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Mapping natural resource-based poverty, with an application to rural Syria

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ABSTRACT

This study presents advances in resource-based poverty mapping. It illustrates how agricultural income distribution maps can be generated at small pixel-level, providing an application of the approach in rural Syria. Census data on agriculture and population are disaggregated based on pixel-level agricultural productivity coefficients derived in a GIS environment. The approach, triangulated with survey results and compared with sub-national poverty maps, shows that the better-income areas of Syria are located in the irrigated and higher-rainfall areas, though lower-income pockets exist due to the presence of ecological and topographic factors or due to high population density. The method can be used for developing high-resolution, low cost maps for rapid detection of resource-driven poverty in low income countries where agriculture is a major source of rural income, and where poverty mapping is rarely undertaken due to the high costs involved.

Introduction

The importance of poverty reduction to the world development agenda has motivated greater interest in the geographic dimensions of poverty and food security (Hyman et al., 2005). In the rural areas of developing countries, poverty is strongly linked with geographical conditions and natural resources availability (Okwi et. al., 2007). The state and trends of natural resources on which rural livelihoods depend have emerged as key determinants of well-being and poverty. Recent maps (WRI and others, 2007) highlight the benefits nature provides to people and the linkages between poverty and ecosystem services in Kenya, showing how map-based analyses of poverty-ecosystem relationships can influence policy development and implementation.

Coefficients derived from agro-ecological constraints (soils, heat, water, slope) can provide estimates for the distribution of resource-based poverty; these can be used to derive high-resolution income distribution maps that provide visual information for policy simulations. Information on the spatial distribution of poverty and environmental degradation is of interest to policy makers and researchers as it can be used to quantify disparities in welfare across regions, to facilitate the targeting of food insecurity and poverty alleviation programs, and to shed light on the geographic factors associated with poverty (Okwi et al., 2006).

International organizations involved in the global effort to reduce poverty have developed different poverty map approaches (Hyman et al., 2005), well synthesized in Food Policy's 2005 special issue on 'Poverty and Food Security Mapping'. The International Centre for Agricultural Research in Dry Areas (ICARDA) has also initiated a wider effort to address resource-driven poverty and better target its interventions where poverty and food security are priority concerns and where natural resource constraints are limiting research and development efforts most.

This study describes ICARDA's experience and contribution to the literature on the topic. In the following chapters, we illustrate how resource-based poverty maps can be generated at small pixel[3] level, introduce the use of poverty maps in the context of countries where natural resource poverty is dominant, with focus on the Syria case study, and provide insights on the opportunity to apply the present approach for rapid poverty appraisal exercises, where these are most needed.

Poverty maps and the environment

Poverty maps can be used to integrate biophysical information and socio-economic data to show a more systematic, analytical picture of human welfare and poverty (Henninger and Snel, 2002). The inclusion of biophysical information greatly helps to

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[3] Pixels are internally uniform cells used in GIS (and other visual) applications.

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Nomenclature

CRI_j	climatic resource index in pixel j
TRI_j	topographic resource index in pixel j
SRI_j	soil resource index in pixel j
$CDBPI$	climatically determined biomass productivity index
AHU	annual growing-degree-days (GDD) above 0 °C
AI_{adj}	adjusted aridity index
opt_1, opt_2	optimum values of the CDBPI
INC_j	income from agriculture (SYL)
APC_j	agricultural production coefficient
$M_{w,j}$	% of irrigated '*ir*', and rainfed '*r*' areas in pixel j
q_i	agricultural production in agricultural sub-zone
p_i	price for agricultural product
n_z	pixel area (number of pixels in the sub-zone)
ARI_j	agricultural resource potential index
lc_j	livestock distribution coefficient
LV_j	livestock value in pixel j
B_k	correction factor for 'useful' biomass in land-use/land cover type k'
$AP_{k,j}$	proportional area of land-use/land cover type k in pixel j
SSE_i	standard settlement equivalent
$SSEa_{ar}$	adjusted standard settlement equation
A_i	area of settlement i (in m^2)
As	standard settlement area (0.03125 km^2)
A_p	size of the pilot area
A_{ar}	size of the agricultural region
FT	township fraction
FV	villages fraction
RF	adjustment fraction
Pop_n	population in the *nahia*
$Pop_{n,ar}$	estimated population in each agricultural region within a *nahia*
n	N of agricultural regions inside a *nahia*
p_{ar}	proportion of the agricultural region inside the *nahia*
$DSSE_{ar}$	standard settlement density for the agricultural region
$DSSEa_{ar}$	adjusted standard settlement density for the agricultural region

Suffixes

z	subzones
j	pixels (~1 km^2)
i	products (e.g. crops, fruits, vegetables, livestock)
w	water availability ('*r*' rainfed, '*ir*' irrigated)
k	different land-use/land cover types
l	livestock

improve the poverty estimates and also enables targeting of poverty reduction work (Okwi et al., 2006). They can improve development efforts by making the spatial allocation of national or international funds for agricultural research and development more effective. They can highlight areas marginalized by resource constraints, help in setting priorities for developing technologies and in transferring resources where they are most needed and likely to have greater impacts on poverty. By identifying *who* and *where* the poor are, poverty maps help to target research and to reveal *why* communities or people are poor.

Various studies have attempted to link sub-national well-being, geographic and environmental variables, using correlation and visual spatial analysis. Spatial analysis uses various techniques and geo-referenced data. As data quality improves with satellite technology, the understanding of the ecological and resource constraints linked to the spatial distribution of poverty also improves.

Geographic location and climate have a large effect on income levels and growth, by affecting agricultural productivity, transport costs, and diseases (Gallup and Sachs, 1999). Sullivan (2002) linked physical indicators of water availability with socio-economic variables and introduced a water poverty index for regional comparisons. Godilano et al. (2000) link disaggregated poverty incidence to environmental risk (flooding) in Bangladesh and area suitability for rice production.

