Application of a revised Water Poverty Index to target the water poor

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ABSTRACT

The Water Poverty Index (WPI) has been recognized as a useful tool in policy analysis. The index integrates various physical, social and environmental aspects to enable more holistic assessment of water resources. However, soundness of this tool relies on two complementary aspects:

(i) inadequate techniques employed in index construction would produce unreliable results, and (ii) poor dissemination of final outcome would reduce applicability of the index to influence policy-making. From a methodological point of view, a revised alternative to calculate the index was developed in a previous study. This paper is therefore concerned not with the method employed in index construction, but with how the composite can be applied to support decision-making processes. In particular, the paper examines different approaches to exploit the index as a policy tool. A number of alternatives to disseminate achieved results are presented. The implications of applying the composite at different spatial scales are highlighted. Turkana District, in Kenya has been selected as initial case study to test the applicability and validity of the index. The paper concludes that the WPI approach provides a relevant tool for guiding appropriate action and policy-making towards more equitable allocation of water resources.

Key words | data management, Turkana district, water poverty, water poverty index

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INTRODUCTION

The issue of resources allocation is crucial in water management. Policy makers are required to deal with an increasing and competing demand, though so often resources to meet these needs remain inadequate. If prioritization is made purely on the basis of where water is accessible, this is likely to be limited in scope and therefore inefficient (Sullivan 2002). A key prerequisite to support effective planning and targeting is to access consistent information through accurate monitoring, backed up by rigorous interdisciplinary science. This would enable decisions to be made on a much wider basis.

It is within this background that Sullivan (2002) developed the Water Poverty Index (WPI), as an attempt to advance the water-poverty interface and provide more comprehensive information to the equitable allocation of water. Water poverty is defined in the sense of not having sufficient water to cover basic needs (Sullivan 2002), and this might be caused either by water unavailability or by income poverty (Lawrence *et al.* 2002). In both cases, there is evidence that lack of adequate and sustained access to reliable water

supplies leads to low levels of output and health (Joint Monitoring Programme 2000; Sullivan 2002; Molle & Mollinga 2003; Sullivan *et al.* 2003).

Taking previous definition as the starting point, the WPI provides an integrated, multi-faceted approach to the evaluation of water, by combining a range of indicators that track the physical, economic and social drivers which link water and poverty. Its core theoretical framework encompasses estimates of water resources availability, people's ability to get and sustain access to water and to use this resource for productive purposes, and the environmental factors which impact on the ecology which water sustains. The index has thus been designed to accommodate into one single value the key issues influencing water provision. Such approach should be adequate to identify which regions may be most in need, thereby enhancing prioritization in the water sector.

The WPI has been applied at different scales (Lawrence et al. 2002; Sullivan et al. 2003, 2006; Cullis & O'Regan 2004; Heidecke 2006; Sullivan & Meigh 2007) and discussed in

several papers (Feitelson & Chenoweth 2002; Molle & Mollinga 2003; Sullivan & Meigh 2003; Al-Hmoud & Edwards 2005; Jiménez et al. 2008; Komnenic et al. 2009; Cho et al. 2010). Nevertheless, and despite the usefulness of this composite to assess water scarcity, the authors of the WPI and literature elsewhere have identified different concerns that arise when constructing the index. First weakness involves how the basic input data are used and the statistical properties of the index, criticizing it for conflating disparate (and often correlated) pieces of information (Molle & Mollinga 2003; Jiménez et al. 2008). Another major shortcoming is the weights assigned to the components of the WPI, which are undefined. Feitelson & Chenoweth (2002) argue that the weightings are subject to biases and individual judgments, though even when equal weighting for all components is in place, results are misleading. Similarly, Heidecke (2006) emphasizes the importance of transparent display of assigned weights to avoid misinterpretation. Finally, a more conceptual weakness is related to the aggregation method. In a linear aggregation, compensability among the different individual indicators is implicit (Munda & Nardo 2005; Nardo et al. 2005), and a shortcoming in one dimension can be offset by a surplus in another. For example in the WPI, water resources availability would compensate a loss of water quality. In a context of poverty alleviation, where a complete compensability is not desirable since different goals are equally legitimate, a non-compensatory logic might be necessary.

In response to previous criticism, a revised method to calculate the index was developed in a previous study (Giné & Pérez-Foguet 2010). This paper is therefore concerned not with the methodology employed in index construction, but with how the composite can be applied to produce easy-to-use data, and how this data may be exploited to support water resource management and effectively tackle water poverty. To this end, the revised approach has been piloted in the Turkana District, in Kenya as initial case study. A number of alternatives to display and disseminate the index are presented. The implications of applying the composite at different spatial scales are highlighted. The paper concludes with a discussion of adequacy of the index as a tool for policy planners to identify target groups and support more equitable allocation of water resources.

