Spatial analysis of grey water in Italian cereals crop production

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Abstract
Explorative spatial data analysis (ESDA) is a set of tools to emphasise spatial structure in case of localised data and widely used for testing effects in the case of environmental data. Grey water indicator is considered as a reliable water pollution indicator able to show the quality of water, useful in agriculture and crops production. In this paper, an analysis on the presence of spatial effects in the grey water indicator for crops production is proposed. This analysis is carried out on four cereals crops (i.e., corn, barley, durum wheat and soft wheat) in Italian regions for the period 2011-2015. The output reveals the presence of spatial effects especially for corn which shows a high level of polarisation between South and North regions. ESDA analysis indicates that grey water descending from cereal crops production is characterised by a persistent presence of positive spatial dependence and spatial heterogeneity. Policy makers should take into account those effects to improve the bundle of policies in the field of water management.

Keywords: water management, water pollution, spatial dependence and heterogeneity, Italian regions, grey water.

1. Introduction

Agriculture is actually the main user of freshwater in the world (Rodriguez et al., 2015) and accounts for about 70% of water withdrawals (Chen and Chen, 2013). Our knowledge relating to water contamination has increased in recent years and there have been many studies focusing on effluent from sewage plants or combined sewer overflows (Schreiber et al., 2015). Agricultural water pollution is a major concern both in European than in developing countries. Many research papers have focused on the relationships between crop yields and water resources (e.g. Wang et al., 2008; Piao et al., 2010; Peng, 2011), water use efficiency (e.g. Deng et al., 2006; Fan et al., 2011), and agricultural management (e.g. Hu et al., 2006). Agricultural practices determine the level of food production but also the state of the global environment (Tilman et al., 2002). The theme of water regards not only the scarcity but also the quality and the environmental consequence in agriculture. The problems of water scarcity and water pollution have become increasingly severe (Zhou et al., 2016). Water resources are widely used for food production and, consequently, its demand is expected to increase in the future due to population growth (Bocchiola et al., 2013; Curmi et al., 2013). A failure to optimally manage many water systems represents an environmental damage; this is more evident in case where activities may cause the degradation of hydrological habitats (Chapagain and Orr, 2009). Ercin and Hoekstra (2014) support the idea that freshwater scarcity and pollution will be aggravated in the future and will decrease its quality. However, through changing in water management is possible to remain at sustainable levels even with increasing populations (Ercin and Hoekstra, 2014).

Water footprint (WF) of a product is defined as the volume of freshwater used to produce it and should be measured over the full supply chain (Hoekstra et al., 2011). To monitor the unsustainable use of global freshwater resources, indicators which make water used patterns transparent are needed (Ridoutt and Pfister, 2010). WF is one of the most common tools used to analyze water management.

Hoekstra et al. (2011) defines the concept of blue, grey, and green water footprint. Blue water footprint measures the amount of water available used in a certain period and so, not immediately returned within the same catchment. Grey water footprint of a process step is an indicator of the degree of freshwater pollution associated with the process step, defined as the volume of freshwater that is required to assimilate the load of pollutants. Green water footprint is an indicator of the human use and refers to the precipitation on land that does not run off or recharge the groundwater, but is stored in the soil or temporarily stays on top of the soil or vegetation. The sum of those three components constitutes WF. In the context of social responsibility, WF has been widely used as an indicator that contributes to a safe and sustainable use of water (Marano and Filippi, 2015). WF is a global tool that could be referred on spatially located data. In this sense, it could be affected by spatial relationships according to "the first law of geography" (Tobler, 1970) that states "everything is related to everything else, but near things are more related than distant things". Performing spatial analysis on these geographically distributed data let us to investigate the spatial patterns of water usage and add more information to the aim of developing better strategies for water management.

In agricultural field, many studies about the WF of different crops have been published. In particular, some contributions have been produced for agricultural products like tea and coffee (e.g. Chapagain and Hoekstra, 2007), tomato (e.g. Chapagain and Orr, 2009), wine (e.g. Herath et al., 2013), rice (e.g. Chapagain and Hoekstra, 2011), and grain production (e.g. Liu et al., 2014). In this work, we decide to focus particularly on grey water footprint because of the special importance of this indicator relatively to the agriculture. Grey water footprint from production refers to the volume of freshwater that is required to assimilate the load of pollutants based on existing ambient water quality standards (Cazcarro et al., 2016). The volumes obtained for grey water are a measure of the pressure imposed, mostly through economic activities, on water resources in a region that, especially compared to the water availability in the region, results in a significant environmental indicator. Microbiological and chemical constituents (nitrates, fertilizers etc.) of grey water can pose hazards to human health and to the environment (Nicholson et al., 2003; Rusan et al., 2007; Rodda et al., 2010). Grey water usually contains high numbers of micro-organisms, some of which can cause disease for those who encounters the plants and irrigated crops, and also contains substances that can reduce plant growth or crop yield if present at sufficiently high concentration. Furthermore, grey water can change soil properties so that it becomes progressively less fertile (Rodda et al., 2010). Specifically, nitrate influences grey water level so that this effect is part of the directive 91/676/EEC included in the Water Framework Directive (Wall et al., 2011).

The global imbalance in the consumption of fertilizers and pesticides inevitably has had great impacts on cereal production around the world, particularly in developed countries, such as those in Europe and including Italy, where the amount of fertilizers and pesticides used has also been high (Liu et al., 2014).

