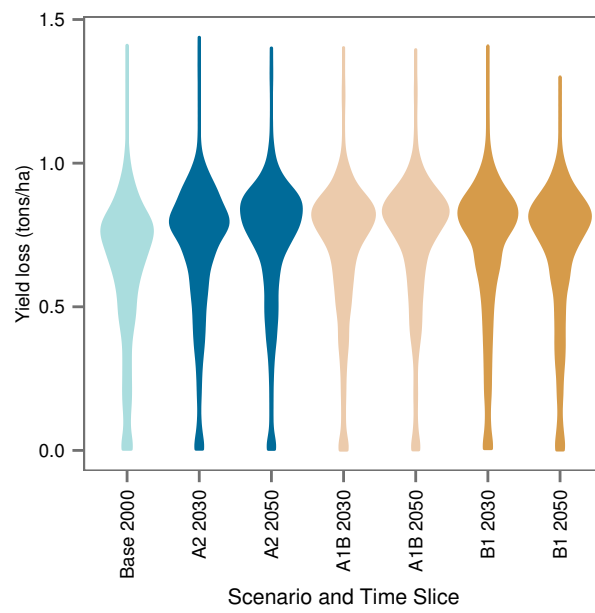
Fig. 6 Yield losses in t ha⁻¹ due to bacterial blight as predicted by the EPIRICE and RICEPEST model three time slices and three IPCC climate emission scenarios.
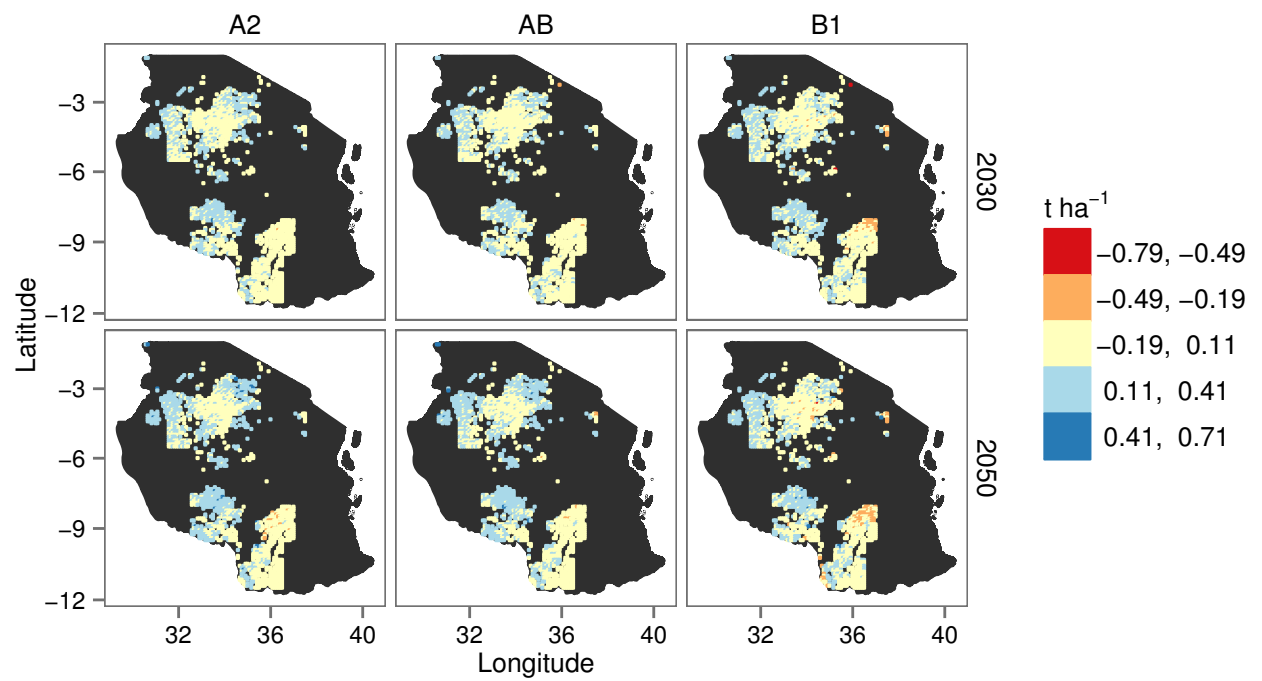
Fig. 7 Changes in yield losses due to bacterial blight disease expressed as t ha^{-1} for all time slices and emission scenarios as predicted using a combination of EPIRICE and RICEPEST models.