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Water efficiency in smart cities: optimising irrigation for public green spaces

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ABSTRACT

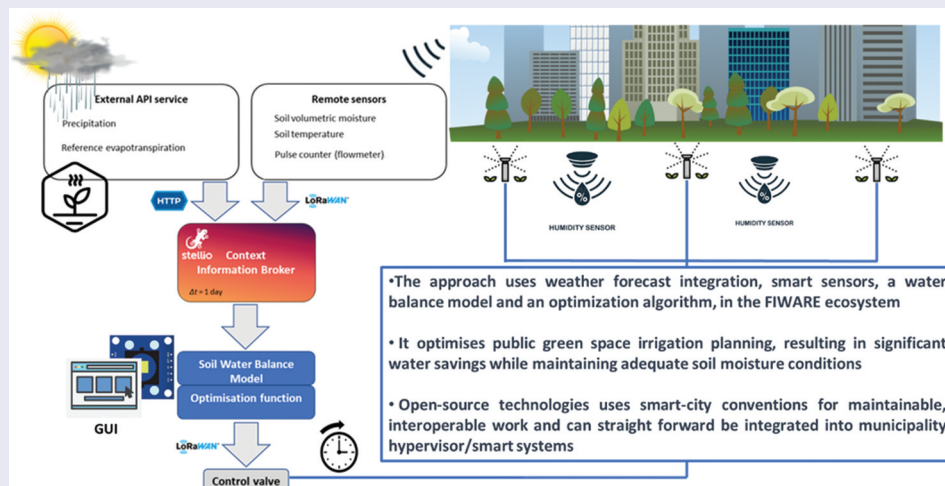
Greening initiatives are urban planning strategies that rely on the development of public green spaces supporting multiple urban system functions. In a global water scarcity context, however, green space irrigation is a key aspect. Dynamic optimisation of irrigation plans is one viable answer for water consumption mitigation, which is not widely implemented at municipal levels in the EU. Yet, hydroinformatics-based mature and market-ready methods and technologies can support its implementation and should allow its embedment within the smart-city concept. Here, a simple interoperable approach for optimisation of dynamic irrigation planning has been implemented in public green space parcels of a French Mediterranean coastal city. The approach relies on smart sensors, a water balance model, an optimisation algorithm, and weather forecast data integration, all encapsulated in the standardised and open-source FIWARE ecosystem. The results of the dynamic irrigation plan led to a 35% water saving during the dry season and to more than 60% water saving during the dry-wet season transition period. The used standard technologies and approach could fit a broad range of smart-city digital platforms without any technical challenge.

KEYWORDS

IOT; NBS; urban planning; interoperability; FIWARE framework

MOTS-CLÉS

IOT ; solutions basées sur la nature ; urbanisme ; environnement FIWARE



Villes intelligentes et optimisation de l'irrigation pour les espaces-verts

RÉSUMÉ

Les initiatives de verdissement sont des stratégies d'urbanisme reposant sur le développement d'espaces-verts publics. Elles soutiennent nombre de fonctions des systèmes urbains. L'irrigation des espaces verts reste un aspect clé de ces stratégies de verdissement. L'optimisation dynamique des plans d'irrigation de ces espaces-verts représente une réponse viable pour atténuer la consommation d'eau associée mais est peu implémentée à l'échelle municipale au sein de l'UE. Néanmoins, des méthodes et technologies matures, basées sur des outils d'hydroinformatique, permettent la mise en œuvre de systèmes d'optimisation dynamique, autorisant par ailleurs une intégration dans le concept de ville intelligente. Ici, une approche simple et interoperable pour l'optimisation de la planification dynamique de l'irrigation a été mise en œuvre dans des parcelles d'espaces verts publics d'une ville méditerranéenne française sur une période test. L'approche repose sur des capteurs intelligents, un modèle de bilan hydrique, un algorithme d'optimisation et l'intégration de données de prévisions météorologiques, le tout est encapsulé dans l'écosystème FIWARE, un standard pour plateformes IoT open-source. Les résultats montrent une économie d'eau de 35% pendant la saison sèche et de 60% pendant la période de transition saison sèche-saison humide. Les technologies et l'approche open sources utilisées s'adapteraient ainsi à une large gamme de plateformes numériques de villes intelligentes sans aucun défi technique.