More than others economic activities, agriculture is strictly associated to the location characteristics so that is meaningful to understand its spatial distribution also in terms of water use and water management. Various elements connected to the location may influence water management in agriculture. Some of that are intrinsically morphological as for soil structure and climatic conditions (Chapagain and Hoekstra, 2007; Chapagain and Orr, 2009; Casolani et al., 2016), others are considered geographically located due to their connection to specific locations, including either common practices and area infrastructure. While dealing with spatially located phenomena (as water resource exploitation and use of fertilizers), discard of spatial effects is considerably affecting the informative potential of any statistical technique (Cliff and Ord, 1973). Ready and available information about location, area extension, and distances can usually convey additional insight and lead to the reconstruction of spatial dependence patterns (Anselin, 1993). Therefore, exploring more the underlying structure of spatial connections in water use practices can enlighten about the spread effects of local environmental policies, help to validate local effects of global regulation, and point out more accurately reasons under why some basin-control policies are ineffective. However, final consumers and all sorts of businesses active along the supply chains of final consumer goods remain out of the scope of governmental policies regarding mitigation of water scarcity and pollution (Aldaya and Hoekstra, 2010).

An important toolkit to study the significant effects of spatial characteristics is the Explorative Spatial Data Analysis (ESDA) (Anselin and Getis, 1992). ESDA is set to analyze the spatial distribution of a certain phenomenon, to highlight the presence of spatial dependence, and to indicate the presence of spatial heterogeneity. In terms of grey water indicator, this means either testing for the presence of a global pattern of spatial correlation, such that close neighbors are expected to be similar, or verify the presence of different regimes due to spatial non-stationarity.

As spatial characteristics are entitled to play a considerable role while studying the level of grey water, the aim of this paper is to perform an application of the ESDA to the grey water indicator, especially for four cereal crops (i.e., corn, barley, soft wheat, and durum wheat), to evaluate the presence of spatial effects in crops production in Italy. Here, the main purpose is to add to the existing literature a new approach to interpret information included in grey water indicator necessary to assess the quality of water management process at a regional level. This information can be used by stakeholders to define appropriate policies. In fact, different tools can be used to achieve the safe management of waste water. Some countries provide incentives for the increased use of available natural resources (including water resources) towards local food production; others may provide subsidies to farmers to maintain a critical human resource base for local agricultural production. Policy makers should create a broader strategic local plan, considering behavioral change and cultural factors, environmental aspects, economic and financial considerations and health protection measures, according to the suggestion of World Health Organization (2006). However, all those aspects are not expected to influence the phenomenon of water pollution at the same way in all context due to presence of climate, cultural, and economic differences in the country (i.e., spatial heterogeneity). Spatial analysis could facilitate to explain spatial variation and to disentangle the presence of contextual influences (Haining, 2003) to the aim of helping stakeholders to improve water management policies at regional level in the case of Italian cereal crop production.

The paper is organised as follows. Section 2 is devoted to the description of data and methodology adopted to define the indicator and perform the ESDA. Section 3 contains the results of the spatial explorative analysis. In Section 4 some implications on policy frames of spatial effects detected in the analysis are discussed. Finally, Section 5 concludes.

2. Methodology

2.1 Grey water calculation

In this paper, grey water for different cereal crops has been calculated following the methodology introduced by Casolani et al. (2016) and Rodriguez et al. (2015). In the computation of our indicator, the values of grey virtual water content for each region were taken from Mekonnen and Hoekstra (2010). Grey virtual water represents the volume (m^3) of water required to dilute pollutants produced for each unit of cereal production (t) to achieve water quality standards. Grey water regional impact on area (GW_{RIA}) is calculated as:

GW_{RIA}= Grey Water regional impact on area (m^3 Km^{-2}) = [VWC $_{\text{Grey } \textit{Region i}}$ (m^3 t^{-1}) × *T.P.* $_{\textit{Region i}}$ (t)] / TRA $_{\textit{Region i}}$ (Km^{-2}).

where:

VWC $_{\text{Grey } \textit{Region i}}$ = Grey Virtual Water content in *Region* $_i$.

TRA $_{\textit{Region i}}$= *Total Regional Area* of *Region* $_i$ (Km^{-2}).

T.P. $_{\textit{Region i}}$= Total production of *Region* $_i$ (t).

Then, grey water impact on agricultural area (GW_{AA}) is computed as:

GW_{AA}= Grey Water impact on agricultural area ($m^3\ ha^{-1}$) = $VWC_{\text{Grey}\ \textit{Region i}}$ ($m^3\ t^{-1}$) × $Y_{p\ \textit{Region i}}$ ($t\ ha^{-1}$).

where:

$VWC_{\text{Grey}\ \textit{Region i}}$ ($m^3\ t^{-1}$) = Virtual Grey Water content in *Region* $_i$.

$Y_{p\ \textit{Region i}}$ = productivity of cereal per hectare ($t\ ha^{-1}$) of Region $_i$.

GW_{RIA} expresses a value of grey water emerging from the total amount of cereal crop cultivated in the region on the regional area. GW_{AA}, instead, indicates a potential value of grey water for hectare of crop and it is a potential value linked to cereal productivity. We consider the GW_{AA} indicator as the best choice to perform a spatial analysis of grey water in Italy as it is a value of grey water normalized on the total extensions of crop cultivated surface.

2.2 The explorative spatial data analysis

Explorative spatial data analysis (ESDA) is defined as a collection of techniques to summarise data property, detecting spatial patterns, and formulating hypotheses based on spatial distribution (Good, 1983). ESDA is considerably augmenting the potential of standard explorative data analysis, and it includes number of indexes (among others Moran's *I*, Geary's *C*, Global and Local *G*, Local Moran's *I*), graphics, and extensive use of maps to visualise results (Anselin et al., 2006).

In presence of spatially located data as regional data, describing the spatial distribution and tracking organised spatial patterns (Upton and Fingleton, 1985) means using a set of tools to individuate and localise both spatial effects: spatial dependence and spatial heterogeneity (Anselin, 1988).

Spatial dependence is referred to the extent of similarity (or diversity) of observed data in space, and it is measured by spatial autocorrelation to capture spatial trends or overall tendencies of similar (or dissimilar) values to be found close (Haining, 2003). Spatial dependence is likely to affect a large variety of localised data including agricultural data, adding consideration among the distribution of data and the spreading of phenomenon under investigation. Understanding the effects of spatial dependence is crucial to a full comprehension of some interdependence effects, spill-overs definition, or misspecifications effects in presence of a model.

