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Climate change may have limited effect on global risk of potato late blight

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Abstract

Weather affects the severity of many plant diseases, and climate change is likely to alter the patterns of crop disease severity. Evaluating possible future patterns can help focus crop breeding and disease management research. We examined the global effect of climate change on potato late blight, the disease that caused the Irish potato famine and still is a common potato disease around the world. We used a metamodel and considered three global climate models for the A2 greenhouse gas emission scenario for three 20-year time-slices: 2000–2019, 2040–2059 and 2080–2099. In addition to global analyses, five regions were evaluated where potato is an important crop: the Andean Highlands, Indo-Gangetic Plain and Himalayan Highlands, Southeast Asian Highlands, Ethiopian Highlands, and Lake Kivu Highlands in Sub-Saharan Africa. We found that the average global risk of potato late blight increases initially, when compared with historic climate data, and then declines as planting dates shift to cooler seasons. Risk in the agro-ecosystems analyzed, varied from a large increase in risk in the Lake Kivu Highlands in Rwanda to decreases in the Southeast Asian Highlands of Indonesia.

Keywords: climate change, food security, *Phytophthora infestans*, plant disease management, plant pathology, potato late blight

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Introduction

The risk of production loss from crop diseases, referred to hereafter as 'disease risk', can be strongly influenced by weather. Infectious plant disease occurs due to the interaction of three main factors: a favorable environment, a susceptible host, and a competent pathogen (Madden *et al.*, 2007). Therefore, changes in weather due to climate change are likely to affect disease risk (Coakley *et al.*, 1999; Anderson *et al.*, 2004; Garrett *et al.*, 2006). There is growing interest in plant disease risk under future scenarios (Pautasso *et al.*, 2010; Chakraborty & Newton, 2011; Juroszek & Von Tiedemann, 2011; Luck *et al.*, 2011; Savary *et al.*, 2011; Sutherst *et al.*, 2011) and how to adapt disease forecasting models to new scales of application for scenario analysis (Seem *et al.*, 2000; Seem, 2004; Garrett *et al.*, 2011; Shaw & Osborne, 2011).

Potato late blight is caused by the oomycete *Phytophthora infestans* (Mont.) de Bary. Late blight is well known for its role in the Irish potato famine of the 1840s and today it remains an important disease in global potato production. Global potato yield loss from diseases, pests, and weeds was estimated to be around 40% of attainable production, with diseases alone accounting for 21% loss (Oerke, 2006), and potato late blight is generally recognized as the most important potato disease. While varieties with partial resistance to late blight are available, most of the popular varieties are susceptible (Forbes, 2012), so disease management is often dependent on the use of fungicides.

Models to predict the effect of weather on potato late blight have been evolving for almost a century (Van Everdingen, 1926; Beaumont, 1947), generally drawing on temperature and atmospheric humidity as the most important predictors (Harrison, 1992). Fry *et al.* (1983) developed the SimCast model, and Grünwald *et al.* (2002) further developed the SimCast model and demonstrated that it also performed well in a tropical highland location. SimCast estimates the risk of damaging levels of late blight, expressed as 'blight units', based on the temperature during the consecutive hours in a day when relative humidity is above 90%. SimCast thus uses hourly weather data as input to calculate the need for a fungicide application to control disease. To rescale the SimCast model for use with larger time steps, from hourly increments to monthly weather observation data, and easier application to wider geographical areas, we previously developed a metamodel of the relationship between weather (temperature and relative humidity) and late blight risk, based on SimCast output

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(Sparks *et al.*, 2011). The metamodel, hereafter referred to as SimCastMeta, uses monthly time-step temperature and relative humidity data to evaluate disease risk expressed as 'blight units'.

Hijmans *et al.* (2000) evaluated contemporary severity of potato late blight indirectly using two tactical decision models, Blitecast (Krause *et al.*, 1975) and SimCast (Fry *et al.*, 1983), to predict the need for a prophylactic pesticide application to control late blight in farmers' fields. These models were then scaled up to estimate the number of pesticide applications necessary to manage late blight globally. Monthly climate data and a weather generator were used to temporally downscale the hourly weather data necessary for these models.

The impacts of climate change on potato late blight have been studied in the Midwestern US (Baker *et al.*, 2005) and Finland (Kaukoranta, 1996; Hannukkala *et al.*, 2007), indicating the potential for increased risk. Our goal was to provide the first global analysis of climate change effects on potato late blight. We used SimCastMeta to evaluate the effects of climate change emission scenarios defined by the Intergovernmental Panel on Climate Change (IPCC) (2012) and the level of disease resistance on the change in disease risk. Furthermore, using the SimCastMeta metamodel to evaluate risk illustrates the potential of metamodels for rescaling short-term forecasting models for scenario analysis. Results are discussed in the context of important potato-producing regions.

Materials and methods

We used georeferenced, gridded historic climate data (for the reference time period) and future predicted climate data as input in the SimCastMeta model (Sparks *et al.*, 2011) to evaluate late blight risk. The EcoCrop crop model, as implemented in the R package dismo (Hijmans *et al.*, 2012; R Core Team, 2013), was used to estimate the three-month potato-growing seasons for each grid cell for reference and future periods. The SimCastMeta model estimates blight units, a measure of the relative risk of damaging levels of potato late blight given an input of monthly temperature and monthly relative humidity (Sparks *et al.*, 2011). Because late blight occurs so widely in potato production systems and the driving factors are generally the weather conditions, temperature and relative humidity, we assumed that inoculum is not a limiting factor in areas where potato is grown.

