AGRICULTURAL ECONOMICS

Agricultural Economics xx (2010) 1–17

Cropland use, yields, and droughts: spatial data modeling for Burkina Faso and Niger

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Received 11 February 2009; received in revised form 20 November 2009; accepted 3 April 2010

Abstract

For countries with recurrent droughts, the design of drought impact mitigation measures could benefit from analyses of determinants of yields and prices of local crops at regional and district level. This study applies dynamic spatial panel data regression models to yields and prices of four major food crops across regions of Burkina Faso and Niger, over sample periods between 1984 and 2006. Results lend support to mainly simultaneous spatial spillovers, particularly for millet and cowpea prices and sorghum yields in Niger, and maize yields in Burkina Faso. After accounting for these effects, most crop yields are found to be weakly price-responsive, as envisaged by a supply-side geographical diffusion hypothesis. Seasonal rainfall elasticity estimates suggest that dominant food crops have slight advantage margins in terms of relative resilience to rainfall shortages. However, this result is to be weighed against low millet yields in Niger, and marked drops in sorghum yields during officially declared droughts in Burkina Faso.

JEL classifications: C23, C49, Q19, R14

Keywords: Food crops; Droughts; Spatial panel data models; Sahel

1. Introduction

Agricultural soil in Africa, particularly in semiarid areas, suffers from low water infiltration and retention capacity. Fertilizer use is estimated to be at least 12 times lower than the global average, also substantially lagging behind other developing regions. This partly reflects backlogs in rural infrastructure development, with expansion of cultivated areas towards marginal lands where farming practices are unable to replace the annual loss in nitrogen, potassium, and phosphate (Agwe et al., 2007; Grimm and Gunther, 2004; UN-ECA, 2007, p. 9). After unusually high rainfalls in the 1950s and except for some recovery in the late 1990s and early 2000s, Sahel countries in particular have severely been affected by successive droughts over the last half century (Brown and Crawford, 2008), with declining soil fertility and land area per household attributed to a combination of market failures, limited access to services, inadequate planting management and shortened fallow cycles, high demographic pressures, and rainfall variability (with discordant views as to which of these factors are more relevant). Among Sahel countries, Burkina Faso and Niger are expected to experience some of the largest increases in number of residents living in water-tension areas by 2050, thus becoming even more exposed to drought risk (Le Blanc and Perez, 2007). More than 80% of these countries' labor force is employed in agriculture and most farmers rely on rain-fed crops and livestock as main sources of food and income, with very low fertilizer use intensity (less than 2 kg/ha in 2002) also compared with other countries in Africa (e.g., 35 kg/ha in Cote d'Ivoire and 65 kg/ha in South Africa; Camara and Heinemann, 2006).

To help cope with these problems, the suitability of specific agricultural crops and grain varieties in drought-prone countries is drawing increasing interest, with various reasons being put forward in support of cassava, sorghum and maize, among others (Appendix I). Most studies on the subject tend to focus on climatic, institutional, and technological features at a cross-country (Thiele, 2004) or cross-village (/household) level (Aker, 2008a). An intermediate regional level appears to be relatively less investigated. Yet, this represents a relevant dimension for

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell, Inc. is not responsible for the content or functionality of any supporting information supplied by the author. Any queries (other than missing material) should be directed to the corresponding author for the article.

DOI: 10.1111/j.1574-0862.2010.00465.x

understanding drought vulnerability and food insecurity across space and over time, with spatial econometric models helping gain insights into, for example, determinants of crop yields and prices in the regions concerned. In this analysis, regression specifications are formulated and applied to cross-region annual yields and prices of four major food crops (sorghum, millet, maize, and black-eyed pea) in Niger and Burkina Faso, for periods between 1984 and 2006. The article is organized as follows. Drawing on literature contributions on crop production, yields, and prices (with focus on arid zones, especially the Sahel), the next section reviews some major variables and hypotheses of concern (including the rationale for spatially lagged variables). Two estimation approaches for spatial panel data regression are presented in Section 3, with reference to their use for modeling crop yields and prices. This is followed by an overview of data and descriptive statistics in Section 4, and a discussion of spatial regression estimates in Section 5. Relative to a few years with available information, the analysis is supplemented with graphical exploratory data analysis on socioeconomic and infrastructure indicators. The last section draws concluding remarks.

2. Hypothesis testing

Using the same symbols of spatial regression variables (list in Tables 2 and 3) and supplementary data analysis in Section 5 (*road* infrastructure development, *hcpov* headcount poverty index, and *inst* crop price instability index), general functional forms for models geared to test determinants of crop yields (*yd*) and prices (*p*) in drought-prone regions of the Sahel, can be expressed by Eqs. (1) and (2), respectively (expected parameter signs under the variables)

$$yd = f(yd_{t-1}, \underset{+}{rainf}, \underset{-}{(rainf)^2}, enso, \underset{+}{road}, \underset{-}{hcpov}, \underset{+}{t}, \underset{-}{h}, ar(i)pc, yd(sp), \underset{-}{cfa}, [\underset{+}{p}, p_{t-1}, p(oc)_{t-1}, \underset{-}{inst}]_A, [\underset{-}{dprior}]_B), \tag{1}$$

$$p = g(p_{t-1}, road, ar(i)pc, t, p(oc)_{t-1}, [cfa]_A, [\underset{-}{yd_{t-1}}, \underset{+}{p(sp)}]_B). \tag{2}$$

In the equations, *t* is a linear trend (accounting for technology changes, mechanization, and similar effects; Aker, 2008a; Pandey et al., 2007, p. 33), *sp* represents a spatial lag, and *oc* refers to a competing crop (e.g., previous year price of sorghum versus millet yields, as in Abdullahi et al., 2006). Besides commonly used variables, the equations encompass two partly contending hypotheses (*A* and *B* respectively, relative to variables in brackets). In the remaining part of this section, variables of common use and related effects are discussed first (climatic indicators, crop diversification, exchange rate, and geographical spillover effects), followed by a comparison of the two hypotheses.

Since soil moisture data are not readily available, rainfall is often chosen as an explanatory variable in quadratic polynomial form (so as to capture declining marginal returns; Fafchamps et al., 1998; Thiele, 2004), eventually supplemented with temperature data (Kurukusalasuriya and Mendesohn, 2007). To avoid the unrealistic assumption of time- and space-wise stochastic independence of rainfall (unless dynamic spatial regressions are used) and problems of noisy climate data, rainfall can be replaced by a dummy for drought years (/months) (Ding et al., 2006). Moreover, lower but well distributed rainfall, especially in the absence of irrigation facilities, may result in higher crop yields than poorly distributed rainfall with heavy floods, which often cause disruptions to storage facilities and hinder access to food from neighboring regions (Boken, 2005). To account for these patterns, intrayear climatic indicators can be used to distinguish between planting or early growing versus late growing season (Odekunle et al., 2007). Additionally, El Niño and Southern Oscillation (ENSO) events tend to exert a worldwide influence on weather patterns including precipitation patterns in Africa, and as such they can be included in regressions along with other possible indicators of weather anomaly (Naranjo Díaz, 2005).

Similarly to the dispersion of land plots and simultaneous multi-crop cultivations as a buffer factor for individual producers against droughts (Nweke, 2005, p. 14), a relatively higher dispersion of croplands within and across regions/provinces (eventually coupled with intercrop rotation) may help reduce exposure to crop failures, yield risk, and vulnerability to pests. This implies a negative expected parameter sign associated with an index of crop concentration in regressions modelling crop yields (e.g., the Herfindahl index *h* in Eq. (1), given by the sum of squared production shares for major crops). Relative to the impact of exchange rate policies, in CFA (*Communauté Financière Africaine*) countries (including Burkina Faso and Niger) the 50% devaluation of the CFA franc (relative to the French franc) of January 1994 is believed to have prevented productivity increases in food and feed crops, by increasing the domestic price of imported goods and providing greater incentives to cash crop production as groundnuts, cowpea, and cotton, with insufficient spillover effects on subsistence agriculture (Grimm and Gunther, 2004; Wyatt et al., 1999). Its impact is likely to have been particularly severe in remote areas, due to high transaction and transport costs.

Unmeasured or insufficiently measured agroclimatic (temperature, sunlight, soil types, etc.) and institutional factors can induce positive (e.g., diffusion of improved crop varieties) or negative productivity spillovers across regions (Druska and Horrace, 2004; Wood et al., 2004). Hazards and other occurrences affecting farmers' cropping decisions in some regions may influence decisions in nearby ones, in terms of both direct (amount of farmland allocated to a crop) and indirect (e.g., water resources for irrigation) effects (the respective theoretical frameworks are referred to as *spillover* model and *resource flow* model, which lead to the same spatial lag econometric specification; Anselin, 2002). Similarly, closeness to main urban centers is likely to allow some rural communities to benefit from lower transport and input marketing costs and measures in support to food crops (such as inputs in kind and cash loans to farmers' cooperatives against stored grain collateral). In the absence of detailed georeferenced information (on market transaction costs, road infrastructures (*road*), and extent of poverty (*hcpov*) across regions), better commercial and transport networks among some regions, and conversely weaker networks and inadequate storage and processing facilities in others, may also be reflected by a high positive spatial lag autoregressive parameter (associated with *yd(sp)* in Eq. (1)). Besides genuine spatial diffusion, spatial dependence may be spuriously compounded by geographical aggregation problems (e.g., weather data are collected at point locations, which do not adequately reflect climatic conditions and related systemic risk by region). For both reasons, in cross-region panel regressions, parameter estimates will be biased and inconsistent if relevant spatially lagged endogenous or exogenous variables are omitted, and inefficient if spatially correlated errors are ignored.[1]

Regarding the above alternative hypotheses, *ceteris paribus*, low and unstable prices of some food crops (*p* and *inst* in Eq. (1)) hamper investment decisions in farming technology, including fertilizers (which may burn the seeds if subsequent adequate rainfall fails to occur, thus damaging the crops). Food crops with more favorable price trends, especially in the presence of lesser climatic risk, face lower market uncertainty, thus allowing the adoption of additional inputs. In this first view (labelled with *A* in (1) and (2) above), drought vulnerability is mainly caused by market failures and structural constraints at local level (with price movements explained by location-specific and policy variables). The impact of shortage and intrayear variability in rainfall and insect plagues on crop supply and yields largely depends on price movements (including exchange rate effects) and adaptive capacity (that is the extent to which local communities can mitigate the effects of these hazards; Dore and Etkin, 2002, p. 16), with causal effects in the direction "staple food price trends/volatility, rainfall and insect infestations → yields → droughts." Regarding crop prices, absence of relevant spillover effects across regions is reflected by high market price disparities in staple foods, wide mark-up margins between producer and consumer prices, and limited commercialization of cereal products (e.g., only 15% in Burkina Faso in the late 1990s; Grimm and Gunther, 2004).