Spatial heterogeneity indicates situations of local instabilities connected to spatial effects and defining the presence of local regimes (Griffith, 1978; Anselin, 1990). The occurrence of spatial heterogeneity is also relevant while analysing geographical data. The consideration of effects connected to spatial heterogeneity is useful, again, to avoid model misspecification and to point out better definition of policies specially referred to precise spatial clusters (Postiglione et al., 2013).

To the aim of detecting spatial effects, ESDA includes a collection of indicators which most famous is Moran's I for spatial dependence (Moran, 1950). Moran's I reveals the amount of spatial autocorrelation included into a geo-localised variable and due to spatial contiguity. For a variable y, Moran's I is:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2}$$

where y_i is the geo-localised variable under observation, n is the sample size, and w_{ij} is the entry of contiguity matrix W expressing adjacency relations between spatial units. If the value of Moran's I statistic is $I > -1/(n-1)$, there is evidence of positive spatial dependence or negative autocorrelation in the opposite case.

Associated with Moran's I statistic, a useful graph can be considered. This chart is denoted as Moran scatterplot, and provides supplementary information to Moran's I. The graph presents a Cartesian coordinate system where the variable y is on the horizontal axis and the spatial lag of variable y (i.e., Wy) on the vertical axis. Moran's I is represented by the slope of the linear relationship between the two variables displayed on the axes of the Moran scatterplot. This chart is very useful to identify clusters of regions and possible outliers that are present in our dataset.

Since one of the main purpose of ESDA is to recognize the source of spatial effects, we also decide to use Getis-Ord (1992) Global G in order to understand if the amount of spatial autocorrelation is linked to the effects of higher or lower values of the variable under investigation (in our case grey water). Global G is defined as:

$$G = \frac{\sum_i \sum_j w_{ij} y_i y_j}{\sum_i \sum_j y_i y_j}, j \neq i$$

Expectation of the statistic in the case of Global G is $E(G) = S/n(n-1)$, where S is the sum of linkages included into the weighting matrix W. A value above the expectation indicates that the spatial autocorrelation is mainly due to the high levels of the variable under observations (i.e., hot spots). Conversely, values under the expectation are related to the presence of low levels of the variable (i.e., cold spots).

Spatial heterogeneity is likely to affect spatial data, imposing an important focus on situations of local instability able to confirm hypothesis of non-stationarity. Hence, situations of spatial heterogeneity are relevant to identify local differences, detect local effects of spatial autocorrelation not evident to whole map statistics, and define local regimes (Anselin, 1996; Wu and Babcock, 2001).

Local indicators of spatial association (LISA) as local Moran (Anselin, 1995) are useful to identify presence of local spatial effects and to spread more light about the presence of spatial heterogeneity.

Local Moran can be specified for each unit as i:

$$I(i) = \frac{n(y_i - \bar{y}) \sum_j w_{ij}(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2}$$

where the expectation of the local statistics is $E\big(I(i)\big) = -(\frac{\eta_i}{n-1})$ and the sum of local neighbour's is $\eta_i = \sum_i w_{ij}$. Values of the statistic above the expectation highlight local situations of positive spatial autocorrelation, while the statistic and the derived moments (Ord and Getis, 1995) can be used to test the hypothesis of local instability.

Local clusters can be visualised using several software allowing us to complete a frame in which different regimes are individuated and plotted. Clusters can be specified depending on the levels of the values spatially correlated, both in the case of correlation between higher values or lower values (e.g., high-high or low-low). The presence of clusters may be considered as clear evidence of spatial heterogeneity. Mapping spatial clusters individuated by LISA indicators highlights the presence of significant local regimes and show situation of local spatial dependence who influences the value of the indicator (Anselin et al., 2006).

3. Results

3.1 Grey water estimation

The grey water indicator has been built for Italian regions, from 2011 to 2015. Data derive from ISTAT database. The indicators are calculated for different cereals productions following the same approach introduced by Casolani et al. (2016).

Four crops were selected (i.e., corn, barley, soft wheat, and durum wheat) as representative of the crops production in the country. Levels of grey water indicator for four crops suggest that corn cultivation in North presents the highest value of GW_{RIA} (14730 m^3 km^{-2}). In the Centre of Italy, soft and durum wheat present higher magnitudes. In the South, the differences between durum and wheat production seem to be evident, with value of GW_{RIA} ten times more for durum wheat. Barley in the Centre and South represents the cereal with minor value of GW_{RIA}.

[Insert figure 1 here. Average value (2011-2015) of GW_{RIA} on Italian area]

GW_{RIA} impact on Italian regions is very heterogeneous across different areas and crops. The highest values for corn are in the North regions (i.e., GW_{RIA} in Veneto=19534 m^3 Km^{-2}; GW_{RIA} in Friuli Venezia Giulia and Lombardy > 14000 m^3 Km^{-2}). Fig. 2 shows the evolution of GW_{RIA} for different cereals crops in Italy: note that, except for corn, the trend of GW_{RIA} from 2011 to 2015 is near constant.

[Insert figure 2 here. Evolution of average values of GWRIA (2011-2015) for different cereals crops in Italy (m3 Km-2)]

Grey water impact on agricultural area (GW_{AA}) is higher for corn; the value in the South is always lower than in other area, as showed in Fig. 3. The trend in North and Centre is similar for soft, durum wheat, and barley.

[Insert figure 3 here. Average value (2011-2015) of GW_{AA} on Italian area (m^3 ha^{-1})]

The quantile maps in Fig. 4 visualises the levels of GW_{AA} indicator localised on the Italian regions. The presence of spatial patterns is clear, a circumstance that justify performing a spatial analysis for all four crops to define appropriate policies for the stakeholders. The next step of our analysis is performed on GW_{AA} indicator.