THE WPI FRAMEWORK: A REVISED APPROACH

The component variables included in the WPI, identified through participatory consultation with a variety of stakeholders (Sullivan *et al.* 2003), are aimed at distinguishing the

broad themes that reflect major preoccupations and challenges in low-income countries related to provision of water: physical availability of water (R), extent of access to water (A), effectiveness of people's ability to manage water (C), ways in which water is used for different purposes (U), and the need to allocate water for ecological services (E). Taking the conceptualization of water poverty adopted in the structure of the WPI, this section outlines the method for index construction developed by Giné & Pérez-Foguet (2010). The district of Turkana in Kenya has been selected as initial case study to pilot and implement the revised methodology, mainly based on availability of data and the fact that the district has been classified as arid (Government of Kenya 2007), thus facing severe water management problems.

Study area

Turkana district is the largest district in Kenya, covering 70.720 km² of some of the most arid parts of the country. It is also one of the poorest, with frequent droughts and famines. Turkana is located in Rift Valley Province, and borders Uganda to the west, Sudan to the northwest, and Ethiopia to the northeast. The district, whose administrative head-quarters is at Lodwar town, is divided into 17 administrative divisions, 58 locations and 158 sub-locations. The population density in the district is low, the total population being estimated at 450,860 (1999 National Census).

Main issues related to water resources are:

- Mean annual precipitation ranges from about 120 to 430 mm, although it is highly variable and unreliable.
 The occurrence of rainfall is higher during the long rain season (April to August).
- Main tributary of Lake Turkana is the River Omo, which
 enters the lake from Ethiopia and contributes more than
 90% of the total water influx. The lake has no outlet, and
 the water level is sensitive to climatic variations. The area
 is exposed to strong winds which, together with high
 temperatures, lead to high evaporation (Odada et al. 2003).
- There are 4 main seasonal rivers (Turkwel, Kerio, Suguta and Tarach). This resource is mainly exploited via gravity (irrigation) and direct access for domestic and livestock uses (United Nations Children's Fund 2006). Turkwel River was dammed in 1991 for hydroelectric power generation at Turkwel Gorge, which has probably impacted on the flow of freshwater.
- Most of the population relies on river and shallow wells for water, especially the shallow groundwater aquifer

- associated with dry riverbeds. Major issue which diminishes potential of this source is poor water quality, rather than total absence (United Nations Children's Fund 2006). Ephemeral rivers are also being increasingly exploited mainly via shallow wells, and seasonal rivers are coming out the most abundant source of water in the district.
- Food security is inextricably linked to the freshwater resources. With the very low rainfall in the region, people are shifting from pastoralism to agro-pastoralism and thus becoming more vulnerable (Odada et al. 2003). Furthermore, an increasing water demand from rivers to adjacent farms and higher populations settling close to the riverbanks are likely to impact on water resources availability and quality, thus rendering the freshwater shortage more acute.
- Proper sanitation facilities are basically non-existent, particularly in the rural areas (Odada et al. 2003; United Nations Children's Fund 2006).
- Health impacts will increase due to lack of sufficient and potable water supplies, and to inadequate sanitation infrastructure (Odada et al. 2003).

Method

The step-by-step methodology employed for index construction is summarized in Table 1 (Giné & Pérez-Foguet 2010): (1) selection and combination of indicators into their corresponding sub-indices, using an equal and dimensionless numeric scale; (2) determination of weights for each sub-index and their aggregation to yield an overall index;

Table 1 | Basic steps in index design

Methodological framework

1stStep: Selection of indicators

- 1a. Compilation and validation of available data
- Definition of indicators and classification based on the conceptual WPI framework (R, A, C, U, E)
- Preliminary statistical analysis of proposed indicators.
 Principal Component Analysis (WPI, 25 indicators)
- Selection of indicators at sub-index level. Principal Component Analysis (R, A, C, U, E)
- 1e. Calculation of 5 WPI sub-indices

2ndStep: Construction of the index

- Assignment of weights for sub-indices. Principal Component Analysis (WPI, 5 components)
- 2b. Aggregation of sub-indices

3rdStep: Validation of the index

3a. Sensitivity analysis

Case Study: Turkana District, Kenya

Data obtained from MIS developed for Turkana District by the GoK and UNICEF

Initial selection of 25 indicators: Resources (3), Access (6); Capacity (6); Use (5) and Environment (5)

PCA generates 12 principal factors (81.1% of the overall variability). Most of these components mix indicators from different WPI sub-indices. PCA does not justify WPI framework, but it does not offer a better alternative either.

PCA generates 2 components out of the 3 initial indicators for the Resource component (85.39 of the variance); 4 components out of 6 for Access (85.3%); 3 components out of 6 for Capacity (81.0%); 4 components out of 5 for Use (89.9%); and 4 components out of 5 for Environment (89.5%). The initial set of 25 variables is reduced up to 17 non-correlated indicators

Linear aggregation of non-correlated indicators to assess 5 subindices (R, A, C, U, E)

Weights are constrained to be nonnegative and sum to one. They are calculated based on the statistical structure of the data set.

