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Ethnographic context and spatial coherence of climate indicators for farming communities – A multi-regional comparative assessment

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ABSTRACT

Accurate seasonal predictions of rainfall may reduce climatic risks that farmers are usually faced with across the tropical and subtropical zones. However, although regional-scale seasonal amounts have regularly been forecasted since 1997/98, the practical use of these seasonal predictions is still limited by myriad factors. This paper synthesizes the main results of a multi-disciplinary ethnographic and climatic project (PICREVAT). Its main objective was to seek the climatic information – beyond the seasonal amounts – critical for crops, both as an actual constraint to crop yields and as identified by the current and past practices and perceptions of farmers. A second goal was to confront the relevance and significance of this climatic information with its spatial coherence, which gives an upper bound of its potential predictability. The ethnographic and climatic analyses were carried out on three very different fields: North Cameroon (mixed food crops associated with a cash crop – cotton – integrated into a national program); Eastern slopes of Mt Kenya (mixed food crops, with a recent development of maize at the expense of sorghum and pearl millet); and Central Argentina (mixed crops and livestock recently converting to monoculture of transgenic soybean, referred to as *soybeanization*).

The ethnographic surveys, as well as yield–climate functions, emphasized the role played by various intra-seasonal characteristics of the rainy seasons beyond the seasonal rainfall amounts, in both actual yields and people's representations and/or crop management strategies. For instance, the onset of the rainy season in East Africa and North Cameroon, the season duration in the driest district of the eastern slopes of Mount Kenya, or rains at the core (August) and at the end of the rainy season in North Cameroon have been highlighted. The dynamics of farming systems (i.e. *soybeanization* in Central Argentina, increasing popularity of maize in East Africa, recent decline of cotton in North Cameroon) were also emphasized as active drivers; these slow changes could increase climatic vulnerability (i.e. soybean is far more sensitive to rainfall variations than wheat, maize is less drought-

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resistant than sorghum or millet), at least for the least flexible actors (such as the non-capitalized farmers in Central Argentina). The cross between ethnographic surveys and climatic analyses enabled us to identify climate variables that are both useful to farmers and potentially predictable. These variables do not appear to be common across the surveyed fields. The best example is the rainy season onset date whose variations, depending on regions, crop species and farming practices may either have a major/minor role in crop performance and/or crop management, or may have a high/low potential predictability.

Introduction

All societies are somehow vulnerable to climate, but the exposure to climate hazards is expected to be larger for tropical and subtropical countries, where a large fraction of gross national product and food supply is provided by rain-fed agriculture (Cutter, 1996; Reilly and Schimmelpfennig, 1999; Salinger et al., 2005; Sivakumar et al., 2005; Fussel and Klein, 2006). In these countries, climatic vulnerability (Turner et al., 2003; Adger, 2006; Gallopin, 2006) is mostly related to rainfall variations and is often very high in semi-arid areas, where low-income populations strongly depend on very scarce and variable water resources (Camberlin, 2010). In that context, seasonal rainfall forecasts (Goddard et al., 2001, 2003; Barnston et al., 2010) are a potential tool for farmers to reduce risks and to optimize gains (Glantz, 1977; Dilley, 2000; Luseno et al., 2003; Meinke and Stone, 2005; Hansen et al., 2006, 2009; Challinor, 2009; Sultan et al., 2010a,b; Roudier et al., 2011, 2014), even though several issues (e.g. scales and timing of forecasts, translation of expert forecasts into decision-making processes at the farm scale, etc.) currently limit the usefulness of even near-perfect seasonal forecasts (Lamb, 1981; Blench, 1999; Broad and Agrawala, 2000; Singh et al., 2009).

Current seasonal rainfall forecasts focus on the regional (i.e. at least several stations and/or a few grid-points covering an area usually larger than 10^5 sq km) and seasonal scales (interannual anomalies averaged over 3 consecutive months, Goddard et al., 2001, 2003; Barnston et al., 2010). These spatio-temporal scales filter out some of the unpredictable noise related to internal atmospheric dynamics and small-scale processes, and enhance the potentially predictable signal related to the forcing of boundary surfaces, including sea surface temperatures (SST). By definition, a temporal sum, as seasonal amount, integrates all rainy events across a season and is thus the most comprehensive variable from the statistical point of view. Its spatial coherence at the interannual time scale gives an empirical upper bound of potential predictability, if we assume that any slow boundary forcing may induce a quasi-constant homogeneous signal at regional-scale (Moron et al., 2006, 2007). Nevertheless, the highest rainfall, close to the mean annual peak, is not necessarily spatially coherent and may reduce the potential predictability of seasonal amounts.

A regional-scale seasonal amount anomaly is not necessarily the "optimal" variable from the farmer's point of view. The rainy season onset date prediction is usually considered by farmers to be more relevant than that of the seasonal amount anomaly (Ingram et al., 2002). Any given intra-seasonal characteristic (ISC) is, by definition, included in the seasonal amount as a specific component of the rainy season (for the onset, the temporal phase of its starting stage), but it may not necessarily convey its predictable part (Moron et al., 2009a,b; Marteau et al., 2009). Additionally, the usefulness of any ISC of the rainy season may not be the same for smallholders and commercial farmers. It may also differ between those engaged in a multi-cropping system and those who have adopted a (monocultural?) system, or between those cultivating a well-adapted and drought-tolerant crop such as sorghum, and those cultivating a less adapted and highly sensitive crop such as maize, but which provides an higher net gain in optimal climate conditions. Considering all these contexts, we cannot deny that the most relevant and useful climate variable for farmers does not maximize the signal-to-noise ratio from the climatic point of view and vice versa.

In this paper we synthesize the main results of a multidisciplinary framework, the PICREVAT project (January 2009–June 2013), combining statistical analyses of interannual and intra-annual variability of rainfall and of crop-rainfall relationships (papers by Boyard-Micheau et al., 2013; Moron et al., 2013; Camberlin et al., 2014; Philippon et al., 2015a,b; Hernández et al., 2015) with ethnographic surveys (papers by Leclerc et al., 2013, 2014; Mwongera et al., 2014; Hernández et al., 2015). All the agro-climatic and ethnographic analyses were carried out on three contrasted fields: (1) North Cameroon in the Sudano-Sahelian belt, mixing cotton with subsistence crops (mainly sorghum and maize); (2) Kenya and North Tanzania (Camberlin et al., 2009, 2014; Philippon et al., 2015a,b) with a focus on eastern slopes of Mt Kenya, where small-scale subsistence farming is based on mixed cropping systems but maize has gradually surpassed traditional (and less drought-vulnerable) crops like sorghum and pearl millet (Leclerc et al., 2013, 2014; Mwongera et al., 2014); and (3) central Pampa in Argentina, where the farming system has recently shifted from mixed crops and livestock to dominant transgenic soybean cropping system (Magrin et al., 2005; Pengue, 2005, 2006; Caviglia and Andrade, 2010; Hernandez et al., 2015). A major goal of PICREVAT was to analyze the critical climatic information for crops, both as a constraint on yields through a classical production-function approach linking observed yields and climate variations (Mendelsohn et al., 1994), and as explicitly identified by local farmers and stakeholders, either through their farming practices or their perception/memory of any adverse

climate events detrimental to farming. To that aim we explored several of the following issues: (1) the perceived and actual role of various ISCs on crops, as well as their spatial coherence and relationship to local- and regional-scale seasonal amounts; (2) the social and cultural contexts of farming systems; and (3) the temporal dynamics of farming systems which are not necessarily induced by climate variations, but potentially modify their vulnerability.

We first present the material and methods used in the different fields (Material and method). Then we describe the farming systems of the three comparative study sites (The context of farming), and present some of the climate information identified as relevant and significant for farming activities (Relevance and significance of climatic parameters for crops and farmers). The spatial coherence of ISCs and subseasonal rainfall are detailed in 'Spatial coherence of rainfall at seasonal and intraseasonal time scales'. A discussion (Discussion and concluding remarks) closes the paper.

Material and method

Daily rainfall data

In Kenya and North Tanzania, we selected 36 rain gauges having at most 25% missing entries from 1961 to 2001 (Fig. 1a). Overall there are 5.9 % of entries missing with 21 stations having fewer than 365 missing days. The mean annual cycle (Fig. 1b) shows two maxima associated with the March–May Long rains (LR) and the October–December Short rains (SR). There are rather large spatial variations in mean rainfall with drier areas in the northeast and some lowland areas in the south, while rainfall is higher along the Indian Ocean coast and over the highlands of Western and Central Kenya. The bimodal annual cycle tends to vanish westward with noticeable rainfall during boreal summer.

In North Cameroon, we selected 33 rain gauges having a maximum of 15% missing entries from 1970 to 2001. 10.7% of the entries are missing in this subset. The spatial sampling rate (Fig. 1c) is the highest of the three networks. Rain gauges are located in the cotton production area in North Cameroon, which lies within the Sudano-Sahelian area with a single rainy season in boreal summer from June to September (Fig. 1d). Cotton is typically grown between the 600 and 1200 mm isohyets that correspond to the limits of the land suitable for rain-fed cotton (SWAC/OECD, 2005).

In central Argentina, we focused on two rural districts of the La Plata basin in Central Argentinean Pampas where agriculture dominates the local-scale economy (Magrin et al., 2005): Junín in the northwestern part of Buenos Aires Province, and San Justo in the north-central region of Santa Fe province. These districts are ~400 km far apart and share a similar temperate humid to sub-humid climate with a long wet season centered on austral warm summer and a shorter and drier season centered on austral cool winter. Daily rainfall values were obtained for 21 stations (Fig. 1e) from the National Meteorological Service (NMS) and the National Institute of Agricultural Technology (INTA). There are less than 3% of entries missing from 1970 to 2010. The mean annual cycle is flatter than for tropical areas of East Africa and North Cameroon; mean annual rainfall ranges from 700 mm (in the West) to 1250 mm (in the North-East), which fall rather regularly from October to March. The dry cool season, from May to September, is far from being absolutely dry (Fig. 1f). Even if interannual temperature variations somewhat impact crop yields in this region we focused on rainfall here since previous studies showed that rainfall variability has a greater impact on yields (Podesta et al., 1999, 2002; Messina et al., 1999; Hernandez et al., 2015).