4.2 Explorative Spatial Data Analysis

ESDA is performed to understand the global extent of spatial autocorrelation and spatial heterogeneity of grey water in Italian regions. In our analysis, the different indexes are calculated using a connectivity matrix that is defined in terms of k-nearest neighbour distance, with $k = 5$.

Studying spatial effects, circumstances in while spatial dependence and spatial heterogeneity are clearly distinct are far from obvious (Anselin and Bera, 1998). Spatial autocorrelation indicates the extent of similarity among neighbours at a global level (Cliff and Ord, 1973; Goodchild, 1987). Positive correlation defines similarity of neighbours; on the other side negative autocorrelation is a situation in which neighbours are very dissimilar.

As shown in the quantile maps (see Fig. 4), GW_{AA} concentrations highlight some persistent spatial patterns for all studied cereal crops. The situation, as expected for other environmental indicators, is very different across the crops. However, widespread presence of global spatial autocorrelation at the regional level is a clear evidence of spatial dependence for the considered phenomena.

[Insert figure 4 here. Levels of grey water GW_{AA} for four crops. Corn (high-left), Barley (low-left), Soft (high-right), Durum (low-left). Average values of period 2011-2015]

Corn plantation is largely characterised by a persistent spatial trend from South to North (see Fig. 4). In this case, Moran's I values showcase large evidence of significant spatial autocorrelation in the period under observation (see Tab. 1). The spatial autocorrelation is positive and, intuitively, is strictly connected to the spatial geographical dichotomy between

North and South. Largest values of the indicator are gathered in the Po Valley, especially on the Northern side, while concentration declines moving to the South of the country.

For barley, spatial autocorrelation is statistically significant so that we can assume that spatial dependence is relevant for the phenomenon of GW_{AA} production over all period under investigation. Hypotheses of the presence of global spatial autocorrelation are also confirmed for durum and soft wheat. In both cases the magnitude of spatial dependence is generally lower than obtained for the other crops (see Tab. 1).

[Insert table 1 here]

One of the main objective of ESDA is to recover an organised spatial pattern (Upton and Fingleton, 1985) which assumes focusing also on the presence of local instabilities. Moran's I does not give any information about the source of spatial patterns. Global G index (Getis and Ord, 1992) can identify this source and can individuate whether spatial structure is generated due to dependence either in the highest (i.e., hot spots) or lowest (i.e., cold spots) values of the phenomenon under investigation.

Tab. 2 reports values for the global G statistic across different years and for all four crops. The four crops display values of G above average, a signal that dependence tend to be originated at the highest levels of GW_{AA} indicator. Not significant values appear only in the case of corn in 2012 and 2013.

Global G suggests more precise information about the spatial distribution of soft wheat grey water management. The values are positive and significant indicating that spatial dependence is characterised by the association between regions with the high level of the indicator. Levels of global G for durum wheat are similar to those of soft wheat, while the value of the index for the 2013 is not significant.

Since global G suggests the presence of hot spots, it is needed to move a step ahead to identify possible situations of local instability. In fact, high or low levels of grey water are likely to produce spatial effects whose spreading should be traced in the sense of local clusters. This is a key point to recognize situations of structural differences to the aim of a better *ad hoc* regulation and policy implementation. To this end, in this paper we use local Moran's I (Anselin, 1995) that is a local indicator of spatial association (LISA) useful for exploratory analysis of local instabilities.

[Insert table 2 here]

The results unveil a picture (see Fig. 3) in which North-South polarisation is still a more explicative and synthetic evidence. Values of grey water indicator are taken in means through the period 2011-2015, as in Casolani et al. (2016).

In the case of corn, high level of the local I indicates the presence of significant positive spatial autocorrelation (regions in red) in Piedmont, Lombardy, and Veneto; as spatial effects decrease moving to the South of the country and autocorrelation is generated by low values of the indicators (blue region).

According to the cluster map, the evidence of barley is similar to that of corn. LISA indicates higher levels in the Northern and Central regions of Lombardy, Piedmont, Veneto, Friuli-Venezia Giulia, and Emilia-Romagna, while correlation between lower levels of the phenomenon affects the region of Molise, Apulia, Basilicata, Calabria, and Sicily.

In the case of wheat, the typical North-South polarisation is again evident. Both durum and soft wheat show a frame in which the North is characterised by higher level of autocorrelation connected to the critical raise of the levels of the GW_{AA} used, while in the South lower levels of grey water are responsible of positive levels of autocorrelation. For durum wheat, the presence of polarisation due to high values of GW_{AA} involves only the North regions of Piedmont and Emilia-Romagna, while low levels of autocorrelation involve significantly several regions of south (particularly, Apulia).

Finally, LISA analysis was performed for each year and the tables including LISA indicators are reported in Annex 1 for the four crops. We observe that the levels of local spatial correlations and significance tend to change slightly from year to year due to possible differences in climate and soil conditions that influences the use of water through the five years. However, we observe that the spatial patterns maintain sufficiently steady in the whole period especially in the case of barley and soft wheat. The pattern of LISA coefficients for corn is less stable across the time and the spatial configuration is more sensitive to the different conditions of the year. Additionally, in all four crops the central part of Italy screens lower and no significant levels of local autocorrelation.

5. Discussion

The indicator of GW_{AA} from 2011 to 2015 reveals higher levels of water pollution derived from crop cultivation for corn, especially in the North. Intensive crop production in Northern Italy is associated to high risk of nitrate leaching (Perego et al., 2012). In the Centre, soft and durum wheat are responsible of major value of grey water indicator. The Centre of Italy, on the other side, is heterogenous in terms of climate and soil conditions, and this influences the lack of a local cluster in the area for all cereal crops. In this sense, climate change has a strong influence on water used, as underlined by Bocchiola et al. (2013).