We used CRU CL 2.0 grid mean monthly temperature, mean monthly relative humidity and mean monthly precipitation data from New *et al.* (2002) as our reference climate data. These data are at a spatial resolution of 10 arcminutes (344 km^2) covering the time period from 1961 to 1990. Future climate emission scenario data were downloaded from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel data (Meehl *et al.*, 2007), that we statistically downscaled and bias-corrected to 10 arcminute resolution using the 'delta method' (absolute difference for temperature, relative difference for precipitation) (Leemans & Solomon, 1993). Only data for the global climate models (GCMs) that provided maximum temperature, minimum temperature, and specific humidity were selected (Table 1), and relative humidity was calculated from these data. Because our goal was to provide a global evaluation of risk, we used an ensemble model approach (Bates & Granger, 1969) to obtain results representative of the current state-of-the-art in climate modeling. Ensemble model averages (Bates & Granger, 1969) of the nonweighted means of the GCM outputs for each climate scenario were created for mean monthly temperature and mean monthly relative humidity.

The global daily average blight unit accumulation per month was calculated from mean monthly temperature and mean monthly relative humidity using the SimCastMeta metamodel for the 1961–1990 reference climate normal (referenced from here on by the mid-point year as the 1975 time-slice), and three future 20-year time-slices, referenced hereafter by the mid-point year of the time-slice: 2000–2019 (2010), 2040–2059 (2050), and 2080–2099 (2090). The relative risk of damaging levels of late blight was then averaged using a three-month moving window to provide the average daily blight unit accumulation for 12 three-month time periods representing three-month potato-growing seasons.

Optimal potato planting dates were estimated using the EcoCrop model using mean monthly minimum and maximum temperature, and precipitation data. The first day of the first month of a three-month growing season in which planting would produce the highest potato yield for each grid cell was calculated. Optimal planting dates were generated for the reference climate normal and the ensemble GCM outputs for each of the three respective future time-slices. These data were used to estimate late blight risk for what would be a

Table 1 Global Climate Models (GCM) selected, which provided maximum and minimum temperature and relative humidity data for the A2 scenario used in SimCastMeta, where model outputs were averaged to create an ensemble model output. Models are freely available for download from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP Working Group on Coupled Modelling (WGCM) website, http://www-pcmdi.llnl.gov/ipcc/info_for_analysts.php

GCM abbreviation	GCM model name
BCCR BCM2.0	Bjerknes Centre for Climate Research Bergen Climate Model Version 2.0
CSIRO mk3.0	Commonwealth Scientific and Industrial Research Organization GCM mark 3
INMCM3.0	Institute for Numerical Mathematics Version 3.0 Model

geographic location's most productive potato-growing season in the absence of pests and disease.

Total rainfed and irrigated potato production by country (Portmann *et al.*, 2010) was used to remove areas where potato production is currently limited. Several countries were selected for further analysis because they are representative of highland or lowland tropical potato production, areas where potato is an important crop for poverty alleviation and where late blight is difficult to manage because of year-round potato production (Garrett *et al.*, 2009). These countries include Colombia and Ecuador in the Andean Highlands; Ethiopia; Rwanda in the Lake Kivu Highlands region; Nepal in the Himalayan Highlands and Indo-Gangetic Plain; and Indonesia in the South-East Asian highlands.

Results

Initially global average late blight units increased for the 2010 time-slice relative to the reference climate data (Fig. 1). The predicted global average accumulation in 2050 was similar to the historic baseline and the projections for 2090 were below the historical baseline. The average global temperature for potato-growing areas during growing seasons indicates a sharp increase, followed by a decline (Fig. 2). Relative humidity exhibited little change (0.9%) throughout the time-slices analyzed (Fig. 3). For a susceptible cultivar, the global average blight units accumulated during 1 month of a three-month growing season was 1.26 for the historical

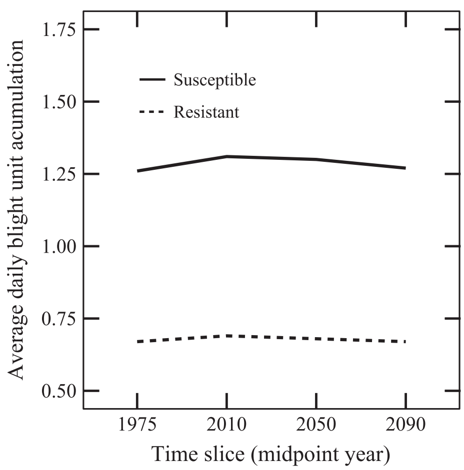

Fig. 1 Average global blight unit accumulation as predicted by SimCastMeta during the growing season as predicted by EcoCrop for four time-slices: 1961–1990, 1975 time-slice (historic normal); 2000–2020, 2010 time-slice (A2 scenario); 2040–2060, 2050 time-slice (A2 scenario); and 2080–2100, 2090 time-slice (A2 scenario). IPCC A2 emission scenario time-slices are represented here as ensemble model averages of three global climate models. Blight units are a measure of the biological risk of damaging levels of late blight of potato developing due to favorable weather conditions and are derived from the SimCast model.

