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Coupling climate risks, eco-systems, and anthropogenic decisions using South American and Sub-Saharan farming activities

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ABSTRACT: This paper provides an analysis of the interplays between climate risks, eco-systems and adaptation decisions using South American and Sub-Saharan African farm surveys. Climate risk indicators such as seasonal Coefficient of Variation in Precipitation (CVP) and Diurnal Temperature Range (DTR) are matched with major eco-systems. Adoption decisions of the six natural resource enterprises are modelled using a spatial Logit model. First, this paper finds that climate risks are higher in the grasslands and meadow eco-systems in South America as they are high in the lowland arid zones in Africa. However, climate risks across the continent are, compared with Sub-Saharan Africa, much lower in South America. Second, a higher temperature implies a higher climate risk in Africa, which is not the case in South America owing to the predominant influences of regional weather events such as the ENSO. Third, while the CVP is a dominant risk factor in Africa, the DTR is a dominant risk factor in South America due to the vast ranges of the Andes Mountain. Winter DTR is predicted to fall by 3 °C under both the UKMO and the GISS scenarios by the middle of this century. Altered climate risks will push a large number of farmers to switch away from a crops-only enterprise due to a large decrease in daily temperature variability. Farmers adapt by increasing a crops-livestock enterprise in the grasslands with wood cover and subtropical drought-deciduous forests. This paper provides a coupled analysis of global (climate), local (eco-systems) and individual (adaptation) processes.

KEY WORDS climate risks; eco-systems; adaptation; South America; Sub-Saharan Africa

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1. Introduction

The Earth has warmed gradually over the past century and is projected to warm significantly in this century and beyond (Hansen *et al.*, 2006; IPCC, 2007). A rapid increase in the carbon dioxide concentration in the atmosphere over the past half century is largely blamed for the warming planet (Keeling *et al.*, 2009). Increasingly, researchers also attribute extreme weather events such as heat waves, prolonged droughts and heavy rainfall events to a changing climate (Tebaldi *et al.*, 2006; Hansen *et al.*, 2012). Agronomists as well as climate scientists are concerned about the impacts of an increased variability and climate extremes on the world's major crops (Easterling *et al.*, 2000; Porter and Semenov, 2005). Although there are only a few economic studies of climate risks, agricultural researchers have indicated that such increases in extreme events will likely lead to severe economic damages (Rosenzweig *et al.*, 2001; Schlenker and Roberts, 2009). However, these studies remain provisional in that a farmer makes adaptive decisions in the face of weather and climate risks as well as taking account of socioeconomic factors, hence such decisions should be carefully modelled. For example, a recent study shows that Sub-Saharan farmers increase an integrated agricultural system when the co-efficient of variation in precipitation becomes large while they adopt animals when diurnal temperature range is larger (Seo, 2012b). Furthermore, the fact that the risks caused by climate factors are closely related to distinct ecosystems has not received much attention up until now. Ecosystems are a key player in the Earth's climate system as well as in farming decisions (Schlesinger, 1991; Ainsworth and Long, 2005; Cowie, 2007; Fischlin *et al.*, 2007; Rosenzweig *et al.*, 2008; Seo, 2012a) but the mechanisms through which future climate risks are contingent upon ecosystem changes or *vice versa* are not well understood in the impact literature (Denman *et al.*, 2007). To improve the knowledge of the complex interplays between climate risks, ecosystems and anthropogenic behaviours, this paper examines the farming decisions that take place in South America and Sub-Saharan Africa and are varied across the ecosystems and climate characteristics of the two continents.

From the number of available variables of risks, two risk indicators of climate are examined (Tebaldi *et al.*, 2006; Seo, 2012b). The first indicator is the Coefficient of Variation in Precipitation (CVP) faced by the farms (Hulme *et al.*, 2001; Shanahan *et al.*, 2009). The second measure is the Diurnal Temperature Range (DTR) which measures the range between daily maximum and daily minimum temperature (Easterling *et al.*, 2000). Both measures are provided by the Climate Research Unit's high resolution climatology at 10 arc minute resolution (New *et al.*, 2002). It must be emphasized that they are not yearly weather fluctuations but climate normals observed for the 30 year period based on about 26 000 weather stations across the globe (Rosenzweig *et al.*, 2001; Deschenes and Greenstone, 2007). That is, these risk measures capture increased risks in climate through a more variable weather pattern.

Ecosystem data are obtained from the major vegetation and land cover data for climate studies compiled by the Goddard Institute for Space Studies (GISS) (Matthews, 1983). This data

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set classifies 37 major vegetation assemblages across the globe at the resolution of a 1° grid cell. For Africa, the Global Agro-Ecological Zone (AEZ) classification by the Food and Agriculture Organization (FAO) was examined (FAO, 2005). Both data sets were often applied to climate research (Easterling *et al.*, 2007). In this study, they are used to identify ecosystems in Africa and Latin America.

Risk and ecosystem characteristics are combined with the farm decision data which come from the rural household surveys collected across seven countries in South America with geographical reference using the Global Positioning System (GPS) (Seo and Mendelsohn, 2008a). This paper examines whether a farmer's adoption of an agricultural portfolio from the whole set of available agricultural products is sensitive to varying degrees of risks posed by climate change. A spatial Logit model is used to estimate the choice of one of the six rural enterprises, both specialized and diversified: a crops-only, a livestock-only, a forests-only, a crops-livestock, a crops-forests, and a crops-livestock-forests enterprise (McFadden, 1974; Seo, 2012a). The role of portfolio diversification as a way to adapt to increased climate risks is examined (Markowitz, 1952; Seo, 2010a).

Unfortunately, existing AOGCM models cannot predict the changes in the climate risk indicators at the moment (Tebaldi *et al.*, 2006; IPCC, 2007). This paper, therefore, proceeds to estimate the future climate risks using the correlations between climate means and climate risks observed at present. Climate predictions of the GISS-ER model and the UKMO (United Kingdom Meteorological Office) HadGEM1 model are used to estimate the future climate risks (Gordon *et al.*, 2000; Schmidt *et al.*, 2005).

This paper proceeds as follows. In the next section, a theory on climate risks and farming decisions faced with such risks and ecosystems is described. In the third section, various data sets and their sources are explained. Section 4 explains empirical results. The following section simulates the changes in the climate risk indicators from the AOGCM predictions and measures the consequences of increased climate risks on farming decisions by the middle of this century. The paper concludes with a summary and discussions.

2. Theory

Given the climate and ecosystem conditions, a farmer makes a decision on which farm portfolio they would manage from a large number of available crops, livestock species and forest products (Seo 2010b; 2012a). They would choose one which maximizes the expected net return from farming activities. A subsistence farmer may not produce to maximize net return but rather to satisfy household consumption of the products. Many farm households also rely on family labours rather than employed labours. A farmer may attach special values to different farming activities due to heritage, culture and history. In these cases, this paper assumes that they are valued by the farmer in making decisions considering trade-offs.