The statistical methods used for rainfall data analysis are detailed in a Supplementary information section.

Ethnological fieldworks

In Kenya, the ethnographic analysis focused on small communities on the eastern slopes of Mount Kenya (methodological details in Leclerc et al., 2013, 2014; Mwongera et al., 2014). Despite the small size of the area, the interannual variability of the seasonal rainfall amounts and ISCs are quite representative of a larger area covering most of Kenya and Northern Tanzania (Boyard-Micheau et al., 2013; Camberlin et al., 2014). Three ethno-linguistic groups, namely the Muthambi, Mwimbi, and Tharaka were investigated. The Muthambi occupy the high altitude, the Mwimbi the high and mid altitudes, whereas the Tharaka are predominantly located at the low altitude with fewer people at the mid altitude. The climate impact on crops on the Eastern slopes of Mt Kenya was assessed with a retrospective survey of seed losses independently reported by 208 farmers from 1961 to 2006, with a total of 13 cultivated crop species and 53 varieties (see details in Leclerc et al., 2013, 2014).

In North Cameroon, we focused on the cotton company "SODECOTON", a semi-public integrated structure that organizes the cotton production and is the only agent to buy seed cotton from producers. The cotton administration consists of nine regions grouped into 38 administrative units and of cotton farmers divided into producers' groups roughly corresponding to the village level (Sadou et al., 2007; Gergely, 2009). There were about 2000 active producers' groups in 2011, which represented an average of about 55 groups per administrative unit.

In Central Argentina, both qualitative (ethnographic method) and quantitative methods (land use and tenancy survey, climate vulnerabilities survey, agriculture household survey) have been applied between January 2009 and September 2010 (methodological details in Hernandez et al., 2015), for a total of 79 interviews. Three different types of producers were defined from the ethnographic fieldworks: agribusiness actors, capitalized farmers and non-capitalized farmers. In Junín, these three profiles account for 32%, 46%, and 21% of the surveyed producers, respectively, and in San Justo 50%, 12%, and 38%, respectively. These percentages broadly reflect what is observed at the district's level.

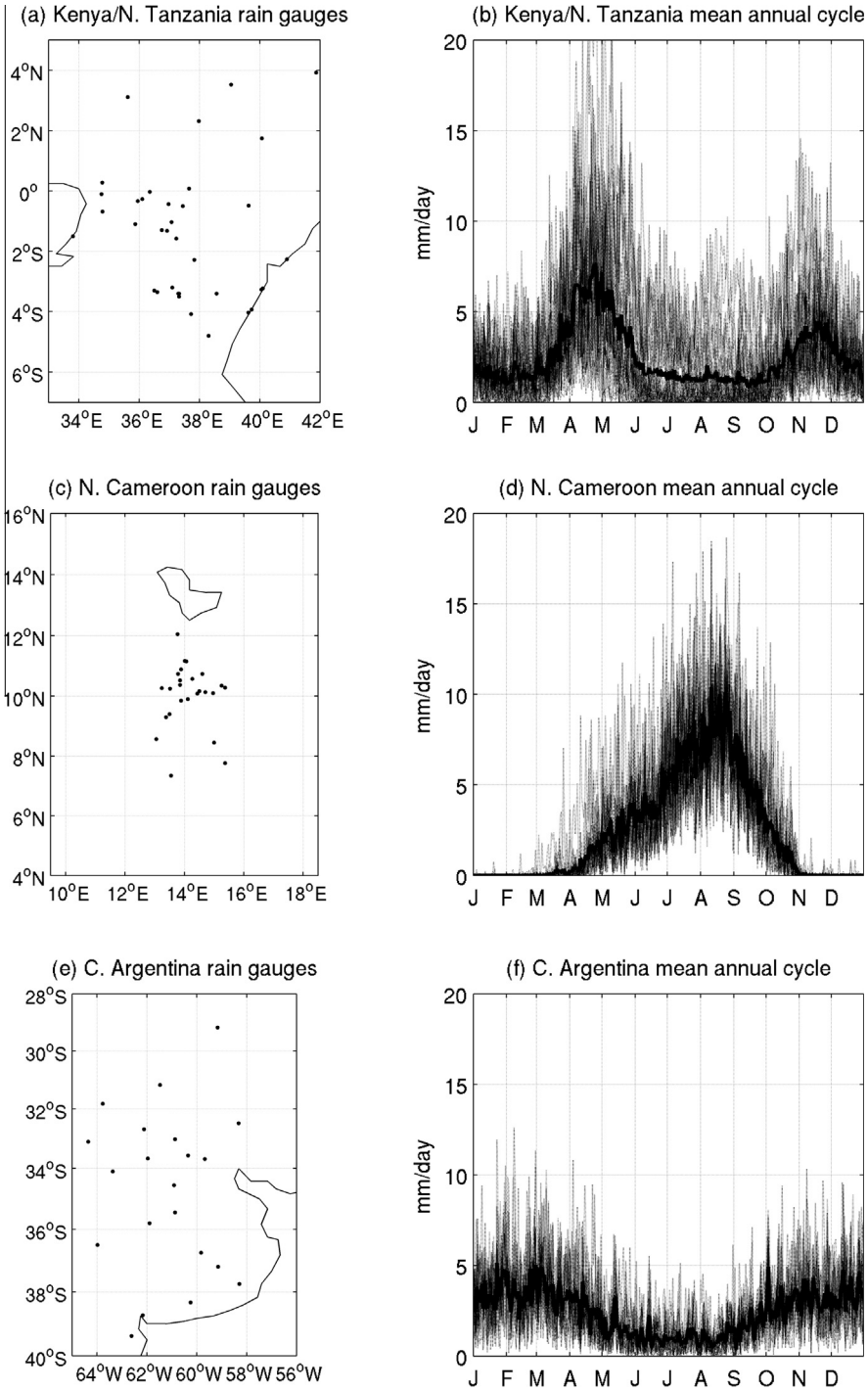

Fig. 1. Location of rain gauges for the three networks with the mean daily rainfall as dotted lines and the spatial average as bold full line.

The context of farming

Kenya: a multi-cropping farming context

On the Eastern slopes of Mt Kenya, the main crops (i.e. sorghum and maize) are present in over 94% of the farms. Beans and cowpeas are also common while sunflower, finger millet, soybean, tobacco, cassava, and black beans are grown in fewer

than 5% of the farms (Leclerc et al., 2014; Mwongera et al., 2014). The average number of crop species per farm is 6.23 (standard deviation = 1.67), with a minimum of two and a maximum of 10 crops. Out of a total of 13 crops, only tobacco and sunflower are grown as cash crops, contrasting with the Cameroon study case. Each farmer grows on average slightly more than one variety per crop, the overall richness being 1.19 varieties per crop and per farmer.

Cameroon: a cash crop farming context

Cotton in Northern Cameroon is a major cash crop and represents the main source of income (Folefack and Enam, 2011). It is grown by smallholders with an average of about 0.6 hectares per farmer dedicated to cotton production (Gergely, 2009), representing about 150,000 hectares in 2010. Farmers often associate cotton with subsistence crops, such as millet, sorghum, and maize, which benefit from the fertilizers, materials, and livestock financed by cotton income (SWAC/OCDE, 2005). SODECOTON, like its Malian, Senegalese, and Chadian counterparts, is still a national monopoly. Inputs (seeds, fertilizer, etc.) are provided on credit by SODECOTON before sowing (from May 20, depending on the latitude) and reimbursed at harvest from the purchase of the cotton seeds to the farmers. SODECOTON then gins and sells the cotton fibers on international markets. In 2005, at the peak of production 346,661 farmers cultivated 231,993 ha while the number of farmers and the cotton growing area dropped by 40% between 2005 and 2010. Farmers abandoned cotton production after a drastic reduction of their margins, mostly due to an increase in fertilizer prices but also to weather-related risks. Moreover, farmers unable to reimburse their debt at harvest were not allowed to renew their credit during the next year (Folefack and Enam, 2011). Lastly, the sector also faces other challenges, such as the isolation of the North of the country and a decline in soil fertility due to increasing land pressure.

Argentina: a commercial and large-scale farming context

Soybean accounts currently for 75–80% of the total production (and more than 85% of the cropped area) of the four main crops (wheat, soybean, maize, and sunflower) in the Junín and San Justo districts (Hernandez et al., 2015). Three different types of producers were defined from the ethnographic fieldwork: agribusiness actors, capitalized farmers and non-capitalized farmers. Agribusiness actors cultivate a large area (usually >1000 ha), owned or rented and possibly spread over several different regions and countries (i.e. Brazil, Paraguay, Uruguay, and Bolivia). These actors are directly related to the international market (mainly for soybean) and organize their production through a business network allowing them to control many factors (i.e. land renting/occupation, third-party labor, professional and expert boards), to negotiate prices at each stage of the productive chain (with agro-chemical suppliers, exporters, etc.), and also to improve raw production (e.g., soybean oil and flour etc.), generating strategic agreements with other commercial, financial, and technological companies (biotechnology, informatics, agriculture machinery). Capitalized farmers cultivate areas around 500–800 ha and may also rent lands to increase their production scale, but they tend to remain within the district; i.e. their rented lands are generally near an inherited nucleus of lands. Their capitalization is mostly based on agriculture machinery, which is used on their own lands and also for agricultural services contracts to ensure a higher profitability. Their production is directed toward both international and national markets. Lastly, non-capitalized farmers organize their production exclusively on their own lands, since the current increase of the rental price of land excludes them from real estate market. Most of their farms are smaller than 200 ha. They may or may not hire third-party services (agriculture machinery is usually too expensive to purchase, so they manage old or refurbished machineries) and their production is directed mostly to self-subsistence and local markets (local and regional fairs). Neither capitalized nor non-capitalized farmers have the capacity to really negotiate various inputs, supplies, and third-party services. Their fixed costs are thus higher (and usually much more) than those of agribusiness (Hernández et al., 2015).