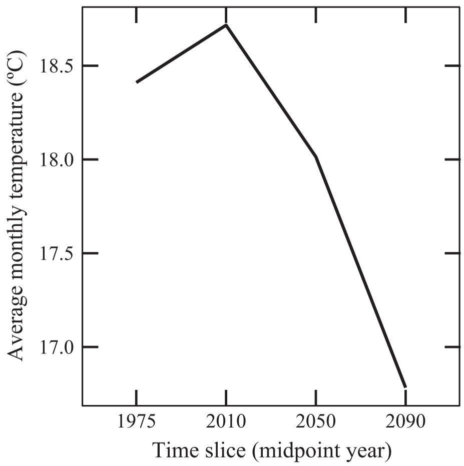

Fig. 2 Average global temperature during the growing season appropriate for a given location as predicted by EcoCrop for four time-slices: 1961–1990, 1975 time-slice (historic normal); 2000–2020, 2010 time-slice (A2 scenario); 2040–2060, 2050 time-slice (A2 scenario); and 2080–2100, 2090 time-slice (A2 scenario). IPCC A2 emission scenario time-slices are represented here as ensemble model averages of three global climate models.

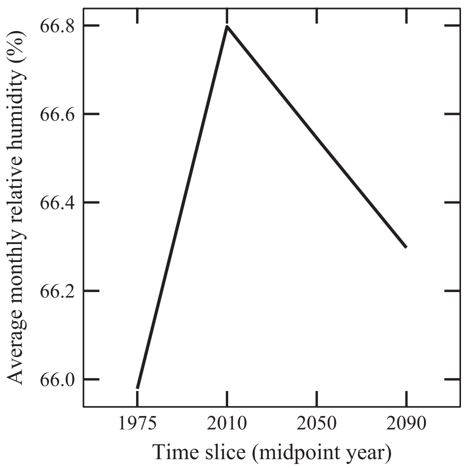

Fig. 3 Average relative humidity during the growing season appropriate for a given location as predicted by EcoCrop for four time-slices: 1961–1990, 1975 time-slice (historic normal); 2000–2020, 2010 time-slice (A2 scenario); 2040–2060, 2050 time-slice (A2 scenario); and 2080–2100, 2090 time-slice (A2 scenario). IPCC A2 emission scenario time-slices are represented here as ensemble model averages of three global climate models.

average, and increased to 1.30 for the average of the 2050 time-slice.

Many of the areas where potato is grown exhibited relatively little or no change (−0.5 to 0.5 difference) in daily mean blight units during the growing season (Figs 4 and 5). However, these changes, while seemingly small, are equal to the difference between using a resistant or susceptible variety in the original SimCast model (Fry *et al.*, 1983; Grünwald *et al.*, 2002). In the original SimCast model, a change in blight unit accumulation of −1 or 1 is equivalent to one fungicide application less or more per month respectively for susceptible and moderately susceptible cultivars (Fry *et al.*, 1983; Grünwald *et al.*, 2002). Blight units increased in parts of East-Central South America, China, Europe, and Canada. The Andes and Himalayan Mountains and Sub-Saharan Africa exhibited a mixture of increasing and decreasing blight unit accumulation. Five of the ten countries experiencing the greatest increases in blight units are located in Africa (Table 2).

Most of the main potato-producing countries exhibited a change in blight units of less than one blight unit per day per growing season (Table 3), with three countries having a decreasing number of blight units. With the minimal changes seen in the main potato producing countries, the effects of host resistance are much less pronounced (Table 3) than among the countries most affected (Table 2). Resistant genotypes are effective in reducing blight risk in all countries, such that no country experiences an accumulation of more than 0.79 average daily blight units during the growing season.

In the countries selected to represent specific agroecosystems, for a susceptible cultivar late blight risk increased in three of the five regions: Andean Highlands, Ethiopian Highlands, and Lake Kivu Highlands. In the remaining two regions, Indo-Gangetic Plan and Himalayan Highlands and South East Asian Highlands, there was a slight decrease in the blight unit accumulation (Table 4). However, shifts in the blight unit accumulations within the growing areas for each country could influence potato production as some areas experience increased late blight severity while others experience decreased late blight severity.

Table 2 Daily average blight unit accumulation and change during the growing season for the ten potato-producing countries experiencing the greatest total increase in blight unit accumulation as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice), and 2040–2059 (2050 time-slice) A2 climate for a susceptible variety. A2 scenario time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotype resistance

	Susceptible blight units			Resistant blight units		
Country	1975	2050	Change	1975	2050	Change
Rwanda	2.41	3.58	1.17	1.43	2.22	0.79
Burundi	2.53	3.13	0.60	1.54	1.93	0.39
Zimbabwe	1.99	2.43	0.44	1.18	1.44	0.26
Portugal	1.19	1.55	0.36	0.65	0.83	0.18
Mauritius	3.45	3.80	0.35	2.14	2.41	0.27
Uruguay	1.87	2.19	0.32	1.05	1.24	0.19
Estonia	2.39	2.68	0.29	1.38	1.59	0.21
Iraq	0.57	0.80	0.23	0.28	0.41	0.13
Greece	0.86	1.09	0.23	0.45	0.57	0.12
Zambia	2.47	2.70	0.23	1.44	1.55	0.11

