Water and the City: Exploring links between urban growth and water demand management.

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Abstract

Urban water management is currently understood as a socio-technical problem, including both technologies and engineering interventions as well as socio-economic dimensions and contexts vis a vis both end users and institutions. In this framework, perhaps the most important driver of urban water demand, at the intersection between engineering, social and economic domains, is urban growth. This paper examines aspects of the interplay between the dynamics of urban growth and the urban water cycle. Specifically, a cellular automata urban growth model is re-engineered to provide growth patterns at the level of detail needed by an urban water cycle model. The resulting toolkit is able to simulate spatial changes in urban areas while simultaneously estimating their water demand impact under different water demand management scenarios, with an emphasis on distributed technologies whose applicability depends on urban form. The method and tools are tested in the case study of Mesogeia, Greece and conclusions are drawn, regarding both the performance of the urban growth model and the effectiveness of different urban water management practices.

Keywords: cellular automata; decentralized technologies; urban growth; urban water management

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Introduction

The demand for long-term infrastructure adaptability in an ever-changing environment is gradually increasing the attention given by researchers and practitioners to more integrated studies that couple socioeconomic and environmental indices with long term infrastructure planning (Engelen et al., 1997; Pataki et al., 2011). This evolution is also reflected in water management, where modern practices tend to look into resiliency (Folke, 2006) and sustainability issues (Brown et al., 2009) while considering a broader range of available distributed technologies, complementing centralised solutions, for managing water within the cities (Makropoulos and Butler, 2010). Technologies for managing stormwater locally, such as Sustainable Urban Drainage Systems (Woods-Ballard et al., 2007; Makropoulos et al., 1999) are now becoming much more common, distributed demand management technologies such as grey-water recycling are emerging (Memon et al., 2007) and local rainwater harvesting, this millennia-old practice, is re-studied (Crouch, 1996) and re-introduced (Partzsch, 2009).

The emphasis put on sustainability in urban water management raises new questions and challenges, linked to urban planning and points towards the need for an extended interdisciplinary collaboration. This is particularly evident in approaches that attempt to organically integrate elements of sustainable stormwater management into urban planning, such as Low Impact Development (van Roon, 2005) and Water Sensitive Urban Design (Brown and Clarke, 2007). Within this context, the perspective of sustainability in urban water management looks more carefully into the localization of the urban water cycle (van Roon, 2007) in addition or even as an alternative to traditional large-scale, central urban water infrastructure. The local scale (neighbourhood or even household) emerges as a key unit with regards to locally-based sustainable urban water services (Makropoulos and Butler, 2010), and hence a scale of interest for (water sensitive) urban planning. It should be noted that while the transition towards Water Sensitive Cities (Bach et al., 2012; Brown et al., 2009; Wong, 2007) has begun in the context of drainage, a long way is still needed to reach the same level of awareness of the interplay between urban planning and water demand or wastewater management.

The paper focuses on this interplay by redeveloping an urban growth model and linking it to an urban water cycle model. The hypothesis is that this coupling will allow us: (i) to investigate the impact of alternative Water Demand Management (WDM) practices, taking into account their suitability under specific characteristics of the urban areas and (ii) forecast the long term evolution of water demand under urban growth projections simulated using the urban growth model. The first outcome could help detect the most suitable intervention practice(s) for the specific areas within the studied region. The second could assist in the development of customised intervention roadmaps.

Outlining the integration potential between urban growth and urban water cycle modelling – Scale, detail and data issues

There exist several practical challenges in the use of urban growth models in an integrated urban water management context. For example, the need for local scale modelling makes typical statistical population models unsuitable to examine links between urban growth and water demand projections within a (necessarily local) water-sensitive urban context. Furthermore, models that involve small-scale geographical components tend to be computationally and data intensive (House-Peters and Chang, 2011) and such data often don't exist, or is scattered between government agencies, water companies and other actors. … Therefore, there is a need for a parsimonious approach to modelling, applicable to data-scarce environments: While the fusion between urban growth and water cycle localization in modelling can in principle be addressed through combined, micro-scale simulation models (e.g. UrbanSim – Waddell et al., 2003), such agent-based micro-simulations are particularly data-intensive and computationally heavy. This limits their suitability to data-ample environments (such as the U.S.A. or Western Europe), and can be of limited help to areas with great interest *par excellence*, such as third-world countries with explosive urban growth patterns (Vlachos, P. E. and Braga, 2001). On the other hand, more parsimonious models, such as Cellular Automata (CA) only provide binary (urban and non-urban) or at best fuzzy (partially urban, with a membership value being assigned to each cell at each time step) classification (Liu, 2008). This is problematic as some localized urban water cycle technologies are only applicable to specific housing types (or urban densities). For instance, suburban houses have ample green space, thus enabling the installation of rainwater harvesting schemes and local sustainable stormwater interventions such as biofiltration trenches, while dense blocks of flats may be more suitable for grey-water recycling schemes at the building level. A clear need hence arises for parsimonious urban growth models (to address issues of data scarcity) that can however also provide (some) spatial characteristics at a neighbourhood or housing scale.

To address this problem, we develop a Cellular Automata (CA) model capable of generating raster images of urban growth patterns with cell dimensions equal to the resolution of maps usually provided by EU Agencies (e.g. 100×100 m^2 for CORINE maps). It is argued that this resolution is of particular interest to urban water management applications, since it is close to the spatial scale of the neighbourhood. Cellular Automata (CA) are a well-known technology for urban modelling (see for example Couclelis, 1997; Batty, 2000; White and Engelen, 1993, 1997; Clarke et al., 1997), offering a range of unique characteristics that are particularly favourable for spatial applications (Liu, 2008), such as simplicity in their modelling structure, proximity to GIS and ability to include probabilistic, stochastic or fuzzy transition rules, thus enabling significant modelling flexibility and experimentation.

In this work, the CA model is equipped with fuzzy inference, allowing it to incorporate a level of human reasoning, via the use of linguistic rules (Mantelas et al., 2010; Liu and Phinn, 2003; Dragicevic, 2004). The basis for our development is provided by a fuzzy constrained cellular automata model, originating from the work of Mantelas et al. (2010). This model is re-engineered to be able to simulate multiple-state cells, instead of binary (e.g. Clarke and Gaydos, 1998) or fuzzy (e.g. Liu and Phinn, 2003) cell states, thus being able to produce different urban densities and consequently housing units with different properties that can be used as input for localized urban water cycle simulation.

This multiple-state nature of the developed CA model enables the meaningful coupling between urban growth and water cycle management models. Multi-state CA models have been initially introduced more that fifteen years ago. For example, Engelen et al., (1997) applied a CA model to Cincinnati, USA, in order to investigate the capabilities of a multi-state CA modelling framework to realistically simulate observed growth and to generate spatial patterns and clusters of activity at the city scale, with promising results. Since then, multi state CAs have mostly been used to model more complex urban phenomena, such as traffic flow patterns (Wang and Ruskin, 2006) although interest in their use for modelling complex urban dynamics is reviving (Ding et al., 2013).

The Urban Water Optioneering Tool (UWOT) (Makropoulos et al., 2008; Rozos et al., 2010; Rozos and Makropoulos, 2013) is then employed to model the complete urban water cycle in a bottom-up logic, allowing for the assessment of the impact of distributed water-aware technologies, defined here as technologies that help to improve the performance of the urban water cycle. Such water-aware technologies include low flush toilets, rainwater harvesting and greywater reuse schemes (Makropoulos and Butler, 2010). UWOT is able to simulate both "standard" urban water flows (potable water, wastewater and runoff) as well as their integration through recycling at a household, neighbourhood or city scale (Rozos and Makropoulos, 2012).

It is argued that this combination of a suitably modified CA model with UWOT provides a balanced approach between parsimony and output detail which drastically improves over the usual binary CAs by providing indications on the type of housing units, thus increasing insights on the potential for water technology applicability at local and regional scales.