Relevance and significance of climatic parameters for crops and farmers

In this section we synthesize the analyses carried out on (1) the relevance of climatic parameters for crop yields and (2) the significance of climatic parameters for farmers, including their farming strategies for coping with adverse climatic events. Note that we have not systematically applied generic methods to the three different terrains. The relevance was estimated using classical production-function approaches linking crop yields and various components of the rainy seasons, but also through ethnographic surveys of farmers and stakeholders about climatic factors having an impact on crops and yields. In East Africa and Central Argentina, analysing current and past farming practices helps reveal the most critical climatic variables.

Eastern slopes of Mt Kenya

The climate impact on crops on the Eastern slopes of Mt Kenya was first assessed with a retrospective survey of seed losses independently reported by farmers from 1961 to 2006 (see details in Leclerc et al., 2014). Rainfall variations were *a posteriori* analyzed (Leclerc et al., 2013, 2014 ; Camberlin et al., 2014) so that causes mentioned by farmers for each yearly loss could be associated with specific climatic events, considering with an open mind not only seasonal amounts but also

intra-seasonal characteristics such as onset, withdrawal, and mean length of dry spells (defined in Supplementary information). The main adverse climate events – mostly drought – as they were experienced and recalled by Meru farmers, fit rather well with what can be inferred from observed rainfall data (Leclerc et al., 2013). In particular, during the LR, seed losses recalled by farmers coincided with six major drought years, including the 1984 drought, which is considered the worst over the last century in Kenya (Nyamwange, 1995; Ogallo and Ambenje, 2005), and was associated with anomalously rare wet days and a shorter rainy season than usual.

The climate impact on crops was also assessed by considering statistics of maize production by districts of the eastern slopes of Mt Kenya for the years 1997–2006, and collected from the Famine Early Warning Systems Network (FEWS NET), Kenya office. They show that for the LR in the drier, lowland district of Tharaka, the duration of the rainy season plays a major role for the crop, with yields strongly controlled by the interannual variations of the withdrawal date of the rains and total production mainly controlled by that of the onset date (Fig. 2). In wetter districts, the correlation between rainfall and maize yields is weaker (not shown).

In Eastern Africa, the onset date of the rainy season is usually considered as the climatic information most awaited by farmers (Recha et al., 2008; Rao et al., 2011; Orlove et al., 2010; Speranza et al., 2008). We evaluated the significance of onset for farmers through a 2-year survey along the eastern slopes of Mt Kenya. Mwongera et al. (2014) randomly sampled farmers at three altitudes (750, 950, and 1100 m), recording sowing dates of all major crops during two SR seasons (2009 and 2010) and two LR seasons (2010 and 2011, Table 1). Observed daily rainfall is unavailable for these seasons and locations. We used proxy rainfall estimates from the second version of the RFE dataset on a 0.1° grid (Novella and Thiaw, 2013) to determine the LR onset date (defined in Supplementary information), after having verified that it is well correlated with available observed rainfall data (correlation of 0.64 with onset dates at Weru station over a 14-year period). Table 1 shows that there is a mismatch between the onset and farmers' sowing dates. Despite the fact that the 2010 and 2011 LR are very contrasted (very early vs very late onset, respectively), the sowings were made ~one month after (or before) the local-scale onset in 2010 (2011), with a difference of less than 5 days between the two years, except at low altitude (Table 1). The mismatch is smaller for both SR seasons even if they are less contrasted from the climatic point of view. It is possible that RFE estimates smooth

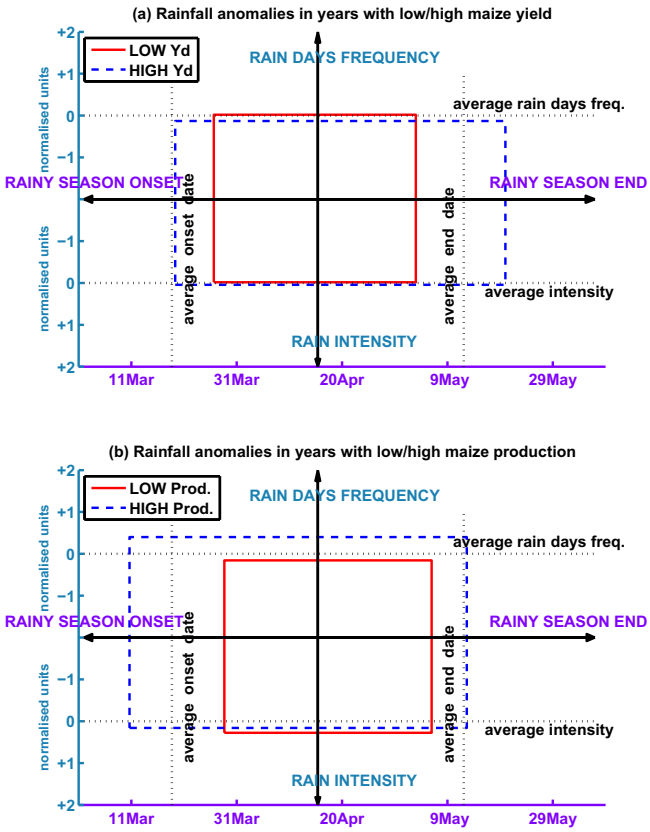

Fig. 2. Rainfall anomalies associated with variations of maize yield, (a) and maize production, (b) in Tharaka district, Kenya, for the Long Rains seasons 1997–2006. Dashed blue lines correspond to the average of the 4 years having the highest yield/production. Solid red lines correspond to the average of the 4 years having the lowest yield/production. The rainfall anomalies of four variables, based on data from Tunyai station, Tharaka district, are shown along four different axes. The long-term averages of these variables are displayed as thin black dotted lines. Wider boxes in the horizontal direction for years with good crop years denote the influence of the rainy season duration. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Mean sowing dates with their standard deviations for the 4 seasons in 2009–2011 along the eastern slopes of Mount Kenya at high (1150 m asl), mid (950 m) and low (750 m) altitudes. The onset date is computed based on RFEv2 daily rainfall data for three grid-points located at 0.3°S and 37.7°E,37.8°E and 37.9°E for the high, mid and low altitudes respectively.

	Sample size	Sowing mean date	Sowing standard deviation	Onset date of the rains
LR 2010 (high)	131	March 12	±9.8 days	Feb 12
LR 2010 (mid)	200	March 10	±9.2 days	Feb 12
LR 2010 (low)	48	March 7	±6.3 days	Feb 12
LR 2011 (high)	191	March 12	±4.5 days	Apr 13
LR 2011 (mid)	136	March 5	±9.4 days	Apr 22
LR 2011 (low)	73	March 17	±22 days	Apr 22
SR 2009 (high)	257	Oct 18	±7 days	Oct 10
SR 2009 (mid)	335	Oct 16	±7 days	Oct 10
SR 2009 (low)	134	Oct 7	±14.6 days	Oct 10
SR 2010 (high)	196	Oct 18	±7.4 days	Oct 22
SR 2010 (mid)	245	Oct 14	±11.1 days	Oct 22
SR 2010 (low)	69	Oct 10	±9.5 days	Oct 22

out the real spatial variations of rainfall, while our analysis samples only two years. However, the absence of any systematic relationship between onset and sowing dates as well as the large spatial variations in sowings raises at least the question of the onset date's relevance in farmer's crop calendar in this area.

North Cameroon

Cotton largely depends on rainfall availability. The role of climate variability in cotton yields in Western and Central Africa has been documented by Albergel et al. (1985), Kangah (2004), Blanc et al. (2008), and Sultan et al. (2010a) using statistical analyses applied to both weather and yield data. Blanc et al. (2008) pointed out the impact of precipitation distribution and timing during the cotton-growing season on yield plot observations in Mali. The onset and duration of the rainy season were recently found to be the major drivers of interannual and spatial variability of yields in North Cameroon (Sultan et al., 2010a). The authors illustrated that the driest locations in northernmost Cameroon are not only the least productive in terms of mean yield but also the most sensitive to climate fluctuations. In the northern part of the cotton production belt, a potential decrease of the mean annual rainfall in the context of climate change would largely decrease the mean productivity and increase the risk of crop failure (Sultan et al., 2010a,b).

From the interviews carried on, it appears that SODECOTON employees perceive climate variability as an important risk for cotton production and express a strong need to receive climate forecasts. More particularly, interviews revealed that their main concern regards the intra-seasonal variability of rainfall. The perceived importance of the rainy season onset corroborates results from statistical analyses (Sultan et al., 2010a). Indeed, an early (late) onset of the rainy season is associated with higher (lower) yields and a forecast of the onset of the rainy season one month in advance would allow them to adjust their planting strategies. For example they might increase (decrease) cropped areas and apply more (less) fertilizer in case of forecast for an early (late) rainy season onset. The interviews also pointed to climate risks that were not yet revealed by scientific analysis, such as the importance of heavy rains in August (core of the rainy season) which have an impact on fruit-bearing organs and may increase weeds and insect pressure. Farmers mentioned that forecasts of such heavy rains in August would help them improve their weed control and optimize their stock of pesticides and herbicides. Lastly, SODECOTON employees also mentioned the risk of heavy rains at the end of the rainy season that affects cotton flocks. Among the adaptation options, interviews revealed that forecasts of these heavy rains would lead to early sowing if the forecasts were issued before the beginning of the growing season or to early harvests if the forecasts were issued few days in advance only.

Central Argentina

Ethnographic field surveys showed that Junín's farmers emphasize drought and flood as adverse climatic events while those of San Justo tend to balance the overall effect of climate with other socio-economic factors (see details in Hernandez et al., 2015). This contrasted sensitivity is somehow verified by a quantitative assessment of the relationships between observed annual rainfall amounts and yields (of wheat, sunflower, maize, and soybean), which, at least in Junín, already reveal some non-linearities (Hernandez et al., 2015). The main climatic risk for soybean and maize is the usually non-linear negative effect of long-lasting dry spells, especially near or after the normal sowing dates, while very wet days (i.e. wet days receiving more than the 90% percentile of daily rainfall excluding dry days) appear to be beneficial, especially from the middle to the end of the cropping cycle. These relationships are strongest for soybean and, to a lesser extent, maize. They are rather weak for wheat, and overall reversed for sunflower, which is the sole crop for which too much rainfall appears to be adverse in mean. The adverse effect of too much rainfall on soybean and maize is less phase-locked and more diluted across the crop cycle and is thus difficult to emphasize in mean (Hernandez et al., 2015).

