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A MULTIDIMENSIONAL ANALYSIS OF WATER POVERTY AT A LOCAL SCALE: APPLICATION OF IMPROVED WATER POVERTY INDEX FOR TUNISIA

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Abstract

Combining the measure of water availability and the socioeconomic capacity to access to it gives new insights in the fields of water resources management and poverty alleviation. This approach lets researchers think about a new multidimensional water scarcity indexes as applied to the definition of the Water Poverty Index (WPI) by Sullivan (2002) in "Calculating a Water Poverty Index". In the methodology initiated by Sullivan and Lawrence (2002) water for the calculation of the WPI was based on equally weighted average for its five components (Resources, Capacity, Access, Use, and Environment) to produce a single components Indexes scores. The main objective of this paper is to improve this procedure by using an objective weighting scheme. For this purpose we use a principal component analysis to give more weight to components with larger variance and to discard components with smaller ones. This improved WPI is applied, thanks to a rich data set collected by our own efforts, to the case of Tunisia. We have obtained high-quality results which could help policy makers to devise better policies to alleviate water poverty in the Inland region which was the bed of the Tunisian revolution beginning.

JEL Classifications: C43, Q25

Keywords: Water Poverty index, PCA, Tunisia, water resources, poverty alleviation.

ملخص

الجمع بين مقياس توافر المياه والقدرة الاقتصادية والاجتماعية للوصول إلى المياة يعطى رؤى جديدة في مجالات إدارة الموارد المائية والتخفيف من حدة الفقر. هذا النهج يتيح للباحثون التفكير فى فهارس جديدة متعددة الأبعاد حول ندرة المياه كما ينطبق على تعريف مؤشر الفقر للمياه (WPI) من قبل سوليفان (2002) في "حساب مؤشر الفقر المائي". تقوم المنهجية التى بدأها سوليفان ولورانس (2002) لحساب WPI على المتوسط المرجح على قدم المساواة لمكونات خمسة (الموارد والقدرات والوصول، والاستخدام والبيئة) لإنتاج فهرس موحد المكونات. والهدف الرئيسي من هذه الورقة هو تحسين هذا الإجراء باستخدام نظام ترجيح الهدف. لهذا الغرض نستخدم العنصر الرئيسي في التحليل لإعطاء وزنا أكبر لمكونات التباين وتجاهل المكونات الأصغر. يتم تطبيق المؤشر المعدل من WPI إلى حالة تونس ، وذلك بفضل مجموعة غنية من البيانات والتي تم جمعها من قبل جهودنا الذاتية. لقد حصلنا على نتائج عالية الجودة والتي يمكن أن تساعد واضعي السياسات على وضع سياسات أفضل للتخفيف من حدة الفقر المائي في المنطقة الداخلية التي كانت مهد بداية الثورة التونسية.

1. Introduction

Combining the measure of water availability and the socioeconomic capacity to access to it gives new insights in the fields of water resources management and poverty alleviation. MikaïlDésamorcer (2007)shows that water shortage is rather a question of means than of resource availability. The reality that large populations of some water rich countries have no access to fresh water and sanitation while dry regions, with high standard of living, benefit from very good water services (Kuwait, Qatar, Emirates, or the huge Los Angeles agglomeration) is an illustrative example. Hence, a water resources management modeling, which ignores the explicit integration of the economic and environmental factors, will leadto failure. Intensive research has been conducted during the last decade to fill this gap. This literature was essentially concerned with the construction of the Water Poverty Index (WPI) and its application to several countries.

The WPI is based on five components: Resources, Access, Capacity, Use and Environment as argued byLawrence (2002). It can be used then through its individual figures or in the form of its components as an inter-disciplinary and monitoring tool that expresses precisely the water situation in various areas. Sullivan (2003) suggested that the WPI is applicable at a range of scales. It has since been applied at an international scale byLawrence (2002),at a water and community scale byHeidecke (2006) and discussed in several papers Molle (2003), Rijsberman (2006), Shah (2006)and recently improved by Manandhar (2011) andPérez (2011) .

The main objective of this study was twofold:

- Firstly we have tried to improve the theoretical and statistical calculation of the WPI and its components. While we use, here, the methodology initiated by Sullivan and Lawrence for the calculation of the WPI based on equally weighted average to produce single components Indexes scores, we will refine this procedure by using an objective weighting scheme. For this purpose we use a principal component analysis to give more weight to components with larger variance and to discard components with very smaller variance. It can be argued that this technique gives a mathematical solution for the problem of arbitrary choice of weighting scheme by considering determined characteristic vectors of the correlation matrix of the original variables as weights. PCA can also be used for objective selection of a smaller set of uncorrelated variables among a wider range of initial variables, accounting for most of the variation in the data set of multivariate(Morrison1967 ;Dunteman1989). To reduce the cost of information collecting and to get a smaller number of sub-indexes in the construction of WPI, which is obviously the main purpose of the present study, we use the PCA method B4, recommended by Jolliffe (1972).
- Secondly we have conducted an application, thanks to a rich data base collected by our own efforts, for the case of Tunisia. Our results show us clearly that the Inland region, which is naturally well endowed with water resources, is characterized by very low WPI, while the coastal governorates, naturally water stressed, have high scores of WPI. These results, issued from the Revolution, which started in the poor Inland governorates, will help future Tunisian policy makers, to correct those inequalities by promoting a better water access essentially to the inland rural populations.

The remainder of the paper is structured as follows: in Section 2, the classical approach of water scarcity assessment is briefly described and compared to the multidimensional one. The water poverty linkages are depicted in the following section (Section 3). While Section 4 is devoted entirely to the improved water poverty index methodology. We will provide also, in this section, a brief overview of data used in the empirical investigations. The analysis of empirical results and water poverty mapping are presented in Section4. The last Section presents conclusions and some policy recommendations.

2. Review of Existing Water Scarcity Indices

During the last two decades, numerous unidimensionnels indices, based particulary on Human Water Requirements and Water Resources Vulnerability have been developed to quantitatively assess water stress Brown (2011). Nevertheless, the main weakness of these indices is the difficulties of integrating all aspects which characterize water resources (availability, use, supply, scarcity, network, etc). To address this problem, methodology used for calculating water scarcity indices has evolved remarkably in the last decades. In 1989, Falkenmark proposed his first water scarcity indicator defined as the fraction of the total annual runoff available for human use. Based on three thresholds, the water conditions in any area can be categorized as: no stress, stress, scarcity, and absolute scarcity as noted in the following Table.