The bi-parametric multi-state CA model

To study the dynamics of urban development and having integration with UWOT as a key requirement in mind, a fuzzy constrained cellular automata model was developed, based on a simpler, single-state model (Mantelas et al., 2012b, 2010). The adopted methodological approach combines Fuzzy Logic (Zadeh, 1965), to incorporate a level of "reasoning", with Cellular Automata (CA), to simulate projections of future residential urban growth. The modelling framework is shown in Figure 1 and includes three main stages:

a) estimation of the **suitability factor** (desirability for urbanisation driven by various spatially related factors, e.g. proximity to transportation network, etc) of the area with the use of fuzzy logic.
b) assessment of the **initial CA model conditions** (initial urban fabric image), with the aid of available GIS input such as land-cover/land-use data and satellite images.
c) execution of the model and **generation of future urban growth patterns** (in the form of raster maps) for the studied period at an annual time step.

Four independent, parallel, fuzzy inference systems (FIS), each focusing on one distinct set of urban growth factors, was developed and used to calculate the suitability of the studied area for urbanisation. The use of independent FIS leads to a highly configurable mapping, which allows for greater versatility in case more urban growth factors need to be taken into account. The FIS inputs that can be used depend on available data, with physical restrictions (slope, land-use, water bodies) and accessibility (transportation network) being of primary importance. In this study the following set of inputs to the FISs were used:

- Accessibility to road networks (including primary and secondary road network, as well as motorway links): areas close to road networks received a high suitability score.
- Proximity to green areas or the sea: areas close to green areas or the sea received a high suitability score.
- Slope of the terrain: areas with mild terrain received a high suitability score.
- Availability of mass transportation availability, expressed as a distance from main transport hubs: areas close to main transport hubs received a high suitability score.

The outcome of this process was the mapping of inputs to a set of fuzzy values that are then inter-connected through fuzzy rules in order to assess the overall suitability in each inference system. The fuzzy inference rule formation deploys logical operators to link different inputs in the case of multiple-input-single-output systems, e.g. in the case of road network accessibility the following combination of factors was used:

IF *'Primary Road Distance is Small'* ***AND*** *'Motorway Link Distance is Small',* ***THEN*** *'overall suitability is Very High'*

After the implementation of the rules, the fuzzy output values are defuzzified with the use of the centre-of-gravity technique in order to provide the final, crisp values representing the Suitability Factor (SF), which is related to the desirability for urbanisation driven by the specific input variable(s). The SF values derived from each FIS are then merged (using, in the absence of any differentiating evidence, equal weighting) to obtain the overall SF, for each cell, with values ranging from 0 (completely unsuitable for settlement) to 1 (completely suitable). The final result is a raster map of overall suitability, which in turn is an input for the Cellular Automata urban growth model. More information about the implementation of fuzzy logic for the calculation of the Suitability Factor can be found in previous works (Rozos et al., 2011; Mantelas et al., 2012a). As discussed above, the urban growth model assumes multiple types of urban growth, which represent varying degrees of urban density. The mechanics behind multiple-state urban growth follow a pattern of cell state allocation and transformation, which comprises the following stages, one at each time step (Figure 2):

- An Urban Growth Algorithm (UGA), similar to the one presented and successfully tested in earlier works (Rozos et al., 2011; Mantelas et al., 2010, 2012b) decides which non-urban cells are to be urbanized in each time step. Two rules of urban expansion and one rule of "spontaneous" growth (in areas without neighbouring urban cores) are applied, as suggested by Mantelas et al., 2012. These rules relate to the binary urban raster map of each time step – in other words decide between urban and non-urban cell types only.

- The State Allocation Algorithm (SAA) designates different cell states to all cells which were urbanized with the previous algorithm, based on neighbouring urban pressure and density. This rule applies only to cells that were turned from non-urban to urban at the specific time-step.
- An Intensification Module (INM) assigns denser urban states to existing, urban cells. This allows cells that are already urban to transform into urban states with greater urban density. This feature is essential to represent a characteristic transformation of urban areas in Greece, where urban density is generally increased[2] in a single-building basis as single-floor houses with gardens transform into densely-built flats within the same, unchanged road network layout.

All rules of transformation within the aforementioned three stages combine the SF with neighbourhood-driven pressure, based on the Moore Neighbourhood pattern (Weisstein, 2005), with different radii of the Moore-neighbourhood being employed by each rule. The rules are all of a probabilistic nature, thus allowing for a more realistic representation of urban growth processes. These rules apply to each cell at each step of the model, taking into account the total amount of urban cells in the neighbourhood, as well as the amount of neighbouring urban cells with specific urban states, with the latter being used in the State Allocation Algorithm. The

[2] Through a legislative system known as 'antiparochi' – see Mantouvalou and Mavridou, 2007

Intensification Module also employs rules based on the urban pressure of the neighbourhood (e.g. urban cells with higher cell states lead to higher urban pressure for the specific cells).

Besides the cell neighbourhood effects, a velocity factor VF in (0, 1] was implemented in every rule, denoting the intensity with which the rule is applied temporally as well as the different paces of different rules. For example, urban expansion is a relatively fast process compared to intensification, so intensification has a much smaller VF parameter in its rules (see Table 1). In order to define the speed at which each rule is applied, the population dynamics of the area need to be known (i.e. population statistics from census studies need to be known at regular time steps). The velocity factor is then calibrated based on the speed patterns of past population dynamics. The formulae and details for each rule of the case study can be seen in Table 1, where PROB is the probabilistic result of cell state change, SF is the Suitability Index of the particular cell, MooreRules are urbanisation ratios driven by neighbouring cells and VF is the velocity factor. All factors are probabilistic in nature and are defined within (0, 1].

The parametric drivers of the rules are the suitability factor SF and the velocity factor VF. In principle, both of them can vary spatially and temporally and are subject to calibration. In some studies, the role of SF is twofold, both representing suitability in an area as well as determining urban growth and densification speed (e.g. Mantelas et al., 2012a; Li and Yeh, 2000). However, we argue that these factors represent different mechanics of urban growth and have distinct roles. This is why in our case a bi-parametric approach was chosen instead, with separate roles between the two parameters; the SF denotes the “desirability to build in an area”, driven by human reasoning, while VF stands for “speed of building in an area”, thus addressing drivers related, for example, to macro-economic variables and with them the temporal evolution of different urbanisation mechanisms, such as urban expansion and intensification. In other words, SF represents a number of socio-geographic factors that make an area desirable, while VF quantifies what drives desirability into action.

Since the socio-geographic factors are unlikely to radically change during short time intervals, SF is expected to exhibit much higher spatial variability than temporal. The opposite stands for VF since speed is directly related to economic growth, population inflow, immigration rates, legislation restrictions and relocation politics, etc. Therefore, in a typical short-term projection case, SF can be a spatially variable, temporally constant matrix, while the opposite can be assumed to be true for the VF. In cases of scarce socioeconomic data, such as this case study, constant VF values can be used, in order to retain a character of simplicity and laconic parameterization, subject only to general population trends for the area of interest.

Temporally variable SF may be used in cases of what-if scenarios (i.e. exploring the evolution of infrastructure and its impact in the urbanization of an area) or additional available spatial information over time, such as the detailed evolution of the road network of the area or a dynamic change in land use over specific areas (land reform projects, infrastructure, parks etc.). On the other hand, VF can be derived through a separate socioeconomic model as an exogenously applied dynamic constraint (if data are available). Obviously, these two factors permit the formation of a number of scenarios, such as new infrastructure and land use policies (with a change in SF) or population and economic growth projections (with a change in VF).

The bi-parametric rationale offers the capability of both spatial and temporal configuration, thus enhancing the operational flexibility of the model. Temporal configuration is, after all, equally important to a Cellular Automata model, but is not often addressed, with the majority of CA models allowing a configuration based on the best fitting between given spatial data sets, without any additional temporal calibration features (Liu, 2008).

The Case study: Mesogeia, Athens

The model was applied in the region of Mesogeia, at the eastern part of Athens, a mostly agricultural area until two decades ago. Then, rapid urban development occurred, resulting in the doubling of its urban cover. Mesogeia is a relatively autonomous region in terms of urban growth (Mantelas et al., 2012a) as it is geographically separated from the rest of metropolitan Athens by Mount Hymettus in the West. Furthermore, it constitutes an "ideal" case of event-driven, peri-urban rapid development, triggered by large-scale infrastructure, due to the fact that it was the region of the 2004 Olympic Games (Couch et al., 2007).