Aggregation of sub-indices through a weighted multiplicative function

Sensitivity analysis to test robustness of the final index

and (3) validation of the composite using a sensitivity analysis. A brief description of the steps taken to calculate WPI is given herein.

The first step in composite indexing involves compilation of available data and selection of appropriate indicators given their relevance to the WPI framework. Data used (step 1a) is obtained from the 'Water, Schools and Health Management Information System (MIS) for Turkana District', which was developed by the Government of Kenya in cooperation with UNICEF as a comprehensive record of all water resources available in the district. Relevant data for each source (644 waterpoints) were obtained and entered into a Geographical Information System (GIS). In parallel, information related to water service level was captured through a questionnaire administered at community scale (488 questionnaires).

Based on these two different information sources, a number of indicators are identified and classified (*step 1b*) according to the WPI structure (Table 2). Data are normalized and to each parameter a score between 0 and 1 is assigned, where 1 represents best performance. Next step is aimed at deciding if selected indicators are adequate to assess each of five sub-indices, in terms of redundancy and comprehensiveness. To this end, a preliminary assessment of the

dataset is performed to statistically validate the composite. A Principal Component Analysis (PCA) is applied (*step 1c*) with the objective of combining the initial battery of 25 indicators into composite variables which explain the maximum possible proportion of the total variance of the set. This approach shows that 12 factors account for 81.1% of the overall variability, and that most of these principal components mix indicators belonging to different WPI sub-indices. Thus, in this case, PCA does not justify WPI framework, although it does not offer a better alternative either. The adequacy of the original structure is then confirmed in terms of transparency and relevance for the purpose of policy making.

After having undertaken a general preliminary evaluation, this process is repeated at sub-index level (*step 1d*). PCA proves to be helpful to reduce the initial set of 25 "correlated" indicators into a group of fewer, 17 "uncorrelated" components (see Table 2). Based on statistics obtained from these five independent analyses (R, A, C, U, E), sub-indices are described as the average of raw indicators that load most heavily on each principal component (*step 1e*).

The assignment of weights is the next step (*step 2a*) before final aggregation of five sub-indices. A multivariate analysis (PCA) is performed and the weighting system is therefore

Table 2 | Structure of the index and variables used

WPI Sub-index	No. of Indicators ^a	Indicators ^b			
Resources	3 (1)	 Water Quantity Sufficiency; Reliability of supply (% time not operational); Seasonal variability of water resources (months per year with water) 			
Access	6 (2)	 Access to improved waterpoints; Access to improved sanitation; One way distance to water source; Waiting time (minutes); Cost of water; Operational status of water source 			
Capacity	6 (3)	 Management system; Ownership over water source; Management issues of Water User Associations (Legal registration; Records kept; Financial control; Funds audited) 			
Use	5 (1)	 Domestic water consumption rate; Conflict over water sources (Human – Human); Conflict over water sources (Human – Livestock); Use of point-of- use water treatment; Livestock water use 			
Environment	5 (1)	 Qualitative assessment of water quality; Protection of water sources; Number of pollution sources around water sources; Number of environmental impacts around water sources; (Human – Wildlife) 			

built on the relative importance of the sub-indices for the principal components. The index is finally calculated at sub-location scale applying a weighted multiplicative function (*step 2b*). Numerically, revised WPI can be formulated as:

$$WPI = \prod_{i=R,A,C,U,E} X_i^{w_i} \tag{1}$$

where WPI is the value of the index for a particular location, X_i refers to component i (R, A, C, U, E) of the WPI structure for that location, and w_i is the weight applied to that component.

In the last stage, the index needs to be validated. A simple sensitivity analysis is conducted (*step 3a*) to test the robustness of the composite (Saisana *et al.* 2005). Such analysis improves the accuracy and interpretability of the final results, thus minimizing the risks of producing a meaningless tool. Correlation analysis is equally useful during validation to check for redundancy, since correlated variables cause double-counting and might bias the outcome (Hajkowicz 2006). It is gleaned from Figure 1 that poor correlation exists among five sub-indices and the final index (low regression coefficients). A revision of the Pearson's correlation (not shown here) confirms that variables are not redundant within them.

RESULTS AND DISCUSSION

This section attempts to analyze the concept of water poverty at the Turkana District. To do this, we highlight that an integrated indicator approach comes out useful and relevant. WPI provides an adequate tool for assisting policy makers in capturing a more comprehensive picture of sector constraints and challenges, thus allowing a more equitable allocation of water resources. However, the way the index is disseminated is essential for this purpose, as this might influence its interpretation. In consequence, we exploit different user-friendly alternatives in an effort to enhance visualization of the final product. The aim should be to provide clear messages and to communicate a picture to decision-makers quickly and accurately.