Agribusiness producers are able to mitigate the effects of floods and drought through geographical (Akponiké et al., 2011) and crop diversification strategies, and to impose its priorities (sowing, harvesting, etc.) to other actors. The availability of

machinery and large equipment gives them more flexibility to tackle any adverse climate events, even those that are barely predictable, and to benefit from any seasonal forecast, even at regional scale. Capitalized farmers share some strategies with agribusiness farmers to mitigate flood and drought damages such as productive diversification, private channeling, and wet grain storage (i.e. plastic bags), but they are less flexible than agribusiness actors due to the fact that they are forced to provide agricultural services to agribusiness actors. In case of adverse climate events, their main strategy is to save on agricultural services and sub-contracting, endangering their own harvests. Non-capitalized farmers are the least flexible, and are thus more exposed to any climatic adverse events. In case of prolonged drought near the onset of wet season, their only passive option is to postpone sowing until it rains enough to have a sufficient amount of water stored in the upper soils. They have no access to specialized private counseling so they turn to the traditional strategy of diversifying risks by combining agriculture on one hand and dairy production and/or livestock breeding on the other hand.

Synthesis

Our main goal in 'Relevance and significance of climatic parameters for crops and farmers' was to confront two complementary approaches of the relevance of rainfall parameters for yields, namely (1) a statistical analysis of the relationship between rainy seasons components and crop yields and productions and (2) an identification of the relevant climate information for coping with climate variability by considering the farmers' perception, knowledge, and practices. Despite the differences between the fieldwork and the methods applied to identify the relevant climate information, several common results emerge detailed hereafter.

The onset seems to be a pertinent ISC from the farmers' point of view since it affects the crop calendar, fixing sowing dates and enabling adaptation options such as the selection of varieties having the best-suited crop cycle length. Onset date variations do affect crop production (e.g., cotton in Cameroon and maize in Kenya) but the 2-year survey along the eastern slopes of Mt Kenya suggests that farmers' sowing dates actually seem to be unrelated to the local-scale onset date. It is impossible to conclude if this mismatch is due to the small sampling of years (even if onset dates in the 2010 and 2011 LR seasons appear to be very contrasted) and/or to the farmers' perception that the onset is too chaotic and largely unpredictable and thus not considered apart from its mean climatological phase.

The farmers' interest and/or crop sensitivity are not restricted to the rainy season onset. For example, rainfall near the seasonal peak (i.e. in August) and at the end of the season are perceived as potentially detrimental to cotton yields in North Cameroon. The statistical analysis of the relationship between ISC and yields in the Tharaka district in Kenya also suggests that the LR duration, which depends on onset and end dates of the rainy season, may also be a relevant ISC, at least for the driest districts on the eastern slopes of Mt Kenya.

Spatial coherence of rainfall at seasonal and intraseasonal time scales

The above section has pointed to relevant climatic variables, i.e. those whose variability is both perceived and estimated as detrimental to crops by farmers and through statistical analyses relating climate and yield time-series. This section proposes a systematic analysis of the potential predictability of several rainy seasons descriptors (ICSs) in our three study sites. Note that we use the term "potential" since the ISCs predictability is only estimated through their spatial coherence; no attempt is being made to relate their variability to any predictor field (e.g. sea surface temperatures).

Spatial coherence of seasonal amounts at interannual time scale

Our first hypothesis is that spatial coherence of the interannual anomalies gives an empirical upper bound of potential predictability (Moron et al., 2006, 2007). We started our analysis with the seasonal amount, which is by definition the most comprehensive characteristic of the rainy season at the local scale, since the temporal aggregation considers all rainy events across the whole season.

The simplest way to estimate the regional-scale signal is to consider the spatial average of standardized anomalies (Katz and Glantz, 1986; Moron et al., 2006). A refined solution is to consider the reconstructed variations from the leading Empirical Orthogonal Functions (EOF, see Supplementary information). Parallel Analysis (PA, Franklin et al., 1995) gives an estimate of the threshold between the "signal" (any covariant variations among the stations) and the "noise" (independent variations among the stations) through the comparison of the observed eigenspectrum with one computed from independent white noise time series.

In all of our three networks, except for LR in Kenya/North Tanzania, only the first eigenvalue of the seasonal amounts is found to be statistically significant using PA. The second eigenvalue is also above the noise level for LR in Kenya/North Tanzania (Fig. 3). We can assume that the first (or two in the case of LR in Kenya/North Tanzania) leading EOF convey(s) the (regional-scale) spatially-covariant interannual signal, which is assumed to be, at least partially, potentially predictable. In the following, this signal is simply computed as the spatial average of the reconstructed time series using only the leading EOF – singular value – PC triplet (together with the second one, for the LR in East-Africa), explaining respectively 50% (LR in Kenya and North Tanzania), 64% (SR in Kenya and North Tanzania), 36% (North Cameroon), and 41% (Central Argentina) of the interannual variations of local seasonal amounts.

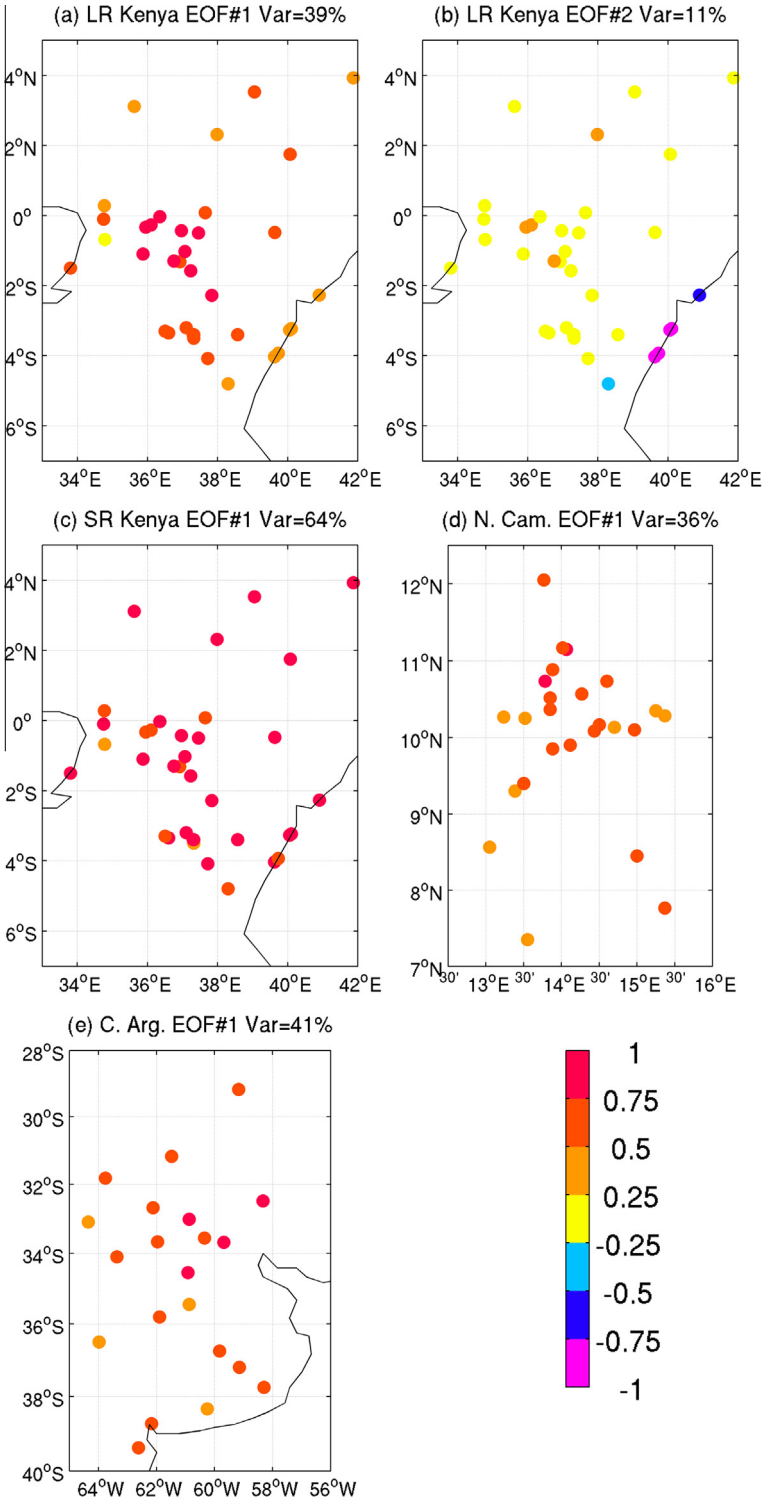

Fig. 3. Loadings (i.e. correlations between principal component and original data) of the significant eigenvectors (of seasonal amounts) according to parallel analysis (Franklin et al., 1995), that is the comparison between the observed eigenspectrum with the one computed with independent white noise time series having the same size as the observed data. The random eigenspectrum is computed 100 times. The eigenvalues above the 99% noise level are considered to convey spatially-covariant signals across the network while the eigenvalues below the 99% noise level do not show anything than independent variations amongst the stations.