In a second view (labelled with *B* in (1) and (2)), cross-region market integration is found to strengthen during drought emergencies and low-production years in Niger (e.g., grain price dispersion decreased during the 1997–1998 and 2004–2005 food crises; see Aker, 2008a; World Bank, 2008). In the absence of excessive hoarding and effective storage capacity, this pattern may be induced by increased cross-market transactions among traders, farmers, and consumers during drought years. Markets in grain-deficit regions tend to follow the price trends in surplus production regions after accounting for transport costs, and the market in both region groups is influenced by grain imports from neighboring countries (Aker, 2008b). Therefore, along with climate factors, agricultural prices can help detect food supply shocks spreading from production centers to other areas. This supply-side geographical diffusion hypothesis implies relatively more severe consequences in terms of food security than droughts that affect specific regions. Given price-inelastic agricultural supply, a dummy for years preceding droughts can be used for modeling unobserved effects prior to extreme climatic events (*dprior* in Eq. (1)) and their impact on yields. The structural relationship between agricultural crop prices and yields is modified accordingly, with a partial reversal in main causal links, and spatial lag effects being more relevant for crop prices than yields: "rainfall/drought and insect infestations → yields → staple food price trends/volatility → food crisis."

3. Econometric modeling

Econometric panel data models on crop yields and prices require an appropriate choice of regression specifications and estimation methods. Once average cropland size is accounted for, yields may face thresholds, beyond which droughts are less likely to be felt in an acute way. This pattern may be detected within a region for specific crops vis-à-vis others, or turn out to be region-specific and largely independent of crops (the latter is likely to reflect a higher dependence of drought-prone areas on insufficient and erratic rainfalls influencing crop yields, while less vulnerable, food staple-surplus regions may benefit from higher levels of soil moisture; Degefe et al., 2001, p. 74). In either case, unobserved heterogeneity across regions can be modeled by fixed-effects ordinary least squares (FE-OLS), which maintains (near-)consistency and efficiency if unobserved effects are correlated with one or more exogenous variables. In a dynamic model with no strict exogeneity, FE-OLS is subject to finite-sample bias (with the autoregressive coefficient biased downwards for small *T* panels; Beenstock and Felsenstein, 2006; Greene, 2003, pp. 287–308). In spatial regressions, the estimator properties are even less likely to hold, with more severe problems of endogeneity and heteroscedasticity (Pinkse and Slade, 2010).

More realistically, a weak exogeneity assumption allows for feedbacks from lagged-dependent variables/lagged errors to current and future values of an explanatory variable, which makes the generalized method of moments (GMM) more suited as an estimator.[2] In this respect, modeling rain-fed agricultural yields, cropland distribution, crop prices, and droughts is bound

[1] A regression specification with a spatial lag endogenous variable is also justified as a correction device for spurious spatial autocorrelation induced by geographical scale errors (Chasco Yrigoyen, 2003, p. 89). In this analysis, the inclusion of spatially lagged exogenous variables is hindered by numerous missing data for rainfall and food crop prices, and is left for future extensions. Even if spatial lag exogenous variables are not explicitly included, spatially lagged endogenous variables have implications in terms of spatial global multipliers associated with modeled (through exogenous variables) and nonmodeled (residual) spillovers (Appendix II).

[2] A variable x_{it} is defined as strictly exogenous if it is uncorrelated with past, present, and future cross-panel residuals ε_{it}. Weak exogeneity implies that

to face problems of simultaneity and lack of strict exogeneity, particularly in the presence of time aggregation. As a creeping, variously defined phenomenon with a relatively slow onset and end (with more than 150 definitions of drought in the literature; Boken, 2005), the impact of droughts is not easily identifiable. Substantial yield decreases are occasionally registered ahead of recorded climatic phenomena related to droughts, and droughts officially declared by aid agencies and public authorities partly arise as a consequence of interactions between intense and prolonged climatic disruptions and local adaptive capacity (Benson and Clay, 2004; Mainardi, 2005). Land use patterns can reinforce or mitigate vulnerability to hydro-meteorological shocks. Relative to both unobserved heterogeneity and simultaneity in yield regressions, retail prices of a cereal product can be influenced by distinct grain varieties and quality gaps between markets, thus entailing that some determinants of price patterns across regions and over time remain "hidden" at this level of geographical aggregation. Similarly, with cereals and noncereal products often competing for the same land, substitution possibilities among rain-fed cereals, and between the latter and other crops (such as cotton in Burkina Faso), imply some degree of endogeneity in cropland area. This variable will be partly influenced by farmers' decisions, based on past and expected price movements and other characteristics of crops.

To deal with the above problems, in this study FE-OLS and, as an alternative approach, orthogonal deviations-adjusted GMM regressions have been estimated relative to each crop/country case. Define a vector x_{it} of variables that are all strictly exogenous (FE-OLS), or a combination of (strictly and/or weakly) exogenous and near-endogenous (GMM). In the regression models (Section 5), these variables represent: (i) climatic factors (*lnrd*, *lnrainf*), crop market concentration (*lnh*), cultivated area per capita (*lnar(i)pc*), and real crop price (*lnrp(i)*), in yield equations; or (ii) cultivated area per capita and crop yields (*lnyd(i)*), in price equations. Maintaining generality, generalized mixed autoregressive-spatial regression specifications (encompassing a number of nested models; Chasco Yrigoyen, 2003; see Appendix II) for panel data with N regions ($i = 1, \ldots, N$), and $t = 1, \ldots, T$, are given by Eqs. (3) and (4), relative to FE-OLS and GMM (in orthogonal deviation form, Δ^{od}; Arellano and Bover, 1995) respectively

$$y_{it} = \mu_i + a y_{i,t-1} + \beta_1 y(sp)_{it} + \beta_2 y(sp)_{i,t-1} + \gamma_1 x_{it} + \gamma_2 x(sp)_{it} + \varepsilon_{it}, \tag{3}$$

$$\Delta^{od} y_{it} = \alpha \Delta^{od} y_{i,t-1} + \beta_1 \Delta^{od} y(sp)_{it} + \beta_2 \Delta^{od} y(sp)_{i,t-1} + \gamma_1 \Delta^{od} x_{it} + \gamma_2 \Delta^{od} x(sp)_{it} + v_{it}. \tag{4}$$

$E(x_{it}, y_{i,t-1}|\varepsilon_{it}) = 0$, but $E(x_{it}|y_{i,t-1}, \varepsilon_{i,t-1}) \neq 0$, that is, x_{it} is uncorrelated with current and future shocks, but not with past disturbance terms and past values of the dependent variable y_{it}. If residuals in levels are uncorrelated and conditional expectations are specified as above, errors in first differences will be first-order autocorrelated, with orthogonality at higher lags (Arellano and Honoré, 2001).

Unlike the strict exogeneity assumption in FE-OLS, in GMM models of crop yields, retail prices, market concentration, and cropland per capita are allowed to interact with the dependent variable and as such can be treated as near-endogenous, while the one year-lagged spatial lag endogenous variable can be regarded as weakly exogenous, and climatic conditions as strictly exogenous (spatial lag exogenous variables are not included due to data constraints; see note 1). Conversely in price regressions, an assumption of near-endogeneity applies to yields and cropland. Hence, lagged values of $y(sp)$ (for yields or prices accordingly) can be used as forward-filtered (orthogonally transformed) instruments, along with the predetermined endogenous variable at different lags as level instruments ($y_{i,t-q}$, with $q = 2, \ldots, 7$).[3] For yield equations, rainfall and rainy days/maximum temperatures (Tables 1 and 2: *lnrainf1*, *lnrainf2*, *lnrd*, *lntemp*) have also been chosen as orthogonally transformed instruments. First difference and orthogonal deviation transformations remove the individual effects μ_i, thus avoiding possible correlation problems with the instrumental variables. Compared with first differences, transformations based on forward orthogonal deviations (whereby each observation is expressed in terms of deviation—weighted to standardize the variance—from the average of future observations in the sample) preserve lack of correlation, or partly correct for its presence, among transformed errors (if original residuals are not serially correlated), while maintaining consistency and asymptotic efficiency of GMM (Arellano and Honoré, 2001; Doornik and Hendry, 2001, pp. 66–67).

4. Data, variables, and descriptive statistics

Geographical reference units are primary subnational administrative areas (delimited by UN-SALB "level 1" boundaries), that is, seven regions in Niger and 30 provinces in Burkina Faso (the latter have been partly rearranged more recently in 45 units; henceforth, the term *region* is used for either country). Information from FAO geo-coded files on crop production and cultivated areas based on agricultural censuses (carried out every five years) and agricultural surveys (www.fao.org/landandwater/agll/agromaps) has been supplemented here with national statistical sources (www.insd.bf; www.ins.ne) for a few years with missing observations. The data sets thus constructed concern sorghum and millet in both countries, cowpea in Niger, and maize in Burkina Faso, and cover the period 1990–2006 in Niger, and 1984–2004 in Burkina

[3] To account for an approximate upper bound in drought periodicity and to avoid a small-sample over-fitting bias, maximum lags of the lagged endogenous variable (yield or price) in the GMM instrument matrix for equations in orthogonal deviations (Section 5), are limited to the range (2, 7). Using T as an upper limit would allow a different number of instruments for each time period, thus ensuring efficiency, but at the expense of biased estimates in small samples (Doornik and Hendry, 2001, p. 68). For millet yields in Niger, forward-filtered instruments include one-year lagged real retail prices (see Table 4).