Small area regression estimation, a widely applied approach for analyzing rural poverty and food security, as reviewed for seven countries by Hyman et al. (2005) shows that topography, soil characteristics, rainfall, evapotranspiration and vegetation are important explanatory factors in describing poverty. You and Wood (2006) use an entropy-based approach to make spatially disaggregated assessments of distribution of crop production using data on crop production statistics, farming system characteristics, satellite-derived land cover, biophysical crop suitability assessments, and population density. Okwi et al. (2007) use a spatial regression to explore the effects of geographic factors on poverty; slope, soil type, distance/travel time, public resources, elevation, land-use and demographic variables were significant in explaining the spatial patterns of poverty. The atlas from WRI and others (2007) overlays geo-referenced statistical information on population and household expenditure with spatial data on ecosystems and services (water availability, wood supply, wildlife population) showing how land, people, and prosperity are related in Kenya. These and other studies point at the strong linkages that exist between rural poverty, access to resources (e.g. owned land, water, animals, machinery), and agro-ecological variables (e.g. climate, soil, availability of water for irrigation) and suggest an existing potential for integrating current and emerging GIS-based data on environmental characteristics with socio-economic data, in order to analyze the interaction between poverty and natural resources.

Agriculture, natural resources and poverty in Syria

Syria is a mid-size country with total land area of about 18.5 million ha of which 13.7 are for agricultural purposes. About half of the total (17 million) population resides in rural areas (CBS, 2004). Almost two third of rural households are involved in agriculture, but poor households rely much more on agriculture (Keyzer et al., 2006). Natural resource endowment is a critical factor for rural poverty. Precipitation varies from 1500 mm in the west to less than 100 mm in the southeast. Drought is inherent in local systems, only attenuated by the gradual expansion of irrigation (1.33 million ha irrigated, out of the 5.42 million arable land, FAOSTAT 2003) mostly in the Orontes river valley in the west and Euphrates valley in the east.

Syria ranks relatively low in human development indicators (UNDP, 2005). However, national-level indicators of human welfare hide a complex picture of rural poverty and food insecurity. While poverty in Syria remains not well documented and the statistical database is not publicly available, recent studies by the United Nations Development Program (UNDP) and International Fund for Agricultural Development (IFAD) have provided a good picture of poverty distribution.

The UNDP study by El-Laithy and Abu-Ismail (2005) was based on the statistical analysis of a sample of 30,000 urban and rural households. The study concluded that in 2003–2004 about 10% of people were below the income poverty line of 2 US$ a day, but that poverty is shallow, with most people clustered just below the poverty line. The North-East of the country, both the rural and the urban areas, shows the greatest incidence, depth and severity of poverty.

The IFAD study (Keyzer et al., 2006), based on a large-scale survey of 30,000 households by the Syrian Ministry of Agriculture and Agrarian Reform, focused on rural poverty and made a finer spatial differentiation of poverty features than the UNDP study. The IFAD maps indicate that rural poverty is highest in the northeast, mainly in Deir-ez-Zor, Al-Rakka and Hassakeh, while living standards are most favourable in the coastal and southern governorates. The IFAD study also shows that extreme poverty, as defined by the 1 US$ a day line, is low in Syria.

At the national-level poverty concerns the availability of land, water, soils, and topographic resources for agriculture; at the household level it concerns the individual household's access to resources. The two are linked, since in areas with a poor resource basis, such as arid or rocky parts of the country, few households have access to quality land, while in areas with good natural resources households may not benefit from the land, either because of limiting property rights or because many people depend on the same resources. Insufficient access to land is most likely a determinant of rural poverty, since the share of households owning land is lower among the poor households than among the non-poor households (Keyzer et al., 2006). Additionally, in Syria natural resource poverty is expressed by the need of parts of the rural people to use land marginal for agricultural productivity or with severe topographic or soil limitations.

Objectives of the study

The objective of this study was to develop a cost-effective and easily transferable GIS-based methodology to link the natural resources endowment to the income from agricultural activities. This approach, usable by development agencies and national statistical services in developing and middle income countries can help in identifying areas that are falling behind in terms of economic development, by detecting the 'hot-spots' of low agricultural income due to resource poverty. The study complements other more data intensive methods, such as those by IFAD and UNDP, by proposing a low cost and more rapid approach to poverty assessment, and to visualize resource poor rural areas where livelihoods and often food security are based on agriculture.

Materials and methods

Our approach is based on the hypothesis that in countries where a high proportion of population has livelihoods based on agriculture the lack of a natural resource base for agriculture (resource poverty) is an indicator of human poverty. If appropriate indicators are chosen, resource poverty is easier to assess than human poverty, thanks to the large public domain database currently available on climate, soils, topography, irrigated areas and satellite imagery. Also, in contrast with the coarse spatial resolution of income related indicators, such as agricultural production, yields and prices, and the scattered nature of household surveys, resource data in most cases have both comprehensive spatial coverage and a finer spatial resolution. In those cases where no direct and comprehensive poverty mapping is feasible, it makes sense to track poverty hot-spots by an indirect method that combines coarse-resolution agricultural statistics, price information, data on population and finer-resolution natural resource data. The methodology we use is therefore based on a spatial representation of the income distribution from agriculture, through a disaggregation procedure that uses agro-ecological data and natural resource constraints.

As seen from the literature review, one very common poverty mapping approach is spatial regression, which requires a large geo-referenced socio-economic (household) dataset, and which was not available in this study. One key innovative aspect of our approach was combining spatial analytical techniques (e.g. interpolation, simulation and modeling) and geographical data with available census data, in order to generate resource-based poverty maps on small pixel-level.

In the next sections we discuss the concept of agricultural resource potential index (ARI) used in the disaggregation procedure, how the ARI was used to disaggregate agricultural income data to the fine pixel-level, and how to adjust the population densities obtained from statistical reporting units to the pixel-level, to generate fine-resolution per-capita agricultural income maps.