To begin, a water poverty map is developed at the lowest administrative scale to show at a glance the level of water poverty (Figure 2). Mapping involves the presentation of certain information in a spatial context, and this enables policy planners to identify the locations in which to focus their efforts for maximum impact (Henninger 1998). Poverty follows a highly heterogeneous pattern, widely varying between and within different geographic and administrative units (Davis 2002); and poverty mapping permits a feasible visualization of such heterogeneity. In addition, it provides a means for integrating data from different disciplines (Henninger & Snel 2002; Sullivan 2002), which is required to represent the broad themes included in the WPI framework. In the water-poverty context, maps have come out a powerful tool for identifying and targeting the most water poor, and therefore supporting poverty reduction initiatives (Cullis & O'Regan 2004).

In Figure 2, a single number represents the water situation at each sub-location. In case this value is used as a performance indicator, the index is able to identify strengths and weaknesses in the water sector at a particular location, as well as to discriminate between different locations (Sullivan

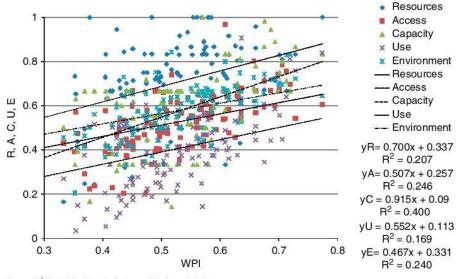


Figure 1 | The Water Poverty Index, and its five sub-indices.

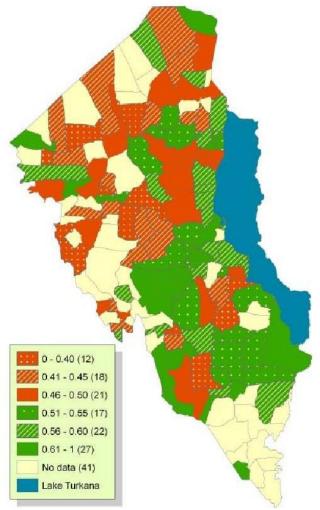


Figure 2 | The Water Poverty Index, at sub-location level. In brackets, number of sub-

& Meigh 2007). A straight comparison can be made in this regard when any location is compared for example to the leader, the laggard or the average performance.

In those cases where water management decisions are more focused on the issue of prioritization, a crucial factor is to determine who is the neediest. Then, final WPI values might serve as the basis to rank all locations and denote different priority, where the "lowest" priority is assigned to the least water poor location (i.e. the highest WPI value). It is gleaned from Figure 3 that 12 sub-locations are identified as areas of greatest needs, with index values lower than 0.4. Another remark from the histogram is that three sub-locations scored 0, since the geometric aggregation does not allow compensation in case null values in any sub-index. Despite being meaningless in terms of water poverty, this shows that

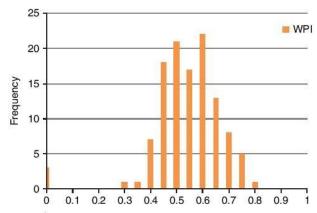


Figure 3 | Histogram of WPI values.

non-compensatory forms are adequate to identify the hot spots of the dataset.

Back to the details

The WPI provides a starting point for analysis. However, an accurate focus on the five sub-indices might help to identify the source of the problem in particular places and direct attention to those water sector needs that require special policy attention. The underlying complexities of the index thus need not be lost, and this is acknowledged by the authors (Lawrence *et al.* 2002; Sullivan 2002) who note that "the information is in the components rather than in the final single number".

Summary statistics for the index and its sub-indices are presented in Table 3, and histograms of these variables are shown in Figure 4. The results suggest that aspects requiring urgent intervention are those related to the "Access" and "Use" components. These two variables present a median value of 0.532 and 0.4 respectively, while three remaining sub-indices score considerably higher; i.e. "Capacity" (0.6), "Environment" (0.591), and "Resources" (0.723). Table 3 also shows coefficients of skewness and Kurtosis. It is noted that neither the index nor the sub-indices are Normally distributed. In particular, a focus on the sub-indices show that the "Resources", "Capacity" and "Environment" components follow a left-skewed distribution, i.e. the bulk of the values lie to the right of the mean. There is also a tendency for positive kurtosis in the datasets of "Resources", "Access" and "Capacity", while rest of sub-indices show a flatter, wider peak near the mean. On the other hand, high Kurtosis and skewness coefficients in the WPI dataset are only justified because of the three sub-locations with null values, otherwise it might be said that the index tend to a Normal distribution (see statistics for WPI').

Table 3 | Summary statistics of WPI and its sub-indices

	Resources	Access	Capacity	Use	Environment	WPI	WPI'
Median	0.723	0.532	0.600	0.400	0.591	0.517	0.526
IQR	(0.83-0.6)	(0.6-0.42)	(0.67-0.44)	(0.51-0.27)	(0.66-0.49)	(0.59-0.45)	(0.59-0.45)
Skewness	-0.864	0.084	-0.422	0.213	-0.303	-1.450	0.133
Kurtosis	0.876	0.654	0.527	0.041	-0.142	4.899	-0.464
Minimum	0	0.203	0	0.033	0.205	0	0.298
Maximum	1	0.966	1	0.905	0.841	0.774	0.774

Note: IQR = Interquartile range; WPI = Index assessed with data from 117 sub-locations; WPI' = Index assessed with data from 114 sub-locations

Complementary conclusions would be drawn by showing all five components in a spatial context, so a set of water poverty maps are developed at this level (Figure 5).

