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Challenging Hydrological Panaceas: Water poverty governance accounting for spatial scale in the Niger River Basin

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SUMMARY

Water poverty in the Niger River Basin is a function of physical constraints affecting access and supply, and institutional arrangements affecting the ability to utilise the water resource. This distinction reflects the complexity of water poverty and points to the need to look beyond technical and financial means alone to reduce its prevalence and severity. Policy decisions affecting water resources are generally made at a state or national level. Hydrological and socio-economic evaluations at these levels, or at the basin level, cannot be presumed to be concordant with the differentiation of poverty or livelihood vulnerability at more local levels. We focus on three objectives: first, the initial mapping of observed poverty, using two health metrics and a household assets metric; second, the estimation of factors which potentially influence the observed poverty patterns; and third, a consideration of spatial non-stationarity, which identifies spatial correlates of poverty in the places where their effects appear most severe. We quantify the extent to which different levels of analysis influence these results. Comparative analysis of correlates of poverty at basin, national and local levels shows limited congruence. Variation in water quantity, and the presence of irrigation and dams had either limited or no significant correlation with observed variation in poverty measures across levels. Education and access to improved water quality were the only variables consistently significant and spatially stable across the entire basin. At all levels, education is the most consistent non-water correlate of poverty while access to protected water sources is the strongest water related correlate. The analysis indicates that landscape and scale matter for understanding water-poverty linkages and for devising policy concerned with alleviating water poverty. Interactions between environmental, social and institutional factors are complex and consequently a comprehensive understanding of poverty and its causes requires analysis at multiple spatial resolutions.

1. Introduction

The relationship between livelihood and poverty outcomes, and water is complex. Not all people who are poor lack water and not all people who lack water are poor, and the numerous causal, dynamic relationships between water, poverty and livelihoods are likely to vary spatially, temporally and institutionally (Chambers and Conway, 1992; Castillo et al., 2007). Broadly speaking, water-related poverty, or water poverty, is socio-economic disadvantage that occurs as a direct result of an unfavourable water situation (Molle and Mollinga, 2003). Water poverty is hypothesised to occur due to the combined effect of factors including increasing and competing water demand, changes in hydrological regimes (potentially due in part to climate change), environmental degradation, reduced water quality, impediments to water access, conflict, corruption, and changing levels of water productivity (Cook and Gichuki, 2007; Kemp-Benedict et al., 2011; Ogilvie et al., 2010).

Although these conceptual links between water and poverty are well developed (Castillo et al., 2007), there remains a need to demonstrate empirically how an improvement in a community's water situation changes the incidence of poverty (Rijsberman, 2006). Identifying the magnitude and drivers of water poverty in a particular setting is a necessary precursor to policy formulation. Analysis conducted at multiple decision levels is more likely to guide water policy to address the causes of poverty, and can identify priority regions where social units are most threatened. In practice this endeavour faces significant challenges, first in defining a complex and contested problem (Funtowicz and Ravetz, 1993; Hisschemöller and Hoppe, 1996; Hoppe, 2005; Sterk et al., 2009)

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and second in developing salient, objective and agreed upon measurement methods, often in the face of data limitations (Cash et al., 2003).

Three broad objectives have been the focus of studies concerned with the spatial relationships of water and poverty published to date. First, the mapping of poverty in itself is a valuable contribution to the information available to policy makers. Second, determining the potential causes underlying the observed patterns allows policy makers to target those most clearly associated with poverty, including water related factors. Third, allowing for spatial non-stationarity combines these two objectives, by targeting particular potential causes of poverty in the locations where their effects appear to be most severe.

This paper pursues these objectives through an analysis of water poverty in the Niger Basin, West Africa. We specifically consider the extent to which different levels of analysis affect the apparent correlates of poverty. Policy decisions are often made at a state or national level, and an understanding of poverty at those levels cannot be presumed to be concordant with the differentiation of poverty, livelihood vulnerability or institutional diversity at a more local level (Hyman et al., 2005). We identify regions of the basin of high relative poverty and then analyse those regions for correlated, potentially explanatory factors. Comparative analyses of basin, national and sub-national levels provide insight into the degree of congruence between different analytical resolutions.

We find that education, land productivity and access to improved water quality are significant and relatively spatially stable correlates of poverty across the entire basin. Other factors, including irrigation, distance to dams, population density, forest cover and malaria prevalence are localised in the magnitude and direction of their potential poverty impact. While our results support the notion that the availability of and access to water is important for poverty alleviation, the nature of the relationship varies considerably across the basin, and across different poverty metrics. This suggests that a full understanding of the water-poverty relationship requires consideration of multiple poverty metrics, and further, that parallel analysis at multiple levels can help identify relationships that are otherwise obscured by aggregation.

We firstly provide a summary of scale considerations in water management and poverty analysis (Section 2), before briefly describing the water related challenges faced by sub-Saharan countries (Section 3), and the Niger Basin countries in particular (Section 4). We then describe our data and empirical approach: firstly with regard to the statistical identification of poverty hotspots, and secondly with regard to the spatially explicit analysis of water related correlates (Section 5). Results, and then a multilevel comparison of those results are presented in Sections 6 and 7 respectively.

2. Scale considerations in water management and poverty analysis

The process of linking biophysical systems to socio-economic and cultural systems is vital for planning, implementing and analysing natural resource management policy (Lee, 1993; Folke et al., 2007). Forging such links requires consideration of the levels that best describe the biophysical and institutional components of the issue at hand. Following Gibson et al. (2000), we define 'scale' as "the spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon". We define 'levels' as the units of analysis located along the scale. Thus scale describes the nature of what is being measured – space, time or institutions, for instance – and levels describe points along each scale dimension. Spatial scale refers to the geographic extent of a phenomenon in question, while the institutional scale refers to the rules and jurisdiction of political institutions that govern that phenomenon (Cash et al., 2006). This study combines elements of both spatial and jurisdictional scales by necessity: water itself is not governed by political boundaries, however water management policies are.

The importance of scale, especially spatial scale, in both water management and poverty analysis is well known (Hentschel et al., 2000; Sivapalan et al., 2004; Syme et al., 2012). In water management, spatial 'misfit' occurs when organizations, such as national governments, catchment management authorities and international water management authorities undertake uniform management action at a level that does not match either the biophysical or socio-economic differentiation of the system (Lee, 1993; Vreudenhil et al., 2010). Management or analysis at the level of river basins is one approach to minimizing such spatial misfit (Moss, 2012). This level is hypothesised to be advantageous given the potential biophysical similarities people may face across such a zone (Rijsberman, 2006), and due to the likely existence of within-basin water use externalities (Falkenmark and Molden, 2008). It should be noted, however, that the operational level of effective water institutions is not necessarily aligned with these aspirations for whole-of-basin management (Syme et al., 2012).

Similarly in poverty analysis, the apparent determinants of poverty will likely depend on the scale and level of analysis. A process that appears homogenous at an aggregated level (or on an inappropriate scale) may have important heterogeneities when analysed on finer levels (or on a different scale) (Stephen and Downing, 2001). Explicitly considering a spatial scale, for instance, allows for the quantification of regional disparities, and furthermore allows for the targeting of policy, both to specific geographic regions and to specific spatially varying causes (Minot and Baulch, 2005).

A key means of considering spatial scale in poverty analysis is through the use of poverty maps (see for instance Elbers et al., 2007; Fujii, 2008). Early attempts to create poverty maps focused on capturing the distribution of the poverty indicator itself. More recent examples, such as those reviewed here, incorporate efforts to explain the distribution of poverty, usually based on statistical correlation. For instance, Bigman et al. (2000) applied community level small-area estimation[2] to map poverty in Burkina Faso. They demonstrated the benefits of a spatially explicit approach to poverty analysis by simulating the impact of both a geographically targeted and untargeted policy intervention. Minot and Baulch (2005) constructed poverty and poverty density maps of Vietnam. They showed that the highest absolute numbers of poor are not always found in the poorest districts. Other studies have constructed poverty maps to assess the performance of past initiatives that may have had geographically localised implications. For instance, Bellon et al. (2005) used small-area estimation poverty maps to assess spill-over benefits of agricultural research trials in Mexico.