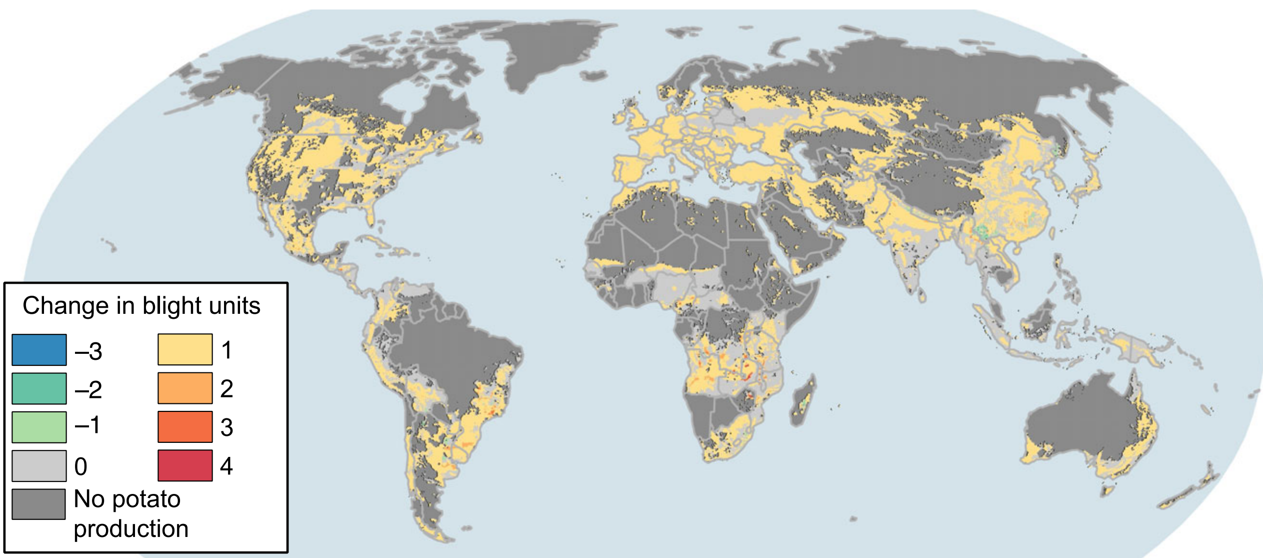

Fig. 4 The change in global potato late blight relative risk as predicted by SimCastMeta model using historical climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a **susceptible** potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

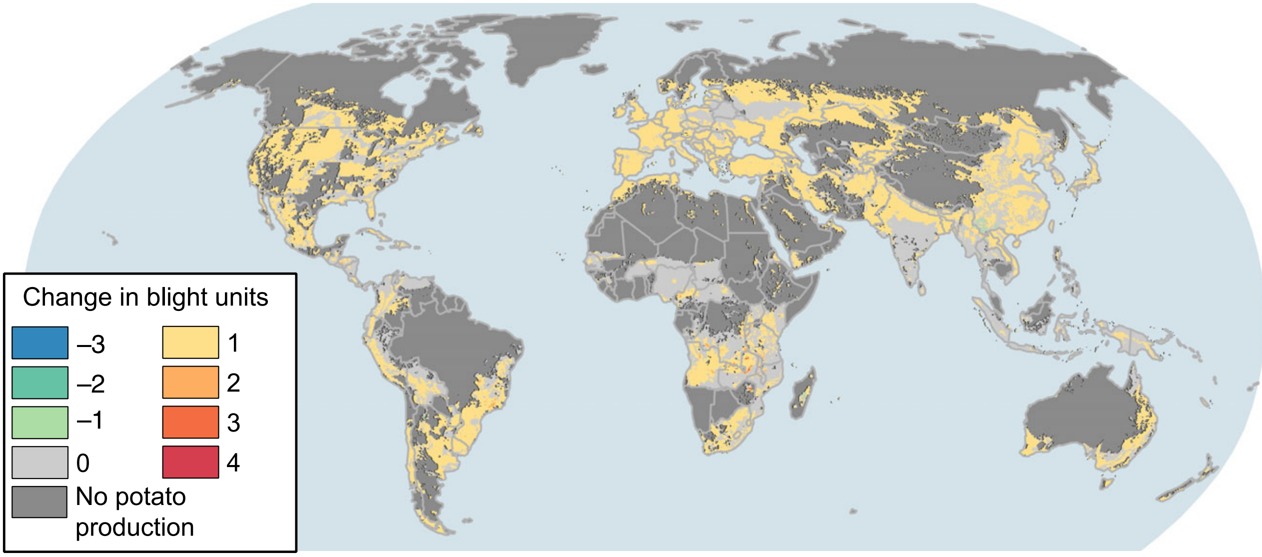

Fig. 5 The change in global potato late blight relative risk as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a **resistant** potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

An examination of temperature and relative humidity in these agro-ecosystems shows that Rwanda has the highest increase in temperature (0.7 °C) and relative humidity (2.9%) (Table 5). Nepal shows a decrease in temperature (−1.6 °C) and relative humidity (−2.4%) with a corresponding drop in blight unit accumulation.