[Insert figure 5 here. LISA cluster and Moran scatterplot (from the top) of corn, barley, soft wheat, and durum wheat. In the LISA red indicates high-high clusters, light red high-low clusters, blue low-low clusters, and light blue indicates low-high clusters.]

Conversely, the results from ESDA open to some considerations about policies and practices concerning water pollution and grey water.

Grey water of crops is largely determined by agricultural management (Rockström et al., 2007; Mekonnen and Hoekstra, 2011). Several strategies to reduce grey water of crops are, for examples: increasing yield (soil nutrients management, optimizing crop rotation, the use of crop residues, erosion control, appropriate tillage, proper application and timing of manure or artificial fertilizer), improving irrigation techniques, proper tillage, and biological pest control (Sadras et al., 2003; Hoekstra et al., 2011). A policy for controlling water pollution in agriculture firstly needs to specify the level of water quality desired and what measures should be adopted to achieve this goal. Protecting water quality is a one of the main important issue of the Common Agricultural Policy (CAP) of the European Union. The main CAP instruments to promote sustainable water management are measures that support investments for improving water quality. One of the tool to achieve this objective is the sustainable use of pesticides and fertilizers for avoiding, in particular, nitrate pollution. Newell Price et al. (2011) presented an inventory of mitigation methods related to water pollution, greenhouse gas emissions, and ammonia emissions from agriculture and the strategy to control these phenomena.

Greater attention from the farmers could reduce significantly this type of pollution and helps the groundwater conditions, according to the groundwater directive 2006/118/EC, that introduces a regime of quality standards and measures to limit inputs of pollutants into groundwater.

However, most of the existing literature on environmental policy regarding water pollution does not consider aspects related to the presence of spatial effects. To the state of our knowledge, this is the first study focusing on the need of including spatial effects in grey water policies, suggesting the necessity of policy integration as a prerequisite for sustainable development.

From our results, we deduce that paying more attention to the presence of spatial autocorrelation and of local regimes help to shape more appropriate policies. In fact, an increase in the level of grey water in a single region of Italy may produce consequences on the levels of grey water in the contiguous regions as effect of spatial spill-overs (LeSage and Pace, 2009).

In this sense, from our analysis we point out that critical levels of grey water may be caused not only by an inefficient water management in a single region, but also affected by inadequate practices performed in the neighbour region as effect of the interdependence. For example, the levels of grey water of regions located on the Po Valley are similar, so that regions tend to influence each other because of their proximity to the water-basin. This is an important reason for which local policies must consider levels of the water pollution in the neighbours and definition of the area of intervention should broadly consider relationship between neighbours.

Hence, policies should take into account measures that consider the effect of spill-overs while choosing a reliable indicator for grey water. In our case, spatial interdependence is likely to affect Italy so that levels of indicators are highly correlated, an aspect which is remarkable for policy makers while evaluating the magnitude of subsides or incentives for improving water efficiency.

Moreover, spatial heterogeneity in crops production individuates two significant clusters, especially for corn, characterized by different level of correlation of grey water level. Heterogeneity of grey water indicators in Italy may be generally linked to relevant features strictly connected to the geographical location, climate, soil conditions, and agricultural management. Agricultural management, particularly includes the real practices, especially in the use of pesticides that strongly depends on climate conditions (Delcour et al., 2015) and impacts deeply on the level of grey water. In our applications, those factors are likely to contribute to a certain level of polarization between North (high-high) and South (low-low) for corn as well for other crops. For those reasons, the presence of dualism between North and South requires a major attention while setting policies. While considering the differences in water management, the use of economic incentives and subsides may represent a valid choice in the South area of Italy. Training programs for agriculture, instead, may be an alternative to disseminate a better accuracy of water management in the North part of Italy. In any case, from our analysis emerges that policy makers should examine a wide set of reasons that contributes to the presence of significant heterogeneity, including the level of diversity in economic conditions (Panzera and Postiglione, 2014).

The presence of significant results of spatial analysis are relevant for the interpretation of water management policies in the frame of agriculture and water management. As for other studies (Irwin and Geoghegan, 2001; Sexton et al., 2002; Bivand and Brusntad, 2003), many actions may be broadly assessed and modified under a better knowledge of the spatial effects as emerged in our analysis. The reason is that some special policies may be particularly influenced by a spatial specification or definition of the levels of grey water, which are sensitive to spatial effects. More actions in the direction of sustainable agriculture that consider spatial effects can be individuated in local practice for controlling water pollution, incentive through specific policies that take into account spill-overs produced by migration and investments, local and peculiar technical assistance and training.

6. Conclusions

In this paper, we performed a spatial analysis on four different cereal crops for Italy across the years 2011-2015. ESDA shows the significant and relevant presence of both positive spatial dependence and local differences (i.e. spatial heterogeneity) which is detected singularly for each crop. This study demonstrates that the complex patterns of water use cannot be solely explained by economic development but other biophysical factors should be considered by focusing on spatial effects. Hence, those patterns may be explicated by referring to climate and soil conditions which are largely influenced by geographical location. The geography generally has a strong influence on real practices that affect the level of grey water. In this sense, the performed analysis might serve as a useful guideline for better understanding the phenomenon of water pollution in Italian cereals production.

The presence of significant spatial effects points out that more attention should be payed to the selection of the appropriate spill-over specification (LeSage and Pace, 2009) and to the critical interpretation of spatial regimes (Panzera and Postiglione, 2014). Moreover, our results obtained on spatial analysis of grey water could be considered in a wider framework that helps policy-makers to improve water management in Italian cereal crops production. Policy makers should consider all the interconnections and diversities revealed by the presence of spatial effects as behavioral change and cultural factors, environmental aspects, and economic connections.