These studies and others (see for instance, Kristjanson et al., 2005; Kandala et al., 2008) are 'global' in their estimation of poverty correlates: a significant determinant is considered to have the same coefficient in all parts of the study area. More likely, the causes of poverty are different in different places, and consideration of the particular importance of a determinant in its locational context is likely to improve policy effectiveness. Quantifying such spatial non-stationarity is permitted by the use of geographically weighted regression (see, for instance Benson et al., 2005; Farrow et al., 2005), or by the spatially explicit modelling of sub-sections of the larger study region. These techniques represent an improvement over global estimates of determinant significance, because explanatory variables that have positive correlation in one location but negative in another may appear

[2] For an overview of poverty mapping techniques, see Davis (2003).

non-significant in the global model. Over highly varied environments, sensitivity to potential spatial non-stationarity is important.

To our knowledge there are few spatially explicit studies that have specifically considered water availability, water access and/or water quality as potential determinants of poverty. Two exceptions are Amarasinghe et al. (2005) and Pérez-Foguet and Garriga (2011). The former authors looked for spatial clustering of poverty in Sri Lanka using spatial autocorrelation diagnostics. In an approach similar to that utilised in the present study, they divided their data into highly-correlated areas of high poverty and highly-correlated areas of low poverty, and identified poverty correlates in both. They find access to irrigation infrastructure – particularly small scale infrastructure – to be an important poverty correlate. Pérez-Foguet and Garriga (2011) mapped water poverty in the Jequetepeque Basin, Peru. They calculated an 'enhanced' water poverty index in different sub-basins and plotted the resulting aggregate across the basin. Although their poverty maps highlight areas of water poverty, they do not test for the presence of a statistical relationship between water-related factors and poverty as in the present study. To our knowledge, no study has estimated water poverty correlates over multiple spatial levels.

3. Water poverty in sub-Saharan Africa

The literature suggests that there is high potential for poverty alleviation through water-related investment and improved water management in Sub-Saharan Arica (SSA) (Van Koppen, 2003; Castillo et al., 2007; Hanjra et al., 2009). There exists high potential for irrigation and hydroelectricity: Less than 4% of the continent's renewable water resources were utilised in 2008, and a 10% increase in utilisation was expected to be required to reach the 2015 Millennium Development Goals related to water (Hanjra and Gichuki, 2008). Only 4% of arable land is estimated to be under irrigation (including floodplain recession planting), of which only 0.8% is estimated to be sourced from groundwater, a particularly underexploited resource in SSA (Giordano, 2006). Realizing such potential is expected to deliver livelihood benefits: Hanjra and Gichuki (2008), for instance, concluded that "irrigation/agricultural water management, however measured, almost always contributes to poverty reduction" in their review of water management in 20 SSA countries in three major river basins. Castillo et al. (2007) argued that improvements in water access can lead to improved food security, health and economic prosperity, simultaneously addressing the multiple dimensions of poverty. Non-water constraints, however, can prevent these benefits from materialising. When such constraints are alleviated, improvement in the water situation can deliver livelihood benefits due to the number and variety of linkages in the water-poverty nexus (Castillo et al., 2007; Hanjra and Gichuki, 2008; Hanjra et al., 2009).

4. The study region

The Niger River is the principal river in West Africa, flowing for over 4000 km through varied climatic zones (Fig. 1). The total basin covers an area of over 2 million km^2, with 1.27 million km^2 regularly hydrologically connected (the active basin). The active basin covers parts of nine countries: Sierra Leone, Guinea, Mali, Burkina Faso, Niger, Nigeria, Benin, Chad and Cameroon, and contains a population of approximately 94 million people (UN Population Division, 2006). A majority of the basin's population is poor and rural, and thus vulnerable to changing climates and water regimes. Parts of the basin have seen a shift in hydrological conditions. A 30% long-term reduction in rainfall in the Sahelian regions since the 1970s may be indicative of a new, drier, climatic regime (Niger Basin Authority, 2005), although consensus is lacking over future trends.

Our study region is the active Niger Basin, which is larger than the study regions used in most previously published poverty mapping studies (which are often limited by country-specific data). River basins are increasingly considered to be the appropriate level for assessing poverty related to environmental factors such as water. The impact of water use in Guinea, for instance, will have a large impact on migrant farmers in the Inner Delta of Mali, 900 km away. Successful development of the Niger Basin's water resources for poverty alleviation will depend on close cooperation between the basin countries. For this reason we consider the advantages of basin-wide analysis to outweigh the challenges faced from data availability and comparability, especially when basin-wide analysis can be complemented by sub-national analysis, as in this study.

5. Data and methods

We compare spatially-explicit regressions undertaken at basin, national and local levels, which consider poverty as a function of both water and non-water variables in the Niger Basin. The way in which poverty is measured is recognised to have a large impact on the level of poverty reported (see for instance Leibbrandt and Woolard (1999)). In order to avoid distortions from such variability, we considered in parallel three dependent variables to represent poverty: child mortality, child morbidity and the Demographic Health Survey's (DHS) wealth index (Measure DHS, 2008). We focus on those results concordant between at least two measures.

5.1. Variables and data sources

Census data for all countries was unavailable so we adopted a coarser resolution, interpolation-based approach using DHS data (Measure DHS, 2008). These surveys are internationally standardized and published with an approximate cadastral reference (Aliaga and Ren, 2006). Data for households were averaged at each survey 'cluster', formed from 20–30 households on average. This was plotted in ArcGIS and used to estimate a variable surface (interpolation). Choice of interpolation procedure and parameters for interpolation were driven by the characteristics of the data set (Robinson and Metternicht, 2006). Of the three common interpolation techniques, inverse distance weighting (IDW), splining and krigging, splining produced evidently distorted results and krigging was unsuitable for some countries with limited data. IDW was used with a variable search radius (12 data points) and an exponent value of 2 (suitable for non-parametric data sets), and the influence of data points across international borders was restricted to simulate policy differences. A cross-validation procedure was used to guide selection of model parameters (see Hofierka et al., 2007). Zonal statistics were then gathered for each third-level administrative district (see Fig. 1). Geographic data were not collected with the most recent DHS survey of Chad, and so Chad was excluded from the analysis (approximately 1% of the total basin).

5.1.1. Poverty measures

Monetary poverty measures often fail to reflect the multiple dimensions of poverty. This is problematic when considering subsistence farming economies (see Cook and Gichuki, 2007; World Bank, 2009). Index measures attempt to capture the multi-dimensional nature of poverty by aggregating a range of selected social-economic indicators, however they rely on subjective or even arbitrary construction of composite indices and attribution of

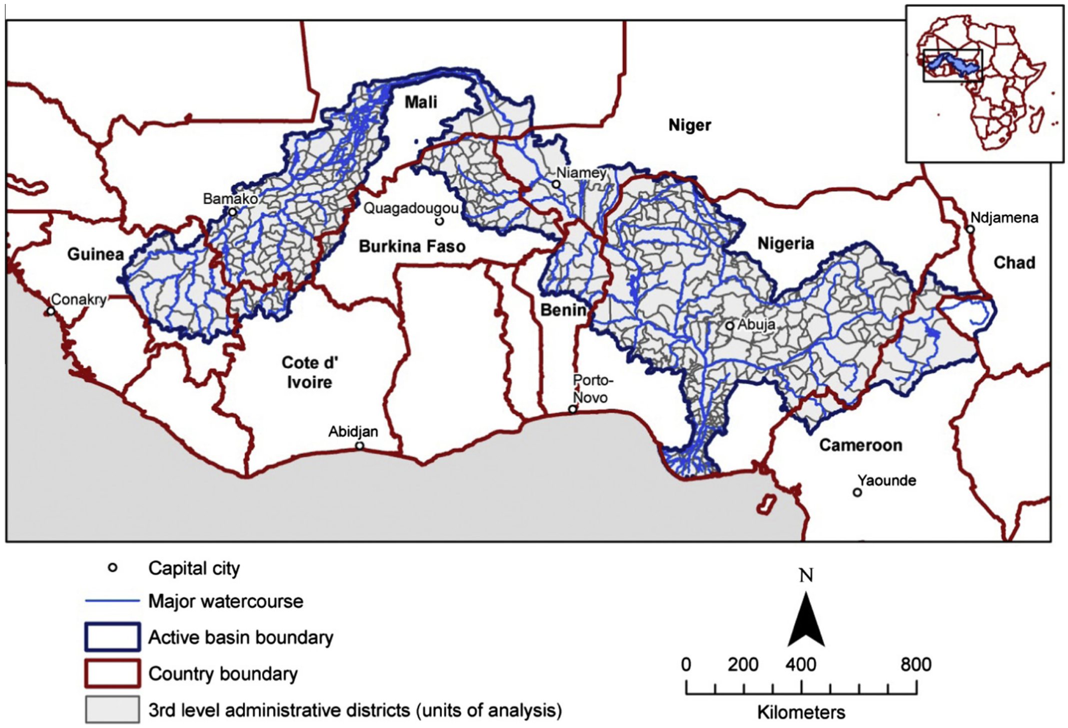

Fig. 1. Study region showing the active Niger Basin, major tributaries and basin countries.