From the "Resources" map, it can be seen that high values occur where surface water is available (in areas located near main rivers). In contrast, achieved results fail to reflect the fact that the district is classified as arid. It should be noted in this regard that no more than two indicators were used to define this variable, thus better access to additional information sources would complete a more precise picture of conditions on the ground. Moreover, assessment of the qualitative variable "Water Quantity Sufficiency" was based on people's perception, and therefore failed to reflect national standards. From the "Access" map, and contrary to what might be expected, it is observed that adequate density of

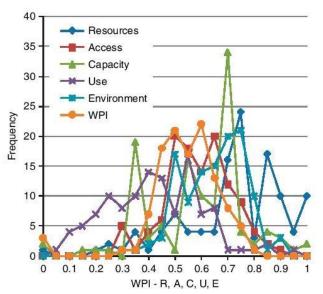


Figure 4 | Histogram of WPI and sub-indices values.

water sources (defined as number of waterpoints per 1,000 beneficiaries) is not sufficient to ensure high scores of this variable. As a result, it is evident that indicators such as "cost of water" or "access to sanitation" also play a key role. According to the "Capacity" map, one might conclude that institutional framework to support communities to manage water facilities is far from being adequate. In fact, few water entities are legally registered, and if registered, they are not able to assume their commitment (in terms of revenue collection, financial control, keeping records ...). It can also be seen that this variable slightly improves in those sublocations where main towns or trading centers are located. Domestic water consumption is generally poor, and this is visualized in the "Use" map. Based on available data, more than 50% of population consumes less than 20 l.p.d. (minimum established by WHO) in 83 out of 99 sub-locations. Finally, the "Environment" map shows that apparently water quality does not appear to be a major problem, though it should be highlighted that information was based on qualitative questionnaires and not on biochemical analysis.

Analysis at different administrative scales

In policy making, it is essential that any assessment tool be applied at the appropriate scale to avoid misleading results. Certainly, the extent to which indices will accurately assess impact of development policies depends on the scales at which they are applied. For example, an index at the regional level may say nothing about local variations; and improvements in access and availability to water at household level might be masked by indices which operate at inappropriate scales.

In an attempt to provide some discussion on the scale issue, a set of water poverty maps have been developed at different administrative levels (Figure 6), by scaling available data from sub-location up to location and division.

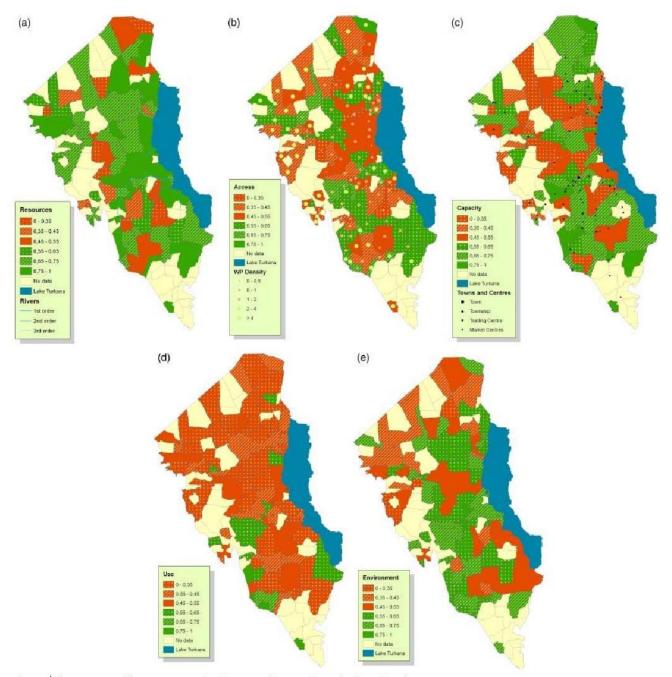


Figure 5 | Five components of the Water Poverty Index: (a) Resources; (b) Access; (c) Capacity; (d) Use; (e) Environment.