Let j be a portfolio and n an individual farmer located in an ecosystem ψ. Let the expected long-term profit be written as the sum of the observable component and the unobservable component by the researcher as follows (McFadden, 1974):

$$\pi_{nj\psi} = X_n\beta_j + \epsilon_j,\ j = 1, 2, \ldots, J. \qquad (1)$$

X is the vector of explanatory variables which is composed of climate risks, soils, geography, socio-economic variables, and household characteristics.

Climate risks, a component of X, occur in the form of temperature and/or precipitation patterns (New *et al.*, 2002; Tebaldi *et al.*, 2006). Precipitation (R) risk is posed by alternating heavy rainfall years and severe drought years which affect agriculture severely in Sub-Saharan Africa but also elsewhere (Hulme *et al.*, 2001; Shanahan *et al.*, 2009). To construct climate normals, an indicator that captures rainfall variability in the long-term is needed, not random yearly fluctuations nor natural shocks (Udry, 1994; Zilberman, 1998; Rosenzweig *et al.*, 2001; Deschens and Greenstone, 2007). Precipitation risk can be measured by the Coefficient of Variation in Precipitation (CVP) for each month (k) based on the 30 year ($T = 30$) climate data as follows:

$$CVP_k = \frac{\sigma_k}{\overline{R}_k} \text{ where } \sigma_k = \sqrt{\frac{\sum_{t=1}^{T}\sum_{d=1}^{D}\left(R_{ktd} - \overline{R}_k\right)^2}{T \times D - 1}} \qquad (2)$$

where d denotes a day, D is the number of days in the month (k), t is a year and T is the total number of years.

The Diurnal Temperature Range (DTR) captures temperature risk by the change in the range between daily maximum and daily minimum temperature. That is, it addresses potential damage arising from the increase (or decrease) in the night time minimum temperature (Easterling *et al.*, 2000). This can be caused by a warming trend of climate or a sustained period of high temperature. The DTR is defined as follows using $TE^{\max}$ and $TE^{\min}$ which denote daily temperature maximum and daily temperature minimum respectively:

$$DTR_k = \sum_{t=1}^{T}\left\{\sum_{d=1}^{D}[TE_{td}^{\max} - TE_{td}^{\min}]/D\right\}/T \qquad (3)$$

Climate factors determine the ecosystems (ψ) found across South America (Schlesinger 1991; Denman *et al.*, 2007). The mechanisms through which the ecosystems are determined are, *inter alia*, carbon cycles, heat, water availability, evapotranspiration, cloud formations, soils, and cryosphere. Growth rates and yields of various types of grasses, plants and trees depend upon these factors (Ainsworth and Long, 2005). To understand the unique ecosystems of the sub-regions, the major vegetation and land cover data set compiled by the GISS (Matthews, 1983) is used. This classification has five major vegetation assemblages and water bodies such as an ocean: deserts, grasslands, shrublands, woodlands, and forests. The last four vegetation assemblages are further divided into detailed vegetation types depending upon the criteria such as forest types, grass height and the size of wood cover.

Conditioned on the climate risks and ecosystems, a farmer adopts a system of agriculture. From the whole array of agricultural and forest activities conducted across South America, this paper examines the following six natural resource enterprises which cover all the farms in the sample with only several exceptions. There are specialized enterprises such as a crops-only, a livestock-only, and a forest-only. There are diversified enterprises such as a crops-livestock, a crops-forest, and a crops-livestock-forests (Seo, 2012a). The classification of the six enterprises is not accidental but in line with the development in the literature on climate change and agriculture. At first, researchers placed an emphasis on major crops and over time they were able to examine non major crops such as pastures and forest products (Adams *et al.*, 1990). On the other hand, animal scientists have made their own but slow progresses (Reilly *et al.*, 1996; Easterling *et al.*, 2007). The six enterprise model puts together these separate progresses into a single decision-making framework of an individual farmer.

In contrast to Sub-Saharan Africa, forest activities are crucial in South America as forest cover (defined as $> 50\%$ cover) accounts for about 44% of the land area while it accounts for about 18% in Africa (WRI, 2005). Also, forest income accounts for 35% of rural income in Latin America while it explains about 18% of rural income in Sub-Saharan Africa (Vedeld *et al.*, 2007). For the analysis of Sub-Saharan Africa, the classification of the three agricultural systems is maintained: a specialized crop system, a specialized livestock system, and a mixed crops-livestock system (Seo, 2011). This is because of the existence of vast areas of arid zones in Sub-Saharan Africa including the Sahel, the Eastern Highlands, and the southern deserts (the Namib and the Kalahari) and the three agricultural system classification is best to capture a distinctive transition of agricultural systems from crops to livestock under such conditions (Seo and Mendelsohn, 2008b).

Assuming that the error term in Equation (1) follows an independent and identical Gumbel distribution after randomly and spatially re-sampling from the defined neighbourhoods, the probability of choosing agricultural portfolio j can be written as follows as a Logit (McFadden, 1974; Seo, 2011):

$$P_j = \frac{\exp\left(X\beta_j\right)}{\sum_{k=1}^{K} \exp\left(X\beta_k\right)} \quad (4)$$

The parameters are estimated by maximizing the Log-Likelihood function defined using the probabilities in Equation (4) and D_{ij} a dummy variable which denotes the observed choice of alternative j by farmer i:

$$LL = \sum_{i=1}^{I}\sum_{j=1}^{J} D_{ij} \times \log P_{ij} \quad (5)$$

The impact of a change in the climate risk from ξ_0 to ξ_1 on the choice of agricultural portfolio j is then measured as the change in the probability after and before climate change:

$$\Delta P_j = P_j\left(\xi_1\right) - P_j\left(\xi_0\right) \quad (6)$$

If the change in Equation (6) is positive, it implies that the farmer will increase portfolio j under the altered risk conditions due to climate change. For the impact at the continental level, the changes in probabilities are summed over all the farms in the sample. For the impact at the ecosystem level, the changes are summed across all the farms in each of the ecosystems.

3. Data

For both South America and Sub-Saharan Africa, climate risk indicators come from the Climate Research Unit (CRU)'s high resolution average climatology of the globe (Section 1 and New *et al.*, 2002). The data were used for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report and available at the Data Distribution Center of the IPCC (IPCC, 2007). Using monthly CVP data, summer and winter CVPs are defined as the averages of the three adjacent months after correcting for the Southern Hemisphere. That is, the average of December, January and February CVPs is used for the summer CVP in the Southern Hemisphere and the average of June, July and August CVPs is used for the winter CVP in the Northern Hemisphere. The same procedure is applied to define summer and winter DTRs.

For Latin America, the newly constructed GPS (Global Positioning System) referenced household survey data are matched with the CRU climate risk data, soils, and climate scenarios (Seo, 2013). Using the GPS devices carried by the interviewers, exact farm locations of latitude, longitude, and altitude were recorded. They are then matched to the cell of the climate risk data. Soil data are obtained from the FAO digital soil map of the world CD ROM which provides dominant soil types at a 0.5° by a 0.5° grid cell resolution (FAO, 2003).