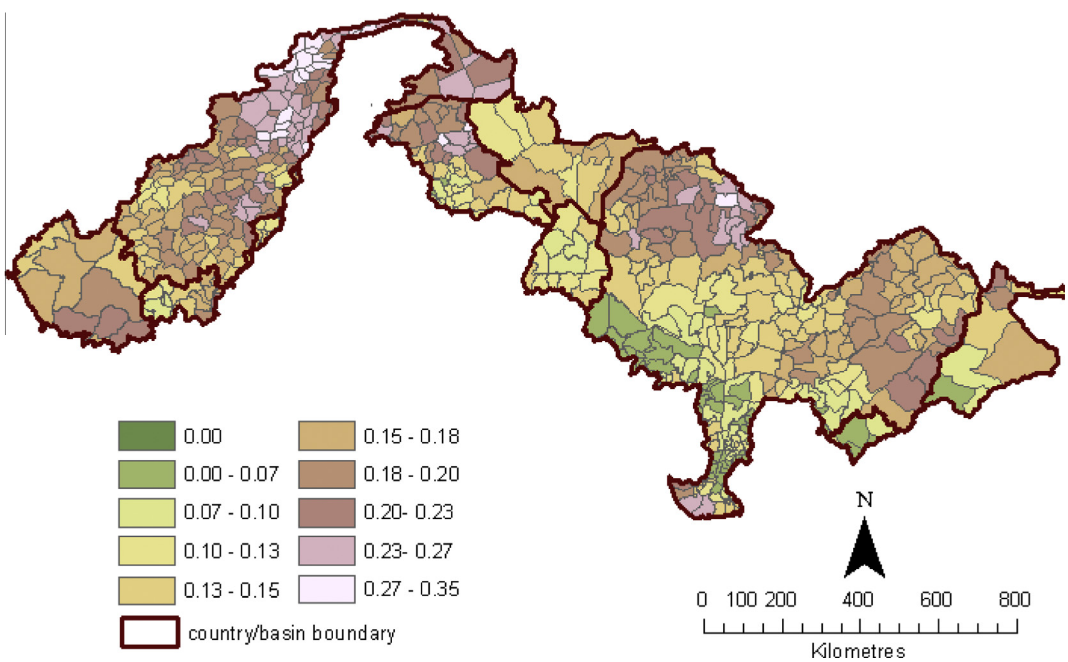

Fig. 2. Estimated child mortality rates (proportion of children who die before age 5) across the active Niger Basin.

variable weights (Vincent, 2004). To capture the multifaceted nature of poverty yet avoid these pitfalls we used two univariate health measures: child mortality and child stunting (height for age ratios). Indicators that objectively measure a single dimension of fundamental health are thought to capture a range of factors influencing the welfare of households (Setboonsarng, 2005). They offer a close proxy for household consumption and are hypothesised to be less susceptible to variation due to cultural, economic and policy boundaries than alternative measures (Molle and Mollinga, 2003; Setboonsarng, 2005). We also used a composite relative wealth index, the Measure DHS, 2008 wealth index. All three metrics have the same spatial resolution (calculated from the same sample).

Child mortality is defined by the proportion of children who die before their fifth birthday. Rates in West Africa are the highest in the world and vary considerably across the region (Balk et al., 2003) (Fig. 2). The proportion of children born since 1980 who died before age 5 was computed for each woman surveyed, and from these proportions the average child mortality rate for that cluster

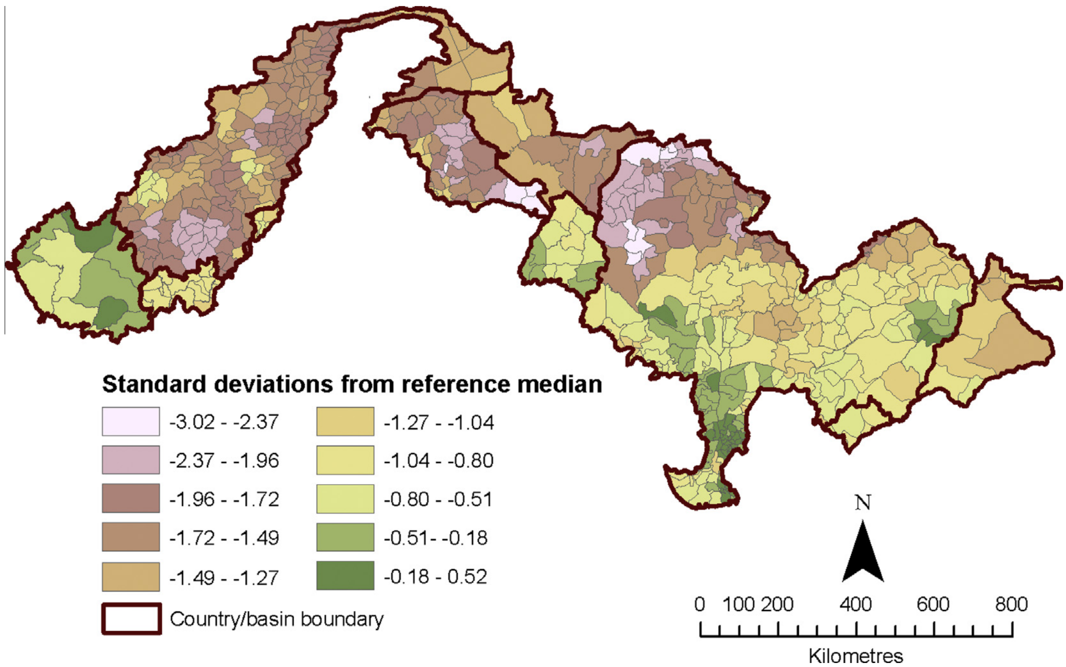

Fig. 3. Estimated child morbidity (average height for age ratio) across the active Niger Basin.

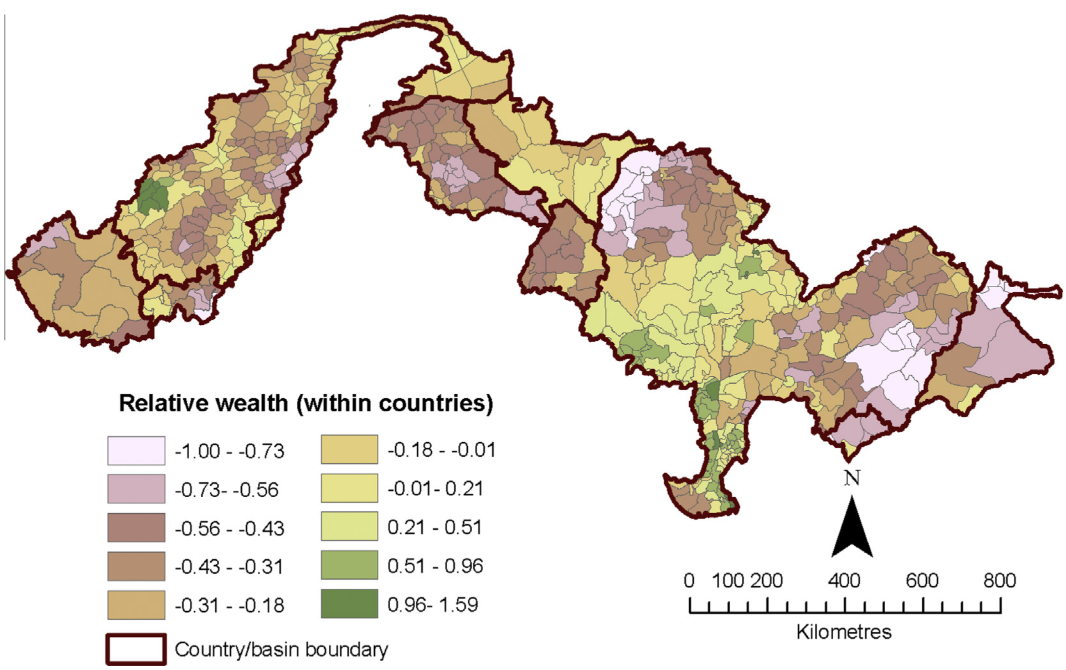

Fig. 4. Estimated relative wealth across the active Niger Basin, as indicated by possessions, land ownership, housing material, employees. Values are comparable within countries only.

point was calculated. A 1990 cut-off provides similar results (not shown).