Relationships between local-scale/regional-scale seasonal amount and intraseasonal characteristics

The next step is to analyze the relationships between local-scale and regional-scale (estimated from the first (or two for LR in Kenya) leading EOF) seasonal amounts (S) on one hand and the whole set of ISCs (Fig. 4). The aim is to picture which ISC most contributes to the seasonal amount predictability. Practically, these ISCs cover the temporal phase (onset, withdrawal) and duration of the rainy season, as well as frequency and duration of dry spells (i.e. consecutive days receiving less than 1 mm) and wet spells (i.e. consecutive days receiving at least 1 mm). The mean daily rainfall intensity, referred to hereafter simply as intensity, is also computed as an ISC. In fact, all of these properties are included in S and they can be analytically inferred from daily sequences of rainfall (Fig. 4). We will analyze the amount of covariance between any local-scale (subscript "LOC") ISC and local and regional-scale (subscript "REG") S, assuming that S_{REG} (i.e. spatial average of S_{LOC} variations reconstructed by the first EOF, except for LR where the two leading EOFs are used) conveys, at the first guess, the potentially predictable signal. The contribution of each local-scale ISC to the interannual variability of S_{LOC} and S_{REG}, and their potential predictability, is analyzed through stepwise regression.

Fig. 5 shows the simplest decomposition of either S_{LOC} or S_{REG} into frequency (F_{LOC}) and intensity (I_{LOC}) of rain days (computed on fixed seasons). By definition (Fig. 4), F_{LOC} and I_{LOC} together explain the whole variance of S_{LOC} (see black dots always = 1 on the left column of Fig. 5). F_{LOC} is the first variable entering the stepwise model for the driest network (the SR, and then the LR, in Kenya and North Tanzania). I_{LOC} is the first contributor for the two other networks. When S_{REG} is the explained variable, F_{LOC} appears to be the first contributor to the four networks, consistent with other observations across the tropical zone (Moron et al., 2006, 2007), suggesting that the interannual variability of S_{REG} is mostly conveyed by systematic variations of number of wet days at the local scale (i.e. an anomalously wet season at regional-scale tends to be mostly associated with more frequent wet days at local-scale rather than higher daily mean intensity of rainfall).

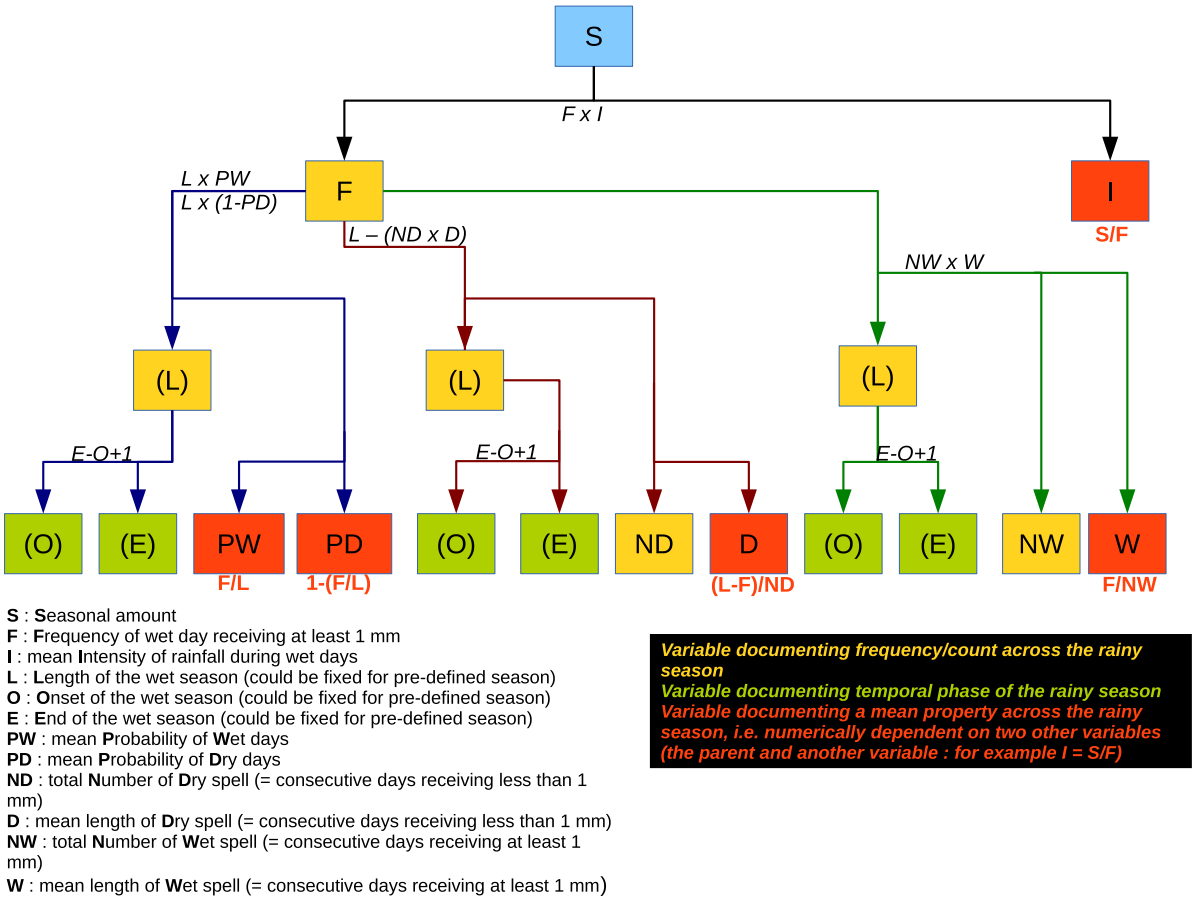

Fig. 4. Analytical decomposition of seasonal amount into intra-seasonal characteristics (ISC) at local-scale. The italicized equations associate any "child" ISC to its "parent" (for example, Length of the season (L) = End date (E)−Onset date (O) + 1). The equations in bold orange associate the "dependent" ISCs, that is an ISC conditional on two other ISCs, its "parent" and another ISC at the same level (for example, Daily mean intensity of rainfall (I) = Seasonal amount (S)/seasonal Frequency of wet days (F). These dependent ISCs could be computed only at the end of the rainy season from other ISCs and could not be directly measured. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

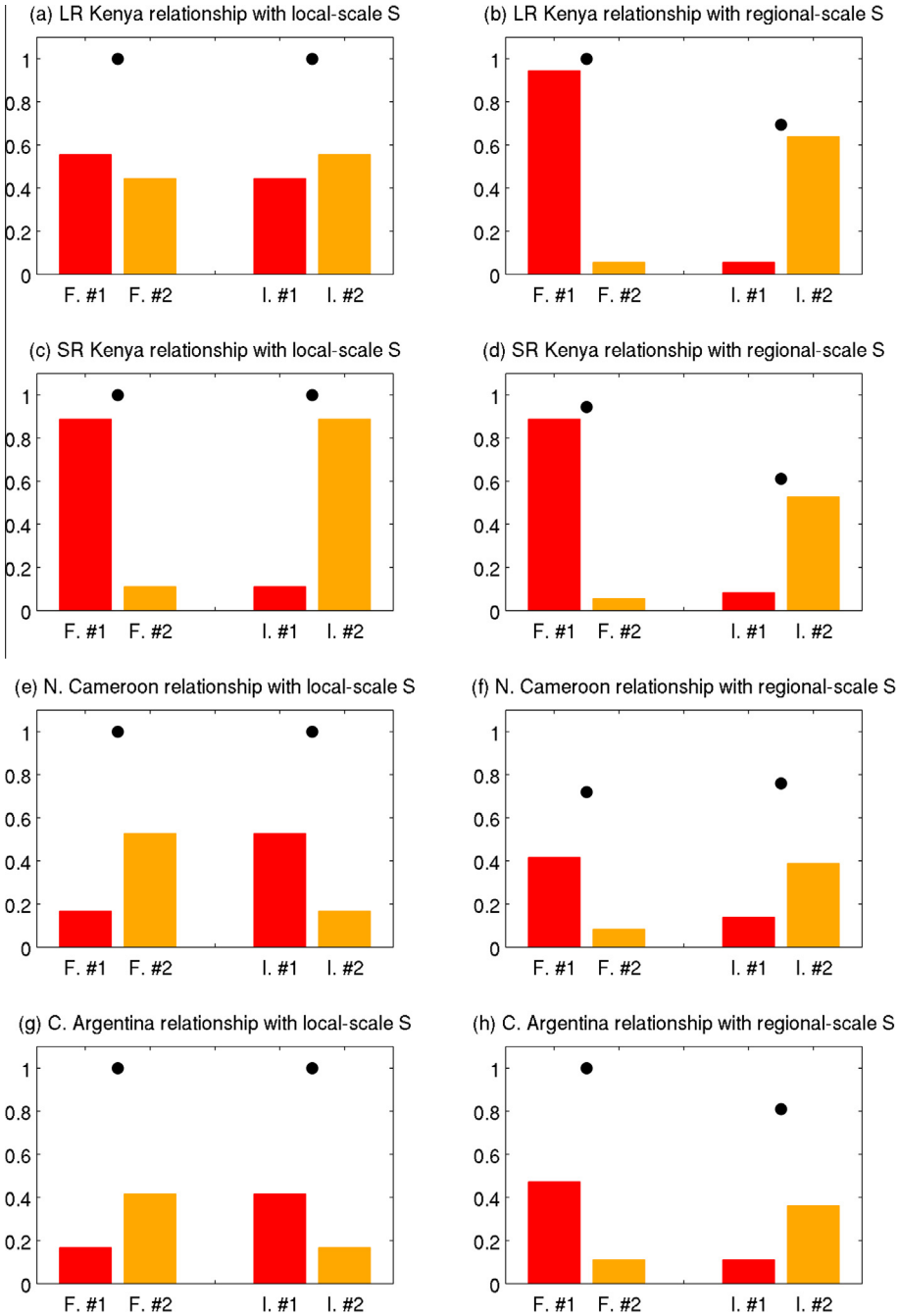

Fig. 5. (bars) relative frequency of rain-gauges where either seasonal frequency of wet days (F) or mean intensity of rainfall (I) contribute significantly (at the 95 % level of significance) to the interannual variability of local-scale (left column) and regional-scale (right column) seasonal amounts (S) according to a stepwise regression. The order (first rank in red and second rank in orange) is the one to which the variable enters the stepwise regression. (black dots) total relative frequency of rain-gauges where either F or I contributes significantly to the interannual variations of S according to the stepwise regression. All seasons are fixed (i.e. FMAMJ and SONDJ for Kenya/North Tanzania, AMJJASO for North Cameroon and SONDJFMAM for Central Argentina). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A more complete decomposition of S_{REG} and S_{LOC} involves I_{LOC} and four other ISCs related to F_{LOC} (Fig. 6): ND_{LOC} (frequency of dry spells), D_{LOC} (mean length of dry spells), NW_{LOC} (frequency of wet spells), and W_{LOC} (mean length of wet spells). The contribution of I_{LOC} is always dominant in S_{LOC}. The second most important contributor is W_{LOC} while the three other ISCs are less important (Fig. 6). In other words, it suggests that the most important contribution of F_{LOC} in S_{LOC} is conveyed through the mean length of wet spells (i.e. an anomalously local-scale wet season is primarily associated with anomalously long wet spells). When seeking to explain the interannual variations of S_{REG}, the contributions of I_{LOC} and W_{LOC} now strongly decrease,