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1. Introduction

In municipalities, public green spaces represent a key component of the urban system whose primary function is to offer embellishment, leisure, and well-being spaces to citizens. These urban green spaces also provide increased infiltration that reduces flood runoff (Benedict & McMahon, 2002; Qi et al., 2023) and reduced air temperature that increases comfort during heatwaves (Augusto et al., 2020; Rocha et al., 2022). The role of urban green spaces in reducing heat and enhancing infiltration becomes increasingly important (Oral et al., 2020; Probst et al., 2022) as climate change increases the frequency of occurrence of extreme heatwaves and rainfall events (IPCC, 2022a, 2022b). Therefore, public green spaces in cities, trendily referred to as parts of nature-based solutions (NBSs), are a constitutive part of greening initiatives in current and future EU cities' urban planning (Castellar et al., 2022; Dicks, 2015; Dorst et al., 2019).

Key aspects of managing these municipal green spaces are maintenance and water consumption (Nouri et al., 2019). For example, in EU Mediterranean cities, water consumption represents on average $1 \text{ m}^3/\text{m}^2$ per year for turf grass ($\pm 20\%$; Domene & Saurí, 2006; Morote-Seguido & Hernandez-Hernandez, 2016). In a water scarcity-driven context, management towards efficient use of the water resource is stressed by the United Nations' Sustainable Development Goals (SDG 6.4, SDG 6.B; UNDP, 2017), and the EU is pushing to make the water efficiency dimension a high priority for the member states (European Commission, 2019). Therefore, strategies are being implemented to mitigate water consumption in public green spaces, such as the selection of species more resistant to water stress or the reuse of treated wastewater (Castellar et al., 2022; Qtaishat et al., 2022; Santana et al., 2019).

Another obvious way to improve green spaces' water consumption efficiency is through irrigation optimisation. In the optimisation of the irrigation of these green spaces, hydroinformatics is a key supporting field, having a transversal role in integrating water sciences (i.e. hydrological, hydraulic and environmental), data sciences (statistics; stochastic, data-driven analytics), computer science and information and communication technologies (ICT), and society (Holz et al., 2014). In this regard, the implementation of the smart city and smart water concepts, supported by the hydroinformatics field, is growing in terms of numbers and types of applications in the water sector (Gourbesville, 2016; Gourbesville & Ma, 2022; Monzon, 2015). However, practical applications in urban irrigation are not yet broadly implemented (Aldegheishem et al., 2022; Monteiro et al., 2021). Moreover, when implemented, no hydroinformatics-based urban irrigation optimisation solutions with

a highly transversal data assimilation level were found [e.g. no applications have been found integrating weather forecast data assimilation outside of the agricultural irrigation sector (Alves et al., 2023)].

The aim of the present paper is to demonstrate the feasibility and efficiency of dynamic optimisation of irrigation plan implementation for urban public green spaces, based on an interoperable hydroinformatics approach. The goal is to illustrate the potential of this type of solution for efficient water resource use and the ease of implementation of this market-ready method and technology, to facilitate its implementation at municipal levels. Here, a simple but holistic irrigation optimisation strategy has been carried out at the level of parcels set in a French Mediterranean coastal city, relying on four key components: smart sensors, water balance model, optimisation algorithm, and weather forecast data integration. The novelty lies in the ease and readiness of implementation which should pave the way to further encompass these types of hydroinformatics-based solutions at the municipal level.

Firstly, the overall concept is presented: the method, the test case characteristics in a semi-arid Mediterranean city, and the tested set-up. Secondly, we present the results at the parcel scale of the solution capabilities in terms of implementation, the outcomes in terms of water savings, and added value for irrigation optimisation strategies and planning. Lastly, added values and limits are discussed and put into perspective.

2. Methodology

2.1. Concept design

The goal of the concept is to provide an optimal irrigation plan for the upcoming week. This plan is to be determined using the architecture and technology components illustrated in Figure 1. The concept relies on the standard and open-source technology framework FIWARE (2020). This allows not only the replicability of the solution but also, due to its structure based on standard generic enablers (Alves et al., 2023), the ease of its implementation in other platforms with broader purposes thanks to the interoperability properties of the FIWARE framework [e.g. smart water platform, municipality-scale hypervisor or extending a digital twin (Lewis et al., 2023)].