In spite of its global acceptance in assessments on international scale, the Falkenmark index was used to characterize water situation at a smaller scale where the data is available. But, this indicator, as other unidimensionals indices, has enormous shortcomings. On the one hand, only physical water scarcity is considered; the water quality information and country's ability to use the resources are omitted. On the other hand, the water availability per person is assessed as an average with neglect of both temporal and spatial variability in certain regions within a country.

Recognizing that water use is more important than water availability, Gleick (1996) developed an improved water scarcity index by including specific and basic Human Water Requirements (BWR) such as drinking, cooking, bathing, sanitation and hygiene [1]. But this indicator has not been applied on a regional scale; it has only been used at the country-level. The Gleickapproach has also been criticized for neglecting water quality, industrial and agriculture uses. In fact, the domestic water use data are insufficient and unreliable, thus other water users, such as industry, agriculture or nature itself, need to be included in the assessment of water poverty.

In response to the critics above, Meigh (1999) took in the GWAVA (Global Water Availability Assessment) model, the temporal variability of water supply into account. Moreover, the Meigh's index includes surface water as well as groundwater resources, and compares the total amount to the domestic, industrial and agricultural demands.

Ohlsson (2000) integrated, for the first time, the new concept ``adaptive capacity'' founded on how economic, technological, or other factors affect the overall freshwater availability status of a region. Ohlsson argued that the capability of a society to adapt to difficult scenarios depends on the distribution of wealth, education opportunities, political participation and others factors.

Since the main contribution of Sullivan (2002), the concept of Water poverty index has known many theoretical developments as well as several applications at international and regional scales. The WPI is a holistic tool, built on Sen's thought, designed to capture the linkages between issues related to water resources availability and human and ecological needs (Sullivan2003;Sullivan2005;Lawrence200;Mlote2002). Both water resource managers and policy makers can take advantage of this composite index to analyze the links between poverty, social deprivation, environmental integrity, water availability and health (Sullivan2002).

[1]In his approach, Gleick (1996) quantified the total of proposed water requirements for meeting basic human needs as 50 liters per person per day.

Sullivan (2002) enumerated four possible methods for the calculation of WPI: time analysis approach, gap method, matrix approach and composite index approach. In this paper, we will focus on the last one; which is based on identifying the physical, socioeconomic and ecologic dimensions of water poverty. The WPI is calculated then as an equally weighted average of these dimensions.

Initially, Sullivan (2002) considered the WPI formula as follows (Eq.1):

$$WPI_s = \frac{1}{3}(w_a A + w_s S + w_t(100 - T)) \qquad (1)$$

where *A* is the adjusted water availability (AWA) assessment including the surface water and groundwater resources as percentage, while *S* is the proportion of the population with access to safe water and sanitation, *T* is the index (between 0 and 100) to represent time and effort taken to collect domestic water and w_a, w_s, w_t are the weights given to each component of the index (so that the sum of weights is equal to 1). All the three components are range between 0 and 100 and to obtain the value of WPI between 0 and 100 the sum of component is divided by three.

Lawrence (2002) in his application has modified the structure of the indice to get a more comprehensive and simple composite index with five components: Resources, Capacity, Access, Use, and Environment (see the following equation Eq.??).

$$WPI_{cl} = \beta_R \times RES + \beta_C \times CAP + \beta_A \times ACC + \beta_U \times USE + \beta_E \times ENV \qquad (2)$$

where RES, CAP, ACC, USA and ENV denote respectively the five components fore-mentioned; and $\beta_R = \beta_C = \beta_A = \beta_U = \beta_E = 0.2$ their weights. Since all the components are expressed on a scale from 0 to 100 with higher values indicating a better water situation, WPI_{cl} ranges from 0 to 100. The same formula of the WPI was recently adapted by Heidecke (2006), Komnenic(2009) and Manandhar (2011) to develop composite WPI for different scales.

In spite of agreement on the relevance and the usefulness of the index and the recognition of the multidimensional nature of water poverty, the computation of the WPI, like that of any other composite index, is fraught with conceptual and practical weaknesses. This research will try to overcome some of them.

Feitelson(2002),Sullivan(2002),Molle(2003), Jiménez (2009) and Giné (2009) discuss various issues in the construction and uses of the WPI. Some criticsconcerns are how the basic input data are selected and combined andthe statistical properties of the index. Dealing with data, the ad hoc variables selection is subject to criticism. As noted by Booysen (2008) using the availability and accuracy of data can guide by itself the selection of variables mainly in data-scarce contexts. It must be said that WPI is closed to the existing data, rather to the data needs identified regardless availability Sullivan (2003). The WPI has also proved to be inadequate for evaluating the complexity of water problems, Sullivan (2002) and Lawrence (2002)[2] themselves argue that the index has some issues concerning defining and including physical water availability, water quality, ecological water demand and institutional impacts of water shortage. They have noted also that the information is in the five components (Resources, Capacity, Access, Use and Environment) rather than in the final aggregate index.

In the same vein, the WPI has also been criticized for its inability to reveal some details that a single variable alone can offer such as the water supply fluctuations and water allocation

[2] The first users of the Water Poverty Index

issues among users.Gleick (2002) andShah (2006)noted in this regard that the main indicator of water poverty is the access component of the WPI.

The weighting and aggregation methods are another major drawbacks that affect the statistical proprieties and interpretability of final values of the indice (Munda2005). The undefined weights accorded to the components of the WPI are subject to individual judgments (Feitelson2002), even when the equal average weighting is inadequately explained. Similarly, Molle (2003) criticized the WPI for assigning arbitrary weights to disparate and correlated components. Thus a transparent display of determined weights is highly recommended to avoid misinterpretation (Heidecke2006). To this end, a multivariate analysis has been used in order to determine the correct weighting scheme and to avoid the problem of multicollinearity between variables (Cho2010;Pérez2011). Furthermore, Munda (2005) stated that additive aggregation necessarily implies full compensability, which is often not desirable, among the various components of the WPI. Additive aggregation induces necessarily the fact that high values of some components can sufficiently offset the poor performance of others.