Assessing agricultural resource endowment

To quantify agricultural resource endowments by means of an agricultural resource potential index (ARI), different resource indices were developed, quantified and merged into a single index that provides the basis for the spatial allocation of agricultural income. The method considers all relevant biophysical factors and allows consistent comparisons between different locations, since all the four indices have a common scale of (0–100). The method allows assessing the contribution of individual environmental factors towards agricultural resource poverty, is scale-independent, and can be applied using GIS global datasets that normally are currently available. The components of the ARI are:

(1) *Climate resource index* (CRI) shows the climatic potential to produce biomass;
(2) *Soil resource index* (SRI) is the proportion of the pixel without problematic soil types;
(3) *Topographic resource index* (TRI) is the proportion of pixel without topographic limits.

The low value of CRI represents severe climate (temperature and lack of water) constrains on production. The low value of SRI represents severe soil constrains to agricultural production. The low value of TRI shows areas where there is severe constrains to agriculture due to slopes. High scores show instead that no limitations are present. The three indices are selected as they represent the key factors of agricultural resource potential under natural conditions (climate, soils, and topography). A fourth factor (presence of irrigation water) is a modifier of the climatic resource index. The indices are not correlated, so that they capture the maximum variation of the agricultural environments. All three indices have the same spatial resolution (0.00833 decimal degrees, corresponding with approximately 1 km^2 grid cell size). These are relatively small regular divisions of the area to be evaluated, equivalent to the 'pixels' of a remotely-sensed image, and are processed using automated methods in a raster-based[4] GIS, at a finer-resolution than other recent studies (e.g. You and Wood (2006) use 25–100 km^2 pixels). Some technical notes on the steps for explaining how resource indices are derived are highlighted in Table 1.

Climatic resource index

The Climatic resource index (CRI) captures the climatic potential for biomass production; it is scaled to the 0–100 range (Eqs. (1)–(3) in Appendix) by using the distance of the Climatically Determined Biomass Productivity Index-values (CDBPI) from an optimum range (Fig. 1). This range was determined empirically from parts of Central and West Asia and North Africa (Szonyi

[4] 'Raster' is a term used in GIS to designate a file structure in which a map or image is stored as a grid-like pattern of values for small, internally uniform cells (pixels).

Table 1
Technical notes on resource indices.

CRI	Step 1: Global climatic databases on precipitation, temperature and potential evapotranspiration are supplemented with national data. Temperature is converted into 'annual growing-degree-days' Step 2: Spatial interpolation, using GIS software, to obtain raster files with 1 km resolution of precipitation, annual growing-degree-days, potential evapotranspiration and aridity index Step 3: Calculation of the CDBPI using Eq. (4) Step 4: Calculation of the CRI by inserting a formula equivalent to Eqs. (1)–(3) in the raster calculator module of the GIS software
SRI	Step 1: Start with a national soil map, already in the database format: mapping unit (soil unit x, % of soil unit x). If soil map is not yet in this format, its conversion may take from 1 day to 1 week, depending on size of the country, detail of the soil map, and complexity of the soil map units. Step 2: Interpreting each soil unit as either 'problematic' or not Step 3: Calculating the percentage of 'problematic soils' in each mapping unit and adding it to the attribute table of the digitized soil map in vector format Step 4: Converting the vector layer to raster at 1 km resolution, using the 'problematic soils percentage' field
TRI	Step 1: Starting with the SRTM digital elevation model with 90 m resolution Step 2: Calculating the slope from the SRTM DEM Step 3: Creating a new grid at the same resolution which contains the information that each grid cell has either a slope below 15% or not Step 4: Calculating TRI by aggregation of new grid using a cell of 100× the original grid (to bring it to 1 km resolution) and summation technique for aggregation
ARI	Step 1: Calculating the minimum of the three indices (CRI, SRI, TRI) using the minimum function in the raster calculator of the GIS software

et al., 2005). The CDBPI is a proxy for the annual atmospheric energy available for biomass production, expressed by accumulated temperature (AHU), and adjusted for drought stress (Eq. (4)). The measure for drought stress was the *aridity index*, which is the ratio between annual precipitation and annual potential evapotranspiration, calculated by the Penman–Monteith method. The input data used to map the CDBPI consisted of 1-km resolution climate 'surfaces'; these are raster files prepared by the spatial interpolation[5] of point climatic data using the thin-plate smoothing spline method (Hutchinson, 1995). Climatic data for individual stations was obtained from the FAOCLIM database (FAO, 2001) and national meteorological datasets. AHU values were obtained from climate surfaces of mean monthly temperature. The aridity index was obtained from surfaces of annual precipitation and potential evapotranspiration. If the AI values exceeded 1, they were adjusted to 1, to ensure that very cold areas (with low AHU) do not get an excessive CDBPI through compensation from high AI (as is often the case in cold areas because of low evapotranspiration rates). In irrigated areas the AI values were also set to 1, to indicate no moisture limitation. For irrigated pixels the CDBPI is thus equal to the AHU. In cold areas, AHU is also very low, so it remains possible to differentiate areas with high rainfall from cold ones.

Soil resource index

The Soil resource index (SRI) is the proportion of the pixel without problematic soil types. Problematic soils are those that are either unsuitable for agricultural production due to severe physical limitations, or soils that are very expensive to reclaim for production. The following problematic soils were considered as relevant to Syria and feasible to be mapped at a national-level: (1) saline soils, (2) stony soils, (3) shallow soils, and (4) soils with textural limitations (too heavy or coarse). The dataset used to develop the SRI for Syria was a 1982 soil survey by the United States Agency for International Development and by the Syrian Ministry of Agriculture (Louis Berger International, 1982). In the case of salinity and soils, despite that more degradation may have occurred since 1982, the data we used is the one commonly used by ICARDA.