Discussion

In this paper, we focused on the higher emission A2 scenario 2050 time-slice because it is a marker scenario used by the Intergovernmental Panel on Climate Change (2000), it most closely matches current emission levels and because the first year of the time-slice, 2040, is a realistic goal for long-term research prioritization. In general, under the A2 scenario, global potato late blight risk is likely to increase in the near future and then begin to decrease after the middle of the 21st century in areas where potato is currently grown. For most potato production in the Northern Hemisphere, this decrease is likely due to a shift in the predominant growing season predicted by the EcoCrop model. The peak season shifts from June to May planting with an increase in other planting dates that occur during cooler parts of the calendar year in the northern hemisphere. Because of the higher temperatures by 2050 and 2090 during the historic growing seasons, optimal productivity in the absence of disease would be achieved by shifting to earlier planting to avoid higher temperatures, and this change might also reduce disease risk.

However, the predicted effects of climate change are not equal across geographic locations, regions or countries. Not all areas experience an initial increase in late blight risk. The later decrease in late blight risk is because the temperatures move out of the optimal range for *P. infestans* to infect. In the original SimCast model, 13–22 °C is the optimal temperature range, requiring the least amount of hours of RH > 90% to accumulate one blight unit. The average temperature observed in the 2090 time-slice is the lowest of all four time-slices in this analysis. In our analysis, the A2 climate data had an increase and then sharp decrease in average temperature across potato-growing regions for the growing seasons, and correspondingly the blight unit accumulations decrease with the increase in temperature while relative humidity changes little (0.9%). The SimCast model also treats temperature effects differently below the 8–12 °C range. At cooler hourly temperatures, accumulation of blight units decreases with lower temperatures. Thus, one would anticipate increased late blight risk for the very coolest potato-growing areas (e.g., the highest parts of the Andes). These areas probably represent a small proportion of total potato production in the countries where they occur and may have simply counterbalanced warmer areas, contributing to a small change in risk at the country or regional level over time.

The effect of regional changes in temperature and relative humidity is notable in the ecosystems that we compared. Rwanda had a temperature and relative

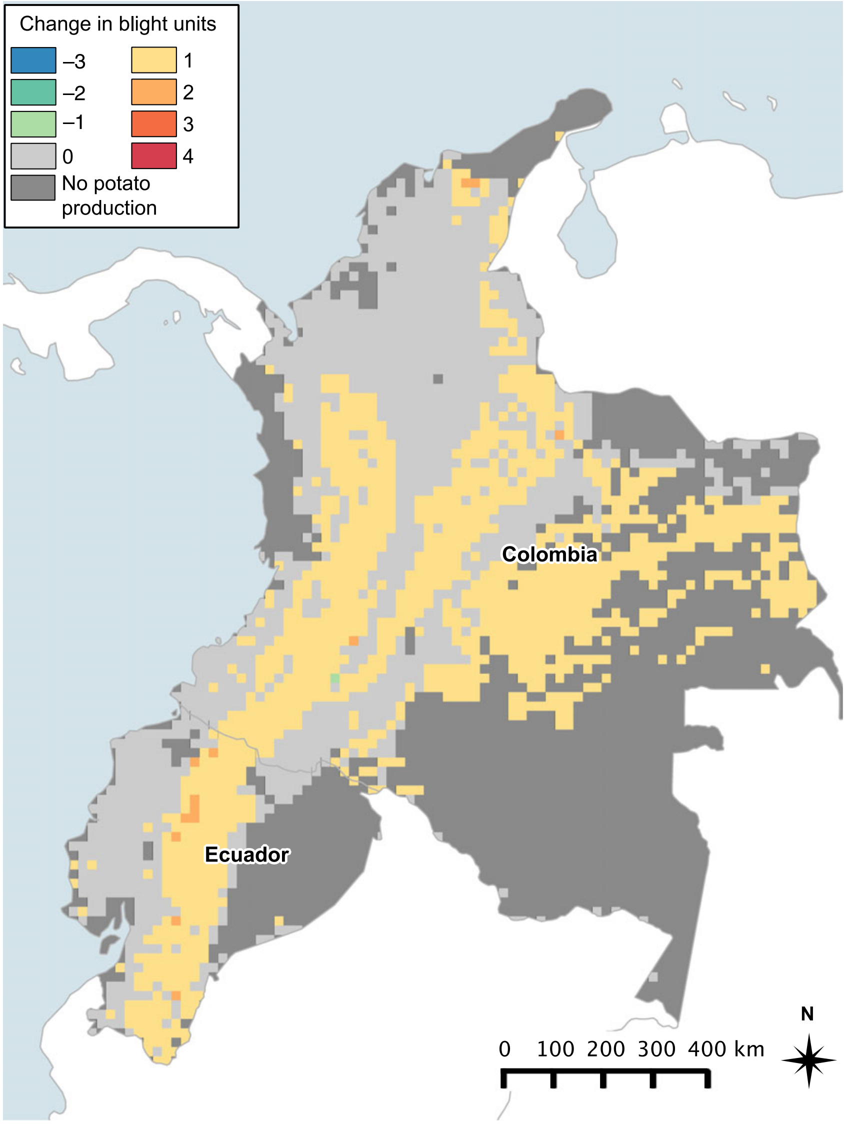

Fig. 6 The change in potato late blight relative risk for the Andean Highlands of Colombia and Ecuador as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a susceptible potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

humidity profile that was already in the optimal range for late blight development during the historic weather data set. By 2050, the temperature increases by 0.7 °C, and relative humidity increases one percent. Contrast this with Nepal or Indonesia, where temperature and relative humidity profiles during the predicted growing seasons in both countries are suboptimal for disease development and temperature decreases (Nepal) or increases (Indonesia). Also note, the relatively nearby Ethiopian Highlands are predicted to have a much smaller increase in blight units because the temperature increases and relative humidity remains fairly low for disease development.