Table 1
List of variables and descriptive statistics: Niger (1990–2006 cross-region panel)

Variable	Definition	Mean	μ (drought years)	μ (other years#)	Standard deviation	Skewness	Kurtosis
yd[sor]	Sorghum yield (tonne/ha)	0.26	0.27	0.24	0.13	0.55	−0.25
lnyd[sor]	(natural logarithms)	−1.5			0.61	−1.09	2.23
yd[mil]	Millet yield (tonne/ha)	0.39	0.4	0.37	0.11	−0.67	0.56
lnyd[mil]	(natural logarithms)	−1.01			0.39	−2.47	8.62
yd[nbe]	Cowpea (*niébé*) yield (tonne/ha)	0.13	0.14′	0.11	0.08	2.13	7.29
lnyd[nbe]	(natural logarithms)	−2.27			0.68	−0.6	0.46
yd[nut]	Groundnut yield (tonne/ha)	0.43	0.42	0.44	0.21	1.87	6.54
lnrp[sor]	Real price of sorghum (1996 retail prices, FCFA/kg)	4.73 (*117.3*)	*137.8**	*99.4*	0.27	−0.37	−0.26
lnrp[mil]	Real price of millet (1996 retail prices, FCFA/kg)	4.82 (*130.4*)	*142.5**	*119.7*	0.31	0.25	0.44
lnrp[nbe]	Real price of cowpea (1996 retail prices, FCFA/kg)	5.24 (*194.3*)	*204.2*′	*185.5*	0.26	−0.51	0.13
lnar[sor]pc	Sorghum-cultivated area per capita (ha/resident)	−2.09	−2.05	−2.13	1.14	−0.45	−0.55
lnar[mil]pc	Millet-cultivated area per capita (ha/resident)	−0.67	−0.67	−0.67	0.31	−1.62	2.79
lnar[nbe]pc	Cowpea-cultivated area per capita (ha/resident)	−1.3	−1.3	−1.3	0.75	−1.37	1.19
lnh	Production market concentration for major crops (Herfindahl index h, range [1/n, 1]; n = 3: sorghum, millet, cowpea)	−0.55 (*0.6*)	*0.57*	*0.61*	0.24	0.04	−0.98
lnrd	Number of rainy days (by region, recorded at local meteorological stations^)	3.76 (*46.2*)	*46.4*	*46.1*	0.32	−0.48	0.47
lnrainf	Rainfall (annual average by region, mm^)	5.99 (*477.7*)	*477.1*	*478.2*	0.5	−0.51	0.01
lnrainf1	April–June rainfall (monthly average by region, mm^)	3.11 (*28.8*)	*34.6*′	*25.4*	0.73	−0.34	0.43
lnrainf2	July–October rainfall (monthly average by region, mm^)	4.51 (*96.4*)	*84.5**	*101.7*	0.35	−0.25	−0.52
lntemp	Maximum temperature (degrees Celsius, by region^)	3.58 (*35.96*)	*36.08**	*35.85*	0.02	−0.21	−0.51
Dummy variables							
cfa	CFA franc devaluation (1 for 1994–2006; 0 for pre-devaluation period 1990–1993)						
dprior	years prior to officially declared droughts (1 for year preceding droughts; 0 otherwise)						
enso	El Niño-Southern Oscillation events (1 years recorded with ENSO events; 0 otherwise)						

Symbols preceded by *ln*: log-transformed variables (except for crop yields—original and log-transformed values in separate rows–mean values of original data are reported in italics). #Including years of locust infestations. Sub-sample means (μ) are based on pooled regressions including intercept term and drought dummy (statistically different at: *1%, ′5% significance level). ^Data based on eight meteorological stations in the regions of Diffa (average estimates for N'Guigmi and Maïné stations), Dosso, Maradi, Tahoua (average estimates for Birni N'Konni and Tahoua stations), Tillabéri and Zinder (nine stations for seasonal rainfall data, including Niamey). *Sources:* see Section 4.

Faso (thus yielding nT-sized panels of 102—excluding Agadez-and 630 observations, respectively). In Burkina Faso, the geographical distribution of villages covered by agricultural surveys broadly reflects population proportions across provinces, with fixed numbers of households chosen per village (e.g., for standard surveys, 706 villages and 5,648 agricultural households). A similar sampling design is followed in Niger, with surveys based on, for example, 7,400 sedentary agricultural households in 499 population count zones, which are randomly selected within each district while roughly complying with a demographic weight criterion (except for the region of Agadez, where rain-fed agriculture is too small to be estimated by survey; Madaï, 2008).

Additional data from the above national statistical sources include: (*a*) rainfall/number of rainy days registered at meteorological stations across different regions of the two countries (Tables 1 and 2) and maximum temperatures recorded by these stations in Niger (Table 1); (*b*) CPI-deflated retail crop prices by region (annual averages relative to markets in (i) each regional capital except Agadez in Niger, and (ii) nine main urban communes in Burkina Faso (in provinces comprising 40% of the national population in 2004: Table 3)); and (*c*) socioeconomic and local infrastructure indicators for specific years. To account for intraannual rain variability and since the dry season in both countries lasts from November to March/April, average monthly rainfall recorded by each station between April and June, and between July and October, has also been relied on (GHCN-monthly version 2: ftp.ncd.noaa.gov; Tables 1 and 2: *lnrainf1* and *lnrainf2*). Farm-gate prices (for which no panel data by region/year are available) can be hypothesized to largely follow patterns of retail prices (Tables 1 and 2: *lnrp(i)*), with mark-ups being nearly fixed for relatively long periods.

As a supplementary source of information, EM-DAT (www.emdat.be) has been relied on to construct a dummy of

Table 2
List of variables and descriptive statistics: Burkina Faso (1984–2004 cross-region panel)

Variable	Definition	Mean	μ (drought years)	μ (other years#)	Standard deviation	Skewness	Kurtosis
yd[sor]	Sorghum yield (tonne/ha)	0.83	0.72*	0.85	0.32	1.69	7.81
lnyd[sor]	(natural logarithms)	−0.24			0.37	−0.41	1.17
yd[mil]	Millet yield (tonne/ha)	0.68	0.63′	0.69	0.23	0.62	0.9
lnyd[mil]	(natural logarithms)	−0.44			0.36	−0.6	0.78
yd[mai]	Maize yield (tonne/ha)	1.03	0.9′	1.05	0.49	0.56	0.51
lnyd[mai]	(natural logarithms)	−0.11			0.6	−1.23	2.13
yd[nut]	Groundnut yield (tonne/ha)	0.765	0.8	0.76	0.3	0.99	3.8
lnrp[sor]	Real price of sorghum (1996 retail FCFA/kg, 1998–2002**)	4.81 (*126.2*)	*143′*	*122.1*	0.22	−0.61	0.64
lnrp[mil]	Real price of millet (1996 retail FCFA/kg, 1998–2002**)	4.9 (*137.7*)	*160.9**	*131.9*	0.21	−0.74	−0.1
lnrp[mai]	Real price of white maize (1996 retail FCFA/kg, 1998–2002**)	4.81 (*125.3*)	*142.3′*	*121.1*	0.2	−0.61	−0.15
lnar[sor]pc	Sorghum-cultivated area per capita (ha/1,000 resident)	4.89	4.7″	4.92	1.03	−2.12	6.75
lnar[mil]pc	Millet-cultivated area per capita (ha/1,000 resident)	4.83	4.82	4.835	0.93	−1.29	2.86
lnar[mai]pc	Maize-cultivated area per capita (ha/1,000 resident)	2.65	2.1*	2.72	1.44	−0.52	1.26
lnh	Production market concentration for major crops (Herfindahl index h, range [1/n, 1]; n = 3: sorghum, millet, maize)	−0.71 (*0.5*)	*0.54**	*0.49*	0.18	0.82	1.6
lnrd	Number of rainy days by region (recorded at local meteorological stations, 1996–2004^)	4.22 (*70.2*)	*67.7*	*70.6*	0.25	−0.51	−0.57
lnrainf	Rainfall (annual average by region, mm, 1996–2004^)	6.64 (*798.5*)	*791.1*	*799.8*	0.31	−0.54	0.19
lnrainf1	April–June rainfall (monthly average by region, mm^)	4.05 (*67.3*)	*41.5**	*70.2*	0.62	−0.8	0.6
lnrainf2	July–October rainfall (monthly average by region, mm^)	4.91 (*142*)	*122.7**	*145.3*	0.32	−0.54	0.02
Dummy variables							
cfa	CFA franc devaluation (1 for 1994–2004; 0 for pre-devaluation period 1984–1993)						
dprior	years prior to officially declared droughts (1 for year preceding droughts; 0 otherwise)						
enso	El Niño-Southern Oscillation events (1 years recorded with ENSO events; 0 otherwise)						
ota	NASA index of global land-ocean temperature anomaly (UNEP GeoData, geodata.grid.unep.ch)						
isohyets	Agroecological classification based on broad isohyetal zones: 1. Sahelian, 2. Sudano-Sahelian, 3. Sudanian (annual average rainfall levels less than 600 mm, around 800 mm, and exceeding 1,000 mm i.e., nearly 1,200 mm, respectively; Wang et al., 2008)						

Symbols preceded by *ln*: log-transformed variables (except for crop yields–original and log-transformed values in separate rows–mean values of original data are reported in italics). #Including years of locust infestations. Sub-sample means (μ) are based on pooled regressions including intercept term and drought dummy (statistically different at: *1%, ′5%, ″10% significance level). **Retail markets in the provinces of Boulgou, Boulkiemde, Gourma, Houet, Mouhoun, Poni, Sanmatenga, Seno and Yatenga. ^Data based on ten meteorological stations in the provinces of Gnagna, Gourma, Houet, Kadiogo, Mouhoun (average estimates for Boromo and Dédougou stations), Nahouri, Poni, Seno, and Yatenga (eight stations and seven provinces for seasonal rainfall data, excluding Gnagna and Nahouri).
Sources: see Section 4.

pre-drought years (Tables 1 and 2: *dprior*, for individual regions or countrywide), so as to test for unobserved effects in a supply-side geographical diffusion hypothesis (Section 2). In this database, natural hazards including droughts are classified as a disaster if they match one or more of the following criteria: a hazard event has left at least 10 people dead, hundred individuals or more have been affected (being in need of immediate emergency relief, relative to food, water, shelter, and medical care, thus including injured and homeless), an official request for international assistance has been made, and/or a state of emergency has been declared.[4]

In relation to a proxy for commodity price instability (as nonsystematic variation in e.g., retail crop prices: Eqs. (1) and (2) in Section 2), Kenen and Voivodas (1994) suggest to use the standard error from mixed autoregressive-deterministic trend OLS regressions (or their generalized differenced form). Alternatively, instability can be proxied by absolute deviations between observed and expected prices, as percent shares of expected prices estimated with truncated distributed-lag

[4] EM-DAT is maintained by CRED (Centre for Research on the Epidemiology of Disasters, University of Louvain), in collaboration with WHO. Given the above criteria, the database does not include relatively "minor" events at a local (e.g., municipal) level (Tschoegl et al., 2006). In landlocked countries in the Sahel, localized food crises due to population movements or local market shocks (not necessarily related to officially declared droughts) tend to occur every year.