Topographic resource index

The Topographic resource index (TRI) was derived from a Shuttle Radar Topographic Mission Digital Elevation Model (CGIAR-CSI online database, 2004) by calculating the slope for each 90-m pixel. In order to match the resolution of the other datasets used to calculate the CRI and SRI, the slope pixels were aggregated to a pixel size 100× larger. The TRI was calculated as the percentage of SRTM pixels with a slope below 15%, which corresponds well with the slope limit delineating what constitutes sustainable agriculture without resorting to terracing.

Agricultural resource potential index

This study is testing an approach to approximate rural poverty through biophysical variables in countries, where household survey data is not available. The thematic indices (CRI, SRI and TRI) were combined as raster themes in GIS, with the same spatial scope and resolution, into the agricultural resource potential index (ARI) (Eq. (5)). The ARI is calculated as the lowest value of the CRI, SRI, and TRI indices for rainfed areas. If, however, a fraction of the pixel is irrigated, only the CRI is considered for the irrigated fraction in the ARI calculation, this assuming that irrigation takes place where soil and topographic conditions are not severely constraining. The irrigation water availability matrix (M_w) (Eq. (7)) shows the proportion of an irrigated pixel (using a previous land-use/land cover map, De Pauw et al., 2004). On steep slopes the ARI normally is low, because the TRI is low as steep slopes are unsuitable for sustainable agriculture. If slopes are terraced, the TRI changes for the better, and the ARI will indicate a higher resource potential.

The approach was developed to provide a simple, yet effective way to integrate aspects of natural resource potential to aid mapping and target poverty. For all countries climatic and topography data and national soil maps are available. In most countries land-use/cover maps are available, and where they are not global products are now becoming available with resolutions from 300–1000 m. The process for calculating the different resources indices and the integrated ARI takes a few days to one week, depending on the state of the initial soil and climate databases (Table 1).

Income distribution based on agricultural resource endowment

For administration purposes, Syria is divided into *mohafazas* (provinces), and each *mohafaza* is divided into *mantikas* (districts). Each *mantika* is divided into administrative units called *nahias* (the

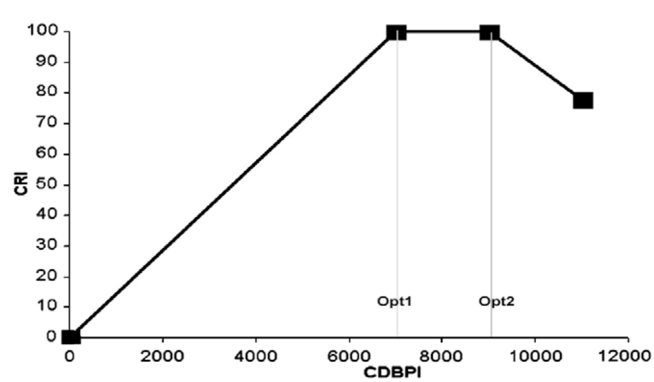


Fig. 1. Empirical relationships between CRI and CDBPI (see Eq. (1) in Appendix).

[5] Spatial interpolation methods estimate geo-variables at unobserved locations based on values at observed locations.

equivalent of counties), each covering a number of villages. There are in total 14 *mohafazas*, 60 *mantikas,* and 211 *nahias* in Syria (CBS, 2003). Besides an administrative zoning, Syria also has an agricultural zoning system with five classes (or 'Agricultural Stability Zones') based on the quantity and reliability of annual precipitation (MAAR, 1994–2004).

The Agricultural Production Database of Syria (NAPC, 2003) provides production and price data for crops, fruits, vegetables and animal products for *'agricultural sub-zones'*, which are the spatial units resulting from the intersections of the provinces and the Agricultural Stability Zones'. Prices of products not included in NAPC were taken from the FAO database or from a local market survey in Aleppo based on year 2000 data. The sum of all agricultural products was multiplied by their wholesale value; this was consistent with the share of agriculture in the national account, equivalent to about 25% of the Gross Domestic Product in year 2000 (NAPC, 2003).

Agricultural income (INC) is a function of prices (p) and agricultural production (q), which depends on agricultural resource conditions (Eq. (6)). Aggregate census data of the *'agricultural sub-zones'* was spatially disaggregated by rescaling the database with the mean of the ARI index for the same area. This derived an Agricultural Production Coefficient (APC) database [from 0 to 2] (with a mean value equal to 1 in each sub-zone), which determined the value of income in each pixel. The distance from the ARI mean value determines if the APC is above or below 1, hence augments or lessens the distribution of the average income. In the allocation of income to the individual pixels from rainfed or irrigated agriculture, the ARI values were weighted according to the proportion of rainfed or irrigated land present in each pixel (Eqs. (6–8)).

Capturing the geographic distribution of income from livestock proved more difficult as some of the statistical data is available only at the provincial level (MAAR, 1994–2004). These are generally large spatial units that may contain much diversity in terms of grazing value. Income from sheep, goat and cattle includes sale of live animals, meat, wool, milk and other dairy products; income from poultry includes the sales of meat and eggs. Eqs. (9)–(11) calculate the disaggregated livestock income. To obtain some reasonable allocation coefficients of the total value per pixel, a livestock distribution coefficient was introduced (Eq. (10)), based on estimates of livestock proportionality by land-use/land cover type (from the land-use/land cover map by De Pauw et al. (2004)). This 67-class system was reclassified using five basic land-use/land cover (LULC) types, characterized by a 'biomass fraction $(B_k)'$, a proportion of the biomass in each LULC class 'useful' to livestock, estimated by expert judgment. Rainfed cultivation was considered to have a livestock biomass fraction of 0.2, irrigated cultivation 0.4, bare land 0.05, forest 0.1 and rangeland 0.7. Each map unit of the LULC map was then assigned a 'Livestock Value' (LV), on the basis of the presence and proportion of basic LULC types in the mapping unit, and their biomass fractions (Eq. (11)). Once all pixels in a province had been assigned a livestock value, the allocated total livestock value per pixel was based on the ratio of the pixel's livestock value to the sum of all livestock values in the province. The agro-industries (e.g. lamb fattening, dairy) are taken into account in calculating livestock income by means of the added value from sales.