Maintaining some compromise between agriculture and human food supply and conserving aquatic systems will be one of the most important future mission of European policy on agriculture: policy makers need to find a balance between what is needed by humans and what is needed in the environment in terms of sustainability of water resources. In this sense, the field of water resources management, especially in terms of water pollution, should continue to adapt to the current and future issues facing the allocation of water and considering several aspects as well as the presence of significant spatial effects.

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Table 1. Moran's *I* statistic results for 4 crops in the period 2011-2015. p-values in bracket.

	2011	2012	2013	2014	2015
Corn	0.338	0.224	0.304	0.353	0.399
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
Barley	0.339	0.319	0.259	0.306	0.321
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Soft wheat	0.127	0.310	0.239	0.300	0.357
	(0.034)	(0.000)	(0.002)	(0.000)	(0.000)
Durum wheat	0.230	0.086	0.031	0.312	0.253
	(0.003)	(0.087)	(0.187)	(0.000)	(0.001)
Expectation =-0.0625					

Table 2. Global *G* for four crops in the period 2011-2015. p-values in brackets.

	2011	2012	2013	2014	2015
Corn	0.417	0.395	0.411	0.413	0.406
	(0.016)	(0.562)	(0.032)	(0.058)	(0.130)
Barley	0.421	0.419	0.416	0.411	0.420
	(0.004)	(0.009)	(0.027)	(0.063)	(0.014)
Soft wheat	0.432	0.443	0.438	0.436	0.436
	(0.001)	(0.001)	(0.003)	(0.004)	(0.000)
Durum wheat	0.420	0.421	0.407	0.417	0.417
	(0.004)	(0.013)	(0.125)	(0.015)	(0.009)
Expectation = 0.397					

Annex

Results for LISA analysis of four crops yearly in the interval 2011-2015. P-values: 0.10 (*), 0.05 (**), 0.01 (***).

Corn					
Exp = -0.0625	**2011**	**2012**	**2013**	**2014**	**2015**
Piedmont	-0.181	0.535*	0.306	0.970***	0.314
Lombardy	0.914***	0.666**	0.281	0.890***	0.483*
Veneto	0.626***	-0.429	0.341*	0.612***	0.402*
Friuli-Venezia Giulia	0.219	0.193	0.184	-0.529	0.667**
Emilia-Romagna	0.614***	-0.284	0.127	0.468	0.277
Tuscany	0.211	0.216	0.242	-0.007	-0.109
Umbria	0.432	0.071	0.619***	-0.027	0.351*
Marche	-0.113	-0.097	-0.239	-0.128	-0.032
Lazio	-0.014	0.011	0.092	-0.061	-0.078
Abruzzo	-0.227	0.011	-0.320	-0.133	-0.001
Molise	0.871***	0.702***	0.678***	0.771***	0.918***
Campania	-0.159	-0.583	-0.331	-0.261	-0.282
Apulia	0.531	0.392	0.481*	0.448*	0.568**
Basilicata	0.962***	0.813***	0.927***	0.958***	1.303***
Calabria	1.074***	0.896***	1.292***	1.148***	1.507***
Sicily	0.197	0.377	0.555**	0.593**	0.111
Sardinia	-0.207	0.323	-0.059	0.301	0.387

Barley					
Exp = -0.0625	**2011**	**2012**	**2013**	**2014**	**2015**
Piedmont	0.092	0.166 **	0.259	0.272	0.245
Lombardy	0.572**	0.613***	0.317***	0.927**	0.292***
Veneto	0.885***	0.968**	1.162***	0.525**	1.144**
Friuli-Venezia Giulia	0.942***	0.694**	0.820***	0.949***	0.729***
Emilia-Romagna	0.522**	0.684	0.544	0.711***	0.654***
Tuscany	-0.153	-0.348	-0.401	-0.339	-0.536
Umbria	0.421**	0.211	0.159	0.040	0.239
Marche	0.452**	0.522**	0.154	0.254	0.401
Lazio	-0.006	0.035	0.157	0.219	0.070
Abruzzo	-0.112	0.017	-0.006	-0.009	-0.033
Molise	0.417**	0.596**	0.431*	0.520**	0.592**
Campania	0.059	-0.289	-0.204	0.087	0.106
Apulia	0.540**	0.539*	0.368 *	0.489**	0.611**
Basilicata	0.719***	0.571**	0.532 **	0.520**	0.650**
Calabria	0.796**	0.607**	0.438*	0.486*	0.557*
Sicily	0.672**	0.488*	0.474*	0.320	0.501*
Sardinia	-0.940	-0.652	-0.789	-0.773	-0.623

Soft Wheat					
Exp = -0.0625	**2011**	**2012**	**2013**	**2014**	**2015**
Piedmont	-0.004	0.092	0.091	0.114	-0.017
Lombardy	0.147	0.475*	0.104	0.501*	0.210
Veneto	0.627***	0.975***	0.924***	0.930***	0.752***
Friuli-Venezia Giulia	-0.353	0.691*	0.590**	0.690**	0.339
Emilia-Romagna	0.392**	0.612***	0.452**	0.469**	0.596***
Tuscany	-0.152	-0.144	-0.092	-0.071	-0.134
Umbria	0.350**	0.384**	0.424**	0.399**	0.785***
Marche	0.492	0.458**	0.347*	0.399*	0.659***
Lazio	-0.023	0.084	0.055	0.065	0.001
Abruzzo	0.045	-0.040	-0.103	-0.131	-0.067
Molise	0.240	0.782***	0.651	0.747***	0.874
Campania	0.150	0.020	0.016	0.239	0.013
Apulia	0.244	0.473**	0.308	0.455*	0.684**
Basilicata	0.319	0.376*	0.314	0.368*	0.579**
Calabria	0.454*	0.458*	0.260	0.226	0.440*
Sicily	0.535*	0.534**	0.768**	0.741**	0.897***
Sardinia	-1.300	-0.963	-1.035	-1.041	- 0.538