Table 3
Spatial panel data model estimates for crop yields in Niger and Burkina Faso

Method	FE-OLS	GMM	FE-OLS	GMM	FE-OLS	GMM	FE-OLS	GMM	FE-OLS	GMM	FE-OLS	GMM
[Model] sample size	[1] 84	[2] 78	[3] 90	[4] 84	[5] 90	[6] 84	[7] 586	[8] 76	[9] 587	[10] 75	[11] 555	[12] 71
Country				*Niger*						*Burkina Faso*		
Agricultural crop	Sorghum		Millet		Cowpea		Sorghum		Millet		Maize	
Constant	2.22	−0.1	−9.9	−0.07	−9.92	0.07	−0.08	0.01	−0.35	−0.1	−0.35	0.01
	(0.2)	(−1.33)	(−1.08)	(−1.62)	(−0.85)	(0.9)	(−0.5)	(0.2)	(−2.11)′	(−2.7)*	(−2.4)′	(0.23)
$\text{lnyd}(i)_{-1}$	0.09	0.12	−0.18	−0.2	0.09	0.09	0.17	0.27	0.14	0.2	0.03	0.2
	(0.79)	(1.0)	(−2.03)′	(−2.25)′	(1.12)	(1.19)	(4.03)*	(2.46)′	(3.31)*	(1.58)	(0.7)	(2.2)′
lnyd(i)sp	0.67	0.73	−0.14	0.08	0.21	0.38	0.57	0.57	0.58	0.5	0.79	0.77
	(2.97)*	(3.22)*	(−0.41)	(0.23)	(1.74)″	(2.6)*	(10.3)*	(4.1)*	(8.53)*	(3.88)*	(14.1)*	(5.24)*
$\text{lnyd}(i)\text{sp}_{-1}$	0.09	−0.13	0.1	−0.16	−0.15	−0.1	−0.29	−0.27	−0.33	−0.51	−0.12	−0.09
	(0.55)	(−0.7)	(0.49)	(−0.78)	(−1.2)	(−0.75)	(−5.07)*	(−2.0)′	(−6.35)*	(−3.5)*	(−2.16)′	(−0.73)
lnrd	0.65	0.62	0.6	0.56	0.89	0.91						
	(1.96)′	(1.93)″	(2.44)′	(2.08)′	(2.35)′	(2.5)′						
lnrainf1	*0.1*		*0.08*		*0.18*		*−0.01(− 0.2)*	−0.01	*0.11(1.66)″*	0.05	*−0.001(− 0.01)*	0.02
[lnrainf1, lnrainf1^2]	*(0.9)*		*(1.2)*		*(1.44)′*		*[0.61″, − 0.08″]*	(−0.23)	*[0.47, − 0.05]*	(0.8)	*[−1.12′, 0.15′]*	(0.24)
lnrainf2	*0.48*		*0.34*		*0.52*		*0.22(2.07)′*	0.25	*0.24(2.24)′*	0.2	*0.65(3.92)**	0.63
[lnrainf2, lnrainf2^2]	*(1.87)**		*(1.89)″*		*(1.73)″*		*[7.01*, − 0.7*]*	(2.25)′	*[5.99*, − 0.6*]*	(1.98)*	*[1.57, − 0, 1]*	(3.77)*
lntemp	−2.33	−5.23	0.91	−1.87	0.84	2.62						
	(−0.7)	(−1.49)	(0.37)	(−0.7)	(0.3)	(0.63)						
lnh	−0.76	−0.48	0.39	0.56	−2.91	−2.87	−0.01	−0.12	−0.21	0.24	−0.23	−0.25
	(−2.25)′	(−1.25)	(1.73)″	(2.23)′	(−8.43)*	(−7.37)*	(−0.08)	(−0.4)	(−2.09)′	(0.8)	(−1.59)	(−0.5)
lnar(i)pc	−0.34	−0.37	−0.16	0.02	−0.54	−0.47	−0.06	−0.09	−0.05	−0.001	−0.01	0.05
	(−2.94)*	(−2.93)*	(−0.6)	(0.07)	(−3.28)*	(−2.47)′	(−2.63)*	(−1.88)″	(−1.41)	(−0.02)	(−0.4)	(1.2)
lnrp(i)	0.35	0.18	0.33	0.17	−0.07	−0.22	*−0.12*		*−0.11*		*0.78*	
	(1.6)	(0.8)	(2.35)′	(1.41)	(−0.26)	(−0.08)	*(− 0.6)*		*(− 0.4)*		*(2.21)′*	
$\text{lnrp}(i)_{-1}$			0.33	0.42								
			(1.7)″	(2.28)′								
lnrp(i)dr	*−0.01*		*0.002*		*−0.02*		*0.03*		*0.03*		*−0.03*	
	(− 0.3)		*(0.1)*		*(− 1.12)*		*(1.77)″*		*(1.68)″*		*(− 0.99)*	
t							0.01′		0.01		0.01	
							(2.4)′		(2.75)*		(1.27)	
cfa	*0.04*		*0.04*		*−0.15*		−0.04		0.07″		−0.03	
dprior	−0.08		−0.22′		−0.15		−0.03		−0.06′		−0.01	
enso							0.07*		0.05*		0.003	
ota							−0.25′		−0.31*		0.02	
Dosso/BFU1	0.51		0.15		−0.08		0.39*		0.27*		0.39*	
Maradi/BFU2	0.64		0.55′		−0.64″		0.32*		0.21*		0.34′	
Tahoua/BFL2	0.8′		0.31		−0.49		−0.2″		−0.18*		−0.39*	
Tillaberi/BFLl	0.65′		0.22		0.1		−0.22′		−0.2′		−0.52*	
Zinder	0.78″		0.43″		−0.84′							
m1	−1.11	−2.93*	−0.62	−3.31*	−1.04	−3.94*	−1.01	−4.86*	−1.55	−4.15*	0.65	−4.13*
m2	−0.63	0.94	−0.04	0.7	0.37	1.04	0.19	2.03′	−0.09	1.85″	−0.06	1.32
$\chi^2(k)$	79.6*(9)	49.6*(8)	52.4*(10)	44.02*(9)	153.5*(9)	132.4*(7)	346.8*(10)	37.9*(7)	368.0*(10)	39.8*(7)	272.1*(10)	71.1*(7)
$\chi^2(d)$	8.7(6)		10.8″(6)		21.7*(6)		140.7*(30)		4, 089.0*(30)		142.0*(29)	
$\chi^2\ (z-k)$		57.2(70)		67.9(70)		64.7(70)		58.4(89)		41.9(89)		46.4(89)
R^2 (adj)	0.63	(0.35)	0.4	(0.29)	0.62	(0.61)	0.57	(0.28)	0.55	(0.29)	0.58	(0.47)

maximum likelihood (ML) models, which reflect adaptive expectations (Glezakos, 1978). Based on an estimator that is less sensitive than OLS and ML to deviations from normality and atypical observations (DasGupta and Mishra, 2004), least absolute deviations (LAD) residuals have been preferred here as a yardstick, with price instability measured as mean percent absolute deviations of rescaled LAD residuals (with estimate for a region i given by $\sum(|\varepsilon_{it}| * 100/p(e)_{it})/n$; $n = 15$ years [1992–2006]) from second-order distributed lag regressions on (untransformed) real prices of food crops, including a dummy for the 1994 CFA franc devaluation (results not shown).[5] Due to missing observations for other crops, the estimation of the price instability index is limited to cowpea and millet prices in Niger over the period 1990–2006 (Fig. 3: *inbe*, *imil*).

Summary statistics of the variables are presented in Tables 1 and 2, relative to the two country panels (among relevant crops other than those examined in Section 5, the tables report groundnut yields, while cassava and fonio have missing data for most regions/years). Based on coefficients of variation (=standard deviation/mean), yields appear to vary on average more than real prices (except for millet in Niger), while mixed results in terms of relative variability are evident for yields vis-à-vis rainfall (characterised by high variability during the early growing season, especially in Niger) and cultivated area per capita. For Burkina Faso, these statistics are not strictly comparable across all variables due to partly unbalanced panels, and this also largely applies to seasonal rainfall data in both countries (due to missing observations). Rightward skewness and platykurtosis (versus zero-centred mesokurtosis) in several variables is corrected (in some cases over-corrected) with logarithmic transformations (Tables 1 and 2). Unlike linear polynomial functions (as for rainfall in Eq. (1), Section 2), double-log regressions directly yield elasticity parameter estimates (with less-than-unit elasticity implying decreasing marginal returns for seasonal rainfall). Limited to Burkina Faso (given sample constraints for Niger), constancy of rainfall elasticity has been tested with log-quadratic specifications (as commented in the next section).

While neither country shows remarkable disparities between drought and nondrought years in terms of average annual rainfall and rainy days, seasonal rainfall, and maximum temperatures register statistically significant differences (in Niger during drought years, substantial rain shortages affect the July–October rainy season, although relatively higher rainfall unexpectedly concerns the pre-growing season; Table 1). While yields in Burkina Faso appear to experience marked drops during officially declared droughts, lack of evidence for Niger is likely to reflect structural weaknesses. These are highlighted by persistent low yields in major food crops, with no significant differences in average yields between drought and nondrought years (even if locust infestations are included among the former). Droughts register marked food price increases, with jumps for sorghum in Niger exceeding one-third of the price in normal years (Table 1). In Burkina Faso, these price jumps appear to be accompanied by shrinking per capita area of sorghum and maize cultivations and decreased market diversification (Table 2: *lnh*). Finally, the dominant crop (millet in Niger and sorghum in Burkina) is also the one achieving relatively higher average yields (Tables 1 and 2).

5. Spatial regression model estimates

With a nonprojected FAO spatial coordinate system, for this analysis spatial weight matrices have been constructed based on arc-distances between regional centroids (estimated with the software GeoDa; Appendix II; Anselin, 2003). For Niger, the cut-off distance was set at an average connectivity level (466 km) between minimum and maximum feasible distances. For Burkina Faso, the minimum level (57 km) was preferred, due to the higher administrative disaggregation and smaller country area. Also, spatial weights for Niger were adjusted for directional effects, captured by each region's population share (in 2006, the number of residents was more than six times higher in the province of Maradi than Diffa, with nearly four hundred thousand individuals living in the latter province). To simplify, isotropy is assumed instead for Burkina Faso. While further analysis would be necessary to test the sensitivity of results to different spatial weights, comparison of econometric estimates between the two countries needs caution in view of these differences.[6]

Dynamic first-order autoregressive-spatially autoregressive (AR-SAR) panel data models, which encompass the hypotheses reviewed in Section 2 (in line with Eq. (1) and specifications (3) and (4); see also Appendix II), have been applied to the selected crop yields. For Niger, *ad hoc* AR-SAR models are estimated for crop prices (based on Eq. (2), and the same alternative approaches as for yields). Econometric results are presented in Tables 3 and 4, for yields and prices respectively (for Burkina Faso, relative to subsample regressions with isohyet

[5] An adaptive expectations model for price levels (with $p(e)_t$ the price expected at year t) can be expressed in Eq. (5). This can be reformulated through successive substitutions as weighted averages of past observed prices, as in Eq. (6):

$$p(e)_t - p(e)_{t-1} = \beta[p_{t-1} - p(e)_{t-1}] \qquad (0 < \beta < 1) \tag{5}$$

$$p(e)_t = \beta p_{t-1} + \beta(1-\beta)p_{t-2} + \beta(1-\beta)^2 p_{t-3} + \cdots. \tag{6}$$

Truncation (e.g., at second-order lag) in distributed lag (*de facto* autoregressive, since the dependent variable is not observed) model estimation of (6) reflects empirical evidence that expected prices are largely influenced by the most recent prices (Glezakos, 1978).