Farm household data were compiled from the World Bank project on rural poverty and climate change in Latin America (Seo and Mendelsohn, 2008b). The project collected detailed information on rural household characteristics and farming activities during the farming period from July 2003 to June 2004. Among others, farmers were asked to write down the number and size of croplands, crops and trees planted/harvested for each plot, and animals owned/sold. To reflect the range of climate and ecological characteristics of South America, surveys were collected from Argentina, Brazil, Chile, and Uruguay in the Southern Cone region, and Colombia, Ecuador, and Venezuela in the Andean region, given the availability of researchers. In each country, clusters were selected to cover a diversity of climate zones and agricultural activities in the country and random sampling was done within each cluster. Under the coordination by the PROCISUR (The Cooperative Program for Technological Development in Agrifood and Agroindustry in the Southern Cone), a group of agricultural scientists in each country conducted interviews making use of the existing network of the country's agricultural research organizations, e.g., Embrapa in Brazil and INIA in Argentina.

Based on published articles and satellite images, the land cover data set classifies major vegetation of the globe at the grid cell level with 1° latitude and 1° longitude resolution. In total, there are 32 detailed vegetation types and water bodies such as the oceans and rivers. The Global Agro-Ecological Zone (AEZ) data are from the Food and Agriculture Organization (FAO) of the United Nations (FAO, 2005). It determines the AEZs based on the concept of the length of growing period for crops.

4. Empirical results

Climate determines the ecosystems of the Earth by affecting biogeochemical and carbon cycles (Schlesinger, 1991; Denman *et al.*, 2007). Seasonal CVPs and DTRs are summarized across major vegetation assemblages in South America in Table 1. The summer CVP is high in meadows, water body (oceans, lakes and rivers) and xeromorphic forests, while the winter CVP is high in the grasslands with $< 40\%$ woody cover. Rainforests-tropical, subtropical, and temperate- have low CVPs. The summer DTR is large in xeromorphic shrublands and tall grasslands while the winter DTR is large in the grasslands with $< 40\%$ woody cover. The DTR is low in the water body, i.e., coastal lands, which may indicate that the DTR is higher inland than on the coasts.

These risk statistics can be compared with those from Sub-Saharan Africa presented at the bottom of the table. The key observation is that Africa's precipitation variability is much larger than South America's. In the lowland semi-arid zones in Africa, the CVP reaches 226% while the meadow in South America, the maximal CVP zone in the continent, has the annual CVP less than 150%, but the DTRs appear to be slightly

Table 1. Climate risks across major ecosystems.

South America	Summer CVP (%)	Winter CVP (%)	Summer DTR (°C)	Winter DTR (°C)
Cold-deciduous forest, with evergreens	89.14	48.49	13.12	8.6
Tall/medium/short grassland, < 10 woody cover	34.32	142.72	7.16	11.48
Tall/medium/short grassland, shrub cover	78.99	69.47	12.05	9.92
Tall/medium/short grassland, 10–40 woody cover	45.33	196.86	10.19	14.62
Meadow, short grassland, no woody cover	161.84	117.63	10.86	11.09
Subtropical evergreen rainforest	64.84	90.65	12.05	11.74
Tall grassland, no woody cover	65.01	85.24	13.63	11.19
Temperate/subpolar evergreen rainforest	88.57	39.98	12.81	7.99
Tropical evergreen rainforest	49.72	86.09	9.67	11.05
Tropical/subtropical broad forest	47.94	90.11	9.85	11.38
Tropical/subtropical drought-deciduous forest	42.83	116.99	9.41	11.93
Xeromorphic forest/woodland	139.86	89.79	12.04	9.92
Xeromorphic shrubland/dwarf shrubland	89.04	124.96	13.9	12.01
Water	142.11	126.93	8.12	7.58
Sub-Saharan Africa	**CVP (%)**		**DTR (°C)**	
Lowland dry savannah	198.36		12.73	
Lowland humid forest	71.33		8.59	
Lowland moist savannah	148.11		11.8	
Lowland semi-arid	226.25		13.03	
Lowland sub-humid	84.27		10.24	

CVP, coefficient of variation in precipitation; DTR, diurnal temperature range.

larger in South America. The second key observation is that the distributions of risks across the ecosystems appear to be similar. Lowland humid forests are the least risky zone in Africa both in terms of the CVP and the DTR and the rainforests in South America are the least risky zone. Arid zones are the most risky zone in Sub-Saharan Africa in the same way as meadows and grasslands are most risky in South America.

The distributions of climate risk indicators across the continent are drawn using the CRU data at the scale of a 10 arc minute grid cell (New *et al.*, 2002). The distributions of the January and July CVPs are shown in Figure 1. The January CVP is higher in the coastal zones in Chile, Venezuela and Colombia. On the other hand, the July CVP is higher in the Brazilian Cerrado and Sertao, Bolivian and Paraguayan highlands, and Chile. This can be attributed in part to the occurrences of the El Niño Southern Oscillation (ENSO) that frequently hit the coasts of these regions in different months of the year. That is, the ENSO events bring wet seasons around January in the coastal zones, while they cause dry seasons around July in the inland arid zones and highlands (Rosenzweig *et al.*, 2001).

The distributions of the January and July DTRs are shown in Figure 2. The January DTR is higher in Argentina and the Andean countries. The July DTR is higher in southern Brazil, Chile and Bolivia. The distributions in Figures 1 and 2 indicate that the CVPs and DTRs are related. That is, the January CVP is higher in the zones where the January DTR is higher. The same is true of the July CVP and DTR.

These distributions show that the high climate risk zones are in the areas that are strongly affected by a regional weather phenomenon such as the ENSO. The high CVP in the northern South America in Figure 1 is commensurate with the ENSO studies which reported one of the most consistent ENSO-precipitation relationships in which 16 dry episodes resulted from 17 ENSOs (Ropelewski and Halpert, 1987; Curtis *et al.*, 2001). A similar but stronger relationship was observed in sub-Saharan Africa. That is, a very high climate risk in the form of severe droughts in the Sahelian region is attributable in large part to the occurrences of the Atlantic Multidecadal Oscillation (AMO) (Shanahan *et al.*, 2009). This implies that regional weather events by and large determine climate risks and the simulations of climate risks in the future will remain difficult for the time being unless scientists have a clear understanding of the links between regional weather events and the long-term climate trend.

Summary statistics of climate risks of the six natural resource enterprises are shown in Table 2. The forest-only enterprise is located in the most variable CVP zones with annual CVP of 112%. The CVP is also high in the crops-only enterprise. The crops-livestock-forest enterprise and the livestock-only enterprise are located in the least variable CVP zones. On the other hand, the DTRs are higher, albeit slightly, in the livestock-only and the crops-livestock-forest enterprises.