The child morbidity measure, height for age ratio, provides an indication of the long-term cumulative effects of inadequate nutrition, including antenatal nutrition (Setboonsarng, 2005) (Fig. 3). The height for age ratio may provide additional resolution that the binary nature of the mortality variable does not, yet is resistant to short term seasonal fluctuations in calorie intake and so remains suitable for comparing data collected at slightly different times. Child morbidity is both an outcome and a determinant of poverty. Good health is requisite for improved productivity, and malnutrition in childhood is recognised as having long term effects on the labouring capacity and intellectual performance of adults (Setboonsarng, 2005). The average height for age ratio was calculated for all clusters based on children up to an age of 5 years. Ratios were recorded as standard deviations from the reference median, as assessed using CDC (Center for Disease Control and Prevention) reference curves. A lower height for age ratio indicates a higher prevalence of stunting (child morbidity).

Table 1
Description and source of independent variable data.

Variable	Description and source	Mean	Std. dev.
Dep. variables			
Child mortality	Proportion of children who die before their 5th birthday. *Source:* Measure DHS (2008)	0.15	0.06
Child morbidity	Average height for age ratio (standard deviations below healthy reference median). *Source:* Measure DHS (2008)	−1.40	0.62
Wealth index	Composite index of possessions (unit-less). *Source:* Measure DHS (2008)	n/a	n/a
Water variables			
Precipitation	Precipitation (millimetres/yr). *Source:* FAO (2007)	1006	563
TARWR	TARWR (total available renewable water resources) of Niger sub basins. Includes actual inflows into sub basin, plus internal water resources (rainfall). All relevant parameters (water volume) measured at the sub basin level (bigger than administrative districts), and are assumed constant across sub basin. (Specified with area and per capita component (m^3/yr/km^2/person) *Source:* FAO (2000)	6.2	54.9
Unprotected water	Proportion of a district whose main water source is surface water or unprotected well water. The average is taken at the household level; estimation based on an inverse distance weighting interpolation across landscape. *Source:* Measure DHS (2008)	0.51	0.23
Water access	Average time taken to collect water from the primary water source. The average is taken at a household level; estimation based on an inverse distance weighting interpolation across landscape. *Source:* Measure DHS (2008)	23.1	14.3
Dams	Average direct distance from district to a large dam ('00 km). *Source:* FAO (2006)	1.11	0.93
Irrigation intensity	The density of irrigation in the most intensely irrigated part of the district (based on 100 km^2 cells) (percent). *Source:* FAO (2007c)	4.2	9.7
Irrigation	Is the percentage of a district that is under irrigation. *Source:* FAO (2007a)	0.5	1.9
Drought economic risk	Economic loss (GDP) due to drought. Calculated both as a proportion of GDP. Global decile scale based on historical experience. Areas with less than 5 persons/km^2 and without significant agriculture are given a zero value. *Source:* Center for Hazards and Risk Research (2005)	7.2	2.3
Other variables			
Population density (2005)	Population density of administrative district in 2005 (people/km^2). *Source:* CIESIN (2005)	167	426
Population (2005)	Population of administrative district in 2005 (number of people). *Source:* CIESIN (2005)	117,794	124,736
Telephones	Proportion of a district with a telephone in the home. The average is taken at the household level; estimation based on an inverse distance weighting interpolation across landscape. *Source:* Measure DHS (2008)	0.05	0.06
Electricity	Proportion of a district with electricity in the home. The average is taken at the household level; estimation based on an inverse distance weighting interpolation across landscape. *Source:* Measure DHS (2008)	0.31	0.27
Access	Average direct distance from district to an administrative centre or large populated place ('00 km). *Source:* FAO (2007b)	0.27	0.15
Education	Average years of education. The average is taken at the individual level; estimation based on an inverse distance weighting interpolation across landscape. *Source:* Measure DHS (2008)	2.7	3.0
NPP (produced)	Net primary productivity (NPP). Net amount of solar energy converted to plant organic matter through photosynthesis (tonnes of carbon per 0.25° cell) *Source:* Imhoff et al. (2004)	2.9×10^{11}	1.6×10^{11}
Malaria	Estimated prevalence of malaria parasite in children 2–9 years. Data is from surveys and modelling based on climate, altitude, vegetation cover and agro-ecological zones (proportion). *Source:* MARA (2008)	0.43	0.18
Human footprint	Normalized scores from the Human Influence Index, a measure of environmental damage. Relative values range from 0 (least influence) to 100 (most influence) for the biome found in that district. *Source:* SEDAC (2005)	29.9	7.8
Forest cover proportion	Proportion of district occupied by closed, open or fragmented forest. *Source:* FAO (2000a)	0.33	0.32
Cattle density	Average density of stock across the district (units/km^2).*Source:* FAO (2007c)	17.2	14.6
Chicken density	Average density of stock across the district (units/km^2). *Source:* FAO (2007c)	90.4	169.6
Sheep density	Average density of stock across the district (units/km^2). *Source:* FAO (2007c)	20.5	23.1
Goat density	Average density of stock across the district (units/km^2). *Source:* FAO (2007c)	31.6	45.9
Pig density	Average density of stock across the district (units/km^2). *Source:* FAO (2007c)	3.7	13.8

Unlike the health-related measures, the DHS wealth index (Fig. 4) cannot be assumed to be comparable across national boundaries. However it remains useful for national and local level analysis. The index is a relative, unit-less measure which is constructed from a principle components analysis of the type and quantity of goods present in a household (see Rutstein and Johnson, 2004 for details). The DHS wealth index includes housing materials, water supply, sanitation facilities, electrical goods, vehicle type, persons per sleeping area, land ownership, domestic servants and other consumer goods.

5.1.2. Independent variables

Independent variables included in the regression models are described in Table 1. Of primary interest are the water-related variables. Other variables were selected to represent different forms of capital: physical (electricity, telephones, roads), human (population density, education) financial (livestock density) and natural (productivity, forest cover, environmental degradation, malaria). These were selected based on the findings of Kristjanson et al. (2005). Variables were compiled in a geographic information system (GIS) and then sampled to provide average values of each variable in each study unit. All variables were initially included in the models, with variables removed on the basis of high multi-collinearity (associated with variance inflation factors >10, Hair et al., 2006, p. 200). The electricity and telephone variables were excluded from wealth index models as they are themselves components of the index. Detailed maps, evaluations of spatial correlations, and values of independent and dependent variables at the level of administrative district can be found in Ward et al. (2009) and Kaczan and Ward (2011).

5.2. Accounting for spatial differentiation

Research on poverty and the environment often concerns patterns and distributions across multiple dimensions such as ethnic, social, economic, political and geographic space. Analysis of water poverty at the landscape level requires jointly accounting for spatial patterning of the poverty metric and the spatial dispersion of its multiple determinants. An important analytical issue when dealing with spatial data is non-stationarity, or significant spatial autocorrelation, which occurs when geographically proximate observations display a non-random spatial pattern (Anselin, 1995, 2005; Boots, 2001). This occurrence may be expressed in either the error terms of the regression equation (i.e. there exists

Table 2
Variables explaining wealth, morbidity and mortality in the Niger Basin.