It can be seen from the maps that when the data is displayed at the division scale, one large area is identified as the most water poor area, while if finer resolution data is used (i.e. at sub-location scale), a much clearer picture emerges of the location of the water poor. For example, the area targeted if attempting to identify the poor (i.e. WPI < 0.5)

at division level represents 44% of total district area, and same percentage at sub-location scale is 37%. Therefore, if decision-making focuses on high resolution maps, not only area of intervention decreases; but a large number of water poor areas are also captured that otherwise go undetected when targeting at rest of scales. One might conclude that

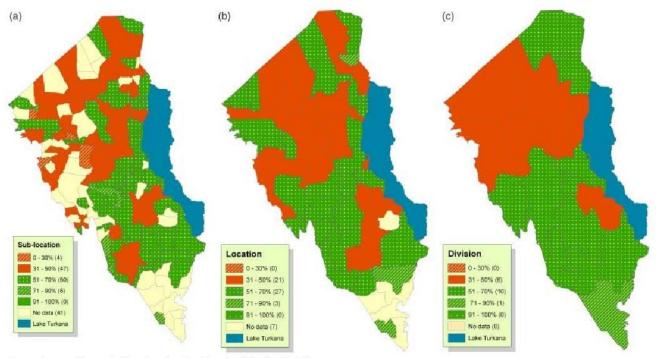


Figure 6 | WPI at different administrative scales: (a) sub-location; (b) location; (c) division.

water poverty maps should be developed at as finest resolution as possible, which requires a balance between logistics and cost with respect to goals.

Finally, the problem of missing data is highlighted in scaling up processes. Due to inaccessibility and insecurity in parts of the district some water sources were not audited, which resulted in various sub-locations being not covered (percentage of population excluded of analysis was roughly 20%). In this study, if data was missing no additional field work was planned. Therefore, data of adjacent sub-locations was considered in up-scaling. From Figure 6, it is gleaned that data from one single sub-location generates the least water poor area at division scale, resulting in a misleading outcome.

Clusters of variables

In previous analysis, the approach adopted for indentifying the neediest communities has focused on the aggregated WPI. It has been stated that this approach yield reasonable classification, albeit at the cost of resolution. The more indicators are aggregated, the more information is lost, and a complementary analysis at sub-index level is needed to describe underlying complexities of water issues. From a policy maker's point of view, it has also been highlighted that the local scale is the most relevant, although in this study this

would require to simultaneously deal with data from a large number of sub-locations.

The use of cluster analysis might come out an appropriate solution to identify groupings of relevant peer sub-locations through a multidimensional approach, whereby WPI subindices can be included and simultaneously considered. A cluster technique is therefore employed in this section to define "comparable" sub-locations and classify them into manageable sets (i.e. clusters), by exploiting their similarity on the index variables. We use the k-means clustering method, which divides the sample in k clusters of greatest possible distinction (in this study, 5 clusters). The algorithm computes the similarity between sub-locations in the dataset, with the aim of (i) minimize the variance of elements within the clusters, and (ii) maximize the variance of the elements outside the clusters (Nardo et al. 2005). Although this is a common method in development planning (Tang & Salvador 1986; Berlage & Terweduwe 1988; Esty et al. 2005), this does not mean that cluster analysis is a panacea. In terms of methodology, the arbitrary decision about the number of clusters employed is subject to criticism (Gelbard et al. 2009). In this study, the goal is to provide a classification of sub-locations that can be used as a basis for planning, so that key criteria to determine number of peer groups were related to the cluster size, in terms of number of sub-locations included and total population (e.g. a cluster with less than 10 sub-locations was not accepted). In this respect, with 4 clusters, one single peer group would represent nearly half of total population; while in the analysis of 6 clusters, one group would only include 3 sub-locations.

A spider diagram is displayed in Figure 7 to summarize the differences in the means between clusters, which are presented in Table 4. Figure 8 shows geographical distribution of sub-locations within clusters. To understand particularities of these five groups allows policy planners to identify target groups and determine specific and more coherent strategies, which in terms of poverty reduction and allocation of resources is more efficient and cost-effective than to launch an equally expensive universal distribution program (Cullis & O'Regan 2004).

It is shown for example that first cluster (which includes 33 sub-locations, 84.617 people) scores best in "Resources", and achieves good marks for the other four components. The level of water poverty is thus low. Cluster 2 corresponds to sub-locations (37; 72.299 people) in which usage of water is inadequate, access to basic services remains low, and water sources are not properly protected from potential pollutant sources. Sanitation campaigns should thus be first promoted to improve hygienic practices and to change behaviors, mainly aiming to raise awareness among the population of the importance to increase domestic water consumption. Furthermore, water sources need to be protected to prevent water from being contaminated, and programs to construct new infrastructure should be launched to improve coverage. Sub-locations included in Cluster 3 (14; 34.568 people) are characterized by facing acute water scarcity, though they lack capacities to manage water facilities, water use is poor and environmental impact on resources is considerable. Conse-

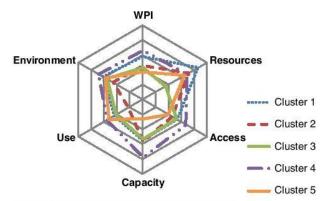


Figure 7 Diagram of WPI components for five cluster classes.

quently, the level of water poverty is remarkable. First intervention should be directed to increase water reservoir availability. In parallel, capacity building of water entities need to be ensured. And equal to Cluster 2, hygiene promotion should be fostered, while awareness of the importance to protect water sources increased in the communities. Cluster 4 (21 sub-locations; 126.481 people) performs notably better, being the least water poor. Only the "use" component needs to be improved, since water consumption remains inadequate, though scoring the highest. Finally, cluster 5 (12 sublocations: 37.887 people) score the lowest WPI values and thus represent the highest degree of water poverty. This group scores badly with respect to "Capacity" and "Access". The direction to be adopted in sub-locations included in this group should be that all water sector actors at local level conduct capacity building through appropriate training, so as to enable water entities to manage the schemes. Additionally, access to water and sanitation needs to be improved by increasing coverage.