These risk patterns do not hold in Sub-Saharan Africa, as shown in the bottom panel of the table. That is, the CVP is on average 158% in the mixed crops-livestock system in Sub-Saharan Africa and even in the crops-only enterprise the CVP is as large as 140%. In South America, the CVP in the crops-only is only about 100% while the CVP in the mixed crops-livestock enterprise is as low as 91%. The DTR in Sub-Saharan Africa reaches 12.7 °C in the livestock-only while it is as large as 11.3 °C in South America. These different patterns may indicate that climate risks are lower in South America and farmers there are concerned less about climate risks than African farmers are. That is, climate risks do not affect farming decisions as much.

The risk statistics in Tables 1 and 2 and their distributions in Figures 1 and 2 indicate major differences between the two continents. A further difference can be observed in Table 3 in which correlations between climate means and climate variability are calculated. In Sub-Saharan Africa, annual mean temperature and the CVP shows a very high correlation of 0.71 but this pattern does not hold in South America: the correlation is −0.40 for the summer. However, other correlation patterns hold. The correlation between annual mean precipitation and the CVP is −0.67 in Africa while it is −0.70 for summer but −0.73 for winter in South America. The correlation between annual mean precipitation and the DTR is −0.45 for Africa, while the correlations in South America show similar patterns.

These differences have major implications for a climate risk analysis. That is, it can be said that global warming (higher temperature) also implies increased risks (higher CVP) in Sub-Saharan Africa. In South America, global warming (higher austral and boreal summer temperature) means decreased summer risks (lower CVP). Predicted changes in climate risks, i.e., extreme events due to climate change, are not uniform among the world's regions and across climate models, as indicated by scientific simulations (Tebaldi *et al.*, 2006).

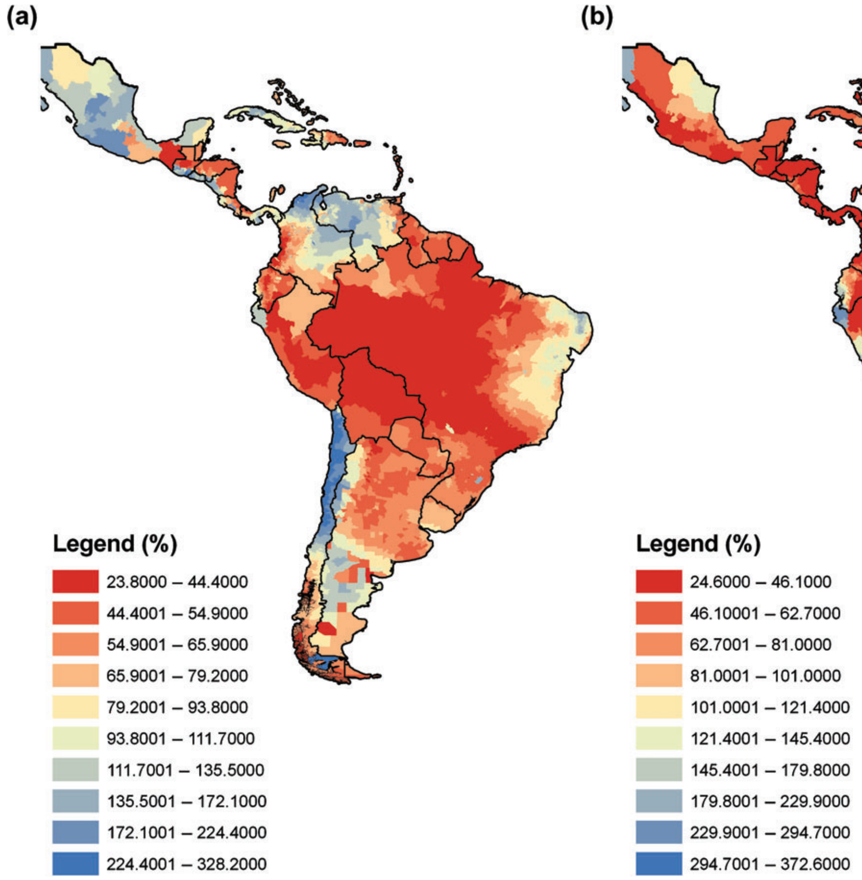

Figure 1. The distribution of the co-efficient of variation in precipitation (CVP). (a) January; (b) July. This figure is available in colour online at wileyonlinelibrary.com/journal/met

Table 2. Climate risks across enterprises.

South America	Enterprises	Number of farms	Summer CVP (%)	Winter CVP (%)	Summer DTR (°C)	Winter DTR (°C)
	Crops-livestock	568	89.14	93.02	11.51	10.50
	Crops-forests	84	79.19	91.64	11.29	10.79
	Crops-livestock-forests	45	68.96	103.76	10.90	11.27
	Livestock-only	277	73.52	94.05	11.83	10.78
	Forests-only	6	101.26	122.43	8.68	9.24
	Crops-only	401	100.71	102.77	11.33	10.97
Sub-Saharan Africa		Number of farms	CVP (%)		DTR (°C)	
	Crops-only	2880	141.78		11.87	
	Crops-livestock	4309	158.06		12.43	
	Livestock-only	444	142.94		12.73	

Given the climate risks, a farmer chooses one of the six enterprises to maximize the net return. The choice of enterprises with climate, soils, geography, household characteristics, and country dummies is explained in Table 4 using a multinomial Logit model. Setting the crops-only as the base case, the parameter estimates for the five enterprises are presented. The model is highly significant according to the Likelihood Ratio (LR) statistic. Climate risk variables are significant for several enterprises. For example, summer CVP is significant for the crops-livestock enterprise. Summer DTR is significant for the livestock-only and the crops-forests enterprises. None of the winter variables are, however, significant.

Many of the soils and geography variables are significant. Under soils, Phaeozems which are dark soils rich in organic matter, a crops-only enterprise is favoured because Phaeozems are fertile soils for crops (Driessen *et al.*, 2001). Fluvisols, which are formed by river action and deposition, are most often ideal for annual crops and orchards (Driessen *et al.*, 2001) so a livestock-only and a crops-livestock enterprise are less frequently chosen. A crops-forest enterprise is less often chosen with Luvisols, washed-out soils most often found in regions with distinct wet and dry seasons (Driessen *et al.*, 2001). Flat terrain is more likely to be used for a livestock-only or a crops-livestock enterprise. High