	Wealth index[a]	Child height for age ratio[a] (s.d)	Child mortality rate[a] (proportion)
(Constant)	0.58071***	−0.46988***	0.08706***
Population density (people/km^2)	0.00011***	2.15E−05	−1.54E−07
Population (people)	7.82×10^{-8}***	−1.35E−07	1.79E−08
Telephones (proportion)	n/a	0.19023	−0.01968
Electricity (proportion)	n/a	0.10096	0.02092***
NPP (produced) (tonnes/0.25° cell)	1.7×10^{-8}***	3.21E−13**	−3.44E−14**
Access ('00 km)	−0.10244	−0.03990	0.01354
Education (years)	0.04235***	0.01642**	−0.00459***
Forest Cover (proportion)	−0.09549*	0.10203**	−0.00592
Cattle density (units/km^2)	−0.00230**	−0.00201**	0.00015
Chicken density (units/km^2)	0.00014	−0.00005	0.00000
Sheep density (units/km^2)	−0.00102**	0.00057	−0.00002
Goat density (units/km^2)	−0.00093***	0.00059*	−0.00004
Pig density (units/km^2)	0.00151*	0.00086	0.00001
Unprotected water (proportion)	−0.49263***	−0.24028***	0.04232***
Water access (min)	−0.00716***	−0.00032	−0.00027**
Dams ('00 km)	−0.02539	0.06691***	0.00977***
Irrigation (%)	0.00518	0.01695***	0.00032
Precipitation (mm/yr)	−0.00019***	−0.00009**	−0.00001*
TARWR (m^3/yr/km^2/person)	−0.00049***	0.00005	0.00000
Drought economic risk (decile)	−0.00309	−0.00698	0.00064
Human footprint (1–100 index)	0.00136	−0.00138	−0.00032
Malaria prevalence (parasite ratio)	0.11724	0.00086	−0.00529
Moran's I for residuals	0.003	0.001	0.004
Akaike information criterion	−137.44	256.03	−2617.4
(Pseudo) Adj. R^2	0.637	0.701	0.667
Spatial weights matrix	2 Nearest neighbour	2 Nearest neighbour	1 Nearest neighbour
Sample size	650	650	650

* Statistically significant at 90%.
** Statistically significant at 95%.
*** Statistically significant at 99%.
[a] K1 spatial weighting matrix.

one or more spatially clustered, unobserved determinants), or as a spatial process operating directly on the dependent variable itself. Both violate the classical linear OLS regression assumption of independent data observations, and as a corollary data must either be remodelled with spatial weighting terms or partitioned into correlated spatial units and re-estimated on a smaller scale (Anselin, 1995; Bateman et al., 2006; Neupane et al., 2007). Failure to account for spatial autocorrelation of the dependent poverty variable can lead to inefficient or biased estimates and hence unsubstantiated or misleading inference (Neupane et al., 2007).

Spatial association can be measured globally or locally. Global measures assume that the processes that give rise to spatial patterning are constant over the entire basin. Local measures, such as 'localised indicators of spatial association' (LISA), account for clustering at defined local levels (Anselin, 1995, 2005; Boots, 2001). Anselin (1995) proposed two interpretations of spatial autocorrelation at the local level. The first is that local spatial autocorrelation provides an indicator of the propensity of similar poverty values to cluster in specific areas, while the second can be treated as a diagnostic for local instability of values. The first interpretation can reveal 'hotspots' of poverty. The second may indicate sensitivity of poverty measures to stimuli. We use both global and localised measures to assess the spatial autocorrelation of poverty at the basin, national and sub-national level.

A common approach to quantifying global spatial autocorrelation is the use of the global Moran's I statistic (adapted from Boots, 2001; Neupane et al., 2007):

$$I = \left(\frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}\right)\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{j=1}^{N}(y_j - \bar{y})^2}\right) \tag{1}$$

where y_i is the observed poverty value for administrative unit $i \in \{1,\ldots N\}$, $\bar{y}$ is the mean poverty value across all administration units, and w_{ij} is a measure of the spatial relationship between cells i and j. The spatial relationship (w_{ij}) can take on a variety of forms. We employ a Kth-order nearest neighbour configuration which provides a weighting based on the inverse distance between an administrative unit i and its Kth-order nearest neighbour administrative units j (see Bateman et al., 2006). The nearest neighbour configuration is appropriate due to the irregularity of the polygons representing administrative units. The value of K used is that which best describes the observed spatial auto-correlation i.e. that which provides a value of Moran's I (MI) of OLS residuals that best approximate the MI of the predicted error, and has the lowest value of MI of the spatial lag residual (Anselin, 2005).

The localised Moran's I is derived by localising the global measure, such that:

$$I_i = \left(\frac{y_i}{\sum_{i=1}^{N} y_i / N}\right)\sum_{j=1}^{N} W_{ij}(y_j - \bar{y}) \tag{2}$$

Values of $I_i > 0$ indicate positive local spatial autocorrelation, implying a cluster of similar poverty values proximate to i that significantly ($p < 0.05$) deviate from $\bar{y}$. Values of $I_i < 0$ indicate a significant negative local spatial autocorrelation of i from adjacent neighbours. Sensitivity of the significance of the local Moran's I statistic was determined using 999 conditional random permutations (following Anselin, 1995, 2005) and was found to be stable for both child mortality and child morbidity. The global and local Moran's I and spatial weights matrices for the poverty data over the entire Niger River Basin were calculated using the spatial econometric software package GeoDa (Anselin, 2005).

Spatial error and spatial lag models are two regression approaches that can be used to address spatial autocorrelation. Following Anselin (1995), comparison of the robust Lagrange multiplier coefficients at the basin level indicated that the spatial lag model (24.319 and 29.584) was superior to the spatial error model (19.013 and 18.865) for child morbidity and child mortality

Table 3
Variables explaining wealth, morbidity and mortality in selected Niger Basin countries.

	Nigeria			Mali			Burkina Faso		
	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)
(Constant)	0.26644**	−0.46342***	0.00097	−0.08640	−1.17980***	0.07171***	−0.19893	−0.62904*	0.12540***
Population density (people/km^2)	0.00005*	0.00007*	0.00000	−0.00160***	−0.00020	−0.00003	0.00266***	0.00315**	−0.00001
Population (people)	0.00000*	0.00000*	0.00000**	0.00000***	0.00000	0.00000	0.00000	0.00000	0.00000
Telephones (proportion)		0.41516**	−0.01264		0.33385	0.00179		−1.30600	−0.05338
Electricity (proportion)		0.06863	0.00964		0.11837	−0.00985		1.16590	−0.05591
NPP (produced) (tonnes/0.25° cell)									
Access ('00 km)	−0.02258	−0.24256*	0.01825	−0.05139	0.14037	−0.00747	0.06491	0.30875	0.03809
Education (years)	0.02688***	0.00835	−0.00203***	0.29516	0.16101***	−0.00798*	0.19099	0.05972	0.00517
Forest cover (proportion)	−0.09039**	0.09254*	−0.00317	0.03360	−0.01980	−0.02282**	0.23598***	0.25819*	−0.02110
Cattle density (units/km^2)	0.00025	0.00142	0.00019**	−0.00141	−0.00278	0.00007	−0.00188	−0.00625**	−0.00081**
Chicken density (units/km^2)	0.00004	−0.00005	0.00000	−0.00026	−0.00061	0.00001			
Sheep density (units/km^2)	−0.00038	0.00003	0.00004	−0.00036	−0.00021	−0.00003	0.00186	−0.00199	−0.00025
Goat density (units/km^2)	−0.00025	0.00036	−0.00004*	0.00034	0.00185	−0.00018	0.00052	0.00051	0.00024
Pig density (units/km^2)	−0.00015	0.00053	−0.00007	0.06464**	−0.03581	−0.00173	−0.01156	−0.00623	0.00057
Unprotected water (proportion)	−0.85852	−0.11133	0.04976***	−0.29077***	0.18116*	−0.00037	−0.09061	−0.13145	−0.01967
Water access (min)	−0.00363***	0.00058	−0.00004	0.00000	0.00580*	−0.00008	−0.00445**	0.00637	−0.00042
Dams ('00 km)	−0.14824***	−0.03149	0.00509**	0.03126*	−0.02579	0.01086***	0.07999	−0.01432	0.00211
Irrigation (%)	0.01601	0.03412*	0.00092	−0.00263	0.01224**	−0.00039	0.14400	0.08724	−0.02578
Precipitation (mm/yr)	0.00022	0.00018	0.00000						
TARWR (m^3/yr/km^2/person)	−0.00017	−0.00005	−0.00001	−0.00052	−0.00036	−0.00006	−0.07032	−0.12726	0.00178
Drought economic Risk (decile)	−0.00336	−0.00665	0.00065	−0.01172*	0.00130	0.00179	−0.00609	0.00589	−0.00073
Human footprint (1–100 index)	0.00142	−0.00542**	−0.00044*	0.00405**	0.00482	0.00016	−0.00432	−0.00106	−0.00169**
Malaria prevalence (parasite ratio)	0.13706**	0.06373	0.00234	−0.18613**	−0.34583**	−0.00505	−0.11803	−0.17512	−0.00826
Akaike information criterion	−186.21	2.7707	−1457.3	−214.44	−7.6107	−790.52	−106.57	23.459	−337.25
(Pseudo) Adj. R^2	0.916	0.924	0.8952	0.888	0.635	0.697	0.799	0.787	0.826
Spatial weights matrix (nearest neighbours)	2	2	3	2	1	2	4	4	2
Sample size	298	298	298	190	190	190	79	79	79

* Statistically significant at 90%.
** Statistically significant at 95%.
*** Statistically significant at 99%.