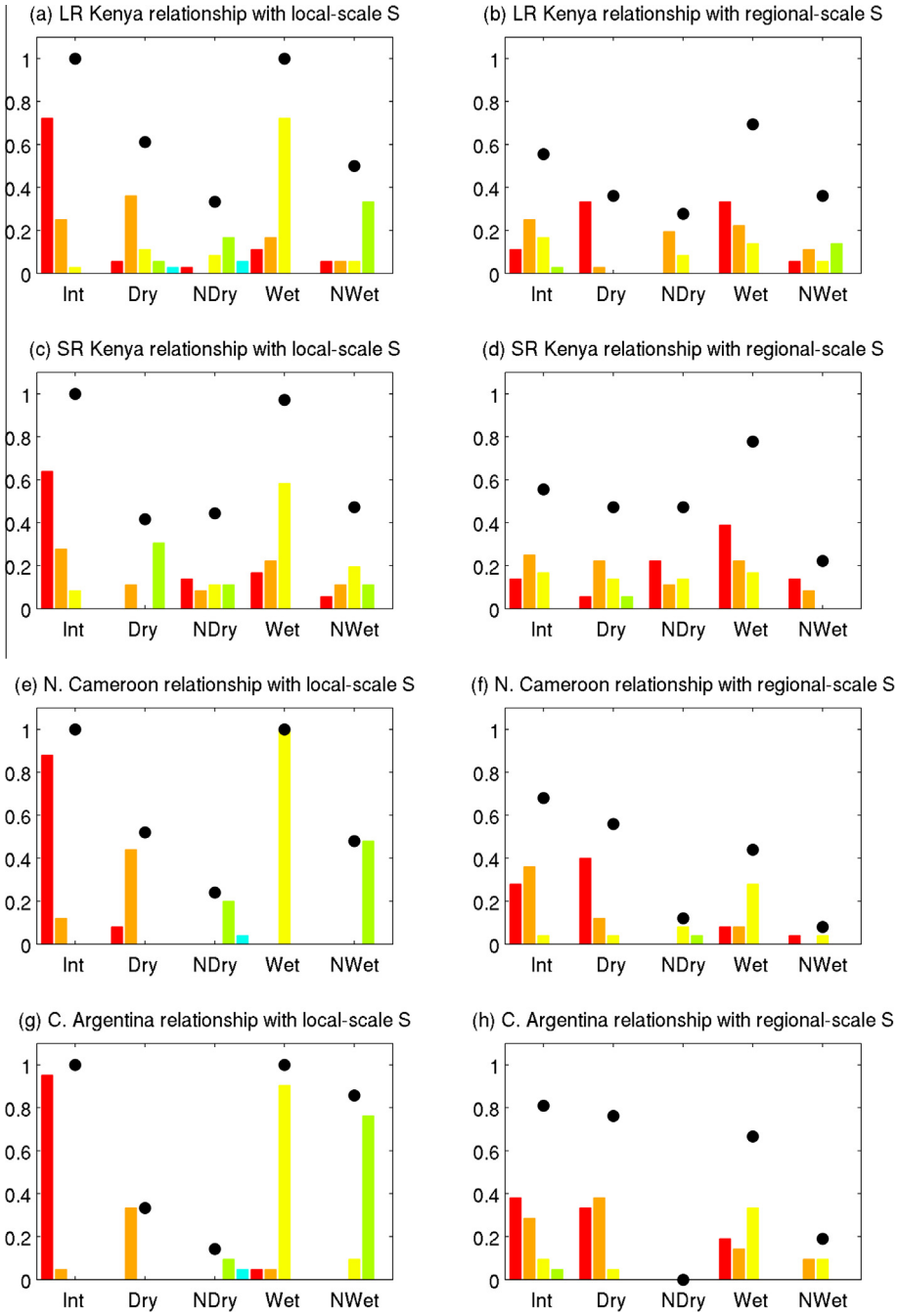

Fig. 6. Same as Fig. 5 except that predictors of the seasonal amounts entering the stepwise regressions are seasonal mean intensity of rainfall (Int), the mean length (Dry) and the frequency (NDry) of the dry spells, the mean length (Wet) and the frequency (NWet) of the wet spells. The 1st, 2nd, 3rd, 4th and 5th ranks in the stepwise regression are indicated in red, orange, yellow, green, light blue, respectively. All seasons are fixed (i.e. FMAMJ and SONDJ for Kenya/North Tanzania, AMJJASO for North Cameroon and SONDJFMAM for Central Argentina). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

while the one of D_{LOC} remains stable or increases (Fig. 6). In other words, a regional-scale drought (i.e. a negative anomaly of S_{REG}) is primarily translated into anomalously long dry spells at the local scale.

The above decompositions of S on seasons of fixed length have the disadvantage of not considering any phase component of the rainy season (including the onset, which is usually considered by farmers to be useful information) and the mean length of dry spells actually merges two different pieces of information: one related to the dry spells occurring before (or after) the actual onset (or withdrawal) and one related to those within the rainy season. Such distinction is possible when onset and withdrawal dates are explicitly computed (Fig. 4).

Considering seasons of variable length (using onset O and withdrawal E with their difference plus one giving the length L of the season) instead of fixed length has almost no impact on the interannual variability of S_{LOC} or F_{LOC} at local-scale; the mean correlations (spatially averaged over the rain gauges) between variable- and fixed-season S_{LOC} equal to 0.95 (Kenya/North Tanzania Long rains), 0.97 (Kenya/North Tanzania Short rains), 0.98 (North Cameroon), and 0.92 (Central Argentina). The correlations are slightly lower for F_{LOC} (mean $r = 0.85$, 0.90, 0.85, and 0.82 for LR, SR, North Cameroon, and Central Argentina, respectively). The impact is still weak on W_{LOC} (mean $r = 0.77$, 0.80, 0.95, 0.91 for LR, SR, North Cameroon, and Central Argentina, respectively) while it is stronger as expected on D_{LOC} (mean $r = 0.42$, 0.51, 0.51, and 0.62 for LR, SR, North Cameroon, and Central Argentina, respectively). Fig. 7 shows the same information as Figs. 5 and 6, but for ISCs computed between the onset and the withdrawal dates of the rainy season. At the local scale (left column of Fig. 7) I_{LOC} and W_{LOC} are still the most important contributors to the interannual variability of S_{LOC} while the contribution of O_{LOC} and E_{LOC} is always small (Fig. 7a,c,e,g). The contribution of duration is higher for Central Argentina. At the regional scale, it is difficult to extract any generic behavior across the 3 networks and it seems that the large contribution of F_{LOC} to S_{REG} (Fig. 7b,d,f,h) comes from the whole range of parameters rather than one single parameter: mostly NW_{LOC} in Kenya and North Tanzania, L_{LOC} and W_{LOC} in North Cameroon, and ND_{LOC} and W_{LOC} in Central Argentina (Fig. 7).

The above analyses start from S due to its "comprehensive" character by considering rainy events on the whole across the season. But the interannual variability of S_{LOC} and S_{REG} could be strongly impacted by a few rainy days not necessarily related to medium-to-large scale climate variability, and this noisy component could hide spatially coherent signals in other ISCs. To overcome this possible bias we have analysed the rainy seasons through the subseasonal scenarios approach developed by Moron et al. (2013).

Rainfall subseasonal scenarios

A subseasonal scenario refers to spatially covariant behavior of rainfall across a season. This analysis has already been performed on LR of Kenya/North Tanzania (Moron et al., 2013, see Supplementary information for technical details), and is now extended to the three other rainy seasons/sites studied. Basically, subseasonal scenarios describe typical temporal behavior of the rainy season across a network of stations by emphasizing the spatially covariant signals. Contrary to the above analysis, this approach does not start from interannual variations of seasonal amounts but rather from the spatio-temporal covariant and persistent signals inside each season.

For LR in Kenya/North Tanzania, four scenarios are retained, as discussed in Moron et al. (2013). Two scenarios, a "wet" one and a "dry" one, show their largest anomalies occurring around March, that is, during the first half of the rainy season and not during the main seasonal peak (Fig. 8c and d). The two other scenarios show (1) a diluted rainy season with positive anomalies on the edges of the season surrounding negative anomalies near the normal seasonal peak (Fig. 8b), and (2) a contracted rainy season with positive rainfall anomalies peaking in April (Fig. 8a). Note that the variations at the coastal stations (identified from EOF#2 of seasonal amounts, Fig. 3) slightly differ from the remaining stations but the general behavior is rather similar (Fig. 8, red lines).

The scenarios for the other networks are summarized on Fig. 9, showing the spatial average +/− one standard deviation amongst the stations of the network. For the East African SR (Fig. 9b), the two subseasonal scenarios are by definition symmetric around 0 except that skewness leads to stronger positive anomalies. The largest anomalies are now phase-locked with the mean seasonal peak from mid-October to late November while anomalies tend to zero thereafter (Fig. 9b). In this case, the seasonal amount is probably the optimal variable to forecast since the interannual anomalies of the rainfall close to the climatological peak are indeed spatially covariant.