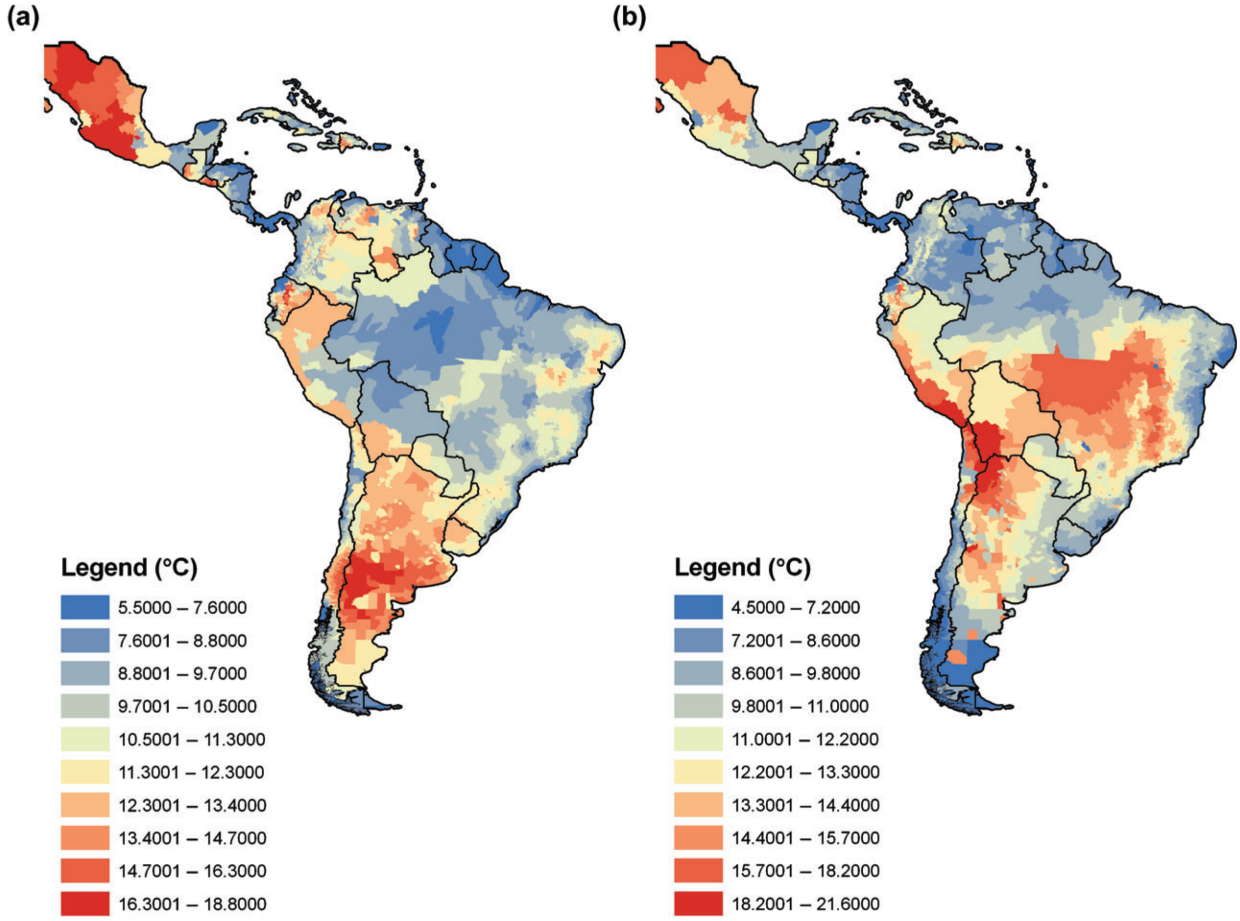

Figure 2. The distribution of the diurnal temperature range (DTR). (a) January; (b) July. This figure is available in colour online at wileyonlinelibrary.com/journal/met

Table 3. Correlations among climate means and climate risks.

South America		Summer CVP	Winter CVP	Summer DTR	Winter DTR
	Summer temperature	−0.40	0.44	−0.18	0.46
	Summer precipitation	−0.70	0.44	−0.48	0.56
	Winter temperature	−0.45	0.47	−0.65	0.34
	Winter precipitation	0.23	−0.73	0.28	−0.62
Sub-Saharan Africa		CVP		DTR	
	Annual mean temperature	0.71		0.10	
	Annual monthly mean precipitation	−0.67		−0.45	

altitudes are less likely to be used for a livestock-only or a crops-livestock-forest enterprise. Clay soils (against sandy soils) are more often used for a crops-livestock, a crops-forest, or a livestock-only enterprise.

Parameter estimates for household characteristics and country dummies indicate that they are important in enterprise decisions. A larger family tends to have a diversified portfolio, i.e., a crops-livestock-forest enterprise, due to the availability of child and female labour for livestock herding. An older farmer is more likely to own a livestock-only enterprise, and so is a more educated farmer. This may be related to a higher risk taking by a more educated farmer or a higher setup cost of this enterprise more suitable for more experienced farmers. A farmer in Argentina, Venezuela and Colombia is less likely to be a crops-livestock or a livestock-only against Brazil. A farmer in Chile is less likely to be a crops-forest or a crops-livestock-forest. A farmer in Ecuador is less likely to be a crops-livestock or a crops-livestock-forest enterprise.

Using the estimated parameters, the current enterprise adoption probabilities are drawn in Figure 3 across the major ecosystems. A crops-livestock enterprise is most frequently adopted in temperate rainforests, grasslands with 10–40% wood cover, and tropical/subtropical broadleaved forests. A livestock-only enterprise is most common in grasslands with shrub cover, grasslands with $<10\%$ wood cover, and tall grasslands. A crops-only enterprise is found most often in meadow and drought-deciduous forests. A crops-forest enterprise is common in cold-deciduous forests and xeromorphic shrublands. A crops-livestock-forest enterprise can be seen in various types of forested ecosystems.

Table 4. A spatial logit of enterprise choices across climate risks.

	Crops-Lvs		Crops-For		Crops-Lvs-For		Lvs-only		For-only	
	Est.	P-value	Est.	P-value	Est.	P-value	Est.	P-value	Est.	P-value
Intercept	5.023	0.09	13.19	0.01	−3.54	0.60	4.794	0.19	−274.1	0.08
Sum CVP	−0.03	0.002	0.013	0.48	0.028	0.47	0.006	0.63	0.111	0.64
Sum CVP sq	6.17E-05	0.03	−1.7E-05	0.75	−0.0001	0.46	−8.5E-05	0.10	−0.0006	0.44
Sum DTR	−0.15	0.73	−1.53	0.04	−0.56	0.59	−1.27	0.01	12.038	0.46
Sum DTR sq	0.018	0.30	0.064	0.02	0.014	0.74	0.056	0.007	−0.814	0.37
Win CVP	−0.0002	0.98	−0.01	0.24	−0.003	0.86	−0.004	0.70	0.146	0.43
Win CVP sq	1.28E-05	0.61	5.87E-05	0.19	7.14E-06	0.89	1.14E-05	0.74	−0.0002	0.66
Win DTR	−0.39	0.26	−0.76	0.19	1.06	0.15	0.270	0.53	48.715	0.11
Win DTR sq	0.003	0.79	0.029	0.22	−0.04	0.11	−0.02	0.24	−2.778	0.11
Phaeozems (0/1)	−2.11	< 0.0001	−2.04	0.0009	−2.50	0.002	−2.01	< 0.0001	−19.3	0.99
Lithosols (0/1)	0.08	0.79	−1.20	0.10	−1.00	0.27	0.55	0.14	−21.46	0.98
Fluvisols (0/1)	−1.3	< 0.0001	−0.05	0.92	0.20	0.78	−1.22	0.0006	−17.60	0.99
Luvisols (0/1)	−0.31	0.26	−1.35	0.04	−0.35	0.61	0.14	0.70	−5.05	0.48
Andosols (0/1)	0.27	0.57	−17.3	0.99	2.06	0.21	0.01	0.98	−14.06	0.99
Flat (0/1)	0.52	0.01	−0.89	0.03	−0.25	0.57	1.07	< 0.0001	0.62	0.87
Altitude (m)	−6.2E-05	0.77	−0.001	0.01	−0.001	0.02	−0.0007	0.04	0.002	0.65
Clay (0/1)	0.49	0.02	0.87	0.04	0.12	0.77	0.39	0.09	−1.21	0.80
House size (n)	0.05	0.13	−0.08	0.29	0.22	0.0006	0.007	0.87	0.066	0.82
Age (n)	0.01	0.08	0.01	0.29	0.009	0.50	0.029	0.0002	0.088	0.20
Education (n)	−0.003	0.86	0.09	0.002	0.024	0.52	0.058	0.005	0.29	0.11
Argentina	−1.20	0.002	−0.87	0.23	−0.95	0.27	−0.01	0.98	−11.69	0.98
Chile	−0.17	0.75	−4.69	0.0003	−3.8	0.03	−0.80	0.24	17.19	0.33
Venezuela	−1.46	< 0.0001	−19.6	0.99	−19.9	0.99	−1.16	0.01	−24.94	0.97
Ecuador	−1.77	0.0006	−20.2	0.99	−2.88	0.01	−20.8	0.99	−25.81	0.99
Colombia	−1.15	0.01	−0.20	0.78	−1.81	0.07	−1.95	0.004	−22.03	0.98