To prepare the suitability factor and the initial urban fabric raster image, a series of geospatial manipulations were performed based on available geographic datasets. The CORINE land-cover raster data for the years 1990 and 2000 (Figure 3) was obtained from the European Environment Agency (EEA, 2011) and was re-projected to the Greek coordinate system HGRS 1987. For the terrain of the studied area, the Digital Terrain Model (DTM) was obtained from the Hydroscope Project (2011). Finally, the transportation network of the area was obtained from OpenStreetMap (2011) and was converted to a raster map containing primary and secondary roads, railway stations and motorway links. Finally, census data were obtained from the Greek National Statistics Agency, ELSTAT (Table 2).

The basis on which key urban growth characteristics and dynamics are identified and outlined were the CORINE datasets. The red areas (darker areas in BW image) in Figure 3 carry the CORINE identification code for “discontinuous urban fabric”, comprising residential areas around the edge of urban district centres, and certain urban districts in rural areas. These units consist of blocks of flats, individual houses, gardens, streets and parks, each of these elements having a surface area less than 25 ha. This type of land-cover can be distinguished from continuous urban fabric by the presence of permeable surfaces: gardens, parks, planted areas and non-surfaced public areas (European Environmental Agency, 2012). Therefore, the red areas could be interpreted as a rough estimation of the borders of urban growth of the study area. The remaining areas are classified according to CORINE as: complex cultivations, vineyards, sclerophyllous vegetation and transitional woodland-shrub.

An analysis of the map of population density provided by CORINE (Figure 5) suggests that a reasonable and parsimonious grouping could be based on three major density classes: up to 2000, from 2000 to 4000 and above 4000 inhabitants per square kilometre. Different urban densities correspond to different urban properties, such as occupancy, number of buildings per cell, pervious and impervious areas etc. To represent the spatial distribution of the urban densities within the multiple-state urban growth model, three different cell states were mapped onto three different density classes with: state ‘2’ being associated to detached, low-storey houses; state ‘4’ to blocks of flats; and state ‘3’ to mixed state. State ‘1’ was set to correspond to non-urban cells, while state ‘0’ to cells that cannot be occupied (due to, for example, physical boundaries such as the sea).

The characteristics of each state (average pervious/impervious areas ratio, number of households, and occupancy) were obtained by manually interpreting satellite images of the study area (Figure 4). Their attributes are given in Table 4. After the state identification, the initial number of urban cells and their spatial distribution inside each residential area were derived by using both the population information from the 1991 census (ELSTAT, 2012) and the map of population density disaggregation provided by CORINE (Figure 5 left).

Urban Growth Simulation

Using the aforementioned procedure, the initial, multiple-state urban fabric image of 1990 as well as the observed urban fabric image of 2000 was generated. The CORINE 2000 image, as well as population time series for each municipality (in this case values for 2000 and 2010) are used to calibrate the model, in terms of both spatial accuracy of the generated urban patterns and population growth rate. The aim was to reproduce the general urban growth pattern, as well as the population influx for each municipality on the basis of historical population data. As explained before, the suitability factor is derived using FISs, while the use of the velocity factor is limited to the general population trends due to lack of more detailed data.

The CA model performance is validated against a number of metrics, comprising:

- Cross-tabulation between the modelled and the observed urban cover (based on the CORINE 2000 data) for each municipality.
- Overall population trends in each municipality compared with available census data. Comparing the estimated and observed population influx is essential both for model validation and proper urban water cycle modelling, since the number of occupants is then given as an input to UWOT and is used to calculate residential water uses.

The overall spatial performance of the model can be viewed in Figure 6, which shows the CORINE2000 general urban boundaries (with a dark gray colour), along with the urbanized cells from the CA model (light gray pixels). White pixels represent cells generated from the CA model that exceed CORINE urban boundaries. It can be suggested that the model performs satisfactorily in all cases of residential zones. It is noted that a number of zones that appear to be without modelled urban cells are characterized by CORINE 2000 data as industrial, commercial or large-scale infrastructure construction zones so the lack of residential development in these cases does not lead to inaccuracies.

Figure 7 shows the fitting indicators of the model (for each municipality and for the whole area of Mesogeia). The metrics used, viz. the Kappa and Lee-Sallee indices (Carletta, 1996; Clarke et al., 1996) imply that the overall spatial reproduction of urban growth is satisfactory, even with a number of inaccuracies present in certain municipalities, notably Artemis and Marcopoulo. The overall kappa index is 71%, which is deemed adequate for an initial application. This is even more so, in view of two points:

- detection of land use from CORINE does not provide spatial data with enough accuracy to be fully reliable for elaborate applications such as urban water management at a household level. While the CORINE provides a basis for model implementation, one should be aware of its limitations, especially when there is differentiation between different types of land use (Diaz-Pacheco and Gutiérrez, 2013).

- a significant part of observed urban growth can be attributed to uses other than residential construction (for instance, commercial or industrial uses) or mixed uses, which is quite common in Athens.

In view of this, the model evaluation was also based on population trends per municipality. This evaluation metric was chosen as a validation measure supplementing spatial metrics, since it is directly linked to water demand and detailed census data was available. In fact, this step is considered essential in the evaluation of the model, as remote sensing cannot substitute but only complement traditional socioeconomic indices (Besussi et al., 2010). Thus, a coupling approach of remote sensing data with socioeconomic indices becomes important at finer scales.

A comparison between observed and simulated population growth (Table 3) shows that the CA model adequately represents occupancy influx and growth rate in most municipalities. Even non-linear population trends are represented satisfactorily, with the exception of Pallini, where the model fails to represent the explosive population growth pattern. This case, however, is very complicated since the municipality borders changed between 2000 and 2010 and hence population numbers are not directly comparable.

Integrating the urban water cycle model

The detailed urban growth projections with multiple states given by the CA model allow the simulation of the total urban water cycle through UWOT at a neighbourhood-level (cellular level) basis. The urban water cycle of each of the three urban states (2, 3 and 4) is modelled in UWOT with the help of what is defined here as the Urban Response Units (URU). We define an

URU as a neighbourhood unit with the same size as a single cell (100×100 m^2), characterised by the following properties:

i. The number of households: Each URU includes a fixed number of identical households. Every household is considered as a structurally independent residential unit with a single connection to the mains.

ii. The occupancy of the household: This is the average number of people inhabiting a household, which may include a single family or many families in case of multi-storey buildings (URUs that correspond to states 3 and 4).

iii. The private and public pervious area (areas occupied by gardens and parks), as well as the private and public impervious areas (road, pavements, rooftops).

iv. The urban water network topology: This refers to the installed water appliances, the existence of any water recycling scheme, the type of sewers (combined/separate), etc.

The first three properties, which relate to the urban density of an URU (i.e. are defined by the urban state), are obtained from satellite images (see Table 4). The fourth property comprises all local water-saving or recycling schemes applicable in the particular neighbourhood. In this study, five different network topologies were employed:

- The first two topologies include the Business As Usual (BAU) solution as well as the installation of low-water consumption appliances (LOW). These two have identical connections between the water components. The specifications of the in-house water appliances and frequencies of use for both solutions are obtained from literature (EEA, 2001; Grant, 2002, 2006; Eartheasy, 2012; ENERGY STAR, 2012a, 2012b) The daily per capita consumption of the conventional scenario is 184 L/p/d, while in the case of low-water consumption appliances it is reduced to 97 L/p/d.

- The next two topologies attempt to achieve additional water saving by implementing a Rain Water Harvesting scheme (RWH), as well as its combination with low consumption appliances in the second case (RWHLOW). The tank capacities used in the RWH scheme are dependent on the building type and are assumed 2, 10 and 20 m^3 for the states 2, 3 and 4 respectively. The rainwater harvesting areas of the three states are 80, 160 and 190 m^2 (average roof area estimated from satellite images). The average annual rainfall depth, as estimated from daily rainfall timeseries (FreeMeteo, 2011) is 376 mm.

- The fifth topology includes local Grey Water Recycling (GWR) (Figure 8) with a local treatment unit that treats water from the shower and the hand basin and supplies treated water to the toilet, the washing machine and for watering the garden. The RWH, RWHLOW and GWR topologies differ from BAU and LOW, since they include a tank, which receives harvested rainwater in the rainwater harvesting schemes or the treated grey water from a local treatment unit in the grey-water recycling solutions. A more detailed description of the simulation of RWH and GWH schemes can be found in Rozos et al. (2010).