[6] In 2006, population by province in Burkina Faso ranged from nearly ninety thousand inhabitants in Bougouriba (in the south-western Sudanian zone) to more than one million three hundred thousand residents in the province of Ouagadougou (Kadiogo). Estimates for years other than general population censuses (www.insd.bf, Table 3.17) are projections based on average intra-census annual compound growth rates. In the construction of spatial weight matrices, a minimum distance is required to ensure that each observation has at least one neighbor. Relative to Burkina Faso, this lower bound chosen as a threshold distance highlights limited connectedness (i.e., one or two neighbors) for four peripheral provinces (Oudalan, Poni, Seno, and Tapoa).

Table 4
Spatial panel data model estimates for crop prices in Niger

Method	FE-OLS	FE-OLS	GMM	FE-OLS	GMM	FE-OLS	GMM
[Model] sample size	[1a] 87	[1b] 87	[2] 81	[3] 96	[4] 90	[5] 96	[6] 90
Agricultural crop	Sorghum			Millet		Cowpea	
Constant	3.58	3.07	0.02	0.34	−0.001	1.0	−0.001
	(6.86)*	(3.77)*	(1.2)	(1.32)	(−0.14)	(1.43)	(−0.05)
lnrp(i)$_{-1}$	0.13	0.39	0.11	0.15	0.15	0.32	0.36
	(1.22)	(2.41)′	(1.26)	(1.4)	(1.4)	(3.12)*	(3.42)*
lnrp(i)sp	0.32		0.36	0.98	0.99	0.9	0.89
	(4.66)*		(5.47)*	(28.2)*	(28.8)*	(11.8)*	(10.7)*
lnrp(i)sp$_{-1}$	−0.2		−0.17	−0.18	−0.18	−0.39	−0.39
	(−2.6)*		(−2.4)′	(−1.58)	(−1.56)	(−3.17)*	(−3.01)*
lnrp(i)sp(dr)	0.05		0.06	0.004	0.004	0.003	0.003
	(6.96)*		(6.78)*	(0.97)	(0.9)	(0.61)	(0.42)
lnar(i)pc	0.01	0.09	−0.001	−0.01	−0.06	0.01	−0.02
	(0.3)	(1.24)	(−0.01)	(−0.17)	(−0.92)	(0.31)	(−0.43)
lnyd(i)$_{-1}$	0.02	−0.09	0.05	0.01	0.02	−0.02	−0.04
	(0.55)	(−1.58)	(1.34)	(0.5)	(0.64)	(−1.36)	(−1.92)″
lnyd(i)dr$_{-1}$	0.0005	0.04		−0.002		−0.003	
	(0.02)	(0.8)		(−0.13)		(−0.3)	
cfa	0.03	0.09		0.02		−0.009	
Dosso	−0.01	0.03		−0.09″		−0.26*	
Maradi	−0.3′	−0.42″		−0.31*		−0.31*	
Tahoua	−0.06	−0.16		−0.04		−0.17′	
Tillaberi	0.02	−0.04		−0.03		−0.02	
Zinder	−0.31′	−0.44″		−0.26*		−0.37*	
m1	−0.23	1.95″	−3.05*	0.4	−2.64*	0.34	−3.14*
m2	−0.8	−4.44*	−0.06	−1.06	−0.44	−0.96	−0.44
$\chi^2(k)$	219.8*(8)	12.6′(5)	208.0*(6)	1,227.0*(8)	1,188.0*(7)	323.3*(8)	313.0*(7)
$\chi^2(d)$	59.9*(6)	17.8*(6)		48.1*(6)		30.1*(6)	
$\chi^2(z-k)$			64.6(70)		69.3(70)		70.5(70)
R^2 (adj)	0.8	0.34	(0.71)	0.94	(0.92)	0.86	(0.77)

Notes for Table 3 and 4.
Dependent variable: *lnyd*(i) (Table 3), *lnrp*(i) (Table 4). Lists of variables: Tables 1 and 2; (i)*sp* spatial lag; (i)*sp*(*dr*) spatial lag slope dummy for drought years ((*i*)*sp* for years of droughts, 0 otherwise]; (i)*dr* slope dummy for drought years). In parentheses: t-statistics under estimated parameters (level of significance: $^*1\%$, $'5\%$, $''10\%$); adjusted R^2 for GMM models ($=1-[\text{var}(\varepsilon)/\text{var}(Y)]$). In parentheses (Table 3): estimated parameters for seasonal monthly rainfall in log-quadratic form. In italics: estimated parameters and t-statistics in regression specifications including seasonal rainfall or real crop price slope dummy for drought years (and real crop price for Burkina Faso). m1 (m2): first-order (second-order) residual autocorrelation test (Arellano and Bond, 1991, p. 282; Doornik and Hendry, 2001, p. 94). $\chi^2(k/d)$: Wald test of joint significance of k estimated parameters (including time dummies if applicable)/d dummies including constant (excluding time dummies). "Outlying" fixed effects for Burkina Faso (other province FE parameters not shown): U1 extreme upper, U2, second upper, L2 second lower, L1 extreme lower (sorghum: U1 Comoé, U2 Zoundweogo, L2 Oubritenga, L1 Oudalan; millet: U1 Kossi, U2 Gnagna, L2 Soum, L1 Oubritenga; maize: U1 Mouhoun, U2 Kenedougou, L2 Soum, L1 Oubritenga). $\chi^2(z-k)$: Sargan test of validity of instruments (over-identifying restrictions, with z number of instruments). Estimation method: FE-OLS (fixed effects-ordinary least squares), GMM (generalized method of moments).

zones instead of provincial effects, partial results are reported in italics).[7] Based on goodness-of-fit measures, price variation is found to be better explained than yield variability (as not strictly suited to GMM, adjusted-R^2 statistics are reported in parentheses for GMM regressions). Relative to sorghum prices in Niger, FE-OLS estimates of a regression without spatial effects (reported for comparative purposes; Table 4, [1b]), are biased and inefficient, with serial and spatial residual correlation (also based on the Moran's I statistic on panel residuals [=0.85]). As for spatial regressions, FE-OLS yields uncorrelated errors in levels, and this mostly applies also to GMM at second-order lags (as in Arellano and Honoré, 2001). The null hypothesis of no correlation between GMM instruments and estimated residuals cannot be rejected by the Sargan test, thus indirectly validating the instruments. Possible enhanced capacity effects over time, captured by linear trend terms, are not present or seem to have had only a minor impact (models including trend parameter estimates are reported in Table 3 for Burkina Faso). The same applies for the presumed role of the CFA franc devaluation, and for unobserved effects in years preceding the beginning of officially declared droughts. The only exception is represented by millet yields, which *ceteris paribus* experience negative effects in pre-drought years

[7] Administrative regions in Mali and Niger approximately correspond to different rainfall areas (defined by isohyets), with millet scattered across different regions, and sorghum more concentrated in semi-arid, relatively more humid zones in south-western regions. Similarly, different vegetative zones can be distinguished in Burkina Faso, corresponding to distinct isohyetal zones, with increasing average rainfall levels and water productivity when passing from north-eastern to south-western provinces. Millet and sorghum are cultivated on sandy highlands and drier areas, while maize is relatively more present in low wetlands, occasionally along with rice (Brown and Crawford, 2008; Wang et al., 2008).

(especially in Niger), and (in Burkina Faso) some improvements in the post-devaluation period (Table 3: [3] vs. [9]).

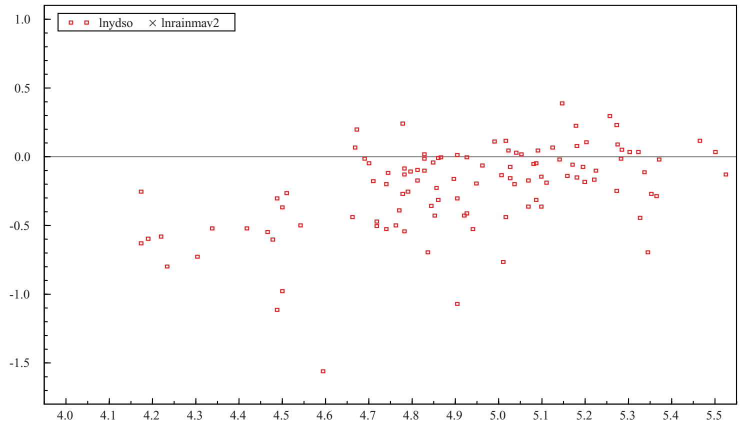
Except for millet in Niger, simultaneous spatial diffusion effects appear to be more relevant for explaining the performance of major crop yields than the respective (time) autoregressive and one-year lagged spatial effects, and similar results hold true for crop prices. In seven models ([1]–[2] and [12] for yields, and [3]–[6] for prices), the simultaneous spatial autoregressive coefficient is close to the unit bound, with no rejection of the unit null hypothesis at 5% statistical significance (for cowpea prices, dynamic spatial effects are smoothed down by a negative parameter of the one-year-lagged spatial lag variable: Table 4). Relative to models [3] and [4] (Table 3), if one-year lagged spatial lag yields are excluded from the regression, the parameter of the lagged endogenous variable remains negative and statistically significant, thus suggesting instability for millet yields in Niger. On the whole, consistent with a supply-side geographical diffusion hypothesis, food crop yields are hardly responsive to their unit prices (except to some extent for millet in Niger and maize in Burkina Faso), and remain substantially so during officially declared droughts (Table 3: real price slope dummy *lnrp(i)dr*) and vis-à-vis unit prices of competing crops in terms of cross-price elasticity (the latter results—not reported—also concern price regressions, partly due to multicollinearity). On the other hand, the contending argument of a stronger causality effect in the opposite direction is not supported by crop price regressions for Niger, with statistically insignificant parameters of lagged yields (except in model [6], Table 4), and no significant interaction effects with drought years (slope dummy $lnyd(i)dr_{-1}$). Relative to sorghum, a statistically significant positive parameter associated with an interaction term between the spatial lag price and official droughts (Table 4, [1a]-[2]: slope dummy *lnrp(i)sp(dr)*) is consistent with previous evidence on reductions of grain price geographical dispersion during drought events (Aker, 2008a).