$N = 1401$. LR (log likelihood) statistic = 2365.4 (P value < 0.001). Sum, summer; Win, winter; Est., estimates; sq, square.

5. Simulating risks and adaptation strategies

The multinomial Logit model shows that the choice of an enterprise by a farmer is dependent upon the climate risk indicators. If the risks were to be altered in the future due to a climatic shift, farmers in South America are expected to make an optimal decision to cope with such a change. This section provides simulations of adaptive behavioural changes of farmers under an alteration in climate risks in the future.

To begin with, there is a major hurdle. That is, there are more than a dozen Atmospheric Oceanic General Circulation Models (AOGCM) in the world that are capable of predicting the changes in global mean temperature and precipitation far into the future (IPCC, 2007). The AOGCMs, however, are not capable of predicting the changes in climate risk indicators such as the CVP or the DTR as Tebaldi and colleagues summarized (Tebaldi *et al.*, 2006). To proceed further, the CVP and DTR changes in South America are simulated using the observed correlations between climate means and climate risks discussed earlier in Table 3. This is obviously a crude way but perhaps a good starting point while waiting for a more rigorous prediction from future scientific research.

In Table 5, the summer CVP is estimated using summer temperature, summer precipitation, winter temperature and winter precipitation. The same is done for the summer DTR, winter CVP and winter DTR. The adjusted R-squares are high in all four regressions while parameter estimates are all highly significant. As expected, a higher summer temperature leads to a lower CVP in the summer but a higher winter temperature leads to a higher CVP in the winter. A higher precipitation leads to a lower DTR in the summer as well as in the winter.

The changes in the CVPs and the DTRs were estimated (Table 6). The two AOGCM scenarios are obtained: the UKMO HadGEM1 model and the GISS-ER model (Gordon *et al.*, 2000; Schmidt *et al.*, 2005). For both models, the A2 emissions scenarios (Nakicenovic *et al.*, 2000) were used. Using the changes in climate means predicted by the two climate models (shown on the left panel of the table), the current climate risks as well as the future climate risks were calculated using the estimated relationships shown in Table 5.

The simulated changes in climate risks are presented in the right columns of Table 6. The CVPs increase under both climate models but only modestly. Under the GISS, the summer CVP increases by 1% and by 4.5% under the UKMO model. A similar but much smaller change can be seen in the winter CVP. The winter DTR decreases by as much as 3 °C under both climate models, while the summer DTR changes only slightly. These results indicate that the changes in climate risks in South America are likely small except for the winter temperature variability (DTR). These results also reflect the predictions by the climate scientists which find some regions in South America will experience a higher risk while others a lower risk in climate (Tebaldi *et al.*, 2006). The large decrease in the winter DTR poses an interesting scenario of a reduced climate risk due to a climatic change. However, the impact of such a reduction in the DTR on agriculture remains to be seen.

Based on the current and the future CVPs and DTRs, the changes in adoption probabilities of the six natural resource enterprises are simulated in Table 7. Using the estimated parameters in Table 4, the current and the future choice probabilities of individual farms and the differences for each of them are calculated. Under the GISS scenario, the crops-only enterprise falls by 10.7% while the crops-livestock enterprise increases by about the same magnitude. The crops-forest enterprise as well as the forest-only enterprise will be chosen more frequently due to the reduced DTRs, but the crops-livestock-forest