In order to assess the demand of the in-house water appliances a series of micro-components are employed (with each micro-component simulating a water appliance), which are then aggregated to calculate the potable water demand of the URU (see Rozos and Makropoulos (2013) for more information on how UWOT accomplishes this). Outputs of all appliances are aggregated and this flow is multiplied with the number of households per cell, which gives the wastewater charge (WW) of the URU. For outdoor uses a constant value given by Grant (2006) was used regardless of the urban density. Finally, the rainfall on the roofs of the households generates runoff, which, after being multiplied with the number of households, is added to the runoff from the public impervious areas and the total pervious area of the cell, resulting in an estimation of total runoff.

The combination of the five network configurations with the three urban states (Table 4) result in fifteen URUs, depicting the full range of feasible technologies at the neighbourhood level for every possible urban state. The urban water cycle of these URUs is then simulated (Table 5), with the use of a daily time step (historical daily rainfall timeseries were obtained from FreeMeteo (2011)) with the simulation period extending from 1/1/1980 to 31/12/1999. The values displayed in this table include average potable water demand, wastewater (WW) and maximum runoff volume (generated from the rainfall on the simulated urban area) for the simulation period.

To obtain the urban water cycle flows at the scale of a municipality for each one of the years 1990, 2000, 2010 and 2020, and assuming no interdependencies between cells in terms of water flows, Table 5 was multiplied with the corresponding number of urban cells per state (see also Figure 1).

Results and discussion

The coupling of UWOT with an urban growth model (albeit a second level coupling according to Brandmeyer and Karimi (2000)) presented here, allows for an assessment of the impact of urban growth on the urban water cycle. It also quantifies the effects of various water-saving technologies at a regional level. For example, Figure 9 shows the evolution of the potable water demand and the indicative maximum runoff volume for each municipality of the study area for the BAU solution. The improvement of the urban water cycle performance by implementing each one of the four WDM measures compared to the BAU solution is shown in Figure 10 for Koropi and Artemis (representative municipalities for high and low urban density respectively), regarding (a) potable water demand, (b) wastewater volume and (c) maximum runoff volume. The results of applying rainwater harvesting (RWH) are shown in Figure 11. The evolution of the overall potable water demand of the study area for all four WDM solutions is shown in Figure 12 (contrasted with the BAU solution). This figure assumes a steady technology uptake rate in existing households of 10% per year.

With that level of output detail, produced by a bottom-up modelling philosophy, key conclusions can be drawn regarding the effectiveness and, therefore, prioritisation of relevant water demand management (WDM) measures in the studied area, both for more detailed and regional scales:

- *Prioritisation of WDM measures in Mesogeia, Athens*: The installation of low water consumption appliances is the WDM measure that achieved the highest reduction of potable water demand (see Figure 10), with grey water recycling achieving a moderate effect. Although this depends on the particular technology mix chosen for testing, all technologies examined are readily available “off the shelf”. Rainwater harvesting achieved a runoff volume reduction up to 40% in the dense urban areas whereas the reduction is limited to 10% at the low urban density areas. The results also underline the beneficial coupling effect of these WDM, as any simultaneous application of measures enables the synthesis of their individual benefits. The most characteristic example is the installation of the combination of low water consumption appliances with rainwater harvesting to reduce both potable water demand and runoff volume (53% and 33% respectively in dense urban areas). It should be noted however that outdoor water demand is largely related to urban form and density (e.g. garden irrigation in low density urban areas). Having said this, the assumption of a constant outdoor demand employed here is not expected to have significant impact on this case study. If a more realistic estimation of outdoor demand was employed instead, arguably, the performance of LOW, which ranked first, would have remained unaffected, the performance of GWR would have decreased proportionally to the additional irrigation demand while the performance of RWH, which ranked last, would have decreased both because of the additional demand and because of the fact that the peak of this demand is during summer, i.e. when precipitation is at a minimum. Nevertheless, more detailed approaches with respect to calculations of outdoor water demand (such as the one described in Rozos et al., 2013) should be used in cases where RWH is expected to be more efficient (e.g. in wet climatic conditions).

- *Prioritisation and temporal analysis of demands*: If the capacity of the existing regional centralised water system (either to supply water, treat wastewater or convey runoff) is expected to be exceeded by the BAU scenario of the projected urban growth then water can become a limiting factor to urban growth. In this case, measures need be taken well in advance using realistic technology uptake and penetration rates. In such a context, the proposed methodology can lead to the formation of charts of water demand evolution for alternative urban growth projections and WDM measures (such as Figure 12) that can be used to plan intervention strategies (roadmaps) and form adaptation policies as the urban area of study changes and evolves. For the preparation of such a roadmap, it should be clear that the accuracy of the forecasts provided by our method is limited by the uncertainty related to the velocity factor. In this study a constant velocity factor was used, which was calibrated based on past population dynamics. This approach presupposes that the socioeconomic conditions during the forecast period remain similar to that of the calibration period. A more sophisticated approach could entail the employment of a socioeconomic model to estimate the velocity factor at each step of the simulation. This would represent, for example, the periods of increased construction activity and the periods of economic relapse when such activity is decreased.

Conclusions

The study demonstrated the coupling of urban growth modelling (a CA model) with urban water cycle simulation (UWOT) for the purposes of planning distributed water management interventions at the regional or city level. It is argued that this type of work could form a basis for deeper integration between urban design and water management, thus leading to more water sensitive urban planning policies and mitigation strategies. While the coupling methodology is straightforward and addresses only a cause-effect relationship between urban growth and water impact, more dynamic links are evident through the framework; for instance, the CA model can be calibrated to include spatiotemporal changes induced by water-aware urban planning (e.g. blue-green infrastructure, see Rozos et al., 2013) or policies that favour specific, low-impact land use. Such links have not been addressed here, but form the ambition of ongoing work. It is finally suggested that the integration of UWOT with urban growth models at a cell level allows for the investigation of even more sophisticated cases, where certain housing units decide to retrofit technologies or adopt new ones while the urban area is evolving, linked for example to changes in income growth and distribution, awareness raising campaigns, rebate and other supporting policies or even population dynamics and characteristics and hence providing policy makers at the city level with long term scenario planning tools for more sustainable water infrastructure.

Acknowledgements

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Tables

Table 1. The general rule formulation used in the CA model.

General Rule Formula: PROB = SF × MooreRules × VF			
	Rule Name	Moore neighborhood radius in MooreRules	VF
UGA	Edge Expansion 1	1	0.75
	Edge Expansion 2	2	0.68
	Spontaneous Growth	3	0.50
SAA	Urban State Allocation (2,3 or 4)	3	-[*]
INM	Intensification, state 2 to 3	2	0.25
	Intensification, state 3 to 4	2	0.10

[*] The urban state allocation step allocates states to urbanized cells based only on neighbouring cell states. Hence, a velocity factor is needless for this rule.

Table 2. Census data for studied area.

	1991	**2001**	**2011**

Pallini	10695	17232	54390[1]
Gerakas	8451	13990	
Anthousa	2889	2389	
Artemis	7077	14719	33800[2]
Spata	7708	10419	
Koropi	16239	24453	30340
Marcopoulo	9356	13644	20070
Paiania	9765	12997	26620[3]
Glyka Nera	5753	6770	
Rafina	7632	10701	19940[4]
Pikermi	1262	2924	

Notes: [1] Includes population of Gerakas and Anthousa, [2] includes population of Spata, [3] includes population of Glyka Nera, [4] includes population of Pikermi.

Table 3. Observed and simulated population growth for each municipality.

	Year	1990	2000	2010	2020
Artemis	Census Data	7077	14719	33800*	
	Simulated	8640	14980	24963	35216
Spata	Census Data	7708	10419		
	Simulated	7171	13019	19653	26615
Peania	Census Data	9765	12997	26620*	
	Simulated	9309	15171	24208	27642
Porto Rafti & Makropoulo	Census Data	9356	13644	20070	
	Simulated	7770	12903	22137	38508
Rafina	Census Data	6370	7777	13165	
	Simulated	6493	9323	11472	15450
Pallini	Census Data	10695	17232	54390*	
	Simulated	9600	14125	21050	23122
Koropi	Census Data	16239	24453	30340	
	Simulated	15900	19047	25300	32212

* This value reflects a growth in municipal borders after new legislation measures.

Actual corresponding size (with the same borders as 2000) is expected to be 20%-25% smaller.

Table 4. Urban density properties of the three states and their corresponding Urban Response Units (URU).