The system is composed of two main sources of data: (i) capacitance sensors, able to measure soil volumetric moisture; and (ii) an Application Programming Interface (API) service providing real-time precipitation and evapotranspiration estimates with forecasts of precipitation and evapotranspiration for the upcoming 14 days.

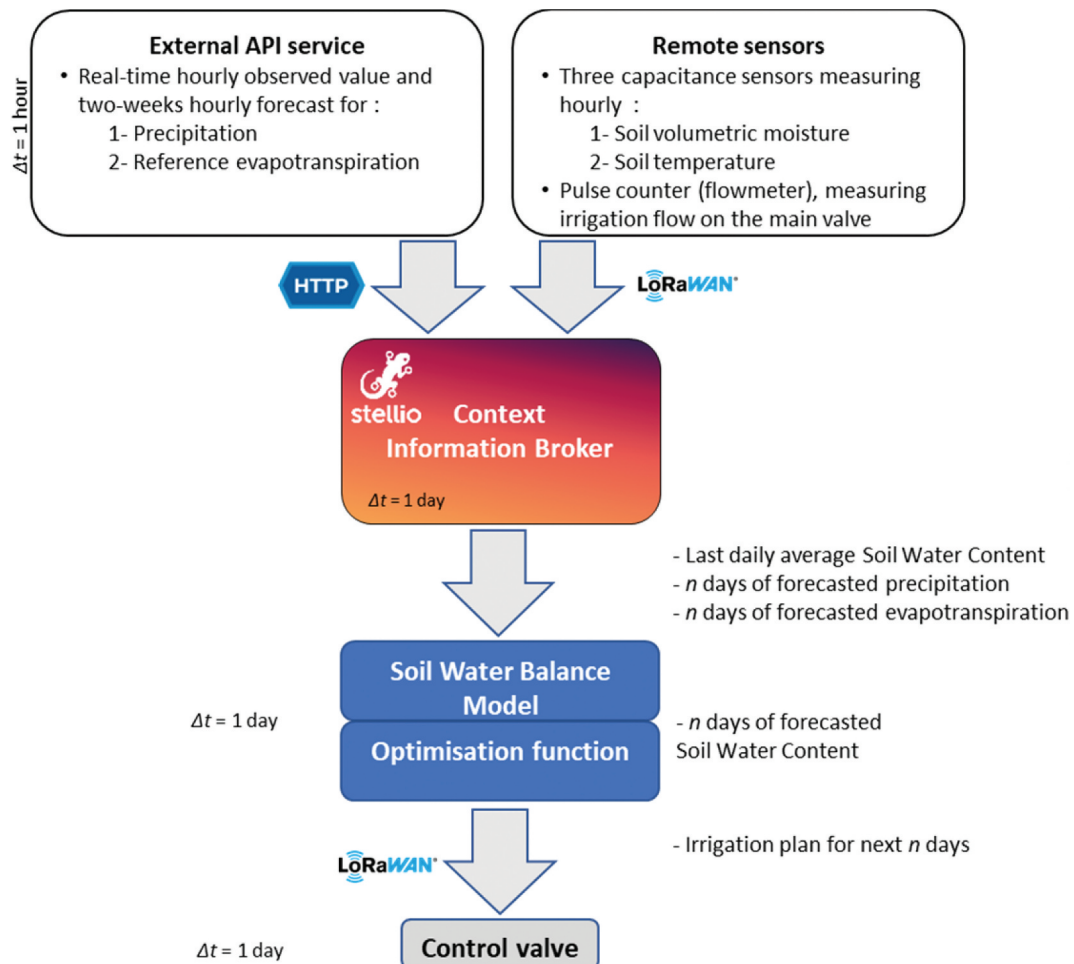


Figure 1. Key layers, components and protocols of the developed system.