For North Cameroon (Fig. 9c), there are strong intra-seasonal modulations of the rainfall anomalies for the three subseasonal scenarios. It means that getting a whole season with positive or negative rainfall anomalies at regional-scale may be a rare event. The "wet" scenario (in blue[1] on Fig. 9c) shows mostly positive anomalies from late July until late September while earlier in the season anomalies are close to zero. The second scenario (in green on Fig. 9c) shows positive anomalies during the first half of the season followed by negative anomalies peaking from late July to late September. The last scenario, which is overall dry (in red on Fig. 9c), shows strong negative anomalies at both the beginning and the end of the season surrounding weak negative anomalies.

Intra-seasonal modulations of rainfall are also evidenced for Central Argentina (Fig. 9d) where the "wet" scenario (in blue on Fig. 9d) exhibits positive anomalies until December, then from late March to early May, surrounding near-normal to negative anomalies in January/February, while the "dry" scenario (in green on Fig. 9d) shows, by definition, symmetrical anomalies.

Discussion and concluding remarks

There are myriad factors limiting the skill and the practical and/or efficient use of current seasonal predictions (Blench, 1999; Broad and Agrawala, 2000; Hansen, 2002, 2005; Hansen et al., 2006), despite their promises to decrease the vulnerability and increase the food security of rural communities, especially in the tropics where malnutrition is still rife. The

[1] For interpretation to colours in Fig. 9, the reader is referred to the web version of this paper.

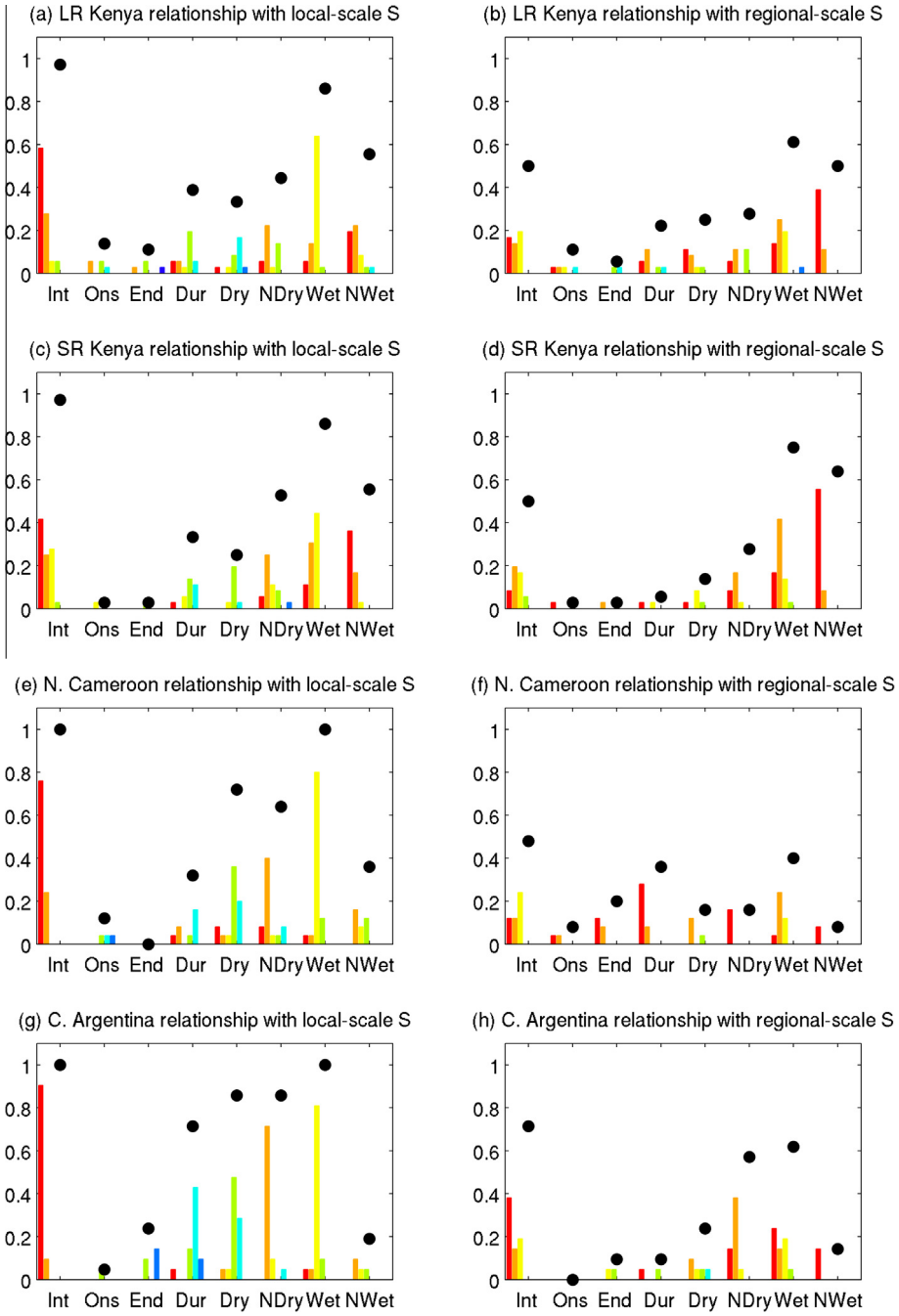

Fig. 7. Same as Fig. 5 except that predictors of the seasonal amounts entering the stepwise regressions are seasonal mean intensity of rainfall (Int), the onset (Ons), withdrawal (End) and Length (Dur) of the rainy season, the mean length (Dry) and the frequency (NDry) of the dry spells, the mean length (Wet) and the frequency (NWet) of the wet spells and the seasons are defined by onset and withdrawal of the season. The 1st, 2nd, 3rd, 4th, 5th and 6th ranks in the stepwise regression are indicated in red, orange, yellow, green, light blue, dark blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

PICREVAT project's initial goals were neither to scrutinize all natural, socio-economic, and political parameters that limit the practical use of seasonal forecasts, nor to explore all ways that can be used to assess the relationships between climate and yields (Hansen, 2002; Hansen et al., 2006), but rather to point at some critical climate information for crops, both as actual constraints to crop yield variability, and as explicitly identified by local farmers and inferred from their practices or memories in three different agro-socio-climatic contexts.

A first goal was to assess the relevance of rainy seasons' intraseasonal components for farmers and their spatial coherence. A first main result is the development of two different methodologies: the analytical decomposition of the seasonal

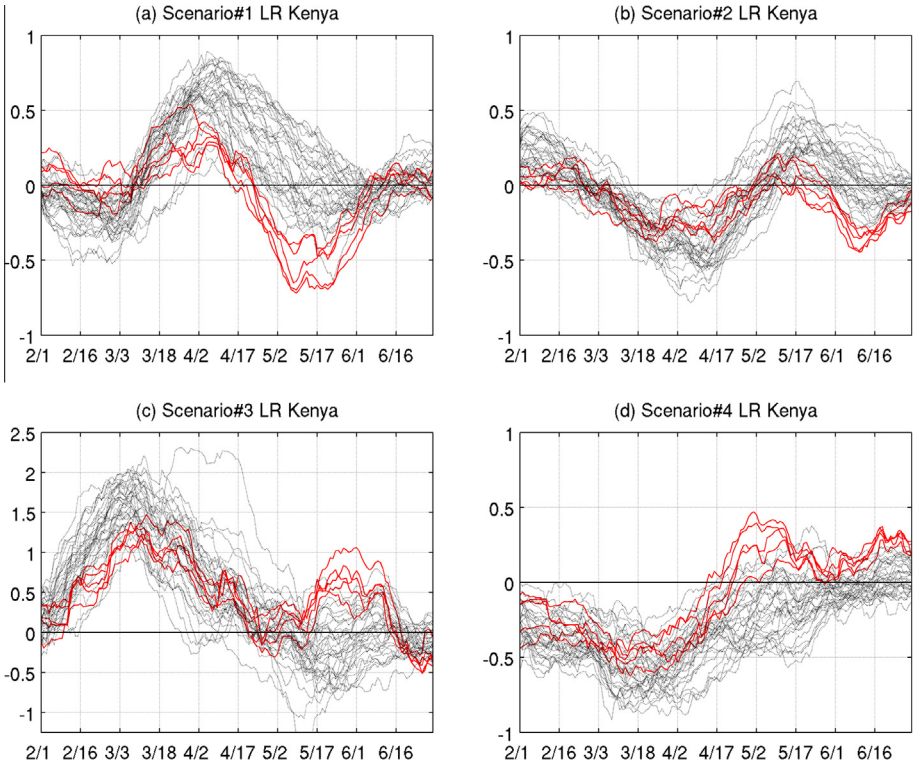

Fig. 8. Rainfall standardized anomalies of the 4 k-means clusters in Kenya in FMAMJ. The rainfall anomalies are reconstructed from a fuzzy k-means in the EOF-space of the significant components (see Supplementary information). The red curves are for the 5 stations along the Indian coast (where EOF#2 absolute loading of seasonal amount is larger than EOF#1). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