Per-capita income distribution from agriculture

To represent the per-capita income distribution from agriculture, population density also had to be disaggregated from the lowest administrative level (*nahia*) for which data was available, to the pixel-level. The population data for the *nahia*, obtained from the latest census survey (CBS, 1994 data), were updated with annual growth rates for rural areas in the different administrative regions (CBS, several years). *Nahia*-level population densities were adjusted to the pixel-level by intersecting the *nahia* with the boundaries of 'agricultural regions'. 'Agricultural regions' are integrated spatial units in which available water resources, climate, terrain, and soil conditions combine to create unique environments, associated with distinct farming systems, land-use and settlement patterns. The agricultural regions were mapped through visual

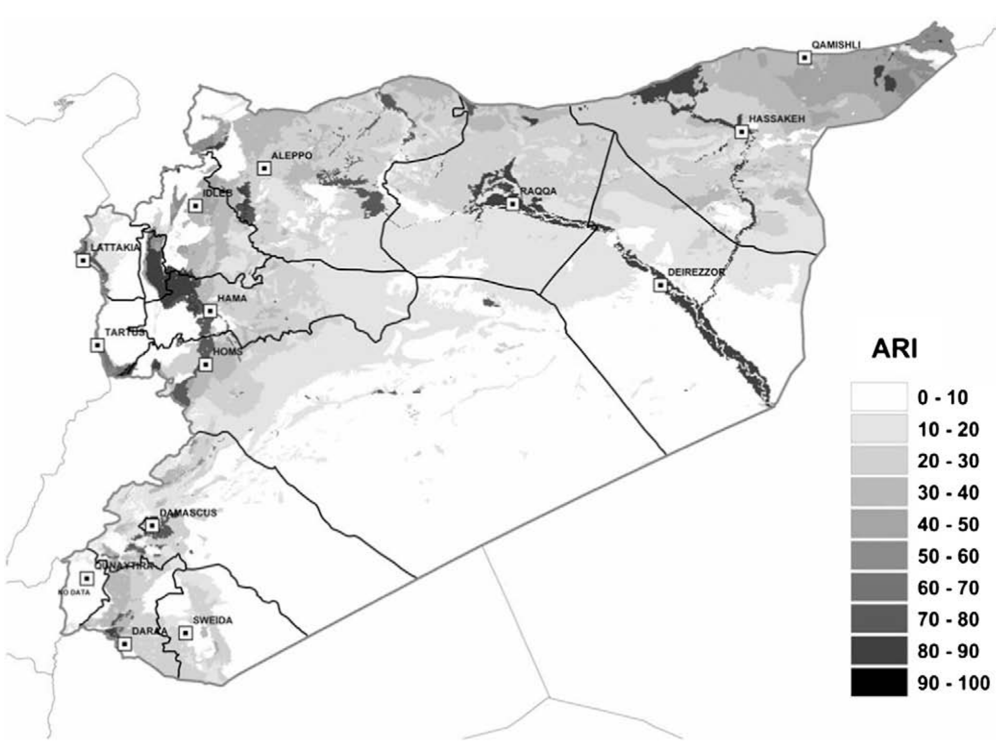


Fig. 2. Agricultural resource potential index (ARI) in Syria.

interpretation of Landsat imagery for the summer of 2002 and the spring of 2003 covering all of Syria by De Pauw (Szonyi et al., 2005). The Landsat imagery was also used to identify and map settlement patterns in pilot areas covering all agricultural regions and about 45,000 km^2 (24%) of Syria. In these pilot areas settlement areas were measured and converted into standard settlement densities for each agricultural region. In a final step the *nahia*-level population densities were recalculated according to adjustment factors applicable to agricultural regions. For each *nahia*–agricultural region combination, weights were applied to the *nahia*-based population densities that reflected the differences in settlement density between agricultural regions. The adjustment of population density to the pixel-level was done by using estimated population density coefficients (Eqs. (12)–(17)) obtained from a mapping procedure based on identified 'agricultural regions' (Szonyi et al., 2005). Characterization of agricultural regions based on settlement patterns (by satellite images), multiplied by the proportion factor (pr) of the sample provides estimates of population density (DSSE), that are used to disaggregate population census data at the pixel-level (Eqs. (12)–(17)).

Results from the Syria case study

The pattern of the ARI in Syria (Fig. 2) is due to two main sources of resource potential: the rainfall gradient from north to south and west to east, and the presence of irrigated areas. Areas with low ARI are associated with low rainfall (especially steppe areas), the absence of sources of irrigation water, and the presence of mountain ranges with steep topography and shallow soils.