Where potato late blight risk increases, what are the implications for management? Potato late blight is a challenge to manage, particularly for resource-poor farmers who may have limited access to appropriate fungicides (Kromann *et al.*, 2009; Blandon-Diaz *et al.*, 2011), and limited knowledge of late blight management. New, effective fungicide compounds have been released in markets in the industrialized countries but these often do not make it to developing countries, or at least not to the more remote areas. Host plant resistance, shown in this analysis to be an effective way of adapting to changing risk, would appear to be a better strategy for developing country farmers than fungicide

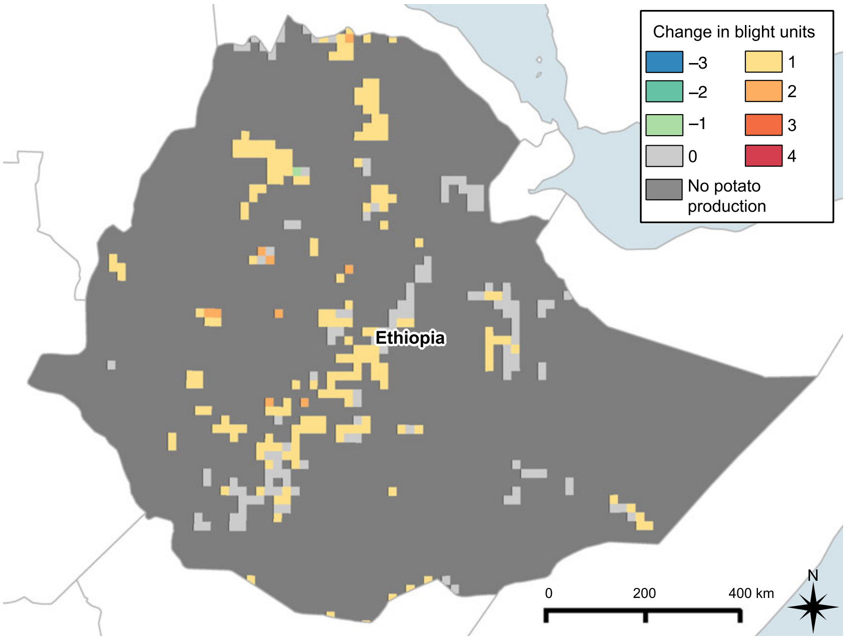

Fig. 7 The change in potato late blight relative risk for the Ethiopian Highlands as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a susceptible potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

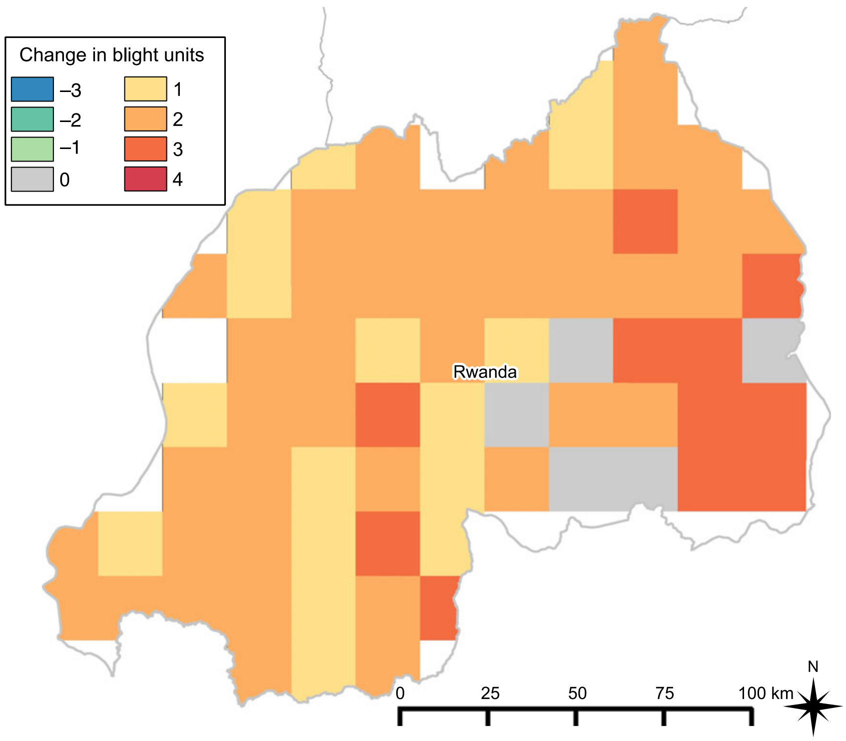

Fig. 8 The change in potato late blight relative risk for the Lake Kivu Highlands region and Rwanda as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a susceptible potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