Table 4 | Final cluster centers

30_	1 st Cluster	2 nd Cluster	3 rd Cluster	4 th Cluster	5 th Cluster
No. Sub-locations	33	37	14	21	12
Population	84.617	79.299	34.568	126.481	37.887
WPI	0.578	0.453	0.428	0.663	0.373
Resources	0.857	0.711	0.347	0.689	0.647
Access	0.531	0.460	0.523	0.673	0.392
Capacity	0.546	0.565	0.527	0.775	0.256
Use	0.440	0.223	0.419	0.555	0.528
Environment	0.618	0.463	0.559	0.690	0.587

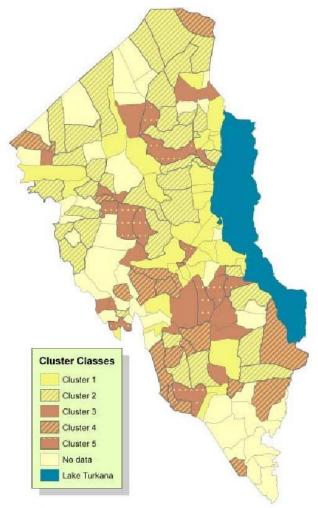


Figure 8 | Map of cluster classes.

CONCLUSIONS

The water management challenge is to deliver water in sufficient quantity and adequate quality to people who still are not properly served, without exacerbating pressure on the environment. In order to do this effectively, equitable allocation of water resources is essential. For the purpose of assessing development needs and assisting water managers in the difficult task of prioritization, we highlight the usefulness and relevance of an integrated indicator approach.

In particular, the WPI combines biophysical, social, economic and environmental information to produce an aggregated indicator, and resulting data-framework comes out adequate to capture a more comprehensive picture of the complexities of water issues. However, it is noted that the usefulness of this approach may not lie in index final values, but rather in the sub-indices themselves. WPI variables thus need to be examined individually, as this provides a means of understanding the links between poverty, resource accessibility and institutional capacity.

The selection of a suitable alternative to present and disseminate the composite is not trivial, and deserves special attention. In this paper we show that water poverty maps provide adequate guidance about where and which investments are most likely to have a positive impact. Water poverty is highly heterogeneous phenomena; and since mapping permits the spatial identification of the poor, they are powerful instruments for allotting efforts and resources more equitably. However, maps should be developed at a suitable scale; i.e. where sector policies and development will be most effective. In this study, results show that the efficiency of poverty mapping improves as the resolution becomes finer, as more precision is gained for identifying the poor.

On the other hand, and for the purpose of policy making, to simultaneously deal with data from a large number of sublocations might hinder the application of the index. Against this background, the use of cluster analysis might come out an appropriate solution to classify all sub-locations into manageable sets. An accurate focus on the particularities of each cluster allows decision-makers to identify target groups, thus providing a good place to start in the search for best practices to tackle those water sector needs that require urgent policy attention.

In sum, the WPI approach provides an adequate policy tool for project planning, performance monitoring, and resource allocation. Yet, if simplicity is its main appeal, it must be recalled that much like many other approaches that attempt to describe a complex reality, integrated indicators present some limitations. This paper attempts to deal with three of these shortcomings: (i) inadequate and limited analysis of index variables, (ii) poor dissemination of final outcome, and (iii) lack of a method to group a large set of enumerator areas (in this study, sub-locations) whereby different variables (i.e. WPI sub-indices) need to be simultaneously considered.