The resource-based pixel-level allocation of total income from agriculture and livestock in rural Syria is given in Fig. 3. The overall pattern of the ARI-modelled income distribution clearly reflects the gradients in precipitation and the distribution of irrigated land. Ultimately these are the key resources of agriculture in Syria, since even livestock income depends on them. Within the better-income areas, pockets with shallow soils or unfavourable topography appear as lower-income spots. One exception is the coastal mountains in the west of Syria, where income is better than expected from its agricultural resource potential. This is explained by large-scale investments by the government and private sector in land improvement, chiefly through terracing and rock removal, which have significantly improved the earning capacity of local agriculture. Fig. 4 shows the overall pattern of per-capita income distribution from agriculture. To avoid artefacts creating artificially high per-capita income where very few people live, a 'mask' was applied to exclude areas with less than 5 persons/km^2. The trend for per-capita income is similar, though more fragmented, alike that of total income from agriculture: where total income is high, so is per-capita income, and vice-versa. Exceptions exist, e.g. the Euphrates plain southeast of Deir-ez-Zor has, despite a high total annual income (SYL 5,000,000/pixel) it has fairly low per-capita income (SYL 10,000–20,000/person/pixel) from agricultural activities. In such areas higher population densities explain the lower per-capita income and could point to a high poverty incidence. In fact, all poverty indicators used by Keyzer et al. indicate the area downstream of Deir-ez-Zor as a major poverty cluster. Though the Damascus area shows high income, this is partially explained by not accounting for urban population in the per-capita account. The model, in fact, does not include urban income. The assumption that agricultural income is generated and redistributed in rural areas, may not be true in some cases (e.g. lamb fattening profit may go to urban businessmen), but may be true in other cases when it goes to local (rural) employees.

Discussion

A comparison of the IFAD poverty indicators with our per-capita agricultural income maps reveals a high consistency in poverty clusters in the hilly system of North Western Syria, in areas east of Aleppo and west of Lake Assad, and partial agreement in the Euphrates and the Khabour river valleys. However, the poverty hot-spot in the transition zone to the rangeland east of Hama is not detected. With the exception of the Deir-ez-Zor area, the spatial patterns of pixel-level per-capita income estimates could not

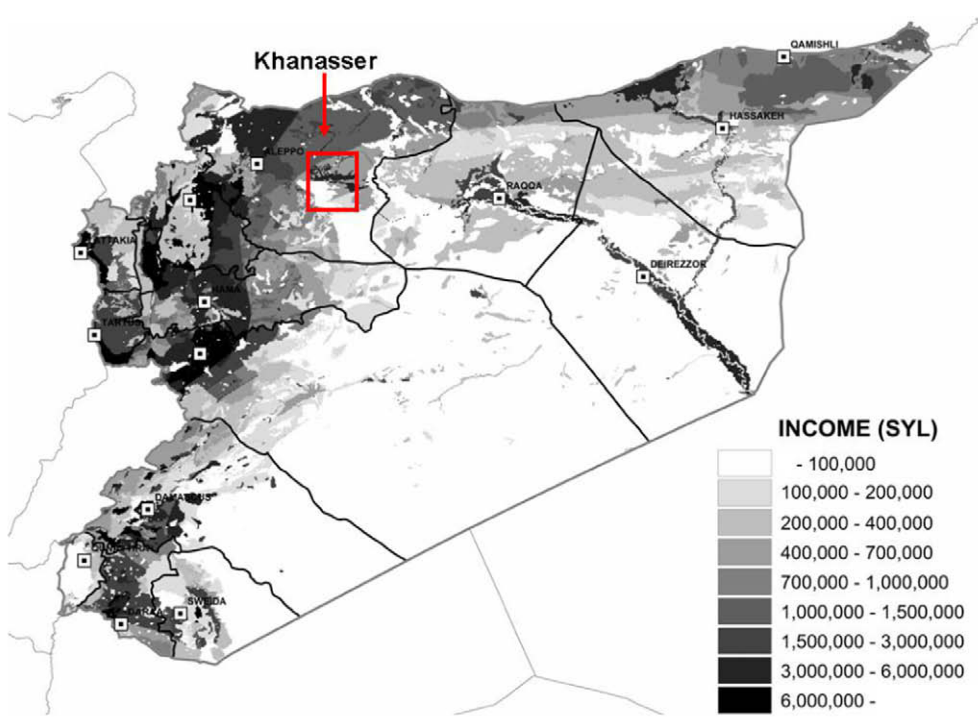
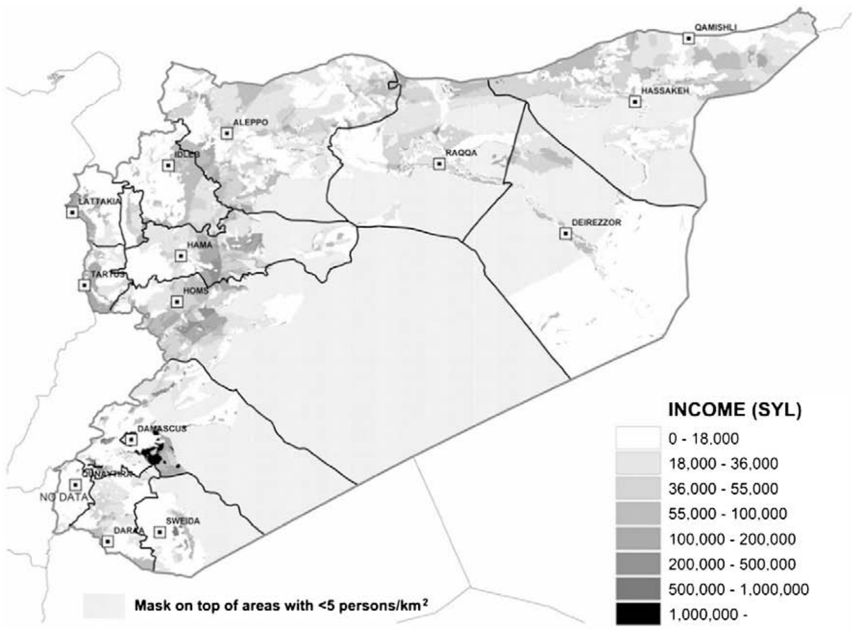


Fig. 3. Spatially disaggregated total income from agriculture (in SYL/pixel/year).



*Annual 36,000 SYL income is equivalent to the internationally used 2 USD/day indicator, but the later includes also non-agricultural income.