	State 2 (low-storey houses)	State 3 (mixed state)	State 4 (blocks of flats)
Occupancy	3.2	7.4	20
Buildings/cell	10	17	15
Urban density (people/cell)	32	125	300
Public impervious (m^2)	1000	4645	3925
Total pervious (m^2)	8200	2635	3225
Building footprint (m^2)	80	160	190

Table 5. Results of simulations of the fifteen (3×5) URUs with UWOT.

		State 2	State 3	State 4
Average potable demand (L/d)	**BAU**	5893	22778	53873
	LOW	3091	11760	27599
	RWH	5305	20574	51527
	RWH LOW	2567	9640	25259
	GWR	4165	15985	37673
Average WW out (L/d)	**BAU**	5718	22481	53610
	LOW	2916	11463	27336
	RWH	5718	22480	53610
	RWH LOW	2916	11463	27336
	GWR	3990	15687	37410
Max runoff volume (L/d)	**BAU**	307806	866066	806880
	LOW	307806	866066	806880
	RWH	297030	724577	502743
	RWH LOW	300893	739763	538959
	GWR	307806	866066	806880

Figures

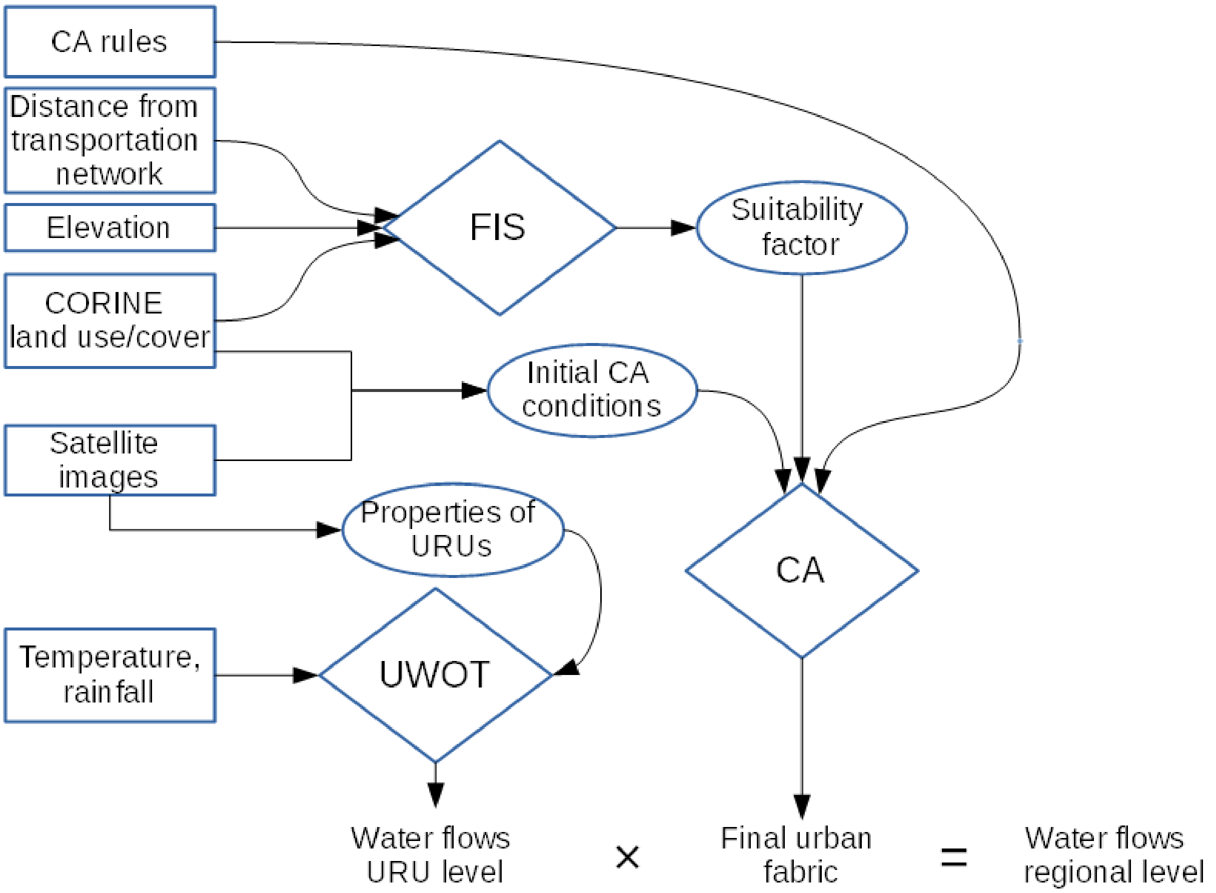


Figure 1. The flow chart of the interaction of the water management model with the fuzzy constrained cellular automata model. Data are symbolized with rectangles, processes are symbolized with rhombi and intermediate results with ellipses.

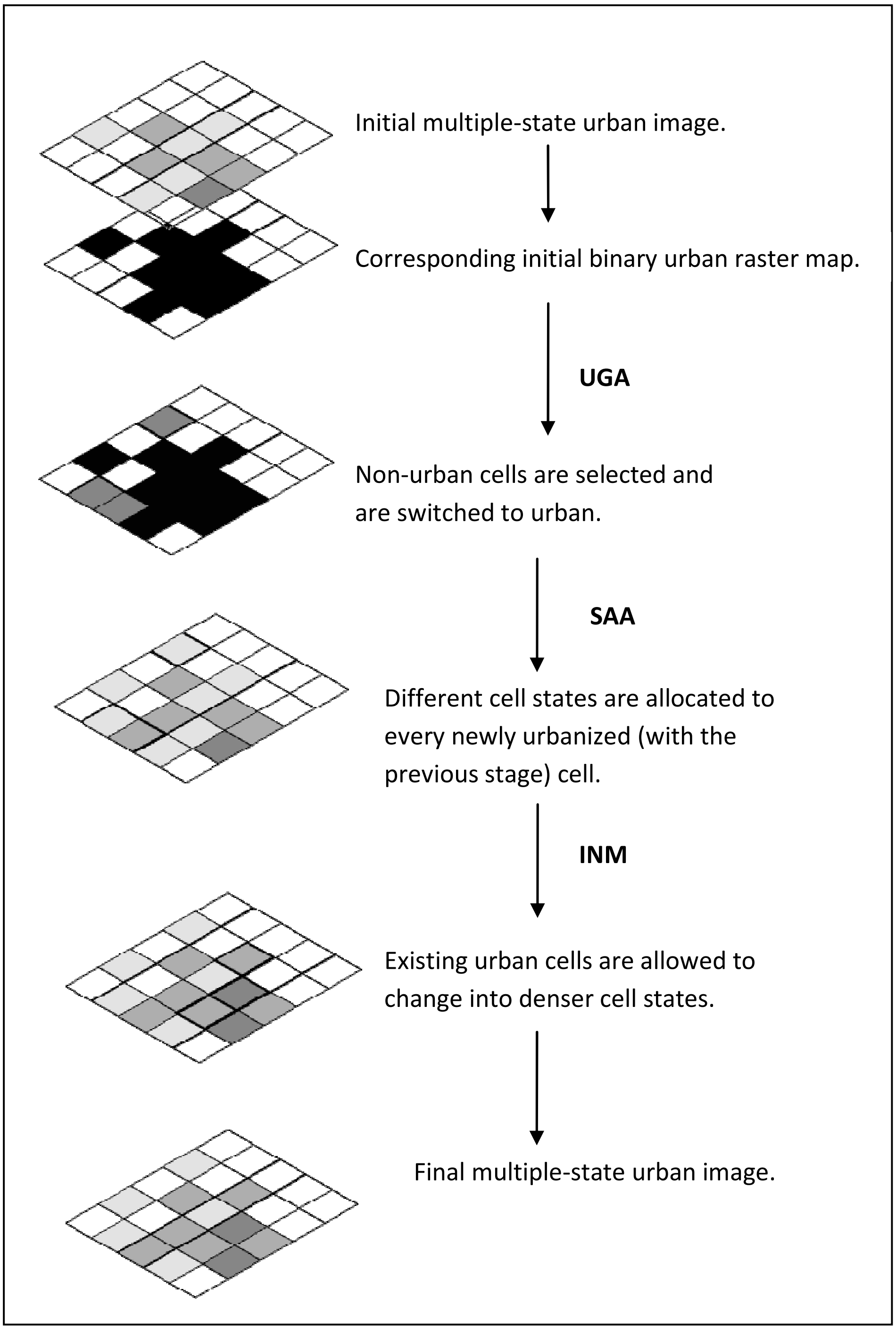


Figure 2. The framework of cell state transformation and allocation that drives multiple-state urban growth.