Durum Wheat					
Exp = -0.0625	**2011**	**2012**	**2013**	**2014**	**2015**
Piedmont	0.082	-0.829	-0.239	0.330	-0.198
Lombardy	0.555**	0.198	0.189	0.869***	0.538*
Veneto	0.896***	0.645***	0.429**	1.166***	1.129***
Friuli-Venezia Giulia	0.078	- 0.085	0.010	-0.009	-0.162
Emilia-Romagna	0.560***	0.321*	0.270*	0.649***	0.602***
Tuscany	-0.272	-0.233	-0.246	-0.206	-0.518
Umbria	0.309*	0.271	-0.253	0.156	0.356*
Marche	0.166	0.294	-0.045	0.048	0.225
Lazio	0.035	-0.001	0.095	0.250	0.086
Abruzzo	-0.026	0.011	-0.106	-0.102	0.001
Molise	0.258	0.261	0.315*	0.459	0.497**
Campania	0.465*	0.062	0.161	0.722**	0.298
Apulia	0.313	0.214	0.130	0.239***	0.426*
Basilicata	0.340	-0.242*	0.153	0.245	0.329
Calabria	0.736**	0.325	0.351	0.548*	0.513*
Sicily	0.573**	0.258	0.488*	0.548*	0.487*
Sardinia	-1.156	0.002	- 1.176	-0.610	-0.306