Data are managed by the Stellio Context Information Broker, which is a platform that allows connection and information sharing between all types of use cases. The main asset of the Context Information Broker is the Next Generation Service Interfaces Linked Data (NGSI-LD) Context Information Management API, which allows easy retrieval of the data with powerful temporal or geospatial queries. It also includes a set of components that satisfy the NGSI-LD specification and are compatible with the FIWARE ecosystem to increase interoperability. FIWARE Draco, which is an open-source data flow manager based on Apache Nifi, is used to process incoming data and perform data validation.

Two processes (described in section 2.3.3) then use those data:

- A soil water balance model that uses the last soil moisture measurement and the forecasted meteorological data for the next *n* days to provide a forecast of soil moisture for the next *n* days.
- An optimisation algorithm that uses those forecasted soil moisture values to provide an optimal irrigation plan for the next *n* days.
- for the drip irrigation sectors: 1 m³ distributed in 90 min, every Monday and Thursday (during the night);
- for the sprinkler irrigation sectors: 3 m³ distributed in four time slots of 5 min (spread over 3 h), every Monday, Wednesday, and Friday (during the night).

2.2. Study area

The test case is a mid-sized French Mediterranean city (30,000 inhabitants) located on the French Riviera which sees its population triple during the summer season when both water resources and vegetation are under the peak stress. The method is tested on 24 parcels of public green spaces, ranging from 50 m² to 300 m² and representing a total area of about 3000 m². Two different irrigation systems are in place: (i) drip irrigation (on six parcels), and (ii) sprinkler irrigation (on 18 parcels). Each parcel is controlled by an auto-valve, which allows the provisioning of different irrigation plans for each sector if needed. The original standard irrigation scheme implemented by the municipality is the following:

Over these parcels, the yearly water consumption is approximately 7000 m³ with this original standard irrigation scheme.

2.3. Data sources

2.3.1. Smart sensors and measurement strategy

Three parameters of interest are measured: (i) soil humidity, (ii) soil temperature, and (iii) quantity of water used for irrigation. The soil volumetric humidity (in m³/m³) and the soil temperature are measured at a depth of 0.15 m by an electrical capacitance sensor (Sensecap VWC sensor) known to be reliable for continuous measurements (Singh et al., 2018). Multiplying the soil volumetric humidity by the depth of the soil allows the estimation of the water content (in mm). To measure the quantity of water used for irrigation, a pulse counter device is used to measure the flow on the main valve (i.e. the flow for all sectors).

Soil humidity and soil temperature are measured at three different locations chosen to be representative of the possible range of conditions of the green spaces in the study case: a full sun-exposed grass-covered parcel, a parcel with mixed shadow/sunny exposure covered by grass, and a bushy parcel (Figure 2). Each of the 24 parcels is linked to the soil moisture measurements of one of the three above-mentioned monitored zones depending on its sun exposure/vegetation cover type.

Measurement data are sent hourly for the sensecap sensors, and each second for the flowmeter via a Long Range Wide Area Network (LoRaWAN) radio communication protocol which provides a low-power wide-area network (Aldegheishem et al., 2022). The data are available in hourly time steps, and the Stellio Context Broker API makes it very easy to obtain any type of temporal aggregation instantaneously to be used later. In this case, the irrigation optimisation algorithm presented below operates on a daily time step.

Measurement campaigns were performed over the course of 7 months, divided into two periods:

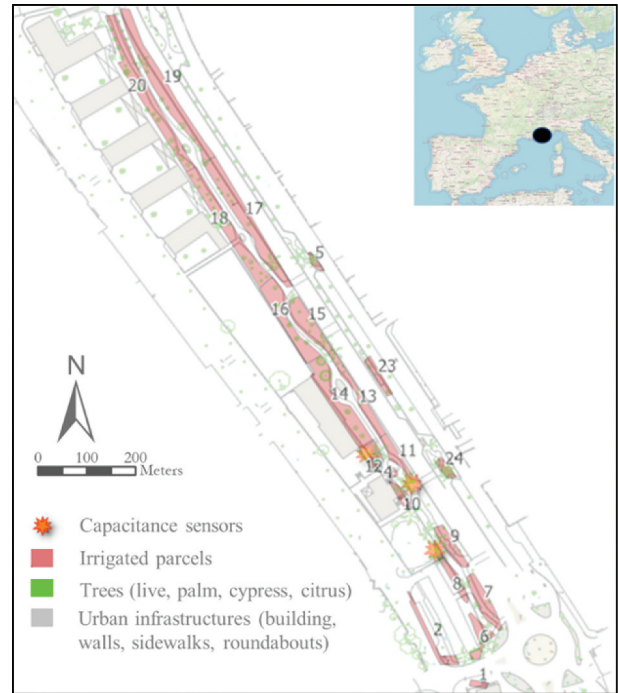


Figure 2. Schematic overview of the instrumented public green space.