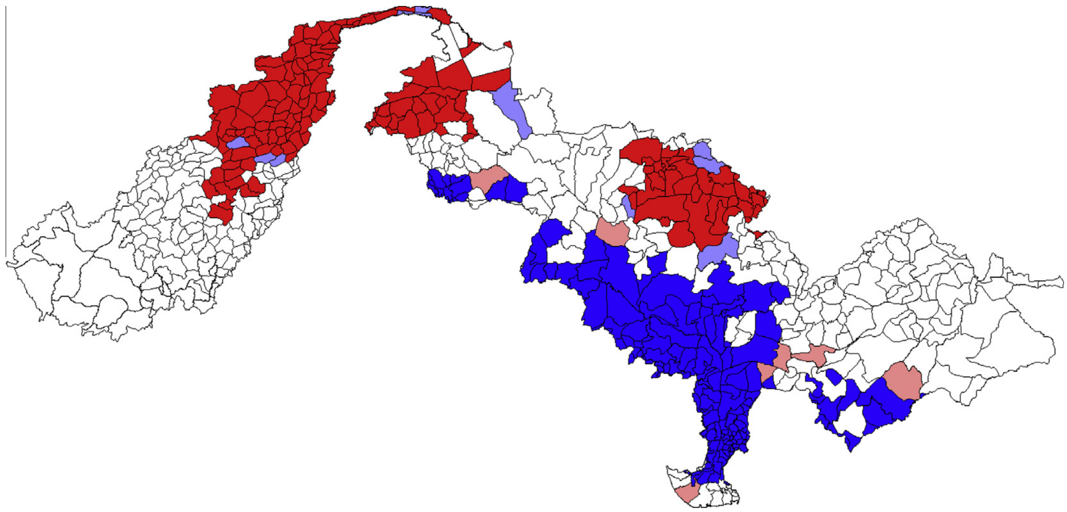

Fig. 5. LISA clusters of child mortality (proportion of children who die before age 5 yrs) across active Niger Basin. Moran's I value of 0.679 indicates moderate spatial autocorrelation in this variable.

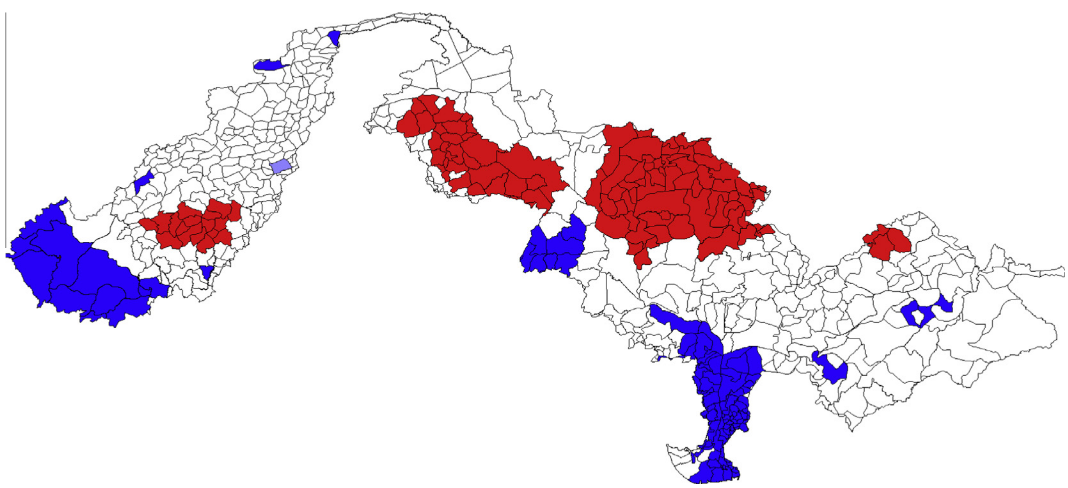

Fig. 6. LISA clusters of child morbidity (height for age ratios) across active Niger Basin. Moran's I value of 0.833 indicates high spatial autocorrelation in this variable.

respectively. Spatial lag models were also superior for the sub-national regressions performed on the LISA hotspots. Consistent with Bateman et al. (2006) we consider n observations of the poverty variable, denoted by the vector $\boldsymbol{Y}$, and n observations of m independent variables denoted by the (n by m) matrix $\boldsymbol{X}$. The traditional OLS model is expressed as:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{3}$$

where $\boldsymbol{\beta}$ represents a vector of regression coefficients to be estimated and ε is a vector of stochastic error terms assumed to be normally distributed across all observations. Spatial correlation occurs if there is a non-random pattern across the error term or significant spatial patterning of the dependent variable. The impact of this on parameter estimates is controlled by including as an explanatory variable the mean of the poverty variable observed in adjacent administrative units for each of the n observations. Eq. (4) describes the spatial lag model which incorporates a linear transformation of Y into the matrix WY, where W is the Kth-order nearest neighbour weighting matrix, and ρ is the spatial lag coefficient of the adjacent mean of the poverty variable:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \rho\boldsymbol{WY} + \boldsymbol{\varepsilon} \tag{4}$$

Anselin (1995) notes that a maximum likelihood framework explicitly accounts for the problem of simultaneity, avoiding biased and inconsistent OLS regressions. Spatial regressions were calculated using the statistics program 'R' and the package 'spdep' (R Development Core Team, 2009; Bivand, 2009).

These procedures determined the extent to which the observed measures of poverty (see Figs. 2–4) displayed a non-random pattern across administrative units. We contend this is crucial as this is the unit of analysis where policy may be formulated and implemented at a level that accounts for heterogeneity and yet maintains administrative feasibility.

6. Results

6.1. Whole-of-basin scale

The first step to estimate the significance of spatial auto correlation was to impute the northing (y), easting (x) and spatial coordinate interaction (xy) as explanatory variables regressed (using OLS) against observed child morbidity and child mortality. Adjusted R^2 values of 0.466 and 0.485 and $F_{(3646)}$ values of

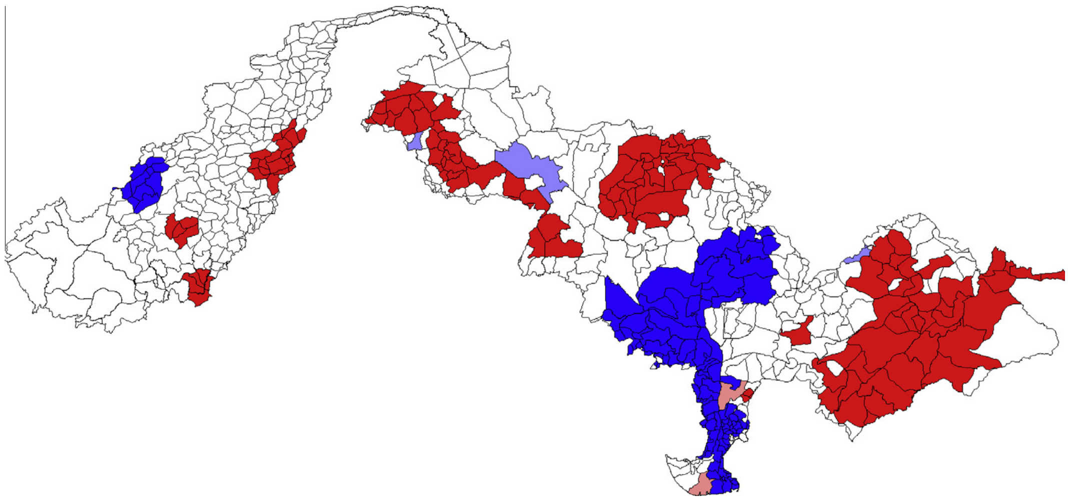

Fig. 7. LISA clusters of relative wealth across active Niger Basin. Moran's I value of 0.767 indicates moderate spatial autocorrelation in this variable.