Fig. 4. Spatially disaggregated per-capita income from agriculture (in SYL/pixel/year).

be matched consistently with the poverty clusters identified by the IFAD study. This is unsurprising given that in Syria income sources are diverse, with wage income the most important source in all provinces, and agricultural income a close second. In the Deir-ez Zor area the share of agricultural income is higher than national averages and the wage income lower, which may explain why a poverty hot-spot shows up in per-capita income from agriculture. Our resource-based income map shows higher percentages of population below 1 and 2 USD/day per-capita than from the UNDP study; the difference, also in this case, can be explained by the high percentage of off-farm income from non-farming work and remittances.

The overall pattern of the pixel-level allocated total income from agriculture corresponds well with the areas of high and low agricultural potential, as identified by resource surveys (e.g. Louis Berger). This strengthens the confidence that the indices used to quantify the resource potential and to downscale agricultural income to the pixel-level can stand reality tests. In fact, a recent study provided site specific validation of the ARI-based allocation method at the landscape level in the Khanasser area, situated in north-eastern Syria between the cropped and rangeland rainfed systems (box in Fig. 3). At 200–250 mm annual rainfall, this agriculturally marginal area of 630 km^2, with a population of 27,000 and a density of 93 persons/km^2, has a quantified total income at 0.5 billion SYL/year, including off-farm earnings (La Rovere et al., 2006). The total income for the same area modelled through our approach is 0.31 billion SYL/year, excluding income from off-farm labour. Adding the local percentage of off-farm income (42% of total income, La Rovere et al., 2006), the total income is 0.53 billion SP/year, very close to the other independent assessment of agricultural income. More case studies to validate the approach are becoming available at ICARDA, for instance in northern Syria, and in Sudan.

A recent survey of the nutritional status of children (Ghosh et al., 2004) compared malnutrition indicators in three villages located in Agricultural Stability Zone 1 (two in a productive irrigated site, and one in an olive and fruit production area), with two villages in Zone 4, where barley and livestock are main livelihood sources. Data in Table 2 suggests that livelihood systems, resource endowments, and the nutritional status of children aged under 10, are closely related. The least vulnerable group comprised children in the irrigated system, where farmers diversify their diets by producing different crops and generating more cash from farming (enabling them to buy the needed food). In the barley/livestock and the olive/fruit-tree systems, however, there is limited opportunity for cash crop production, and less income is generated as local environments are poor in resources. This case study also illustrates how the ARI is more capable of detecting resource poverty due to soil or topographic constraints, as is the case of the Yakhor village.

In terms of approach, the ARI index is of critical importance for this study. A key component for assessing the ARI is a land-use/land cover layer that represents irrigated areas, since these are in dry areas those with highest agricultural productivity and major source of agricultural income. Another key component is a soil map that: (i) can be reliably interpreted in terms of agricultural management properties at the spatial scale of the assessment,

Table 2
Comparison of the ARI and the percentage of stunted and underweight children (under the age of 10) in different production systems in north-western Syria.

System (Zone)	Annual rainfall (mm)	Villages	Stunted[a]		Underweight[a]		ARI
			Boys	Girls	Boys	Girls	
Irrigated (1)	600+	Zerifa, Mastura	12.5	12.5	5.6	1.4	20
Olive/fruit tree (1)	350–600	Yakhor	22.8	18.9	13.0	13.5	10
Barley/livestock (4)	200–250	Serdah, Ruwayhib	17.3	28.3	15.4	13.4	10

[a] Source: Data on child nutrition taken from Ghosh et al. (2004).

and (ii) is sufficiently up-to-date to show main land improvements (e.g. de-rocking, terracing) or degradation (e.g. salinization) that may influence the soil potential. Also, the network of climatic stations in the area should be sufficiently dense to allow a realistic interpolation for estimating the climatic resource index.

The approach presented has various advantages. First of all, it does not require a survey. It uses national statistical data and a system of equations to disaggregate in a limited time the data based on geophysical data. In this study we relied on pre-existing household surveys only to validate our results. The other advantage is that in poor countries poverty mapping, with its requirement for large-scale sampling for statistical significance, is often too expensive to be undertaken at an appropriate scale and to be repeated quickly to be useful for informed poverty reduction strategies.

The approach for downscaling statistical information using agro-ecological data adds a natural resource base context to sub-national production statistics, and is easy to adopt by the national statistical services. It provides an option that can contribute to solve the well-known pitfall of spatial data: the Modifiable Areal Unit Problem (MAUP). Minot and Baulch (2002) have in fact analyzed the MAUP effect in poverty mapping and advocated caution in the use of aggregated data, since it tends to exaggerate the differences between poor and less poor areas.

The main value of the disaggregated income maps and their supporting databases is in linking statistical information on agricultural production, prices and population, to the resource base for agricultural production, at a spatial scale fine enough to detect the hot-spots of resource poverty. While the latter cannot be consistently linked to human poverty, even in Syria, with its low level of extreme poverty, it can represent a major contributing factor (cf. with Hyman et al., 2005).

Whereas our approach is most useful at a macro-scale, it can be improved by strengthening the link with micro-level analysis and by accounting for local income distribution inequalities based on the existence of diverse household types, productive assets, and net production values. Given that large parts of rural income in Syria is from outside agriculture, a real picture of poverty can be gained by linking our approach to household surveys covering the rural non-farm economy.

The present paper also provides a valuable and empirical basis for further research in:

(1) Recurrent mapping at regular intervals coinciding with census surveys can provide rich databases for future predictions, and poverty estimates for non-census years (see Emwanu et al., 2006; Okwi et al., 2006 for low cost methods on panel data for non-census years).
(2) Incorporating feedback of human induced impacts (e.g. land degradation, resource use) or impact of natural ecological phenomena on agricultural productivity. This can greatly enhance the dynamic feature of maps to support environmental and development policy.
(3) Integrating other dimensions of poverty, like access to markets, or access to clean water, nutritional and health indicators, etc. For example the CRI can provide a spatial dimension to the water poverty index (Sullivan, 2002), by visualizing water supply constraints.