Regarding climatic factors, sorghum and millet crop productivity in Burkina Faso appears to be negatively influenced by temperature anomalies (Tables 2 and 3: *ota*), although slightly less so during ENSO events. The respective crop yields in Niger turn out to be unaffected by these anomalies (results not shown), but relatively more sensitive to rainfall shortages during the rainy season (Table 3, [1] vs. [7], and [3] vs. [9]: July–October rainfall). Based on these elasticity parameters (as an approximate indicator of relative resilience to rainfall shortages), the dominant crop in either country seems to have a slight advantage margin relative to competing crops within each country. However, relative to Burkina Faso, this is limited to the April–June period for sorghum relative to millet, while in the rainy season the two crops show similar rainfall elasticity (see also Fig. 1).[8] Concerning other crops, Niger's cowpea has very low yields (as occurring in other Sahel countries: Perret, 2006, p. 3) and appears to be vulnerable to rain shortages across different isohyetal zones (also in terms of annual rainy days; Table 3, [5] and [6]).

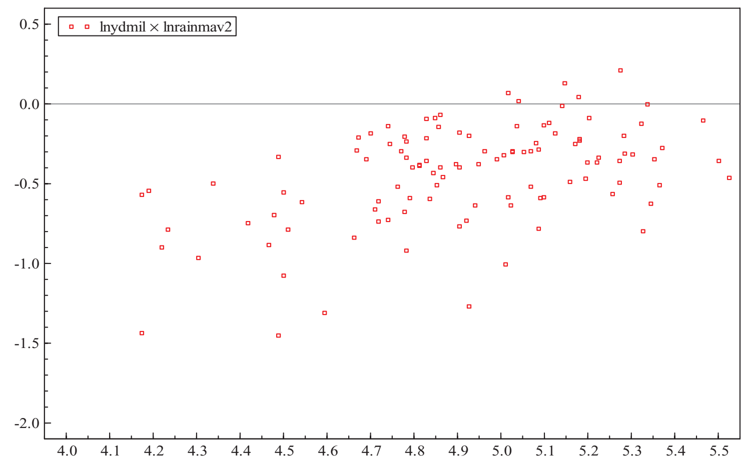
The hypothesis of a negative impact of insufficient yield-risk diversification through balanced inter-cropping cultivations is substantiated in two cases (sorghum and cowpea in Niger), but rejected or only partly supported in others. Relative to sorghum in both countries and cowpea in Niger, statistically significant negative parameters associated with the control variable for cultivated areas per capita imply that, other conditions being equal, regions/years with relatively larger extension of cropland per resident have fared comparatively worse in terms of average yields of these crops. This result may reflect increased soil conservation efforts and input intensity to compensate for smaller planted areas, but it is also likely to be influenced by spatial aggregation problems, as discussed in Section 2. Over the sample period analysed for Niger (1996–2006), no consistent cross-region patterns of yield vulnerability can be detected based on region-specific fixed effects. *Ceteris paribus*, while Diffa (implicit dummy for Niger), Dosso, and Maradi lag seriously behind other regions in terms of sorghum yields, other regions score poorly compared with the south-central provinces of Maradi and Zinder relative to millet yields, and the latter in turn fall short of others relative to cowpea yields (Table 3: [1], [3], [5]). As for Burkinabé provinces, a more distinct pattern, largely associated with isohyets, is revealed by fitted regression residuals: some eastern, south-central and south-eastern provinces (including Comoé, Kenedougou, Kossi, Mouhoun, and Zoundweogo) stand out for relatively better productivity in one or more of the three food crops, whereas opposite cases are represented by Sahelian provinces, such as Oudalan and Soum (but also Oubritenga in the Central Plateau; Table 3: [7], [9], [11]).

If the dominant crop is focused on, both millet in Niger and sorghum in Burkina Faso present marked year-to-year variation in cross-region yields (illustrated by quantile maps in Figs. 2 and 4, relative to two years). High crop price instability in Niger seems to be especially present in (and thus possibly to negatively affect) regions with more limited scope for crop yield improvements, such as the southern regions of Maradi and Zinder for cowpea (a more heterogeneous pattern can be observed for millet: Fig. 3). Unexpectedly relative to Eq. (1) (Section 2), no clear patterns in terms of poverty headcount indices (www.ins.ne, *Statistiques structurelles*; UNDP, 2007: T.3.10), nor interactions between the latter and for example, road infrastructure backlogs (Fig. 5), are observable so as to further explain regional differences in crop yields. However, as suggested by quantile maps of estimated incidence of poverty in Niger (not shown) and levels of malnutrition in Burkina Faso (Fig. 6), disparities in socioeconomic and nutritional indicators vary from one year to the next also as a result of different

[8] Indirect estimates of elasticity are based on the first derivative of log-quadratic specifications with respect to *lnrainf2*, given estimated parameters and sample mean of this variable. The average elasticity thus estimated amounts to lower values than those estimated directly, that is, 0.16 and 0.12 during the rainy season for sorghum and millet respectively (Table 3: parameter estimates of the two log-polynomial terms reported in parentheses).



(a) *Sorghum yields (t/ha) vs. July-October monthly average rainfall (mm), in natural logarithms*



(b) *Millet yields (t/ha) versus July-October monthly average rainfall (mm), in natural logarithms*

Fig. 1. Crop yields versus wet season monthly rainfall in Burkina Faso (1984–2004).

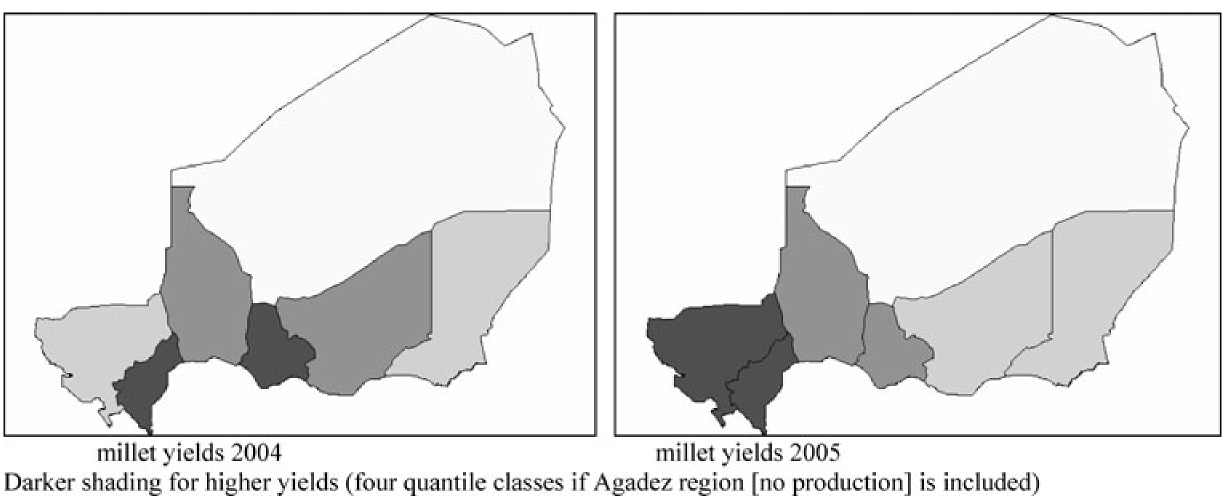


Fig. 2. Millet yields by region: Niger (2004–2005).

survey methodology, thus limiting the use of these indicators in a cross-region panel. Moreover, relative to Burkina Faso, the Moran's index of local spatial association allows us to visualize the presence of significant spatial clustering effects among neighboring provinces within some parts of the country. These effects are induced by factors that need to be analyzed at a more disaggregate geographical level (e.g., local effects from dominant crop—sorghum—on millet yields, and influence of

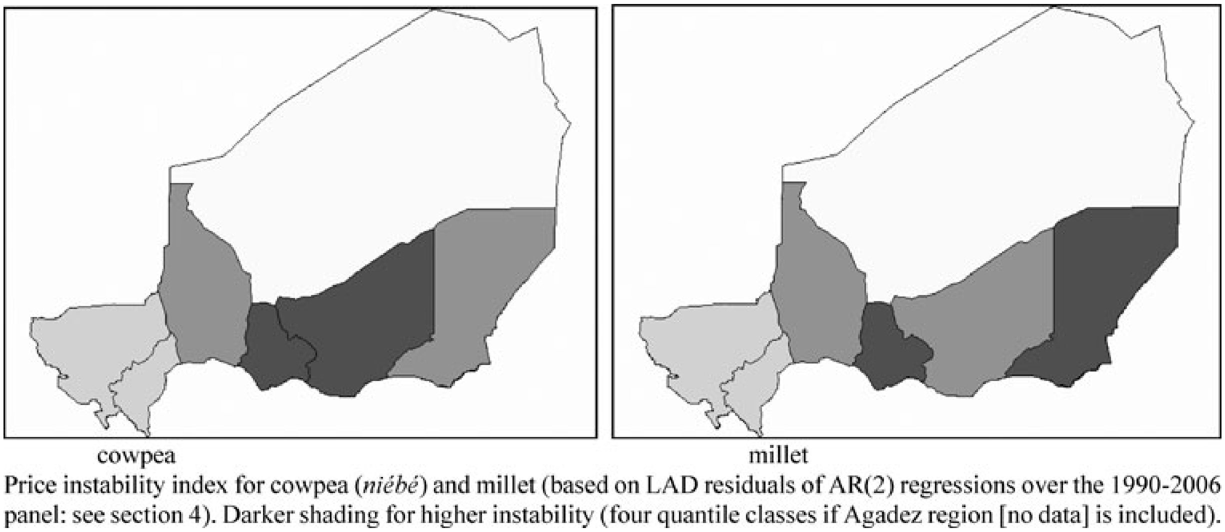


Fig. 3. Crop price instability: cowpea and millet in Niger.