In sum, the significance of the WPI and its usefulness as a meaningful policy tool tend to be spoilt by these fore-mentioned shortcomings. That's why we propose in this paper some improvements to avoid these drawbacks and to get a meaningful, robust and enhanced WPI.

3. Water and Poverty Linkages

Recently, there is an increasing agreement that water is strongly related to poverty. However, these linkages are too complex to be depicted and analyzed; their nature and direction are unclear (Meigh1999). On the one hand, many assume that water has a positive effect on socio-economic development. Adopting this view, the massive investment in water infrastructure and promotion of water governance can make a contribution to both absolute and chronic poverty alleviation in developing countries by supporting such broad purposes as economic growth, rural and agricultural development and national food security. On the other hand, a contradictory view holds that in spite of these positive outcomes, water resources development can be considered directly or indirectly unsustainable and destructive to the environment.

Despite the divergence of these two extreme views, there's an agreement that water resources play a vital role, either positively or negatively. Water can contribute to domestic welfare, agricultural production, industry and conservation of the environment, while it can brings water-borne diseases such as malaria and other dangerous diseases and causes a land degradation through water logging and salinization.

In addition to these views, Savenije (2000) assumes that the lack of water for agricultural production is due principally to the physical limitation of water resources, while the lack of water for domestic purposes is, in most of the cases, linked to social, political and economic problems a community or country faces. These problems could be the main cause of low or lack of access to safe water which results directly or indirectly in decreasing human productivity. This closed loop nexus between poverty and shortage of water is often neglected in world wide discussions on poverty eradication. The new concept of ``water poverty'' offers a new dimension to clarify this neglected connection. Adopting the Saveiji's view, Salameh (2000) argues that water poverty can be defined as insufficiency of existing water resources for domestic use and food production to meet domestic and production needs and occurs when the water demand is less than the availability for the population of a certain area. In his definition, Salameh (2000) does not account for the social causes of water shortage.

4. Improved Water Poverty Index Methodology

Based on thestudies of Sullivan (2001) and Sullivan (2003), our approach aims to realize an integrated assessment of resources availability, socio-economic characteristics and ecological dimensions of water poverty. A battery of indicators (fourteen indicators) were selected and sorted into five components as summarized in the following Table2.

In the normalization step, various methods are developed so far; we selected, in this study, the most simplest and commonly used, the minimum-maximum method [3] to collate indicators into a standard comparable scale from 0 to 100 (Sullivan2003; Sullivan2005; Sullivan2007; Van2010). Generally, for each indicators, specific thresholds (or benchmarks) were used as maximum and minimum values.

4.1 IWPI components

The WPI framework adopted here, as cited above, consists of five components and 14 indicators. Their conceptual description, calculation and normalization is developed as follows.

Resources

The Resource component concerns the physical availability of water resources in the chosen study area (Tunisia). A higher value of this component reflects a better water situation[4] (i.e abundant water resources with less variability). It combines four indicators divided into two sets; three indicators (RES1, RES2 and RES3) assessing respectively surface water availability[5], phreatic groundwater availability, deep groundwater availability and one indicator measuring the variability of rainfall (RES4). In order to indicate the population pressure over available water resources, particulary the groundwater resources, the indicators RES2 and RES3 [6] were measured on per capita basis (Ohlsson2000;Sullivan2001). Indicating a better water situation when they reached high values, the first three indicators of this component i.e. the availability indicators were normalized using min-max approach as shown in Eq.3 :

$$RESj = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \quad (3)$$

where RESj is availability indicators (j = 1, 2 and 3), X_{min} and X_{max} are maximum and minimum values of considered variables (see Table2). The last indicator in the Resources component is the variability index (RES4) which measures spatial and temporal variation of water resources; due to lack of groundwater data, the coefficient of variation (CV) of rainfall can be used as a proxy for that variability indicator (Babel2009;Van2010;Manandhar2011). A higher value of CV imply higher variability of water resources which may also reflect higher climate induced risks and vulnerability of resources (Alessa2008;Hamouda2009). We stated that the CV greater than or equal to 40% means a most vulnerable situation (Manandhar2011). Thus, this variable is normalized as proposed by (Van2010) using the following Eq.4:

[3] Abbreviated usually as min-max

[4] And vice versa

[5] In the study area, per capita annual surface water resources data were not available at administrative boundaries (i.e., governorate level), whichis the reason thata rainfall variable is used as proxy measure of this important indicator of the Resources component. This variable, though may not give an accurate measurement, can still be useful for estimating water resources in scarce-data context (Heidecke2006).

[6] The rainfall indicator isn't calculated on per capita basis as precipitation is generally measured in millimeters.

$$RES4 = (1 - \frac{X_i}{0.4}) \times 100 \quad (4)$$

where X_i is the coefficient of the variation of rainfall of the i^{th} governorate. To obtain a reliable indicator of variability, the CV is calculated for each governorate using more than 25 years of annual average rainfall data from selected meteorological stations.

Capacity

The Capacity component comprises a set of socio-economic indicators which can exhibit the effectiveness of people's ability to supply and manage water and sanitation services. Appelgren (1999) has emphasized the importance of such social and economic capabilities to managing water scarcity. The first indicator of this component, related to human welfare and quality of life, measures the economic capacity through the average per capita expenditure which is a simple and available variable.

Higher value of this indicator means higher economic capacity to get sufficient safe water, to access regularly water resources and technology and to cope with water related stresses (Appelgren1999;Adger2004). It is normalized, like the availability indicator, as follows (see Eq.5):

$$CAP1 = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \quad (5)$$

where CAP1 is value of the indicator ranging from 0 to 100 , X_i, X_{min} and X_{max} are respectively the current, minimum and maximum values of the considered variable. The remaining indicators of this component (Employment(CAP2), Education (CAP3) and Health (CAP4)) aimed to assess the social capacity that allows people to become aware of access to respectively improved water, sanitation, health and environment (Sullivan2003). As the parameters, expressed in percentage, unemployment and illiteracy rates are negatively correlated with the WPI i.e high values of these variables means that the region is in a worse situation, they are normalized as follows (Eq.6):

$$CAPj = 100 - X_i^j \quad (6)$$

X_i^2 is the unemployment rate (%) and X_i^3 is the illiteracy rate (%).