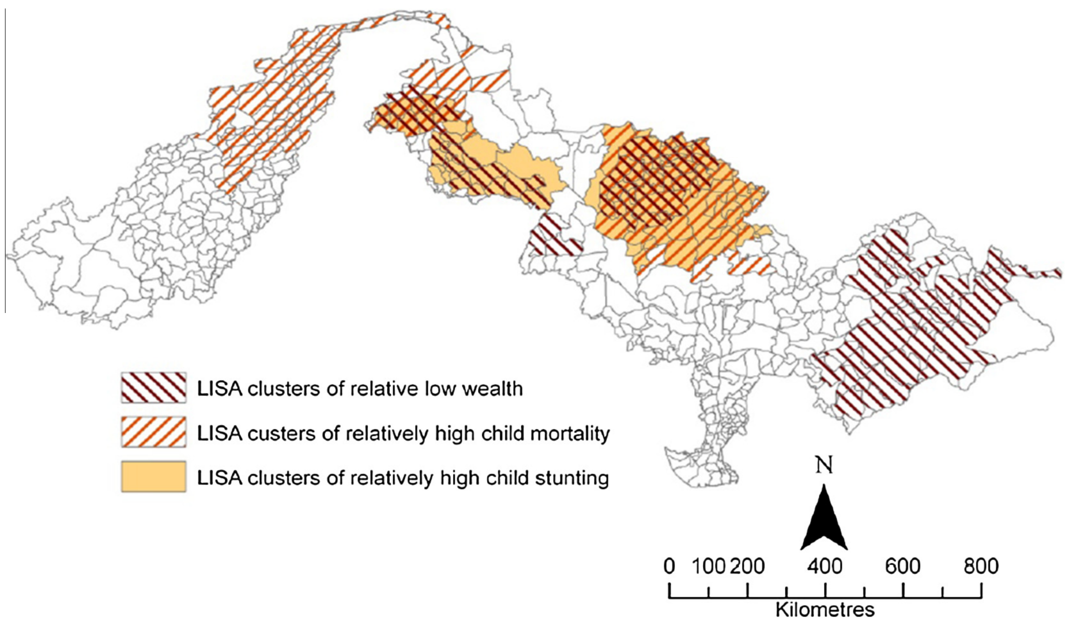

Fig. 8. Overlaid map of major poverty hotspots.

187.654 and 202.457 ($p < 0.05$) indicates a significant spatial pattern of child morbidity and child mortality respectively. The slope of residuals plotted against observed child morbidity and child mortality values (0.534 and 0.515 respectively) suggests that additional non-cadastral variables are likely to play a role in explaining the observed variance of both poverty metrics, as expected.

To test for global spatial autocorrelation, Moran's I statistics were calculated for all poverty variables, estimating a significant spatial pattern of child morbidity (Moran's I = 0.869, $p < 0.001$), child mortality (Moran's I = 0.873, $p < 0.001$) and the wealth index (Moran's I 0.824, $p < 0.001$).

Maximum likelihood spatial lag regression models for the whole Niger Basin (650 data points) are presented in Table 2. Analysis at the basin scale identified broad potential poverty determinants, which are relatively homogenous in their correlation with poverty across the basin. Given the discrepancies that exist between different measures of poverty – even between measures that are closely related such as child height for age ratios and child mortality – we use the three dependent variables in parallel and consider most reliable those results supported by at least two of the three poverty metrics. We do not draw conclusions from the wealth index alone at the basin level given its inconsistency across national boundaries. We stress that these regressions, like those in previous quantitative studies of water poverty incidence, are capable of identifying correlations only. The complexity of socio-ecological systems means that some level of omitted variable bias or endogeneity is likely and thus claims of causality cannot be defended.

Average levels of education are strongly associated with lower levels of poverty for all three metrics with an extra year of education associated with a 0.46% decrease in child mortality rates. However, as demonstrated in the regional models, local effects can vary considerably from this. Water quality, or the proportion of people accessing their primary water source from unprotected wells or surface waters, is similarly correlated with poverty reduction, as expected. A 1% reduction in people using such water sources (as opposed to piped water or protected wells) is associated with 4.2% lower child mortality. The significance of these two variables is important (if further research were to find causality) due to their ability to be influenced by policy, as opposed to

Table 4
Variables explaining wealth, morbidity and mortality in selected poverty hotspots of the Niger Basin.

	North west Nigeria			Central Mali and the Inner Delta			East Burkina Faso		
	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)	Wealth index	Child height for age ratio (s.d)	Child mortality rate (prport$_n$)
(Constant)	−0.32330**	−2.90450***	−0.07228*	−0.16539	−1.71010***	0.14522***	−0.05808	−1.99870***	0.16177**
Population density (people/km^2)	0.00017***	−0.00018**	0.00001	0.00137**	0.00040	−0.00004	−0.00043	0.00049	–
Telephones (proportion)	–	1.32720**	0.05563	–	0.74888	−0.10982	–	−0.67647	–
Electricity (proportion)	–	–	0.01361	–	−0.39659	0.10017	–	–	–
Education (years)	0.07467**	0.08867***	−0.00655***	0.22160***	0.20625*	−0.03104**	0.26254***	0.40189***	0.05140***
Forest Cover (proportion)	−0.16014	0.22228	0.01170	−0.17428	0.04348	0.00325	−0.25285***	–	–
Cattle density (units/km^2)	−0.00217	−0.01003**	−0.00076**	0.00001	0.00443	0.00055	–	–	0.00125
Chicken density (units/km^2)	0.00130***	–	0.00024	−0.00024	0.00031	−0.00029	–	−0.00209**	–
Sheep density (units/km^2)	0.00003	−0.00381**	0.00021	−0.00081*	−0.00172	0.00025*	−0.00038	−0.00123	−0.00008
Goat density (units/km^2)	–	0.00257	0.00006	−0.00107	−0.00457	0.00013	−0.00067	–	−0.00034
Pig density (units/km^2)	–	−0.01177	−0.02104***	−0.01497	−0.06780	−0.00559	−0.00119	−0.09706	–
Unprotected water (proportion)	−0.73068***	−0.34122	0.10797***	−0.20029***	0.32213	−0.00789	−0.48590***	−1.15100***	−0.01365
Water access (min)	−0.00046	−0.00408	0.00171***	−0.00282	0.02090**	0.00038	0.00351*	0.03837***	−0.00126
Dams ('00 km)	−0.23005***	0.03517	0.00041	–	–	–	−0.13353**	0.15614	−0.00242
Irrigation (%)	0.00645	0.04289*	0.00126	−0.00631***	0.01206*	−0.00090	–	–	−0.00500
Precipitation (mm/yr)	0.00083***	0.00064	0.00008*	–	–	–	–	–	–
TARWR (m^3/yr/km^2/person)	−0.00014	−0.00034	−0.00015**	0.00871	0.01864	−0.00406	0.13582	−0.65692***	0.00108
Drought economic risk (decile)	0.00346	−0.01672	−0.00159	0.01388*	0.03840*	0.00311	0.00976***	0.04691***	–
Human footprint (1–100 index)	–	–	0.00109	0.00120	0.00667	0.00059	−0.01362***	–	0.00463**
Malaria prevalence (parasite ratio)	−0.43230*	0.44091*	0.03178	−0.18819**	−0.26380	−0.06278*	–	−1.83810***	–
(Pseudo) Adj. R^2	0.96	0.92	0.89	0.81	0.63	0.60	0.82	0.75	0.27
Model F (LL)	62.038	14.98	192.42	86.75	3.243	180.38	59.527	16.66	63.84
Sample size	34	65	71	83	83	83	32	34	26

* Statistically significant at 90%.
** Statistically significant at 95%.
*** Statistically significant at 99%.

environmental variables that are less amenable to intervention. Net primary productivity, which is closely related to rainfall but also soil type and nutrient levels, has a significant, negative coefficient across all three models. Hence increased land output, as measured by raw quantities of vegetative matter, is associated with reduced poverty. The time taken to collect water has a positive association with two poverty measures (mortality and wealth), as expected, and is non-significant for the third. Irrigation area is a significant explanatory variable of child morbidity at the whole of basin level but not of child mortality, nor the wealth index. However, it may be that the benefits of irrigation do not yet accrue to the people engaged in its practice, or that they do so at levels too small to register in these analyses.

6.2. National level

Analysis at a national scale revealed additional explanatory variables not significant at the basin scale, demonstrating the considerable implications of spatial heterogeneity. Table 3 presents maximum likelihood spatial lag models for Nigeria, Mali and Burkina Faso, three Niger Basin countries with a large number of local administrative districts falling within the basin boundary. Results are based only on variables significant for at least two of the three poverty measures for the same region. Our caution against interpreting causality remains relevant.