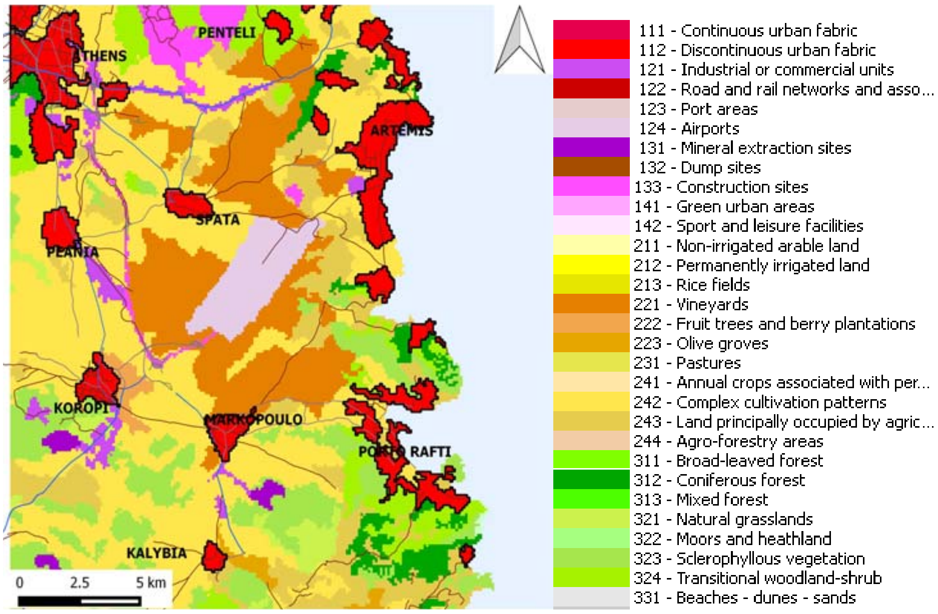


Figure 3. Land uses and transportation network of the study area (resolution of the raster map is 100×100 m^2) according to CORINE 2000. Coordinates at the centre of the map for EPSG:3857 are (37.9372, 23.941).

Figure 4. Satellite images of urban areas (100×100 m^2) of the states (from left to right) 2, 3 and 4 respectively.

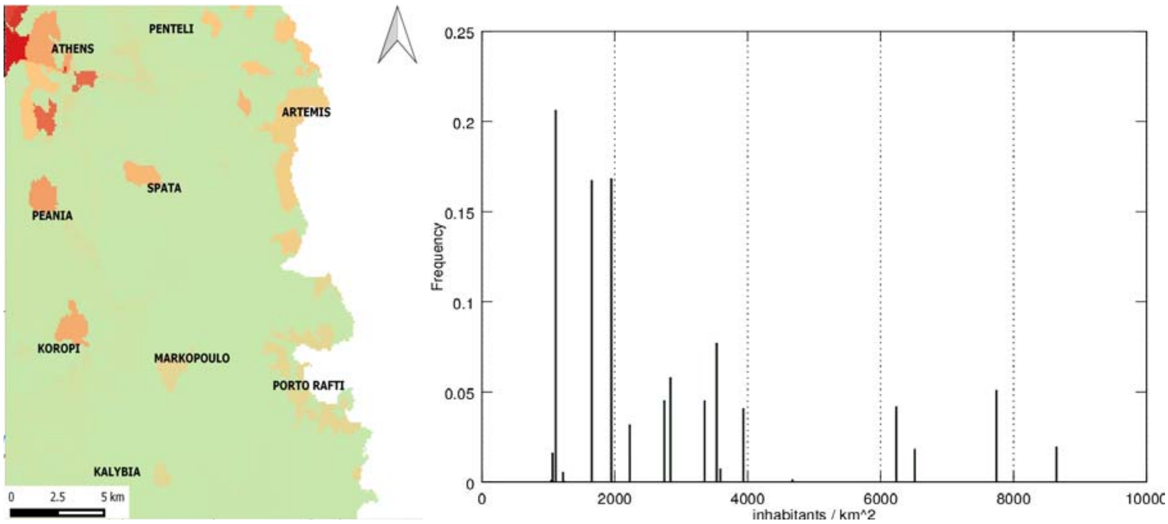


Figure 5. Left: map of population density distribution according to CORINE 2000 (resolution of raster map is 100×100 m^2). Right: Frequency of population density values of the CORINE map.

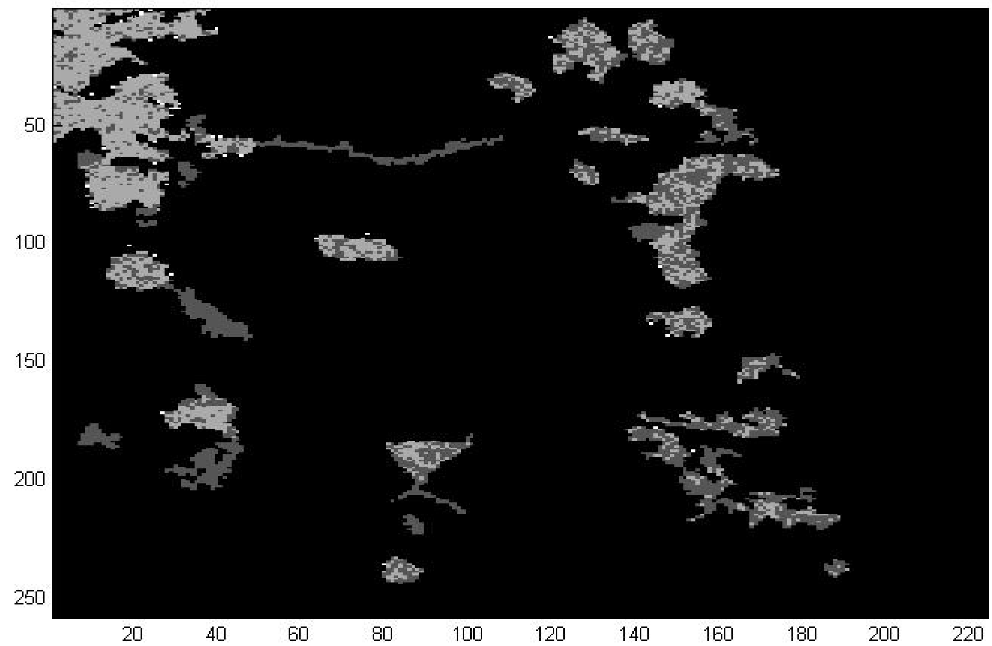


Figure 6. Overlay of the CORINE 2000 urban boundaries and the simulated residential patterns.