The last indicator of the social capacity gauges the ability of the governorate to provide quality services for patients in hospitals. This variable is normalized to comparable range 0-100 as follows (see Eq.6):

$$CAP4 = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \quad (7)$$

Where X_i is the number of beds per capita and X_{max} , X_{min} are the minimum and maximum values of the variable.

Access

Regular and adequate access to improved drinking water encourages necessarily better hygiene and sanitation conditions (Curtis2000) but is not sufficient to counter extreme poverty (Sullivan2003). Contrariwise, inadequate access to safe water will eventually lead to loss of time spent collecting water that could be used for productive activities.

Due to lack of data related to Access, this component includes only the access to water supply coverage indicator [7] which considers population with reasonable access to an adequate amount of safe drinking water for better health and well being (Sullivan2003;Sullivan2007;Hamouda2009). The access variable is expressed in percentage so we don't need a normalization to transform it in standardized form.

Use

The Use component is aimed to capture the use people make of water resources and its contribution to the wider economy because water use is a basic pre-requisite to various human activities and tends to increase with economic development (Sullivan2001). It combines the domestic and agricultural indicators, which are the main water uses in the study area. The domestic water use per capita (USE1) indicates the current level of water use in daily household activities like cooking, hygienic purposes and others (Howard2003) and reflects its future prospects (Sullivan2003;Cullis2004;Hamouda2009). Any difficulties of provision of safe water used domestically may cause a significant loss of time and effort in water collection. It is assessed by water use per capita per day and normalized as shown in Eq.8 using the same min-max approach used in previous indicators.

$$USE1 = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \qquad (8)$$

Where the X_{min} is the minimum water requirement taken as a reasonable threshold of 20 liters-per-capita-per-day (lpcd) (WHO/UNICEF 2000) and X_{max}, taken as 100 lpcd indicates, is the maximum water use that fulfills all water requirements (Howard2003). Governorates below the minimum have a lower value (USE1 = 0) and governorates above the maximum have a higher value (USE1 = 100).

The second indicator to calculate the Use component is the agricultural water use (USE2); It reveals the irrigation facilities available in each governorate. There is evidence that development of irrigated agriculture improves agricultural production, stabilizes income and improves employment opportunities by reducing the natural risk of agricultural activities and contributing in livelihood improvement (Han2005;Saleth2003;Sullivan2003;Namara2010).

The indicator used to assess this agricultural water use is the ratio of irrigated land to total area used for agriculture[8] (expressed in percentage) (Sullivan2003). A lower and higher value reflects respectively lack and sufficient water for irrigation.

Environment

Finally, the Environment component comprised a number of indicators which not only cover water quality (ENV1) but also variables linked to ecological integrity such as the sanitation coverage rate (ENV2) and the number of environmental studies (ENV3). The water quality is assessed by the use of bacteriological analysis of drinking water; it's equal to the rate of fit cases after analysis. The second indicator (ENV2) is calculated by multiplying the total sanitation coverage by the urbanization rate. Sanitation services such as wastewater disposal and stormwater drainage are essential not only for healthy living but also for clean environment and improved water resources.

The last indicator (ENV3), which is normalized as the economic capacity (Eq.5), reflects a general concern of the government for environmental issues in each governorate.

[7] Based on definition provided by the Joint Monitoring Programme (2000)

[8] The most widely indicator of agricultural water use was the ratio of irrigated land to irrigable land (land suitable for irrigation). In our application, we have remarked that data of irrigable land did not reflect the true reality; thus we have decided to replace it with total land useful for agriculture.

4.2 Multivariate analysis

Principal component analysis (PCA) is a traditional multivariate statistical method that uses an orthogonal transformation to convert a large set of possibly correlated variables into a smaller set of uncorrelated variables called principal components that still retain most of the information in the original data matrix (Dunteman1989;Morrison1967). Each principal component is a linear combination of the original variables with mathematically determined characteristic vectors of the correlation (or covariance) matrix as weights. Thanks to this multivariate technique we can solve the problem of arbitrary choice of weighting scheme (Cho2006). The first principal component explains the largest percentage of the variation in the original set of variables and the second principal component captures the second largest percentage of variation unaccounted for by the first and so on. Therefore the first few principal components account for the largest proportion of the total variation whereas the remaining principal components make fewer contributions. Generally, when we have p variables, p principal components, at most, can be extracted. Yet, when the data contains highly correlated variables, only a few principal components are extracted. The proportion of variation attributed to each principal component is calculated by dividing the associated characteristic root by the sum of all the characteristic roots which is the total amount of variation. Moreover, the PCA can be commonly used for objective selection of a few predictive variables to resolve the problem of multi-collinearity and double-counting (Bair2006). In this study, we have used the ``PCA method'' B4, described by Jolliffe (1972), in order to reduce the number of indicators per components in the construction of composite WPI. This method, recommended by Jolliffe (1972), entails retention of the variable that has the highest loading (or correlation) with the first principal component of the initial data followed by the variable that has the highest loading with the second principal component and so on until the selection of required number of variables. In this respect, Jolliffe (1972) suggests that the number of selected variables must be equal to the number of principal components that have characteristic roots of the correlation matrix greater than 0.7.

5. Empirical Analysis

5.1 Calculation of the five components indices

Before applying PCA to data set and discarding correlated variables, we must analyze the overall significance of the correlation matrix of indicators for each component (i.e., Resources, Access, Capacity, and Environment) using Bartlett's sphericity test. It is also recommended, for each component, to test the factorability of all indicators collectively and individually using the known Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) (Hair2006).

The Access indicator contains solely one variable, that's why multivariate analysis to calculate it is not needed. The Bartlett's test for the remaining sub-indexes, which indicated the presence of nonzero correlations, is significant only for Resources and Capacity indicators at the 0.01 level (see the Table3 for more details). Even the overall MSA values of these two indices, which looks both the correlations between variables and their patterns, are respectively 0.544 and 0.713 which are in the acceptable range (greater than the threshold value 0.5); thus we can proceed with principal component analysis. Regarding the Resources index, the individual MSA values are 0.532 for RES1, 0.545 for RES2, 0.514 for RES3 and 0.580 for RES4; they are all higher than 0.5.