Of the non-water variables, education is notable for its consistent significance across poverty metrics in Mali and Nigeria. However, there are differences in the magnitude of findings. While an additional year of education is associated with a 0.20% decrease in child mortality in Nigeria, the same improvement is associated with a 0.80% decrease in child mortality in Mali. The prevalence of the Malaria parasite is significantly associated with worse child morbidity and reduced wealth in Mali but not in Nigeria or Burkina Faso. The proportion of forest cover is significant in Burkina Faso, with areas of higher forest cover associated with increased wealth and improved child morbidity. This finding in Burkina Faso is supported by Leenders et al. (2004) and Rasmussen et al. (2001) who noted that drier regions of Burkina Faso face problems of wind erosion and fertility, partially mitigated by increased forest cover. No such relationship was apparent at the basin level. Population density is significant and positively associated with wealth and improved child height for age ratios, as expected, in Nigeria and Burkina Faso. This is expected given the probable increased levels of services provided to such areas. No such relationship is found in Mali, and the relationship is more ambiguous at the basin level (population density is only significant in the wealth model).

Water related variables are largely inconsistent or insignificant. In contrast to the basin-level results, water quality was associated only with reduced child mortality, and only in Nigeria. A 1% decrease in the use of unprotected well and surface water sources is associated with a 5.0% decrease in child mortality rates here. Proximity to large dams was significant for two poverty measures in Nigeria also. A 1% increase in distance to a large dam is associated with a 0.5% increase in child mortality respectively. At the national level, net primary productivity and precipitation are highly collinear (unlike at basin level) and were excluded from these regressions.

6.3. Sub-national (local) level

Localised poverty analysis was undertaken as an alternative to a whole of basin or national-level analysis, enabling the identification of poverty hotspots at a sub-national level. We use a LISA to identify clusters in the spatial pattern of poverty, classed as areas of significant spatial correlation ($p < 0.05$) characterized by either high relative poverty (hotspots) or low relative poverty (cold spots). Our LISA is a local Moran's I statistic estimated using the Kth-order nearest neighbour spatial weighting matrix.

Fig. 5 shows child mortality hotspots (colored red[3]) in central Mali and the inner Niger delta, north Burkina Faso and north–west Nigeria. Fig. 6 shows hotspots of child morbidity (low height for age ratios) clustered in southern Mali, north–eastern Burkina Faso and north–west Nigeria. Fig. 7 shows hotspots of low relative wealth (colored blue). As previously emphasized, the wealth index cannot be compared internationally, however we see similar results to the other metrics. Poverty hotspots occur in south Mali, east Burkina Faso and north–west Nigeria. There is also a large area of low relative wealth in east Nigeria. With this one exception, there is broad convergence in the location of poverty clusters. Communities situated in regions of intersecting hotspots for all three metrics (Fig. 8) are those expected to face the greatest poverty challenges.

One research hypothesis is that each poverty hotspot is subject to differing local conditions and thus observed poverty is correlated with a different vector of explanatory variables. Individual, maximum likelihood spatial lag regression models were estimated for each hotspot for each poverty metric, in the same fashion as the country level analysis. However, the hotspot dimensions used in each regression differ slightly depending on how the hotspot was defined by the relevant metric during the LISA analysis above. Compared to the previous analysis at basin and national levels, multi-collinearity was more prevalent due to smaller sample sizes and hence more variables were removed (based on a variance inflation factor criteria >10). The results reported in Table 4 indicate that the ability of each model to explain poverty levels varied widely, with very high (pseudo) adjusted R^2 results for the wealth index (0.82–0.95) and lesser (pseudo) adjusted R^2 results for the health variables (0.27–0.92). East Burkina Faso was the least completely modelled hotspot, with limited concordance across poverty metrics.

In north–west Nigeria, water quality is the primary water-related factor correlated with poverty. A 1% decrease in the number of people who access their primary drinking water from unprotected well or surface water is associated with a 1.1% decrease in child mortality and an increase in wealth. Weaker evidence (supported by only one model) was found regarding improved water access and increased total water availability (TARWR), both associated with lower child mortality. Education is the strongest non-water correlate: A one year increase in average years of schooling is associated with a 0.7% decrease in child mortality rates, a 0.088 standard deviation improvement in average height-for-age ratios and an increase in the wealth index.

The central Mali region contains the Niger Inner Delta – a highly productive flood plain covering an area of more than 80,000 km^2. This region is characterised by average child mortality rates of 240 per 1000 live births. The relationship between water and poverty is ambiguous in this region, with no significant associations concordant between at least two models. With regard to non-water variables, a one-year increase in the average years of schooling is associated with a 3.8% decrease in child mortality rates, a 0.21 standard deviation improvement in height for age ratios and an increase in the wealth index.

In east Burkina Faso, the use of unprotected water is significantly correlated with decreased wealth and height for age ratios, while surprisingly, water access has a negative correlation with these poverty measures. The distance to a dam variable is negatively correlated to the wealth index and TARWR is negatively correlated to child morbidity. Also contrary to expectations, risk of

[3] For interpretation of color in Figs. 5 and 7, the reader is referred to the web version of this article.

drought was correlated with greater wealth and height for age ratios. An increase in environmental degradation, as measured by changes in the World Wildlife Fund's 'Human Footprint' score was significantly associated with an increase in child mortality and a decrease in wealth. A one year increase in education was significantly associated with an increase in wealth and height for age ratios, but with an increase in child mortality.

7. Discussion and conclusions

Water poverty was treated as a combined function of water availability, water access, water quality and water related infrastructure, on poverty. The distinction between physical constraints affecting access and supply, and institutional arrangements affecting the ability to utilise the water resource reflects the complex nature of water poverty and points to the need to look beyond technical and financial means alone to reduce its prevalence.

An important focus of this research was the development and application of spatially explicit statistical methods capable of aligning water management and poverty data at multiple spatial levels. The levels – whole of basin, national and the local administrative unit – were chosen with a view towards the administrative and political feasibility of water management decisions and poverty targeting measures. Poverty was mapped at each level according to the spatial distribution of child mortality, child height for age ratios and a composite wealth index, to account for a high proportion of subsistence livelihoods and a large non-market, hybrid economy in the study region. Sub-national regions were selected for further analysis when at least two of the poverty metrics indicated high poverty rates. Poverty hotspots were identified in Mali (including the Niger Inner Delta), north–east Burkina Faso and north–west Nigeria (Fig. 8). We note that the analysis identified correlations between variables only, and causality cannot be assumed. The statistical significance and the magnitude of the relationships identified may involve unobserved relationships with omitted variables, or be biased by endogeneity in the socio-ecological system. However, the results highlight important trends of association.

The spatial lag regression results indicate that education, land productivity and access to improved water quality are consistently significant and relatively stationary across the entire basin. Across levels, education is the most consistent non-water predictor of poverty, while access to protected water sources is the most consistent water related predictor of poverty. Other variables are found to be significant correlates. These include water related factors of distance to dams and area of irrigation, and non-water related factors of population density, forest cover and malaria prevalence. However, we find these to be statistically non-stationary, suggesting they are localised in the magnitude and direction of their potential poverty impact across the basin (Tables 3 and 4). These variables may be more appropriately addressed using a fine resolution, geographically targeted policy approach.

The literature argues that the availability of and access to water for consumptive and productive purposes (particularly in agriculture) plays a crucial role in poverty alleviation (Castillo et al., 2007). Our results support this notion, but do reveal few water-related factors which consistently explain the observed variance across (1) all poverty metrics utilised, or (2) across all spatial levels analysed. With regard to the former, area of irrigation, for instance, is correlated with the observed variance in child height for age ratios at the whole of basin level, and at the national and sub-national levels for Nigeria and Mali. However, this correlation is not observed with the child mortality or the wealth index measures. This suggests that multiple measures of poverty are valuable for understanding the full range of impacts that water-related factors may have on poverty. Secondly, comparative analysis indicates that there is limited congruence between the potential explanatory variables at different spatial levels. Regional differences, seen in the sub-national analysis for instance, can cause non-significant or contradictory results in more aggregated levels of analysis. An objective of this paper was to demonstrate how parallel analysis at multiple levels can help identify relationships between poverty and its potential causes that are otherwise obscured.

Our regression-based analysis of water related poverty correlates, combined with GIS mapping, is intended to provide an objective and easily-interpreted diagnostic tool. This has at least two complementary applications: (1) to facilitate exploration of the biophysical and socio-economic dimensions of water management geared to mitigate water related poverty, concentrating on priority hotspots in the Niger Basin; and (2) to enable the community, policy makers and administrators to visually evaluate the distribution and magnitude of water poverty, and the potential relative effectiveness of alternative policy strategies implemented at different administrative levels.

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