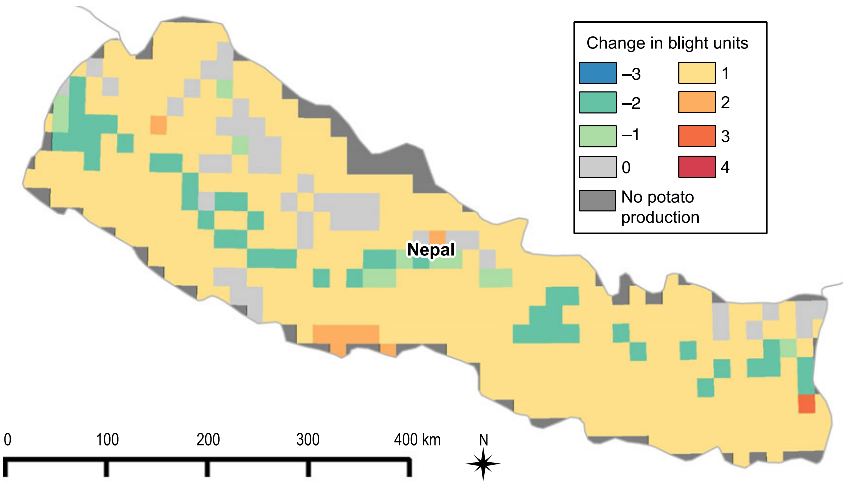

Fig. 9 The change in potato late blight relative risk for the Indo-Gangetic Plain and Himalayan Highlands in Nepal as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a susceptible potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

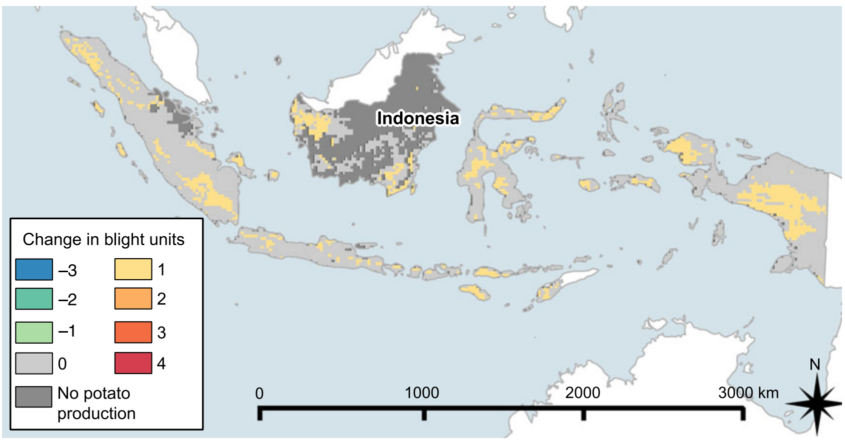

Fig. 10 The change in potato late blight relative risk for the South-East Asian Highlands in Indonesia as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario for a susceptible potato genotype. *IPCC* A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance.

use, but development and adoption of resistant cultivars have been slow for several reasons, including the low multiplication rate of potato, lack of functional seed systems in developing countries and the ephemeral nature of resistance in most cultivars that have been released (Forbes, 2012). Current levels of resistance provide some benefits, and there is the potential for technological advances to increase the level and/or durability of late blight resistance. There is also the potential for advances in the quality and durability of fungicides used for potato late blight management. Other agronomic practices can also contribute to late blight management, including adjusting planting dates to avoid conditions that favor late blight (Devaux & Haverkort, 1987), use of field sanitation, and crop genotype mixtures in the field (Pilet *et al.*, 2006), though the utility of these practices can also depend on environmental conditions (Garrett *et al.*, 2009).

Our study of global disease risk includes a number of assumptions that merit discussion. First, our study focused on risk of late blight in the future but did not address the suitability of these areas for potato production in the future. It is possible that along with a change in risk of late blight, the suitability for potato production in these areas also changes due to a changing physical or social environment. Second, another aspect of future scenarios that is not addressed by evaluations of average conditions is the potential effect of weather

Table 3 Daily average blight unit accumulation and change during the growing season for the top ten potato-producing countries by number of hectares planted to potato as predicted by SimCastMeta model using historic climate normal, 1961–1990 (1975 time-slice) and 2040–2059 (2050 time-slice) A2 climate scenario. A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotype resistance

Country	Hectares of Potato	Susceptible genotype blight units			Resistant genotype blight units		
		1975	2050	Change	1975	2050	Change
China	4401727	1.40	1.34	−0.06	0.79	0.75	−0.04
Russia	3229000	1.12	1.18	0.06	0.61	0.65	0.04
Ukraine	1600000	1.28	1.31	0.03	0.70	0.72	0.02
India	1410000	0.88	0.92	0.04	0.34	0.34	0.00
Poland	811979	2.17	2.21	0.04	1.24	1.27	0.03
Belarus	540000	2.02	1.79	−0.23	1.15	1.01	−0.14
United States	516590	0.89	0.91	0.02	0.48	0.49	0.01
Germany	284078	1.81	1.96	0.15	1.02	1.11	0.09
Peru	271185	1.45	1.36	−0.09	0.71	0.62	−0.09
Romania	270000	1.99	2.08	0.09	1.12	1.18	0.06

Table 4 Mean change in blight units from historic climate normal, 1961–1990 (1975 time-slice) to 2040–2059 (2050 time-slice) for the A2 climate scenario for select highland or lowland tropical potato production areas where potato is an important crop for poverty alleviation and where late blight is difficult to manage because of year-round potato production. A2 time-slices are ensemble model averages of three global climate models. Blight units are a predictor of biological risk based on weather and potato genotypic resistance