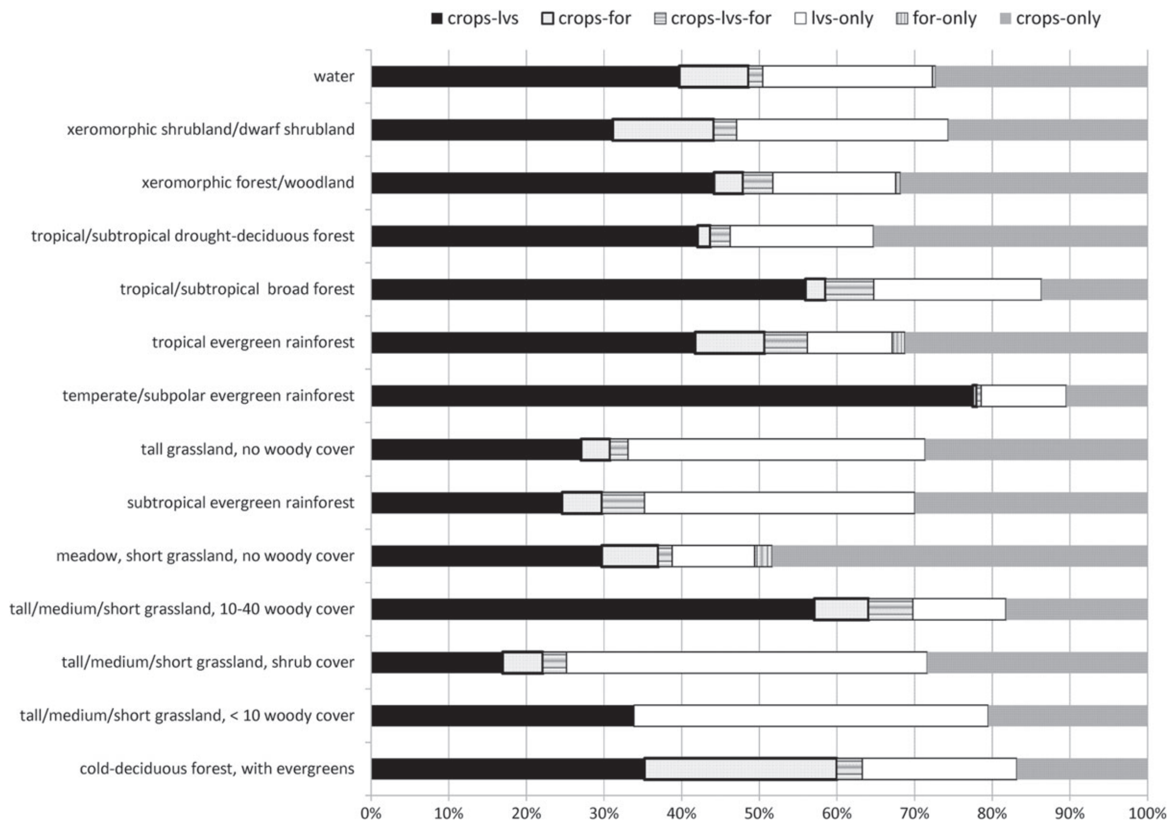

Figure 3. Distribution of enterprises across ecosystems at present.

Table 5. Estimations of climate risks.

	Summer CVP		Summer DTR		Winter CVP		Winter DTR	
	Est.	HC P-val.	Est.	HC P-val.	Est.	HC P-val.	Est.	HC P-val.
Intercept	180.895	< 0.0001	8.01873	< 0.0001	127.783	< 0.0001	9.46359	< 0.0001
Summer temperature	−2.10877	< 0.0001	0.38033	< 0.0001	−0.73212	0.0186	0.1398	< 0.0001
Summer precipitation	−0.53461	< 0.0001	−0.00135	0.0183	0.06582	< 0.0001	0.01502	< 0.0001
Winter temperature	1.15391	< 0.0001	−0.34096	< 0.0001	0.80746	0.0001	−0.15083	< 0.0001
Winter precipitation	−0.07484	< 0.0001	0.00379	< 0.0001	−0.41852	< 0.0001	−0.01443	< 0.0001
Summary statistics								
N	1401	—	1401	—	1401	—	1401	—
Adj R^2	0.50	—	0.66	—	0.56	—	0.57	—

HC P-val. = P values for the heteroscedasticity corrected standard errors.

enterprise will fall. Under the UKMO scenario, similar changes are expected to occur with slightly smaller magnitudes. Nonetheless, the UKMO results indicate that the small changes in the CVP will have only minor impacts on farming decisions.

The finding that the crops-only enterprise falls by a large percentage presents a fresh insight. That is, an increase in climate risks may not be a harmful thing to agriculture all the time. To be more specific, a sufficient daily variation in temperature may be a key ingredient for the successful crop production. A decrease in such a variation may lead to a large reduction in the choice of crops and consequently crop production. This result is consistent with the crop literature which reported that an increase in daily minimum temperature may harm some major crops (Easterling *et al.*, 2000, 2007). What the present paper reveals is that South American farmers would mix crops with livestock or forests under a lower daily temperature variation. An alternative interpretation of the above result is that geography is a key determining factor of climate risks and eco-systems, and consequently farming decisions. That is, the existence of the vast ranges of the Andes Mountain forces the farmers to rely on crops while the Pampas plains in Argentina and Brazil are preferred for livestock management. At the same time, the rugged ranges of the Andes bring the high variability of daily temperature. In the high mountain ranges where the DTR risk is high, farmers adapted through various types of crops. Interestingly, Sub-Saharan farmers adapted through livestock management in the lowland arid zones where the CVP risk is very high (Seo, 2012b). Researchers must, therefore, understand not only climate change but also the unique geography to predict climate risks.

Finally, the changes in the adoption probabilities of natural resource enterprises across major ecosystems in South America are drawn in Figure 4 assuming the UKMO scenario. The changes in enterprise choices are prominent in the grasslands with wood cover or tropical forest zones. They most often switch from a crops-only to a crops-livestock enterprise. In

Table 6. Simulated changes in climate risks by 2060.

Changes in climate means			Changes in climate risks		
	GISS	UKMO		GISS	UKMO
Summer temperature (°C)	+2.03	+2.54	Summer CVP (%)	+1.06	+4.59
Winter temperature (°C)	+1.53	+2.11	Summer DTR (°C)	−0.05	−0.06
Summer precipitation (mm month^{-1})	+2.97	−3.76	Winter CVP (%)	+0.03	+1.61
Winter precipitation (mm month^{-1})	−2.52	−7.15	Winter DTR (°C)	−3.21	−3.06

GISS, Goddard Institute for Space Studies; UKMO, United Kingdom Meteorology Office.

Table 7. Changes in enterprise adoptions (percentage points) under changes in climate risks by 2060.

	Crops-livestock	Crops-forests	Crops-livestock-forests	Livestock only	Forests only	Crops only
Baseline (%)	41.92	5.41	3.40	20.44	0.47	28.36
ΔGISS (%)	10.71	1.87	−1.70	−0.49	0.29	−10.68
ΔUKMO (%)	8.75	2.12	−1.45	−0.15	0.02	−9.29

the grasslands with wood cover, farmers increase the crops-livestock enterprise by a large percentage by decreasing a crops-only and a livestock-only enterprise. Similar changes would occur in the tropical/subtropical drought-deciduous or broadleaved forests, but a crops-livestock-forest enterprise also declines there. In the cold-deciduous forests, tropical rainforests and xeromorphic forest, a crops-forest enterprise would increase. A livestock-only enterprise increases into meadow zones and xeromorphic forests. A crops-only enterprise falls across the continent except in the coastal zones.

These results can be interpreted with the help of Figures 1 and 2. As can be seen, winter DTR is high across the Brazilian arid zones such as the Cerrado and the Sertao, the Peruvian/Chilean highlands, and the Paraguayan/Bolivian inlands, and is low in the rest of the continent. A reduced winter DTR in South America under the UKMO scenario in these meadow zones, xeromorphic forests, drought-deciduous forests and grassland with substantial tree cover would increase the mixed crops-livestock enterprise by reducing the crops-only enterprise because of the decrease in the range of diurnal temperature in these regions adequate for crops.

6. Conclusion

This paper examines the interplays of climate risks, ecosystems, and anthropogenic behaviour using South American and Sub-Saharan African farming decisions. Seasonal Coefficients of Variation in Precipitation (CVPs) and Diurnal Temperature Ranges (DTRs) are used as indicators of climate risks. Risk characteristics of the major ecosystems are examined. Climate risk indicators are matched with adoption decisions by the farmers of natural resource enterprises. Using a spatial Logit model, choices of the six rural enterprises in South America are modelled. From the two Atmospheric Oceanic General Circulation Models (AOGCMs), future risks that would occur due to climatic changes are simulated. Expected changes in the distributions of the natural resource enterprises due to the changes in climate risks are simulated.