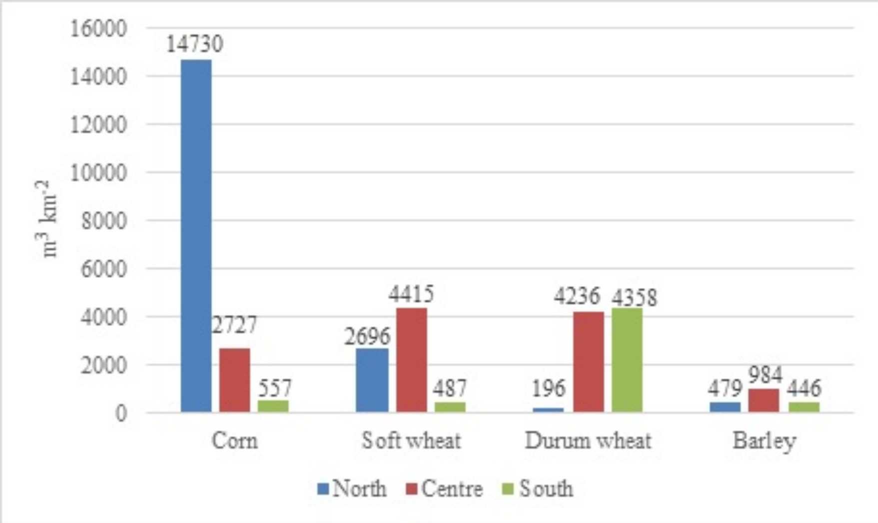


Figure 1

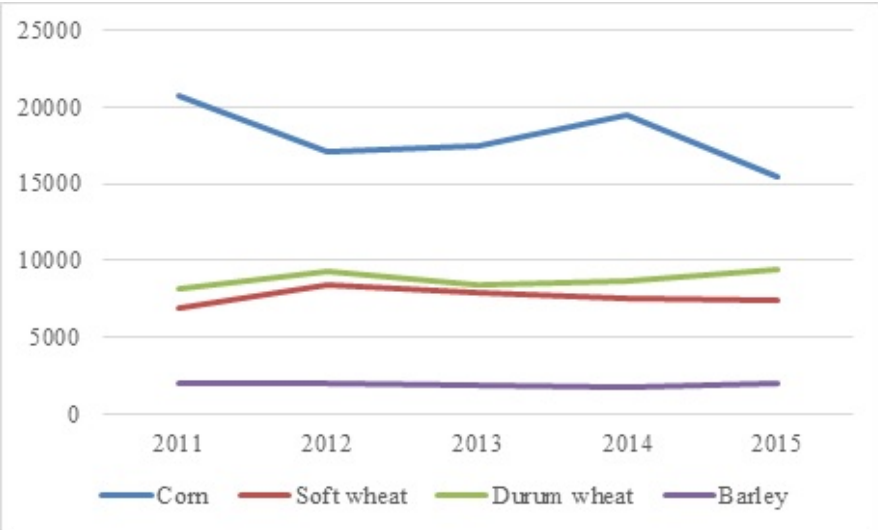


Figure 2

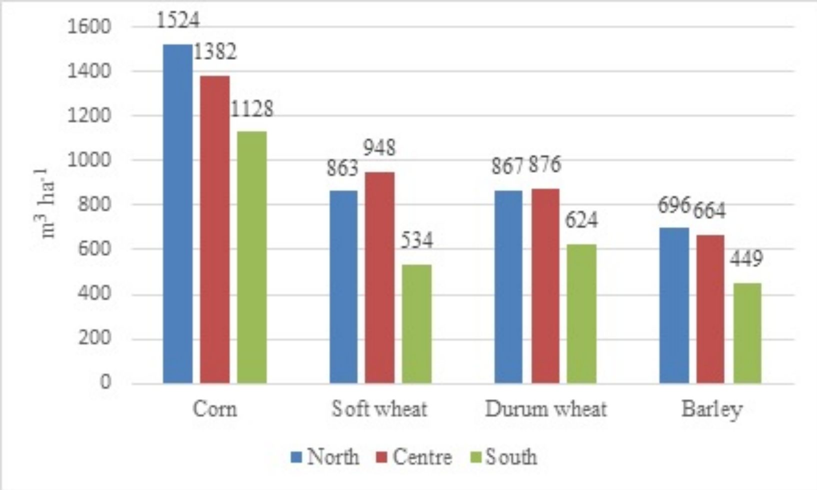


Figure 3

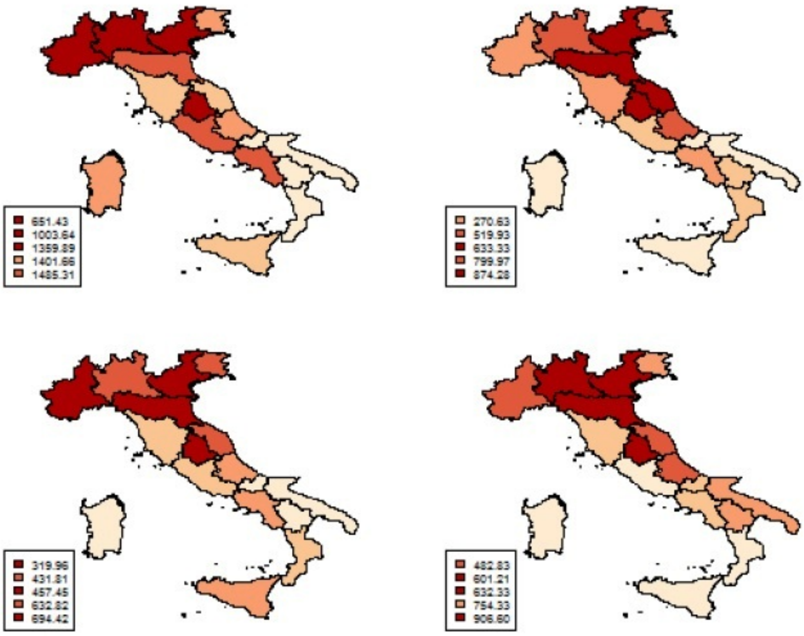
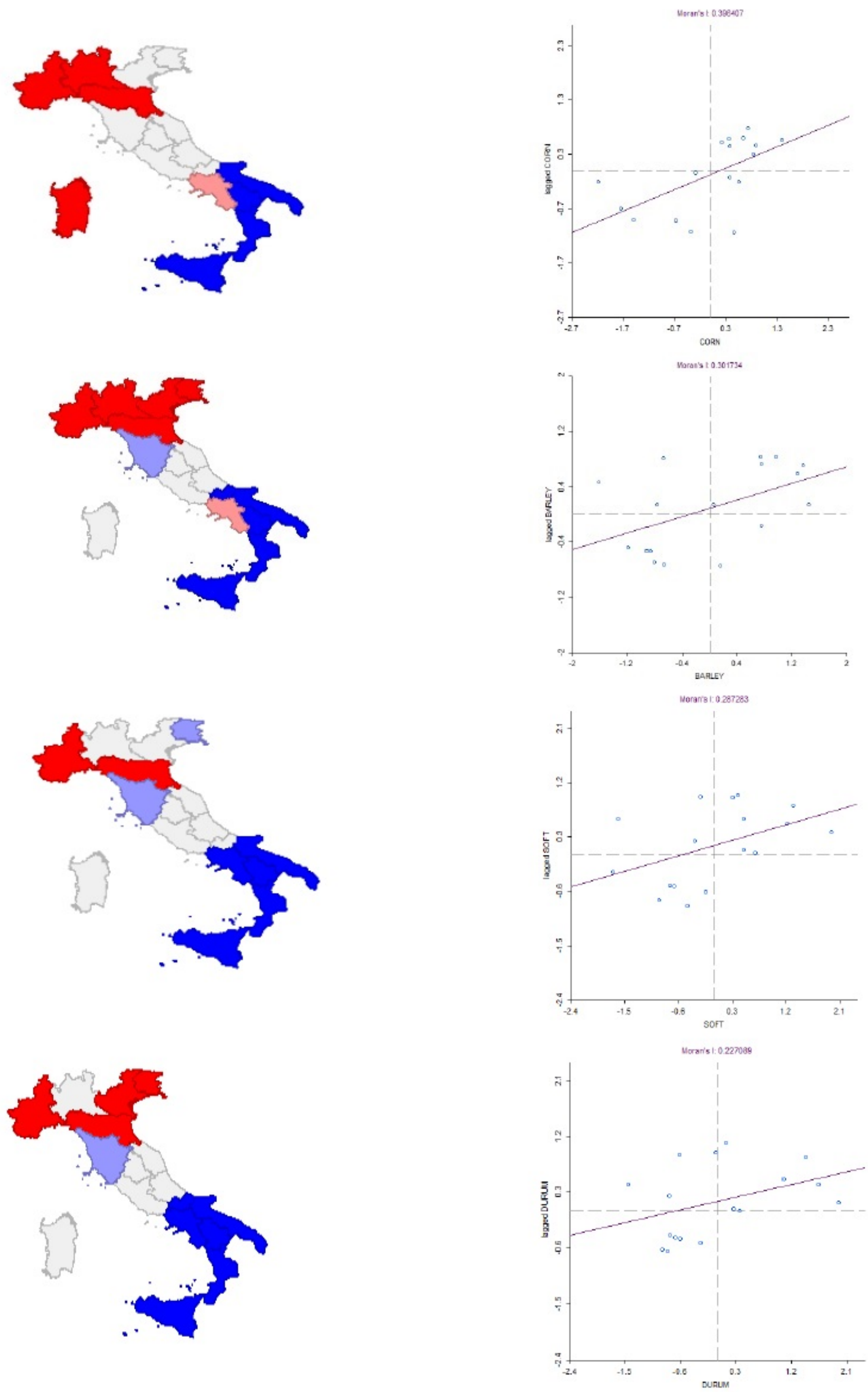


Figure 4



Moran's I: 0.396407
lagged CORN
CORN
Moran's I: 0.301734
lagged BARLEY
BARLEY
Moran's I: 0.287283
lagged SOFT
SOFT
Moran's I: 0.227089
lagged DURUM
DURUM

Figure 5