As indicated in this table, we conclude that the first two principal components, associated with eigenvalues greater than 0.7 and accounting for approximately 91% of the four indicators variation, could be retained with respect to Jollifie criteria. The values of the characteristic vector associated with these two principal components extracted, reported in Table4, show that RES1 and RES2 have respectively the higher loading (correlation) on the first and the second principal components. According to the ``PCA method B4" afore-mentioned, we retain then only these two indicators and discard the rest. After deciding the number of indicators to keep, the combination of the retained indicators (RES2 and RES3) is the next step. At this level, since variables in the same indices can compensate each other's performance, an additive aggregation is employed. Moreover, all variables are considered having the same importance, i.e. no weighting is introduced. The Resources indices could be then computed as follows: (Eq.9)

$$RES = 0.5 \times RES1 + 0.5 \times RES2 \qquad (9)$$

Repeating the same procedure to calculate the Capacity index (using the Jollifie criteria), the first two principal components, which account for nearly 83% of the total variation, should be retained but not the third one (see Table5).

We find that two of indicators CAP2 et CAP4 could be selected to get the following formula of Capacity (Eq.10):

$$CAP = 0.5 \times CAP2 + 0.5 \times CAP4 \qquad (10)$$

Since the PCA for the remaining components could not be used, as explained above, each of these indices are calculated as average of their indicators components as shown in the following equations:

$$USE = 0.5 \times USE2 + 0.5 \times USE3 \qquad (11)$$

$$ENV = 0.33 \times ENV1 + 0.33 \times ENV2 + 0.33 \times ENV3 \qquad (12)$$

5.2 Aggregation and weighting

Last step is the aggregation of indices calculated above to assess water poverty level for each governorate. The most appropriate aggregation function is the weighted multiplicative function, as it does not allow compensability among the different components of the index (Pérez2011). The weighting system is assigned through the same multivariate techniques afore-mentioned, which determine the better set of weights that explain the largest variation in the original components (Slottje1991).

Since one of the main objectives of the present paper is to determine optimal weights for the components constituting the Improved Water Poverty Index IWPI, factor loading scores were used to determine the weights. As indicated in the Table6, the first three principal components accounting for approximately 97.49% of the variation in the five indexes; could be retained as the characteristic root associated are higher than 0.7 (Jollifie criteria). Clearly, these first principal components contain most of the statistical information embedded in data. To get the final weighting scheme, principal components retained must be weighted with the proportion of variance calculated by dividing the square root of eigenvalue of the corresponded principal component by the sum of square root of eigenvalue of the three principal components extracted ($\frac{\sqrt{\lambda_k}}{\sum_j \sqrt{\lambda_j}}$). The greater the proportion, the higher the weight.

The list of five components along with their weights is presented in the Table7.

Numerically, the IWPI can be formulated as follows (Eq.13)

$$IWPI = \prod_{i=R,C,A,U,E} X_i^{w_i} \qquad (13)$$

Where $IWPI$ is the value of the improved water poverty index, X_i refers to value of component i which can be RES, CAP,ACC, USE and ENV, and w_i is the weight associated to that component.

5.3 Main empirical results

Table8 gives us the main results obtained owing to the original detailed data and the improved methodology for the calculation of the WPI. The third column of this table shows the IWPI for the 24 Tunisian Governorates. The Index values vary from 22 for Kasserine (the poorest region, remember that the Tunisian revolution has started the 17^{th} of December 2010 from this region) to 71 - 77.42 for the five governorates which form the district of Tunis and the littoral region (the most prosperous zones of Tunisia). Looking to the resources component (RES), illustrated by the fourth column, notice the opposite values. Indeed the water rich governorates are located mostly in Inland (Sidi Bouzid, Jendouba, etc.) while the poorest are situated in Coastal zones (Tunis, Sousse, etc.). This table could be easily divided in two sub-tables: the first for the inland poor governorates (from Kasserine to Kebilie) and the second for the coastal relatively zone (from Mahdia to Ben Arous).

Figure 1 (Resources Component) and the Figure2 (IWPI) illustrate those important results more clearly. Map 1 shows the huge differences between the Inland (relative water resources abundance) and Coastal regions (Water poor region). Map 2, which illustrates the IWPI, shows that the Coastal region has good water services while the Inland governorates are characterized by low IWPI indicating their poverty in terms of access, sanitation and necessary water services.

Figure 3 in the Annexes provides another way to illustrate the WPI component values at governorate scale. The Figures (4 to 8) gives us a more detailed illustration of the different IWPI components between inland and coastal region.

6. Summary and Conclusions

A great deal of effort has been made recently into the development of alternatives to assess water scarcity. The water poverty index (WPI) could be considered the most accurate and holistic tool that permits more effective water policy making and better understanding of water and poverty linkages. It provides a robust methodology for the assessment of inadequate management of water services and the related socio-economic and environmental impacts. The WPI concerns, at the same time, policy-makers, stakeholders, academics, donors and resource managers. Exploring, initially, the different weakness and strengths of the index, a revision is presented here in response to the various criticisms which had been addressed recently to the WPI.

The refinements, proposed in this paper, aimed to increase theoretical and statistical soundness of the index. For this purpose, an enhanced methodology is described which can be summarized in three essential steps: selection of variables to calculate indicators, discarding the correlated ones using the ``PCA method B4'', aggregation of the remaining indicators to calculate the five components indices (R,C,A,U and E), assignment of weights for each index and finally using the geometric function to aggregate indicators to obtain the Improved Water Poverty Index (IWPI). This approach has been piloted in Tunisia on a governorate scale to test the applicability and usefulness of this composite index. To obtain more accurate interpretations IWPI's components are examined individually and then mapped to identify visually those governorates that need urgent policy acts. The results disseminated through the components and IWPI maps (Figures4 to 8) in the Annexes indicate that water poverty in Tunisia follows an heterogeneous spatial pattern.

This modest research, mainly with its empirical results, demonstrates that the Tunisian inland water rich regions have low IWPI, while coastal regions characterized by very limited water resources, have high IWPI. The limited access to water with minimum quality, to sanitation and to the basic social infrastructures, can explain, at least partially, why the Tunisian revolution has started in those inland regions woefully neglected by the ancient regime. Our results will give the new decision makers the means to promote an equitable and sustainable development able to narrow the huge gaps between regions. This policy will be the only way to stabilize the country and to guarantee a sustainable development necessarily to the promotion of a real democracy and justice.