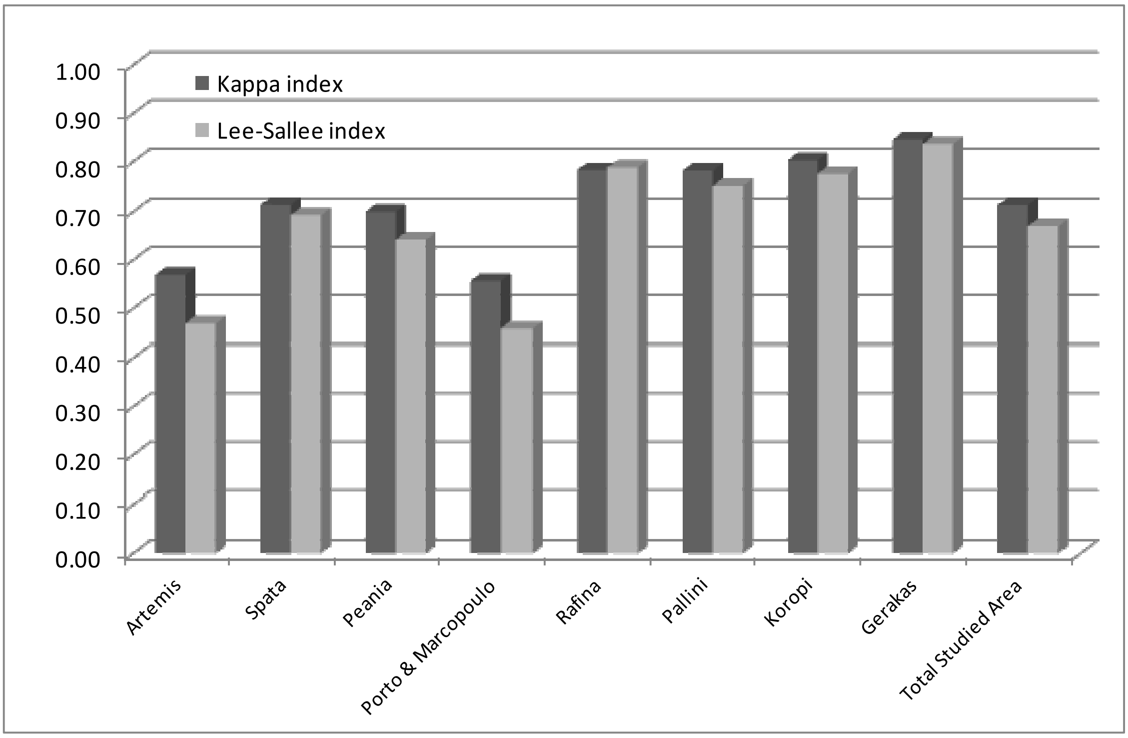


Figure 7. Fitting indicators for the model results, as compared to the CORINE2000 urban cover.

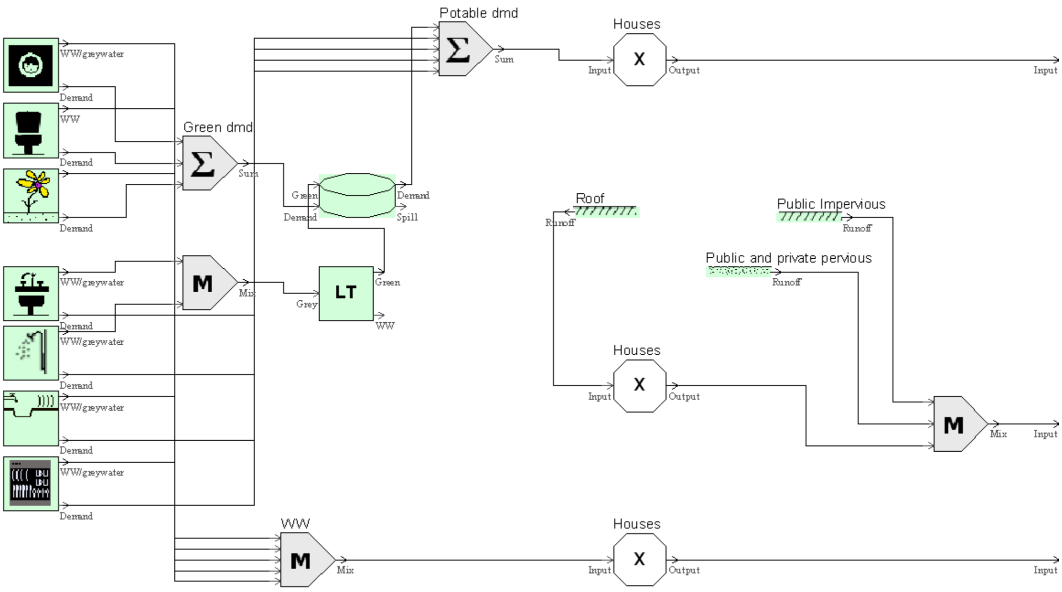
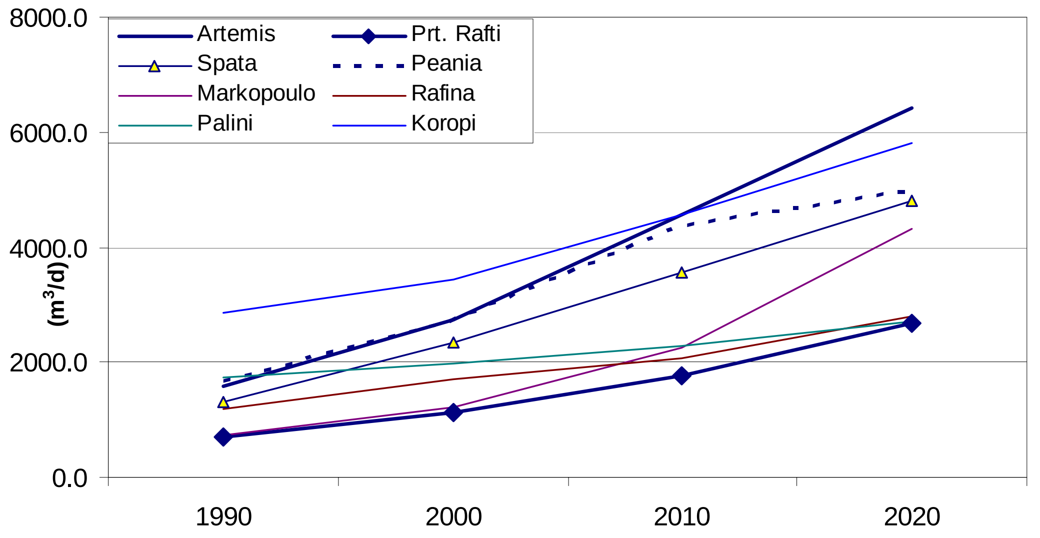


Figure 8. Indicative network topology of the GWR solution, modelled in UWOT.



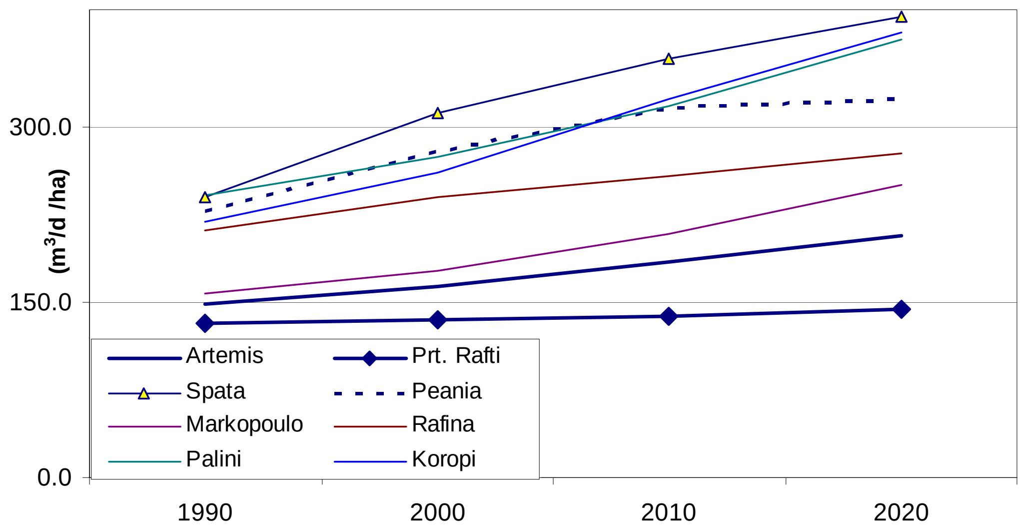
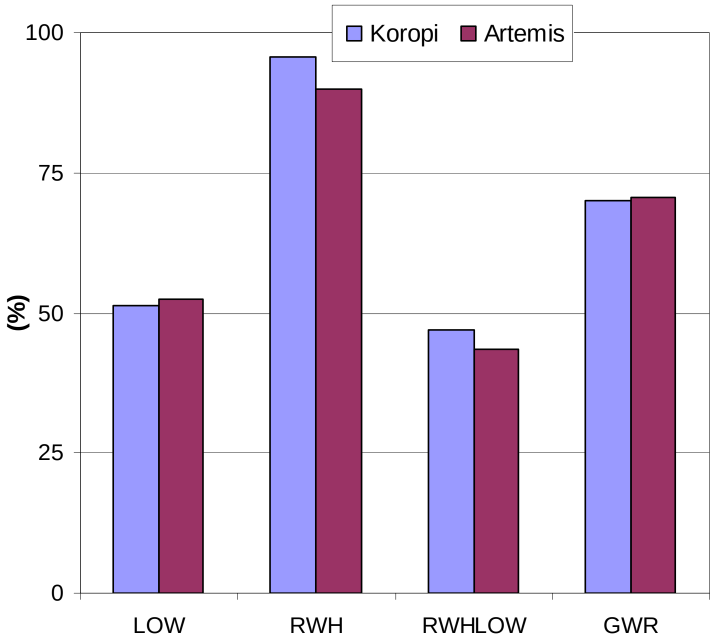
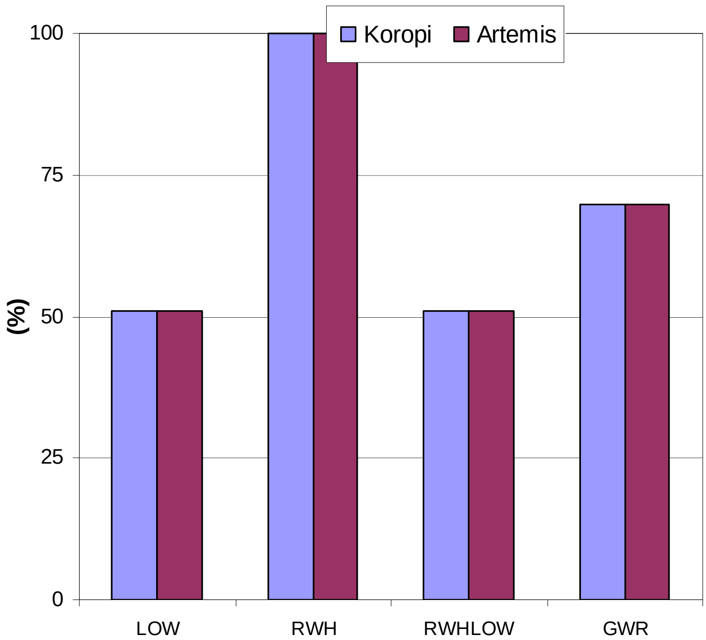