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REFERENCES

- Al-Hmoud, R. B. & Edwards, J. 2005 Water poverty and private investment in the water and sanitation sector. Water International 30(3), 350–355.
- Berlage, L. & Terweduwe, D. 1988 The classification of countries by cluster and by factor analysis. World Development 16(12), 1527–1545.
- Cho, D., Ogwang, T. & Opio, C. 2010 Simplifying the Water Poverty Index. Soc. Indic. Res. 97(2), 257–267.
- Cullis, J. & O'Regan, D. 2004 Targeting the water-poor through water poverty mapping. Water Policy 6, 397–411.
- Davis, B. 2002 Is it possible to avoid a lemon? Reflections on choosing a poverty mapping method. Food and Agricultural Organization of the United Nations, Rome.
- Esty, D. C., Levy, M., Srebotnjak, T. & de Sherbinin, A. 2005 2005 Environmental Sustainability Index: Benchmarking National Environmental Stewardship. Yale Center for Environmental Law & Policy, New Haven.
- Feitelson, E. & Chenoweth, J. 2002 Water poverty: towards a meaningful indicator. Water Policy 4(3), 263–281.
- Gelbard, R., Carmeli, A., Bittmann, R. M. & Ronen S. 2009 Cluster analysis using multi-algorithm voting in cross-cultural studies. Expert Systems with Applications 36(7), 10438–10446.
- Giné, R. & Pérez-Foguet, A. 2010 Improved method to calculate a Water Poverty Index at local scale. *Journal of Environmental Engineering* In press.
- Government of Kenya 2007 National Policy for the Sustainable Development of Arid and Semi Arid Lands of Kenya. Office of the President, Government of Kenya, Nairobi.
- Hajkowicz, S. 2006 Multi-attributed environmental index construction. Ecological Economics 57(1), 122–139.
- Heidecke, C. 2006 Development and Evaluation of a Regional Water Poverty Index for Benin. In: EPT Discussion Paper. International Food Policy Research Institute, Washington, DC.
- Henninger, N. 1998 Mapping and Geographic Analysis of Human Welfare and Poverty: Review and Assessment. World Resources Institute, Washington, D.C.
- Henninger, N. & Snel, M. 2002 Where are the poor? Experiences with the development and use of poverty maps. World Resources Institute, Washington, D.C.
- Jiménez, A., Molinero, J. & Pérez-Foguet, A. 2008 Monitoring Water Poverty: A vision from development practitioners. In: Llamas LMC, M. R. & Mukherji, A. (eds) Water Ethics: Marcelino Botin Water Forum 2007. Taylor & Francis.

- Joint Monitoring Programme 2000 Global Water Supply and Sanitation Assessment Report 2000. Joint Monitoring Programme for Water Supply and Sanitation, WHO/UNICEF Geneva/New York.
- Komnenic, V., Ahlers, R. & Zaag, Pvd. 2009 Assessing the usefulness of the water poverty index by applying it to a special case: Can one be water poor with high levels of access? *Physics and Chemistry of* the Earth, Parts A/B/C 34(4–5), 219–224.
- Lawrence, P., Meigh, J. & Sullivan, C. 2002 The Water Poverty Index: an International Comparison. Keele Economics Research Papers. Keele University, Staffordshire.
- Molle, F. & Mollinga, P. 2003 Water Poverty Indicators: conceptual problems and policy issues. Water Policy 5(5), 529–544.
- Munda, G. & Nardo, M. 2005 Non-Compensatory Composite Indicators for Ranking Countries: A Defensible Setting. Joint Research Centre European Commission, Ispra.
- Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A. & Giovannini, E. 2005 Handbook on Constructing Composite Indicators: Methodology and User Guide. In: OECD Statistics Working Paper. OECD, Paris.
- Odada, E. O., Olago, D. O., Bugenyi, F., Kulindwa, K., Karimumuryango, J., West, K., Ntiba, M., Wandiga, S., Aloo-Obudho, P. & Achola, P. 2003 Environmental assessment of the East African Rift Valley lakes. Aquat. Sci. 65(3), 254–271.
- Saisana, M., Saltelli, A. & Tarantola, S. 2005 Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. J. R. Stat. Soc. Ser. A-Stat. Soc. 168, 307–323.
- Sullivan, C. 2002 Calculating a Water Poverty Index. World Development 30(7), 1195–1210.
- Sullivan, C. & Meigh, J. 2003 Considering the Water Poverty Index in the context of poverty alleviation. Water Policy 5, 513–528.
- Sullivan, C. & Meigh, J. 2007 Integration of the biophysical and social sciences using an indicator approach: Addressing water problems at different scales. Water Resources Management 21(1), 111–128.
- Sullivan, C., Meigh, J. & Lawrence, P. 2006 Application of the Water Poverty Index at Different Scales: A Cautionary Tale. Water International 31(3), 412-426.
- Sullivan, C. A., Meigh, J. R., Giacomello, A. M., Fediw, T., Lawrence, P., Samad, M., Mlote, S., Hutton, C., Allan, J. A., Schulze, R. E., Dlamini, D. J. M., Cosgrove, W., Priscoli, J. D., Gleick, P., Smout, I., Cobbing, J., Calow, R., Hunt, C., Hussain, A., Acreman, M. C., King, J., Malomo, S., Tate, E. L., O'Regan, D., Milner, S. & Steyl, I. 2003 The water poverty index: Development and application at the community scale. *Natural Resources Forum* 27(3), 189–199.
- Tang, J. C. S. & Salvador, P. A. 1986 Classification of countries for international development planning using cluster analysis. Socio-Economic Planning Sciences 20(4), 237–241.
- United Nations Children's Fund 2006 Water, schools and health Management Information System (MIS) for Turkana District. Final Report. In: UNICEF - Kenya Country Office, Nairobi.