Agro-ecosystem	Country	Susceptible genotype blight units			Resistant genotype blight units		
		1975	2050	Change	1975	2050	Change
Andean Highlands	Colombia and Ecuador	2.25	2.20	0.05	1.03	1.04	0.01
Ethiopian Highlands	Ethiopia	0.63	0.71	0.08	0.33	0.37	0.04
Lake Kivu Highlands	Rwanda	2.41	3.58	1.17	1.43	2.22	0.79
Indo-Gangetic plain and Himalayan Highlands	Nepal	1.49	1.46	−0.02	0.85	0.81	−0.04
South East Asian Highlands	Indonesia	1.85	1.78	−0.07	0.75	0.65	−0.10

Table 5 Mean change in temperature and relative humidity from historic climate normal, 1961–1990 (1975 time-slice) to 2040–2059 (2050 time-slice) for the A2 climate scenario for select highland or lowland tropical potato production areas where potato is an important crop for poverty alleviation and where late blight is difficult to manage because of year-round potato production. A2 time-slices are ensemble model averages of three global climate models

Agro-ecosystem	Country	Temperature (°C)			Relative humidity (%)		
		1975	2050	Change	1975	2050	Change
Andean Highlands	Colombia and Ecuador	22.3	22.8	0.5	83.6	84.7	1.1
Ethiopian Highlands	Ethiopia	20.2	21.2	1.0	59.2	62.9	3.8
Lake Kivu Highlands	Rwanda	18.4	19.1	0.7	78.7	81.6	2.9
Indo-Gangetic plain and Himalayan Highlands	Nepal	15.1	13.5	−1.6	73.2	70.8	−2.4
South East Asian Highlands	Indonesia	25.0	25.4	0.4	82.5	83.6	1.1

extremes and weather variability (Rosenzweig *et al.*, 2001; Garrett *et al.*, 2013). Climate data represent weather means, but not the typical variation in weather. The average effect of late blight across years may be different than the late blight effect in an average year. Late blight risk will likely be affected differently across years as a result of changing weather patterns not represented by climate means. Third, this model evaluates average daily risk during the three-month growing season determined to be optimal for potato yield in the absence of disease. The average risk approach used here can be viewed as a conservative estimate of differences in risk, while 'compound interest' (Vanderplank, 1963) pathogen reproduction across the season may produce larger differences in disease risk between time-slices and between areas. Fourth, we assumed that inoculum was not limiting, an assumption that is generally reasonable for potato late blight. However, for more detailed regional analyses it might be important to evaluate whether inoculum might be limiting in particular locations, and how locations may be linked to sources of inoculum (Sutrave *et al.*, 2012). Effects of regional inoculum load or 'risk neighborhoods' could be incorporated in more detailed analyses (Skelsey *et al.*, in review). All else being equal, a location will experience higher late blight risk if its neighbors have higher risk. Spatio–temporal models such as those developed by Skelsey *et al.* (2009) can model regional interactions of inoculum loads. At larger scales in future scenario analyses, the level of confidence in estimates of fine-resolution weather events may not warrant such detailed model evaluation. Finally, our analyses do not include evolution in pathogen responses to the primary driving factors, which in this case are temperature and RH. As noted, the predicted decrease in blight units after 2050 occurs because, at higher temperatures, longer periods of RH are required for infection to occur. Pathogen change at the population level for temperature and RH responses has been recorded in the past (Mizubuti & Fry, 1998) and even resulted in the reparameterization of a simulation model (Andrade-Piedra *et al.*, 2005).

Synthesis of socio-economic models, crop yield models, and data such as generated by SimCastMeta could provide a more integrated view on the effects of climate change on potato yield in the future. Previous studies have incorporated crop growth models with socio-economic effects, but apparently have not simultaneously included the effects of climate on plant disease (Wei *et al.*, 2009). Other types of more detailed socio-economic models could incorporate farmers' decision-making about use of fungicides and resistant varieties, where the regularity of disease impact may influence adoption (Lybbert & Bell, 2010). For example, the adoption of resistant varieties could be surveyed or modeled and then coupled with the outputs from a plant disease severity model such as SimCastMeta for an estimate of the potential impact of releasing a resistant crop genotype. Additionally, adoption of plant disease management that reduces greenhouse gas emissions per unit product can, itself, be considered a form of climate change mitigation (Mahmuti *et al.*, 2009).

We have discussed some of the areas for improvement in biological and socio-economic models above. Another area for improvement will be the development of coordinated data sets for the global presence of disease (Jeger & Pautasso, 2008; Shaw & Osborne, 2011). Even though potato late blight is one of the most intensively studied plant diseases, extensive maps of observed disease severity are not available. This is an even greater problem for less-studied diseases. Without such data sets, ground-truthing of model predictions is limited. Future scenario analyses will also need to be updated, as new information about environmental requirements for pathogens becomes available. A dramatic example of a change in environmental tolerance is the global spread of more heat tolerant and aggressive populations of the wheat stripe rust pathogen (Milus *et al.*, 2006; Hovmoller *et al.*, 2011). There is the potential for *P. infestans* to develop a different range of temperature optima or greater tolerance for dry conditions, a type of evolutionary change, which could modify risk for any of a number of foliar pathogens (Huber & Gillespie, 1992; Caubel *et al.*, 2012). Combining new information about environmental requirements for pathogen lineages, host resistance effects, and climate scenarios will support prioritization in potato research and breeding programs, development agency investment, and extension programs into the future.

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