Figure 9. Indicative potable water demand per day (upper) and maximum runoff volume per hectare (bottom) for each municipality of Mesogeia, BAU solution.

697

Koropi
Artemis
100
75
50
25
0
(%)
LOW
RWH
RWHLOW
GWR

698

Koropi
Artemis
100
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RWHLOW
GWR

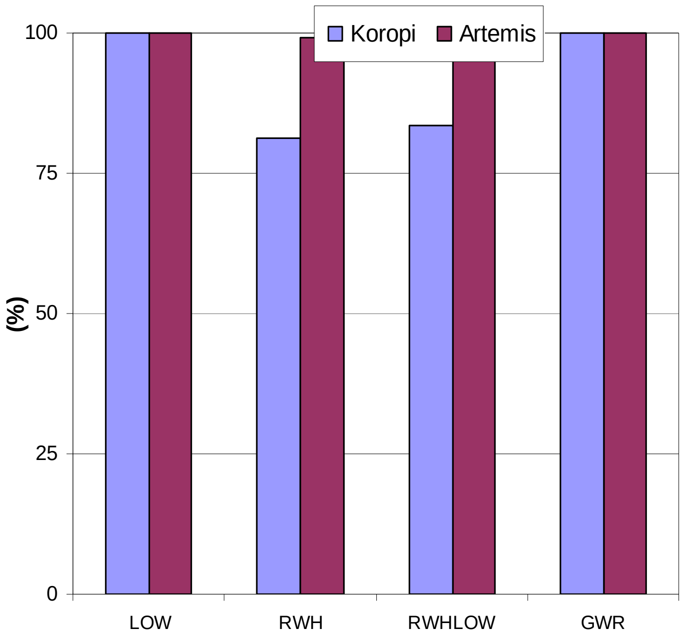

Figure 10. Potable water demand (a), wastewater volume (b) and runoff volume (c) for each WDM measure, presented as % of the BAU solution, for the municipalities of Koropi and Artemis.

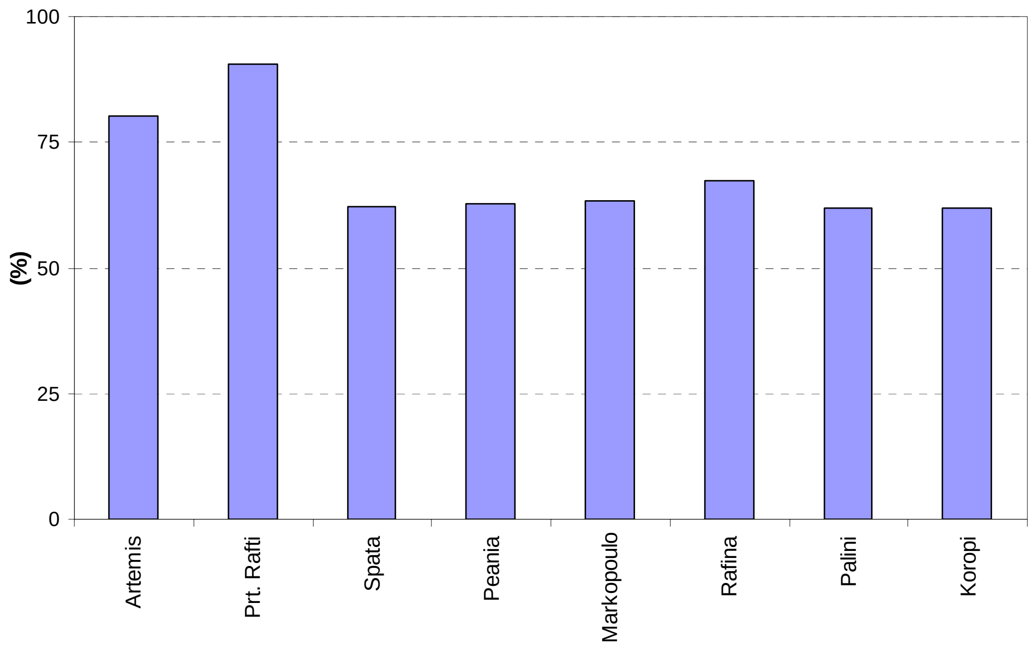

Figure 11**.** Runoff volume per municipality for the RWH solution, presented as % of the BAU solution.

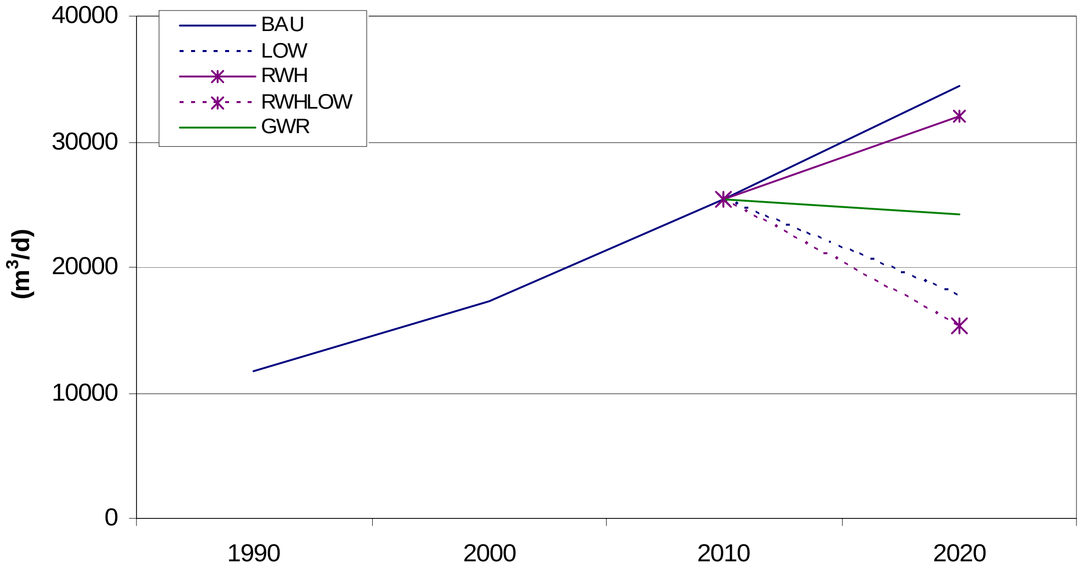

Figure 12. Comparison of the evolution of potable water demand over the whole study area for the different WDM measures.