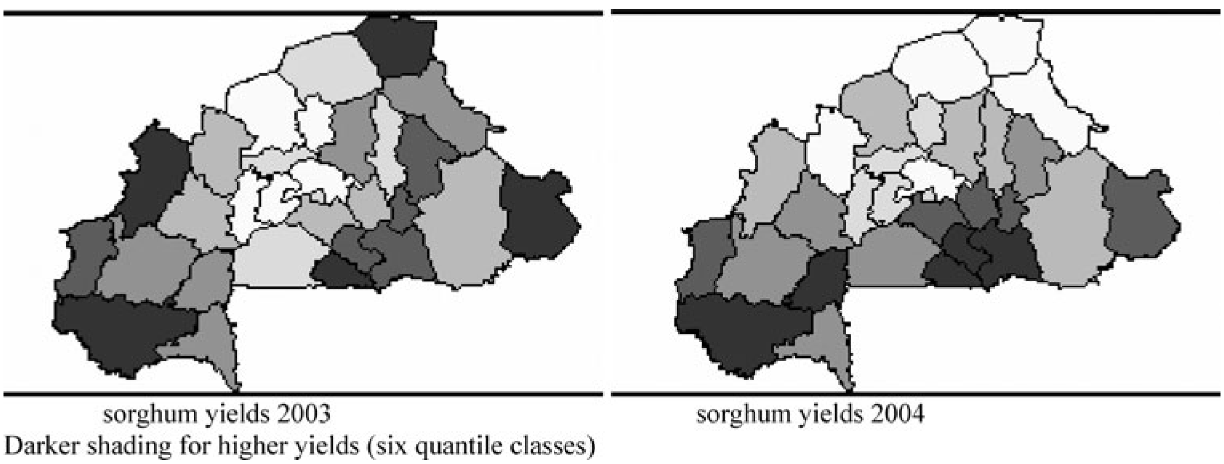


Fig. 4. Sorghum yields by region: Burkina Faso (2003–2004).

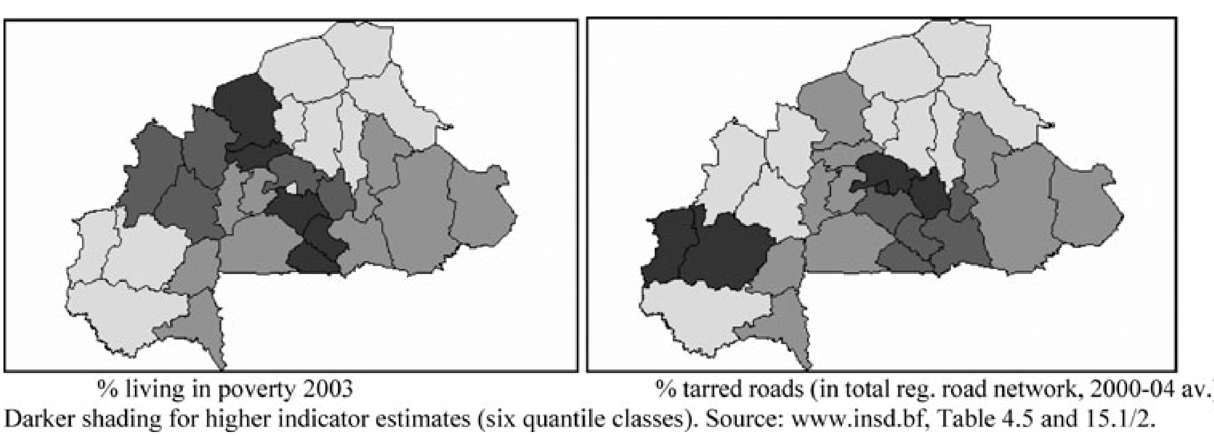


Fig. 5. Incidence of poverty and road infrastructure backlogs by region: Burkina Faso.

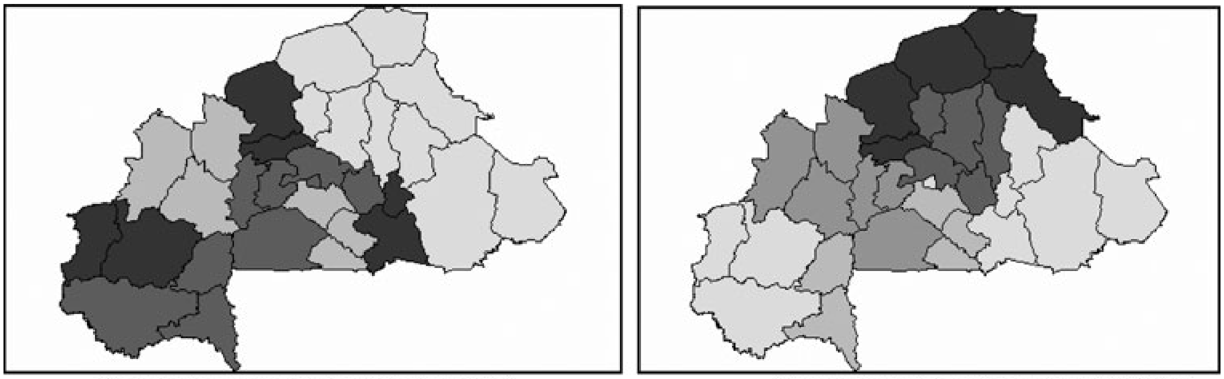


Fig. 6. Incidence of malnutrition by region: Burkina Faso (2003–2005).

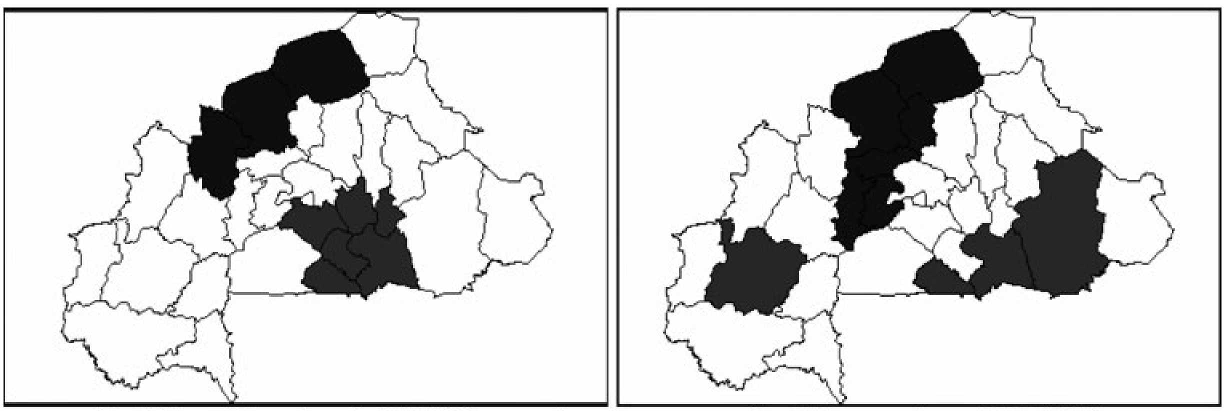


Fig. 7. Sorghum yields versus road infrastructure, and millet versus dominant crop (sorghum) yields: spatial spillover effects in Burkina Faso (LISA cluster maps).

the state of the road network and transport facilities on sorghum yields, with cluster "core hotspots" highlighted in Fig. 7; for a review of local spatial statistics, see Getis and Ord, 1996).

6. Conclusion

In drought-prone countries, studies of determinants of crop yields and prices across regions can contribute to the analysis of the impact and incidence of droughts, and strengthen the design of strategies for reducing exposure to droughts and food insecurity. Econometric modeling of spatial dependence in crop yields and cropland distribution across regions has also become a useful tool for harvest risk management (Druska and Horrace, 2004; Holloway et al., 2007; Zhu et al., 2009). The use of spatial panel data estimation techniques is in its infancy, due to computational requirements and less developed theoretical underpinnings (relative to panel data and spatial econometrics as two separate domains). However, spatial panel data models can help avoid some of the identification problems typically encountered in (spatial) cross-section econometrics, such as the mixing of *true* and *apparent contagion* (Appendix II; Anselin, 2002). In this respect, a relevant question concerns the extent to which weak adaptive capacity and vulnerability to droughts can be explained by location-specific (regional/subregional) factors, which are largely independent of crop and land use choices. Among possible factors of improved response capacity in front of emergencies, easy accessibility to main urban centers and local availability of carryover stocks may dampen price shocks and reduce supply disruptions during drought years.

Relative to four major food crops in Burkina Faso and Niger, in this study yields and prices are found to undergo significant spatial diffusion processes, with feedbacks turning out to be mainly simultaneous and generally more relevant than autoregressive effects. Spatial spillovers, revealed by spatial lag elasticity parameters, turn out to be particularly strong for millet and cowpea prices and sorghum yields in Niger, and maize yields in Burkina Faso (where some provinces lie structurally behind others in terms of yield levels for this and other cereals). These results imply that shocks affecting food crops have tended to spread relatively quickly across neighboring regions (in either country) within their year of occurrence, with time effects likely to be overstated if the econometric analysis disregards spatial effects. On the other hand, with broad geographical reference units, positive spatial lag autoregressive parameters may be biased upwards as a consequence of partly spurious spatial interdependence (similar to what is observed relative to long-run persistence properties of annual economic time series, as partly "a figment of temporal aggregation"; Rossana and Seater, 1995). When sufficient statistical information becomes available at higher levels of spatial detail (such as districts within UN-SALB "level 2" boundaries), the sensitivity of spatial regression estimates to geographical scale and aggregation (including a possible "modifiable areal unit problem") should be tested for. Attention could also be addressed to spatial spillovers between neighboring countries and from main urban centers, as well as space- and time-related interactions between food crop performance and livestock activities (such as price disruptions in opposite directions during drought periods; World Bank, 2008). This would allow an assessment of specific factors, such as transport infrastructure and marketing systems, which remain largely undetected at higher levels of spatial aggregation.

Acknowledgments

The author wishes to thank three anonymous referees for useful comments and suggestions, and J.-M. Scheuren (CRED) for the EM-DAT data. The usual disclaimer applies.

Appendix I: Drought tolerance, price affordability, and nutritional adequacy in the Sahel: selected food crops

Along with sorghum, millet has a history of cultivation in the Sahel dating back to 3,000–5,000 years ago (Diakité et al., 2008). Despite being regarded as relatively more drought-resistant and advocated as a priority target for food crop management, millet is often less preferred to sorghum due to its longer maturation period (Abdoulaye and Sanders, 2006; Ingram, 2005; Wyatt et al., 1999). Among millet species, white fonio (*digitaria exilis*) is characterized by high nutritional properties and short growing season (six to eight weeks), and has proven to be highly adaptable to sandy and stony soils. The assumed superiority of improved varieties for harsh climatic environments is questioned by studies pointing to lower yield stability compared with old varieties, with higher yields in good years, and conversely in bad years for sorghum and millet (this may explain a reversion to old varieties in Niger following drought periods in the late 1980s; Maredia et al., 2000).