The approach also provides an option to spatially improve policy decision support systems. In fact, the coefficients commonly used in regional macro models, e.g. Input–Output models (see Leontief, 1986), in sectors with a distinctive spatial dimension like agriculture, have often lacked high-resolution visualization. Recent advances in satellite technology and spatial mapping have opened a new set of opportunities. We suggest using the exogenous APC coefficient to link the output of agricultural production with its geographic location, so to allow high-resolution spatial maps and to better visualize the distribution of agricultural income. This can expand such models with a third, spatial dimension and allow enhancing the effectiveness of targeting the efforts of research organizations (e.g. ICARDA) and development or government institutions to the poor.

Conclusions

The relevance of the approach is in its rapid appraisal of natural resource-based poverty and the novel mechanism it provides for integrating fine-resolution agro-ecological data with coarse-resolution statistical summaries. The method can become a cost-efficient policy tool to visualize areas in low- or medium-income countries where resource poverty, in combination with a high dependency on agriculture for livelihoods, is a determinant of human poverty, and where the financial resources and population data are inadequate to conduct fully-fledged poverty studies.

The ARI coefficient allows mapping the potential and limitations of agricultural environments through simple combinations of indices related to the state of climatic, soils, terrain and water resources at fine spatial resolution. These indices can be calculated on the basis of public domain GIS datasets. As the latter keep improving in resolution, quality and availability, the value of this approach to researchers, international organizations, and national decision-makers involved in poverty alleviation increases.

The quality of the results obtainable from this approach depends on the quality of the available geo-referenced and local statistical (census) data. The approach requires that the databases on the state of the natural resources are sufficiently accurate and up-to-date. If data is poorly available, other techniques can be used to estimate crop patterns and production, e.g. by global agricultural production databases, or GIS approaches to estimate land-use patterns, though the results might not be as accurate. Some global crop maps are also available, but few national statistical offices can count on geo-referenced data.

Verifying the results with local surveys allows validating the quality of the average income per-capita generated at the aggregated village level, but it does not show income differences amongst households. At local-level targeting should be combined with a local selection procedure of poor households. Yet the strength of the method is that it highlights the poorer areas and explains the resource or population based reasons why people are poor. One advantage is that this approach is built on GIS data and, given the recent fast advances in satellite technology, this approach may improve so fast that it can catch up with econometric based methods in terms of quality of data.

Comparisons with national and local-level case studies in Syria indicate that where agriculture is the main source of livelihoods and resources are a key problem, either due to poor quality or scarcity, our method can capture well the poverty hot-spots. The method can become very useful when it can show the spatial implication of regional policies. It also provides a solid empirical and practical basis for further applications and more research aimed at rapid, cost-efficient policy impact scenarios at country-levels, and for better targeting development policies.

Although in terms of precision and quality of data our approach is no substitute for poverty maps based on extensive household data, it does address resource and rainfall-related poverty, and is a more rapid and lower cost option useful where country-level poverty maps are rarely undertaken due to the high cost involved (cf. with You and Wood, 2006). Policies often must be designed based on information that cannot wait for large sums of money to be mobilized to run extensive surveys; policy makers will thus benefit of having a choice between data intensive approaches, such as those being used by UNDP and IFAD, and the lower cost, more rapid one we propose.

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Appendix A. Equations

Climate resource index

$$CRI_j = CDBPI_j/opt_1 * 100, \quad if \quad CDBPI_j < opt_1 \tag{1}$$

$$CRI_j = 100, \quad if \quad opt_1 \leqslant CDBPI_j \leqslant opt_2 \tag{2}$$

$$CRI_j = \left(1 - \frac{CDBPI_j - opt_2}{opt_2}\right) * 100, \quad if \quad opt_2 < CDBPI_j \tag{3}$$

$$CDBPI_j = AHU_j * AI_{adj} \tag{4}$$

Agricultural resource index

$$ARI_j = MIN(CRI_j, TRI_j, SRI_j) * M_{'r',j} + CRI_j * M_{'ir',j} \tag{5}$$

Income (excl. livestock)

$$INC_{w,j,z} = APC_{w,j,z} * \left(\sum\nolimits_i q_{i,w,z} * p_{i,w,z}\right)/n_z \tag{6}$$

Agricultural production coefficient

$$APC_{w,j,z} = \frac{ARI_{w,j,z} * M_{w,j}}{(\sum ARI_{w,j,z})/n} \tag{7}$$

and

$$\left(\sum\nolimits_j APC_{w,j,z}\right)/n = 1 \tag{8}$$

Livestock income

$$INC\_l_j = lc_j * \left(\sum\nolimits_i q\_l_{i,z} * p_{i,z}\right) \tag{9}$$

Livestock coefficient

$$lc_j = \frac{LV_j}{\sum_j LV_j} \tag{10}$$

and

$$LV_j = CRI_j * \sum\nolimits_k (B_k * AP_{k_j}) \tag{11}$$

Standard settlement equivalent

$$SSE_i = \frac{A_i}{As} \tag{12}$$

and

$$SSE_{ar} = \frac{\sum_{i=1}^{n} SSE_i}{A_p} x A_{ar} \tag{13}$$

Adjusted standard settlement equivalent

$$SSEa_{ar} = SSE_{ar}[FT + FV * (1 + RF)] \tag{14}$$

Density and adjusted density of standard settlements

$$DSSE_{ar} = \frac{SSE_{ar}}{A_{ar}} \times 100 \tag{15}$$

and

$$DSSEa_{ar} = \frac{SSEa_{ar}}{A_{ar}} \times 100 \tag{16}$$

Population density

$$Pop_{n,ar} = \frac{Pop_n * p_{ar} * DSSEa_{ar}}{\sum_i^n p_{ar} * DSSE_{ar}} \tag{17}$$

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