This paper finds that climate risk indicators in South America are quite different from those in Sub-Saharan Africa. In addition, the ways South American farmers have coped with climate risks are distinct from the ways African farmers have coped. First, climate risks in South America are much lower than in Sub-Saharan Africa. For example, while the mixed crops-livestock system in Africa is faced with the CVP greater than 150%, it is faced with less than 90% of the CVP in South America. The grasslands face the CVP of 140% in South America while lowland semi-arid zones in Sub-Saharan Africa face the CVP of 226%. However, climate risks are higher in the grasslands and meadow ecosystems in South America, analogous to the findings in Sub-Saharan Africa where climate risks are very high in the lowland arid/semi-arid zones.

Second, differences can be seen in the relationships between climate means and climate risks between the two continents. Whereas a higher temperature is strongly positively correlated with the CVP in Sub-Saharan Africa (+0.71), a higher temperature is negatively correlated with climate risks in South America, especially in the summer (−0.40). These results again indicate that climate risks are rather determined by regional weather events such as the ENSO (El Niño Southern Oscillation) in South America and the AMO (Atlantic Multidecadal Oscillation) in Sub-Saharan Africa than climatic shifts (Shanahan *et al.*, 2009).

Third, this paper finds, using the observed relationships between climate means and climate risk indicators, that a large decrease in the DTR is the primary risk concern for South African farms. The summer and winter CVPs are predicted to increase only by 4.5 and 1.6%, respectively, under the United Kingdom Meteorological Office (UKMO) scenario by the middle of this century and change only negligibly under the Goddard Institute of Space Studies (GISS) scenario. On the other hand, winter DTR is expected to fall by about 3 °C under both the UKMO and the GISS scenarios.

Fourth, changes in climate risks will push the farmers to choose the crops-livestock enterprise more often by more than 10 percentage points by decreasing primarily the crops-only enterprise. This is again due to a large decrease in the daily temperature variability. Despite the concerns on climate risks, a sufficient variability in daily temperature may benefit crop growth and yields (Easterling *et al.*, 2000, 2007). A large decrease in winter DTR also leads to the reduction in the crops-livestock-forests enterprise which is at present located in high winter DTR zones such as Bolivian highlands and Brazilian Cerrado. Across ecosystems, farmers will increase the crops-livestock enterprise by decreasing a crops-only and a livestock-only enterprise in the grasslands with wood cover, tropical/subtropical drought-deciduous or broadleaved forests. In the currently forested zones such as cold-deciduous forests, tropical rainforests, and xeromorphic forests, a

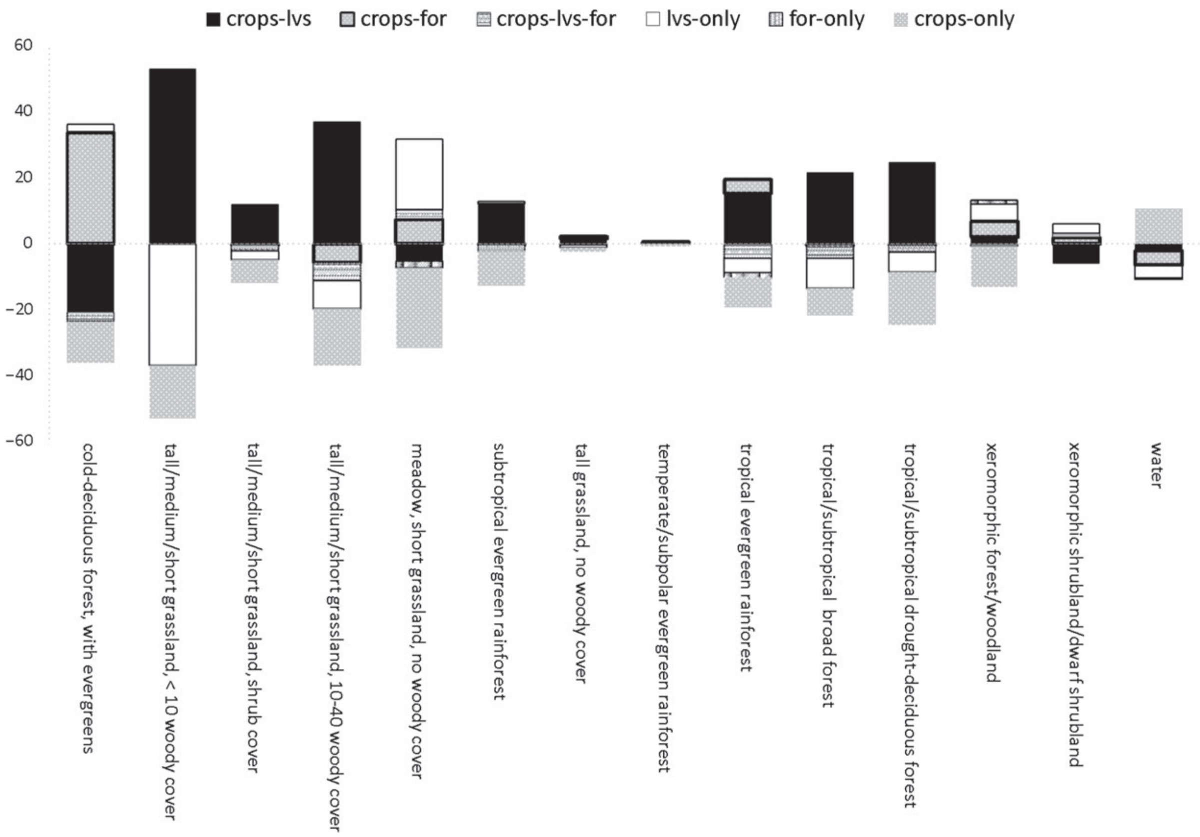

Figure 4. Changes in enterprise adoptions across ecosystems under UKMO by 2060.

crops-forests enterprise would increase. A livestock-only enterprise increases into meadow zones and xeromorphic forests while a crops-only increases in the coastal zones.

Coupling of climate risks, ecosystems and anthropogenic decisions provides novel insights into the existing biogeochemical models of climate change (Denman *et al.*, 2007). That is, it explicitly introduces anthropogenic decisions into the complex climate processes and provides an integrated analysis of global (climate risks), local (ecosystems), and individual (adaptation) processes. In addition, this paper shows the ways how farmers have coped with climate risks, which fills the important gap in the impact literature on climate risks and extremes (Rosenzweig *et al.*, 2001; Schlenker and Roberts, 2009). In an analysis of climate risks faced by farmers, local factors such as weather events and ecosystems must be carefully studied in addition to the global climate processes. In South America, climate risks are much lower than in Africa and simulated changes also indicate relatively small changes. Climate risks are largely determined at present by regional weather events such as the ENSO and the dominant geographical characteristics such as the vast ranges of the Andes Mountain. Increased climate variability, e.g., an increased DTR, may have beneficial effects on some crops in South America. This paper finds a large increase in a crops-livestock enterprise at the expense of a crops-only enterprise when climate risks are altered. Future research is guaranteed on many aspects of science, agronomy, geography and economics with regard to climate risk.

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