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Figure 1: Spatial variation of Resources Index

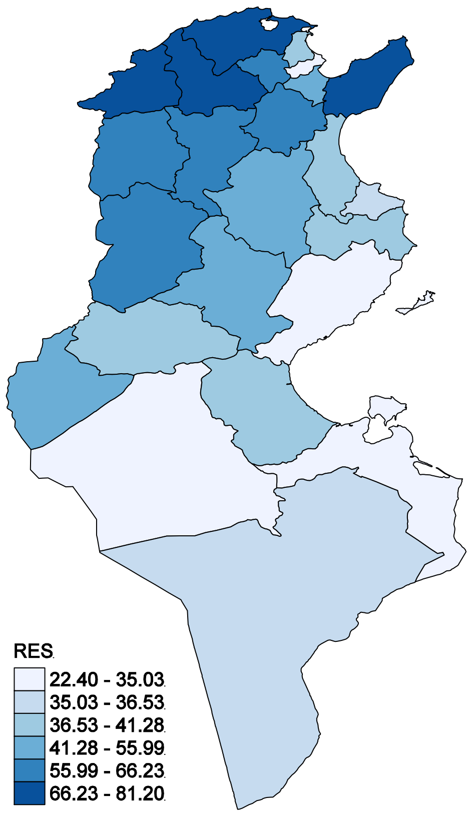

Figure 2: Spatial variation of the Improved Water Poverty Index

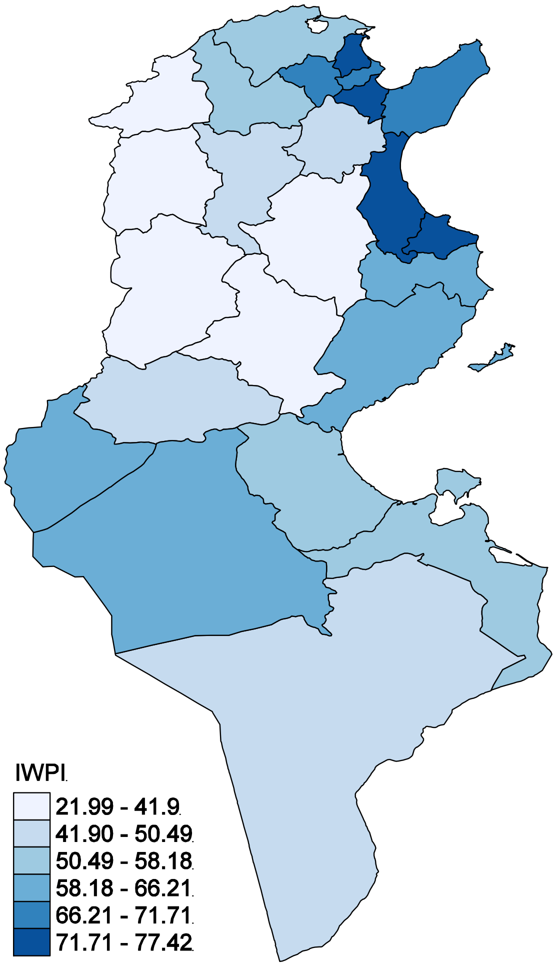

Figure 3: The WPI Component Value at Governorate Scale

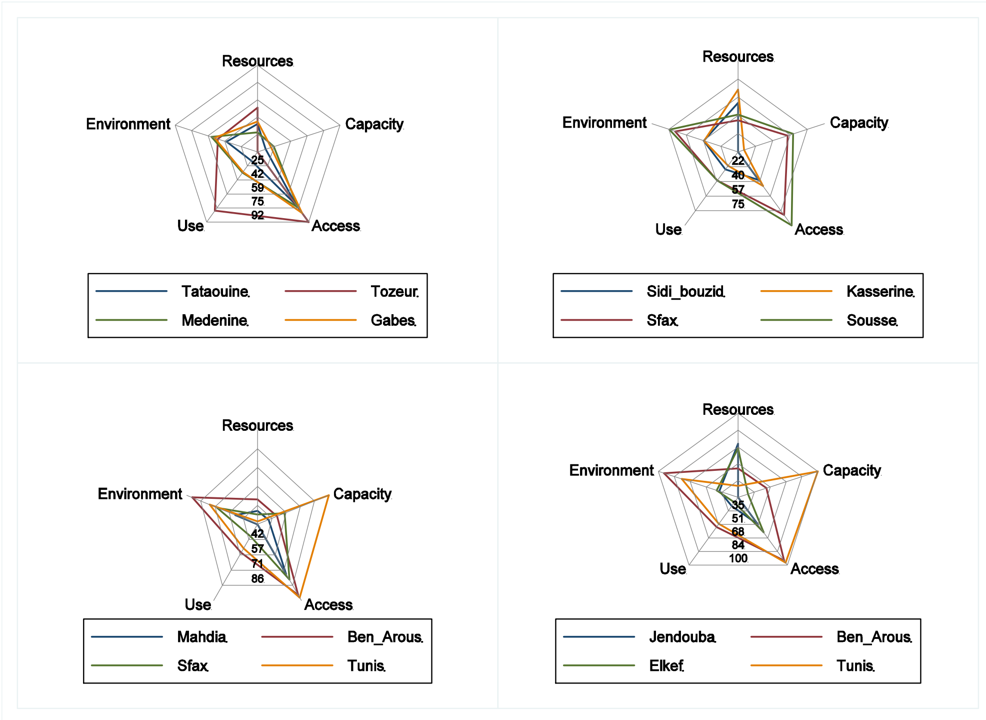

Figure 4: Resources

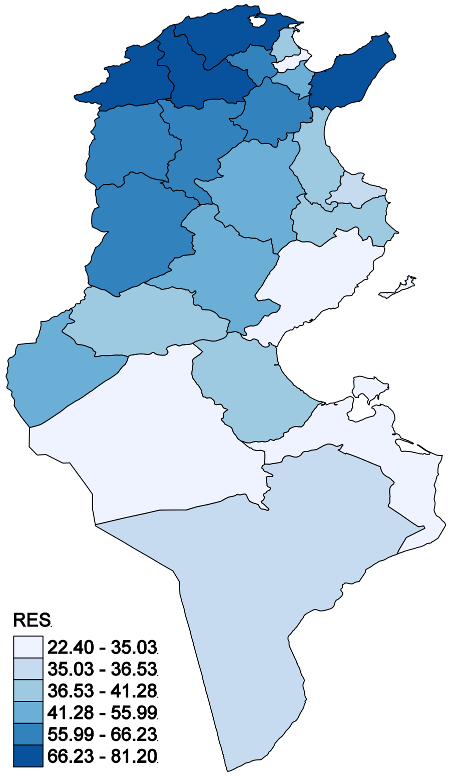

Figure 5: Capacity

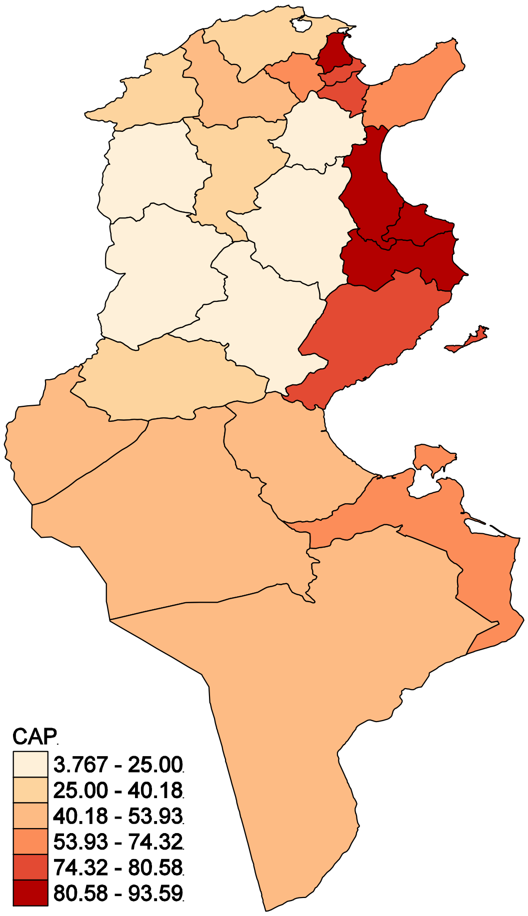