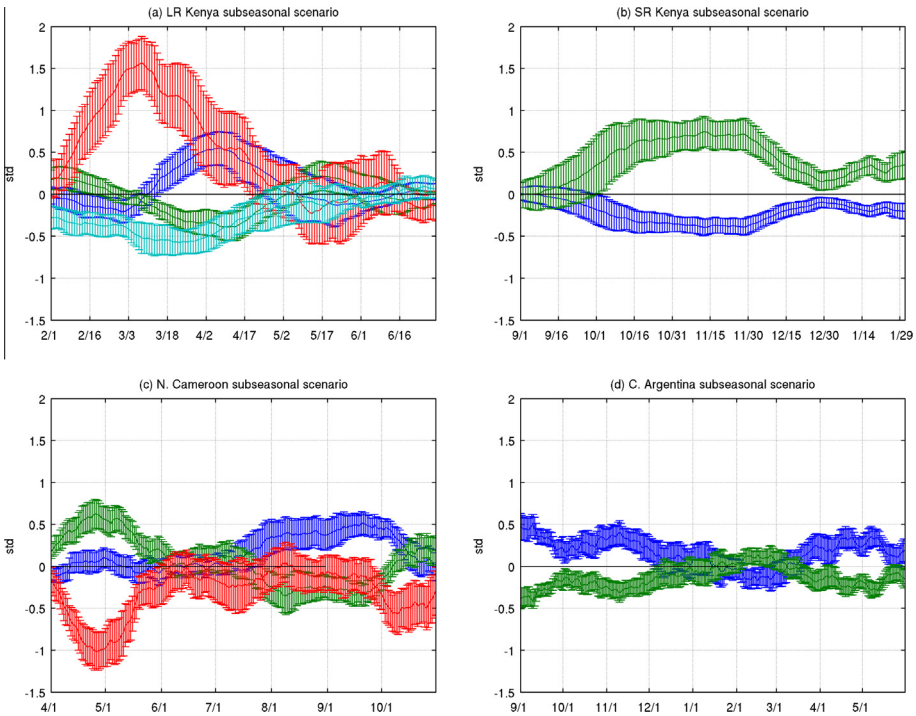

Fig. 9. Spatial average of standardized rainfall anomalies associated with the subseasonal scenarios (the error bars are +/− one standard deviation across stations).

rainfall amount into ISCs (Fig. 4) and the extraction of typical subseasonal variations of rainfall. Both approaches allow us to evaluate the potential predictability of rainfall beyond that of seasonal amounts, i.e. toward finer time and spatial scales, which are theoretically better-suited for impact studies and can be tailored for practical use. The seasonal rainfall amount is the most comprehensive variable by definition, and is almost the only target of current seasonal predictions. But seasonal amounts may be strongly impacted by a few heavy rainy days spread across the season, thus hiding relevant climate signals. The analytical breakdown of seasonal amounts into ISCs is appealing in that it targets climate components (e.g. the onset of the rains, the length of dry spells, the intensity of the rains) with a potential significance in terms of both agronomy and rainfall dynamics. The drawback is that it decreases the signal-to-noise ratio since some of the intra-seasonal characteristics, typically the onset and withdrawal, are related to a single wet event inside each rainy season. It is actually trivial that splitting the interannual information conveyed by the most comprehensive variable, i.e. the seasonal amounts, increases the risk of getting purely local, and thus unpredictable, variations, even if the resulting quantities would perfectly fit with farmers' needs. The subseasonal scenarios, recently used by Moron et al. (2013) in Kenya and North Tanzania, appear promising in that they avoid the arbitrary definition of onset/withdrawal while still giving some information on the phase of the rains. A possible side effect is the sensitivity to parameters of the cluster analysis (see Supplementary information).

Climatically speaking, our results suggest a modulation in the spatial coherence, thus potential predictability (Moron et al., 2006, 2007), of the ISCs or of specific phases of the rainy season (Figs 5–9). It is important to target the most predictable ISCs/phases within the rainy season, and to identify those which will be harder, or even impossible, to predict. For the variables considered predictable from the climatic point of view, the lead-time for practical use by farmers is also a critical issue. The onset, which is usually awaited by farmers to sow, is suggested to be potentially predictable in some regions, such as East Africa during the LR, Indonesia (Moron et al., 2009a), and the Philippines (Moron et al., 2009b), but not in the three other cases studied, nor in Niger, despite a surprisingly good match between sowing dates and rainy season onset dates (Marteau et al., 2009).

The case of North Cameroon is interesting since the spread between the three subseasonal scenarios is large – from April until mid-May – suggesting a potential for onset forecasts, but then suddenly decreases around the mean date in early June. The scenarios are then undifferentiated, with rainfall anomalies close to zero in June and July, but tend to spread again toward the end of the season, suggesting again a potential for end forecasts (Fig. 9c). This behavior tends to fit with farmers' expectations since the performance of both the beginning and the end of the season (in particular the occurrence of heavy rains at this time) seems decisive for crops according to cotton growers and statistical analyses of yields vs rainfall.

In Central Argentina, the two subseasonal scenarios differ more in September–November than at the end of the season from early April (Fig. 9d). The SR in East Africa (Fig. 9b) illustrate a case where the internal modulation of spatial coherence seems phase-locked with the climatological seasonal peak, i.e. the highest rainfall amounts in mean are the most spatially-coherent. In this specific case, the seasonal amount is probably the optimal characteristic to predict, and it is perhaps easier to infer ISCs from predicted seasonal forecasts than try to forecast ISCs directly or through subseasonal scenarios. This corroborates the fact that the predictive skill is much higher over East Africa in October–November (Mutai et al., 1998; Philippon et al., 2002; Hastenrath et al., 2004) than in March-May (Camberlin and Philippon, 2002).

The translation of climate information into action requires three elements: salience, credibility, and legitimacy (Travis and Bates, 2014). Salience refers to the relevance of the information to the needs of decision makers while credibility and legitimacy refer to the accuracy and the perception of the climatic information provided. The onset of the rains is *a priori* salient information since it is usually termed as awaited information and often coincides with sowing (Marteau et al., 2011), which is a direct action of farmers. However, its salience may be questioned based on the experience gained from the Eastern slopes of Mt Kenya where dry sowings, independent from the agronomic onset, are common, at least during the SR (Mwongera et al., 2014). Does this practice come from the integration of past knowledge/memory and the difficulty to in predicting onset? The credibility of onset from the climatic point of view (that is, its *skill* in climatological terms plus its usefulness) clearly varies geographically, at least among our limited set of terrains. In North Cameroon, and in the Sahel in general (Marteau et al., 2009), the agronomic onset, as defined here, may hardly be predictable while there are some promising signals over East Africa during the LR associated with the large dispersion amongst the subseasonal scenarios (Figs. 8, 9a). The salience of onset is likely to decrease when the wet season is long and/or when the transition from dry to wet conditions is very gradual, as in Central Argentina. In this case, the spread between the two subscenarios is rather large in September and October during the transition between drier and wetter season.

A second goal was to assess the interest (1) in analysing climate/society relations in a more integrated way, i.e. considering the ensemble of environmental, climatic, and social dynamics (Meze-Hausken, 2004, 2007) and (2) in considering dynamical changes in farming systems as a decisive modulator of the vulnerability associated with any climate events. Based on observations made in Kenya, North Cameroon, and Central Argentina, we found that climate events perceived by the end-users are neither stable objects nor independent of the social and environmental context in which those actors drive their farming system. For example, we observed that in Central Argentina, soybean yields, and then those of maize, are the most sensitive to rainfall anomalies. This is especially relevant because of the recent transition of Argentinean Pampas from a mixed cropping system (cereals, oil seeds, livestock, etc.) toward a more specialized one, dominated by a transgenic soybean crop strongly linked to the stock markets. Thus, the agricultural sector became somehow more vulnerable to rainfall variability partly due to this *soybeanization*. This sensitivity has turned into a crucial cognitive tool allowing the producers to consider and plan their activity in an integrated way, i.e. elaborating successful strategies that enable some of them to cope

with adverse climate events, but non-capitalized farmers do not share the mitigation and adaptive capacities of agribusiness and capitalized farmers.

Slow changes, such as *soybeanization*, preferably induced by socio-economic background and agricultural policies rather than climate variations, are also illustrated by the increasing popularity of maize at the expense of sorghum and pearl millet in Kenya, and also by the recent decline of cotton in Northern Cameroon. Fundamentally, these changes in farming practices may deeply modify the overall vulnerability to climate, even in stationary climatic conditions. Under such circumstances, any long-term climatic trend, such as the recent rainfall decrease during the LR in East Africa (Lyons and DeWitt, 2012; Leclerc et al., 2014), superimposes a climate-induced risk to an already increased risk induced by a change from drought-resistant crops (sorghum and pearl millet) to a less resistant one (maize). In the same vein, crop and/or variety diversification is the usual option for dealing with uncertainty resulting from climate or other sources (Mongi et al., 2010 among others). Moreover, varieties and/or crop diversification are usually more or less the only available adaptation option for smallholders, even though this last term does not have the same meaning on the eastern slopes of Mt Kenya, where gardening on very small plots is the usual practice, and in Argentina, where "small" farms refers to fewer than 200 ha (depending on the region). Note that while we do not consider the potential positive effects of slow changes in dominant crops (e.g. *soybeanization* in Argentina and shift to maize in East Africa) which are due to price variations on national/international markets or to their possible higher resistance to pests and diseases (as for maize in East Africa), the fact remains that such dynamical behavior should be considered in any studies, including seasonal forecasting and of course climate change studies. This also raises issues about the classical production-function approach, which generally assumes that the set of crops/varieties and cultural practices remain unchanged (Jones and Thornton, 2003; Thornton et al., 2009) vs a more integrated approach, as the Ricardian one, which uses economic value rather than individual crop yields as the main predictand variable (Mendelsohn et al., 1994; Sultan et al., 2010b).

Finally, our study emphasized the fact that climate-induced vulnerability may vary inside a given region to a considerable extent. For example, the three different producers in Argentina do not cope with the same adverse events with the same efficiency and their possible options may be strongly reduced, especially in case of monoculture. In East Africa, the vulnerability differs based on the altitudes, even on subtle gradients as demonstrated by Mwongera et al. (2014); crops originating in communities living at an altitude of 1100 m are more sensitive to long dry spells after sowing in the medium altitude zone (950 m) than crops originating in lower altitudes (750 m). Seed exchanges in the medium altitude belt are mostly practiced among farmers of the same community rather than between farmers of different communities (Leclerc and Coppens d'Eeckenbrugge, 2012), which in the long run results in a significant difference between communities in their crop responses to long dry spells. This varying sensitivity could increase the vulnerability when a less drought resistant crop like maize is adopted independently of the subtle variations of drought frequency.

Overall, our results show that vulnerability to rainfall variations is a highly dynamical topic, not only due to the phase-locking of adverse conditions during critical crop stages, but also due to the extreme variety of expectations and strategies used to mitigate and adapt to these events (Cooper et al., 2008).

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Appendix A. Supplementary information

Supplementary information associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.crm.2015.03.001.

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