Among other crops deemed to be relatively resistant to droughts and desert locust infestations and as the third most relevant source of calories in tropical developing countries after maize and rice, cassava is promoted by NEPAD (New Partnership for Africa's Development) for increased food security and rural income stability, especially for farmers relying on marginal land (Madamombe, 2006; Nweke, 2005, p. 17; Spencer, 2005). World production has more than tripled since the early 1960s, with major increases in West and Central Africa: over the last decade, Africa as a whole has become the largest cassava-producing world region (UN-ECA, 2007). Compared with maize, cassava is cheaper and easier to grow, is less vulnerable to low rainfall and poor soil, and its yields are at least three times as high on average. However, unimproved cassava varieties provide lower protein and starch content, grow slowly (almost two years needed to reach maximum yields), face rapid post-harvest deterioration, and are exposed to severe disease problems (Mwangi, 1996). Under rain-fed conditions, maize is more responsive to fertilizer use and is preferred by many farmers.

Unlike neighboring coastal countries, in landlocked Sahel regions traditional coarse grains as sorghum and millet constitute the main staple (e.g., in Niger, grains cover nearly 75% of calorie consumption per capita; Aker, 2008b). This contrasts with shortage of roots (cassava is used more as livestock feed) and vitamin A-rich food in the diet (Zagré et al., 2002). Severe malnutrition is widespread particularly in agro-pastoral areas. With nearly half of its population estimated to be chronically undernourished, Niger is particularly vulnerable to droughts and food insecurity (Lopriore and Muehlhoff, 2003). Urbanization has stimulated demand for maize products and imported cereals, with consumption shifting away from traditional staples. As in a Boserup-type framework (Nweke, 2005), growing population pressure in the southern Sahel may foster intensification of agricultural production, thus favoring the adoption of improved (higher-yielding and shorter-cycle) varieties of maize, millet, and other food crops. Whether these effects comply with long-term sustainability, it remains uncertain, depending on factors such as susceptibility to pests and crop diseases, and social tensions due to high pressure on land tenure. Since most seed supply is provided through informal village grain markets, certified improved seeds cover a minor share of main cereal crops (in Mali, 10% for millet and 20% for sorghum; Diakité et al., 2008; for maize in Burkina Faso, see Maredia et al., 2000).

In recent years, a progressive shift of livestock activities out of Saharan desert margins into southern Sahel regions has led to increased encroachment between cattle-grazing and agricultural cultivations. As a consequence, many farmers have moved towards better-watered and more productive areas further south (or south-west, for Burkina Faso), while others have cleared land for cultivation in northern regions benefiting from temporary episodes of sufficient rainfall (Trench et al., 2007). In some cases, improvements in cereal and cowpea storage facilities and participatory management of natural resources (e.g., integrated farming and livestock production in Toukoumous, in the outskirts of Niamey; Fleury, 2008) have contributed to contain conflicts between farmers and herders. The implications of the ongoing reshaping of population distribution and land use are controversial. While farmers in the northern Sahel are particularly vulnerable to climatic fluctuations, harvest failures and hikes in market prices can have disruptive effects in southern, densely populated regions, thus aggravating food insecurity in urban and rural areas.

Appendix II: Spatial regression with panel data

Regression models accounting for spatial effects fall into two broad categories, depending on whether geographical interdependence follows a pattern of (a) spatial autocorrelation or (b) spatial heterogeneity. The presence of the latter can be detected with spatial regime proxies, while a common specification for case (a) is the spatial autoregressive (SAR) model, where a spatially lagged endogenous variable ($\mathrm{y(sp)_{it}}$ in Eq. (7) below) is constructed as a weighted average of the dependent variable in neighboring locations. Alternatively, relative to unidentifiable neighborhood effects, spatial autocorrelation can be captured by random disturbances in a spatial error (SER) model (Anselin, 2006). As for unobserved heterogeneity in cross-section samples, panel data allow a clearer distinction between two partly interrelated determinants of spatial clustering, which reflect the above patterns, namely spillover effects from one region to another and within-cluster similarity in indicators with a spatial dimension.

A panel data univariate dynamic SAR model with first-order time and spatial lags is represented by Eq. (7)

$$y_{it} = \mu_i + \alpha y_{i,t-1} + \beta_1 y(sp)_{it} + \beta_2 y(sp)_{i,t-1} + \varepsilon_{it}, \tag{7}$$

$$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \delta_1\varepsilon(sp)_{it} + \delta_2\varepsilon(sp)_{i,t-1} + \eta_{it}, \tag{8}$$

where ε_{it} denotes a cross-time/space idiosyncratic error (which may exhibit serial, spatial, and/or lagged spatial correlation, as in Eq. (8), thus implying a mixed SAR-SER model), and μ_i a region-specific fixed effect. Consistent panel data estimators maintain this property in a spatial regression model as Eq. (7) if $\rho = \delta_1 = \delta_2 = 0$ (although with slowed down asymptotics), and are asymptotically efficient if the error variance is constant across regimes (Anselin, 2006; Anselin et al., 2008). In the presence of contemporaneous spatial residual correlation, parameter identification, and avoidance of simultaneity bias require that y_{it-1} and $y(sp)_{it-1}$ be weakly exogenous, that is, that $\rho = \delta_2 = 0$ (Beenstock and Felsenstein, 2006). Estimation is then by fixed-effects instrumental variables (IV), single-equation GMM, or extended (system) GMM. If an exogenous variable x_{it} with linear additive parameter γ is included in (7) and $\rho = \delta_1 = \delta_2 = 0$, a dynamic SARX (AR(1)-SARX(1)) model is obtained, which can be expressed as

$$\begin{aligned} y_{it} &= \mu_i[1-\beta_1 B^s]^{-1} + [\alpha + \beta_2 B^s][1-\beta_1 B^s]^{-1} y_{i,t-1} \\ &\quad + \gamma[1-\beta_1 B^s]^{-1} x_{it} + [1-\beta_1 B^s]^{-1}\varepsilon_{it}, \end{aligned} \tag{9}$$

where B^s is a spatial lag operator associated with a contiguity criterion s (with row-standardized spatial weights, that is, $B^s x_{it}$ represents the weighted average sum of values x_{jt} corresponding to spatial units "around" the spatial unit i). In partial analogy with the Koyck representation in distributed lag models, specification (9) implies a (time-/space-wise) long-run global diffusion response of $\mathrm{y_{it}}$ to $\mathrm{x_{it}}$ equal to $\gamma[1 - \alpha - (\beta_1 + \beta_2)B^s]^{-1}$. This requires the stability condition $0 < \alpha + (\beta_1 + \beta_2)\, B^s < 1$, besides the stationarity conditions on individual parameters, that is, α within the parameter space $(-1, 1)$ and β_1 and β_2 within the interval $(1/\omega_{\min},1)$ (where ω_{min} is the smallest [most negative] characteristic root of the row-normalized weight matrix, hence possibly $1/\omega_{\min} < -1$; Elhorst, 2010).

Controversial empirical issues concern (i) the spatial weight matrix, (ii) the timing and strength/speed of a spatial diffusion process, and (iii) the scope for spurious relationships and spatial trend nonstationarity. Econometric theory on the last two points is still at an early development stage. Relative to (ii), synchronic and time-lagged spatial effects may be hardly distinguishable when time series are highly correlated and spatial correlation is weak (López and Chasco Yrigoyen, 2007). As for point (i), predominant directional effects (from upstream to downstream locations) justify the use of scale-adjusted measures of geographical distance, with the latter (d_{ij}) adjusted by relative regional population shares (Beenstock and Felsenstein, 2006) or other suitable scale indicators. In this case, the weight matrix (row-standardized to unit-sum) would comply with the following conditions: $w_{ij} = 0$ for $i = j$ or $d_{ij} > d_{\max}$ (diffusion cut-off distance), $w_{ij} = (1/d_{ij})[Z_{it}/(Z_{it} + Z_{jt})]$ for $i \neq j$ and $d_{ij} < d_{\max}$ (with Z a scale proxy). This approach contrasts with an isotropy assumption, with equal influences in both directions of a diffusion process between regions and weights based on pure geographical distance metrics (arc-distance for unprojected spherical maps, Eucledian distance for projected planimetric surfaces).

Anselin and Bera (1998, p. 244) argue that "indicators for socioeconomic weights should be chosen with great care to ensure their exogeneity [to avoid problems of identification and interpretability], unless their endogeneity is considered explicitly in the model specification" (see also Anselin et al., 2008). In either case, a unit row-rescaling is usually applied in spatial regression analysis, so as to construct spatial lags as weighted averages of neighboring observations. However, this may result in loss of information for the interpretation of the decay function, especially if an unrestricted form is relied on (e.g., based on a spatial lag parameter in Eq. (7): $\beta_1(1/(d_{ij})^{\zeta})$. Even if a unit restriction ($\zeta = 1$) is imposed on the decay function and unless all cross-region coordinates are connected (with the longest distance chosen as $d_{\max}$), a trade-off in a suitable choice of spatial weights is unavoidable: on the one hand, scale effects may be preferable to isotropy, but on the other, asymmetry in the weight matrix with scale effects originates from two sources, that is row-standardization and directional effect rescaling.

Relative to point (iii), in an nT panel, spurious spatial regression problems may occur, and are found to get worse with larger

T and smaller n (sample of spatial units: Kao, 1999; Lauridsen and Kosfeld, 2004). Time and spatial nonstationarity impinge upon statistical inference with increased probability of type I error. Their presence can be detected by very low Durbin-Watson statistics and very high Moran's I statistics for regression residuals, respectively (although the latter is a diffuse test, which does not clearly distinguish between stationary positive autocorrelation and nonstationarity; formal tests are proposed by Lauridsen and Kosfeld, 2004). As a spatial analog of dynamic (Phillips-Loretan) cointegration regression, dynamic SAR specifications as Eq. (7) help reduce the risk of spurious results (Mur, 2002). For heterogeneous panel data models with partly changing intercept and/slope parameters across regions, the (pool) τ-bar statistic has better size and power properties than other panel unit root and cointegration tests (Kao, 1999; McCoskey and Kao, 2001). However, even if they incorporate cross-section dependence, panel unit root tests have size distortions if spatial error correlation in the true model is disregarded, particularly in large T panels (while being less reliable in small T panels; Baltagi et al., 2007).

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