Figure 6: Access

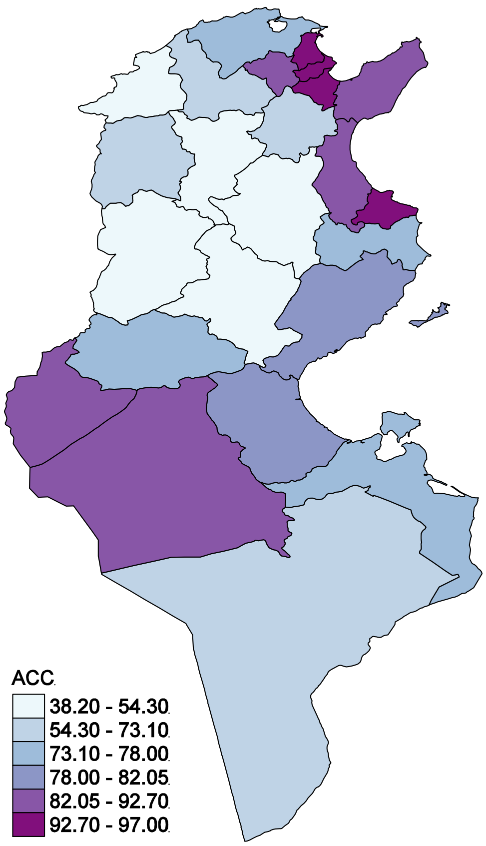

Figure 7: Use

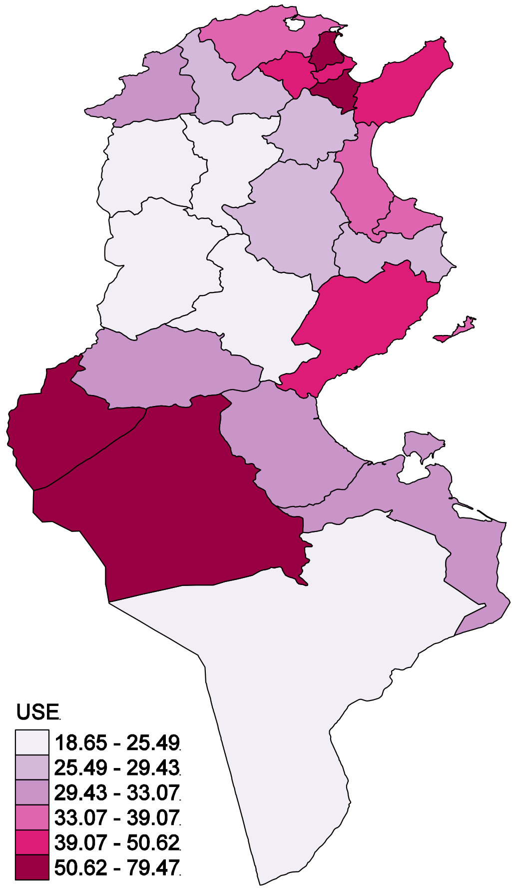
USE
18.65 - 25.49
25.49 - 29.43
29.43 - 33.07
33.07 - 39.07
39.07 - 50.62
50.62 - 79.47

Figure 8: Environment

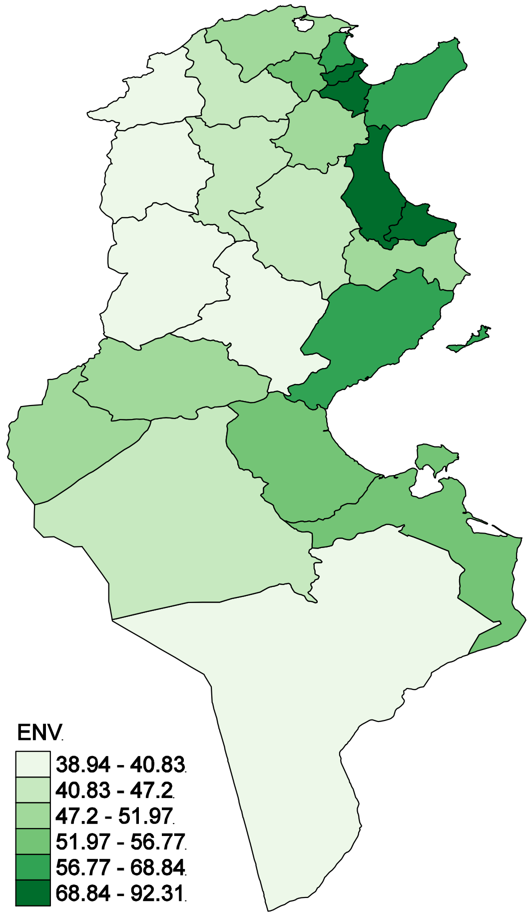

Table 1: Falkenmark Water Stress Indicator

Index (per capita per year m^3)	Category
$>$ 1 700	No Stress
1 000 - 1 700	Stress
500 - 1 000	Scarcity
$<$ 500	Absolute Scarcity

Table 2: Water Poverty Index structure

Components	Indicator	Variable
Resources	Surface water Availability (RES1)	Annual average rainfall [9]
	Phreatic groundwater Availability (RES2)	Phreatic groundwater resources per capita
	Deep groundwater Availability (RES3)	Deep groundwater resources per capita
	Variability (RES4)	Coefficient of variation of rainfall
Capacity	Economic capacity (CAP1)	average per capita expenditure
	Social capacity (employment) (CAP2)	unemployment rate
	Social capacity (Education) (CAP3)	Illiteracy rate
	Social capacity (Health) (CAP4)	Number of beds in hospitals (per capita)
Access	Percentage of population with access to safe water (ACC1)	
Use	Domestic water use (USE1)	Per capita per day domestic water use
	Agricultural water use (USE2)	Portion of irrigated lands to lands useful for agriculture
Environment	Sanitation (ENV1)	Percentage of population with access to sanitation services
	Water Quality (ENV2)	% of unfit cases after bacteriological analysis
	Environment studies (ENV3)	Number of environmental studies

Table 3: Factorability Tests

Statistic	RES	CAP	USE	ENV
Determinant of the correlation matrix	0.073	0.241	0.997	0.826
Overall KMO index	0.544	0.713	0.500	0.416
Bartlett test of sphericity				
- Chi-square	54.433	29.612	0.064	4.054
- DF	6	6	1	3
- p-value	0.000	0.000	0.800	0.256

Table 4: Results of the PCA (Resources Index)

	Principal Component		
	Comp 1	**Comp 2**	Comp 3
Eigenvalues	2.33	1.32	0.25
Proportion of variance explained	58.29	33.07	6.27
Cumulative proportion of variance explained	58.29	91.36	97.63
Eigenvectors			
RES1	**0.5758**	0.3645	0.0518
RES2	-0.3611	**0.6677**	-0.6510
RES3	-0.5158	0.4305	0.7273
RES4	0.5215	0.4858	0.2113

[9]The average rainfall is calculated over the period 1901 to 2007.

Table 5: Results of the PCA (Capacity index)

	Principal Component		
	Comp 1	**Comp 2**	**Comp 3**
Eigenvalues	3.00	0.60	0.31
Proportion of variance explained	75.08	14.97	7.88
Cumulative proportion of variance explained	75.08	90.05	97.93
Eigenvectors			
CAP1	0.5245	-0.3678	0.4352
CAP2	0.4267	**0.8349**	0.3337
CAP3	0.5075	0.0969	-0.8308
CAP4	**0.5342**	-0.3978	0.0954

Table 6: Results of the PCA (IWPI)

	Principal Component			
	Comp 1	**Comp 2**	**Comp 3**	**Comp 4**
Eigenvalues	3.21	0.76	0.70	0.20
Proportion of variance explained	64.29	15.28	14.00	3.92
Cumulative proportion of variance	64.29	79.57	93.57	97.49
Eigenvectors				
Resources	-0.354	0.366	0.834	-
Capacity	0.501	-0.294	0.161	-
Use	0.376	0.809	-0.170	-
Access	0.521	0.202	0.262	-
Environment	0.459	-0.289	-0.680	-

Table 7: Weights of Components

Components	**Weights before normalization**	**Weights after normalization**
Resources	.11	.14
Capacity	.22	.29
Access	.34	.43
Use	.08	.09
Environment	.04	.05
Total	0.79	1

Table 8: The Improved Water Poverty Index and Sub-Indices

Rank	Governorate	IWPI	RES	CAP	ACC	USE	ENV
1.	Kasserine	21.99	64.76	3.767	45.5	21.17	39.94
2.	Sidi Bouzid	34.19	52.06	25	38.2	25.49	40.74
3.	Kairouan	38.5	53.11	21.92	53.4	27.34	41.69
4.	ElKef	41.43	66.23	21.69	60.8	24.88	40.83
5.	Jendouba	41.9	70.74	27.17	51.2	29.47	38.94
6.	Zaghouane	44.16	63.45	21.67	67.1	29.26	50.62
7.	Siliana	44.36	60.73	36.08	54.3	20.26	46.4
8.	Gafsa	47.13	41.28	25.84	78	32.04	51.97
9.	Tataouine	49.18	35.1	47.22	71.6	18.65	40.39
10.	Beja	51.81	69.14	40.87	64.1	29.39	42.49
11.	Gabes	56.36	37.56	47.91	81.5	32.28	52.11
12.	Medenine	56.86	26.97	65.37	74.6	33.07	55.75
13.	Bizerte	58.18	76.49	39.48	77.3	36.14	51.91
14.	Kebilie	61.15	22.4	53.93	90.5	79.47	41.84
15.	Mahdia	62.05	38	81.6	74.7	27.59	51.01
16.	Tozeur	65.33	50.96	43.31	92.1	78.51	47.99
17.	Sfax	66.21	35.03	80.58	80	39.07	68.84
18.	Nabeul	70.27	81.2	61.06	82.6	46.55	57.8
19.	Manouba	71.53	58.88	70.89	90.2	39.79	55.27
20.	Tunis	71.71	29.79	77.74	97	50.62	73.9
21.	Sousse	72.38	40.75	80.92	92.7	38.99	73.37
22.	Monastir	73.36	35.5	93.59	93.2	35.11	73.12
23.	Ariana	77.27	39.63	88.01	95.1	59.31	66.36
24.	Ben Arous	77.42	46.73	79.45	94.6	54.43	92.31