- a 1 month (mid-May to mid-June) dry period;
- a 4 month (mid-September to mid-December) dry-wet transition period.

The period between mid-June and mid-September is not used since the irrigation in the area was shut down at a regional scale due to a severe drought leading to governmental irrigation restrictions.

2.3.2. Weather forecast provider

The reference evapotranspiration and rainfall intensity nowcast and the 7 day forecast datasets are provided by an external API service. The data are received and processed using FIWARE Draco. This weather forecast service provides real-time measurement and forecasted values for many different types of weather data (Zebiri, 2020).

A comparison between forecasted and observed values was performed (Figure 3) to assess the quality of the provided forecast, and the root mean square

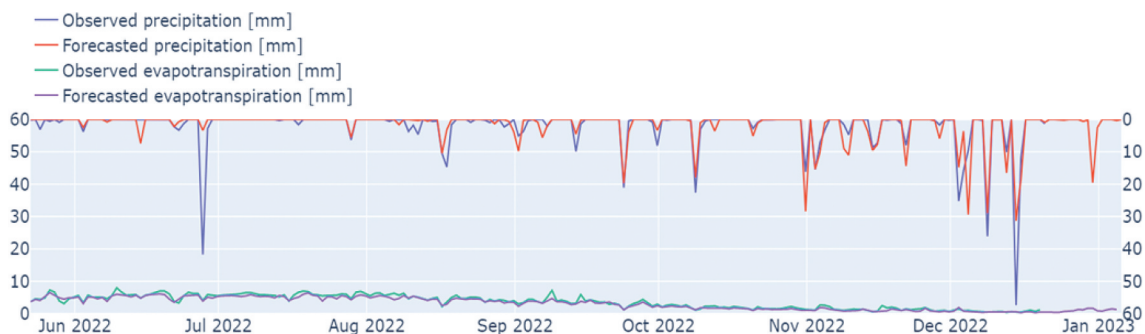


Figure 3. Difference between observed and forecasted daily values for precipitation and evapotranspiration data.

error metric (RMSE) was calculated to quantify the accuracy. Forecasted values are available for 14 days with daily updates. Here, the next 7 days forecast window is used. For evapotranspiration, the forecasted estimated values 7 days in advance are very close to the observed ones; the RMSE is 0.6 mm, which translates correct accuracy. However, for precipitation, the occurrence of events higher than a $2 \text{ mm}\cdot\text{day}^{-1}$ threshold is properly captured but the intensity of the precipitation is not reliable, as illustrated in Figure 3. The error on the high-intensity episode leads to a worse global accuracy and a higher RMSE of 4.1 mm.

2.4. Mass balance and optimisation algorithms

The two principal components of the irrigation planning computation method are:

- (1) a mass balance model, which allows prediction of the soil humidity based on measurements and forecasts;
- (2) an optimisation function that adjusts the irrigation quantity for a design period (here, 1 week) based on the mass balance model. The objective of the optimisation model is to determine the lowest water quantity that can be delivered, while still maintaining the soil moisture at a sufficient level (i.e. minimising the risk for the plant).

The mass balance model is based on water input and output over a soil volume. It is a simple yet still widely used model in the irrigation area (Pereira et al., 2020; Sammis et al., 2012). The mass conservation equation can be written as follows:

$$\Delta SWC = P + I - ET - SR - DP + CR \quad (1)$$

where SWC is the soil water content, P is the rainfall precipitation, I is the applied irrigation, ET is the evapotranspiration, SR is the surface runoff, DP represents the deep percolation and CR is the capillary rise. The balance is estimated with a daily time step which yields:

$$\Delta SWC(t) = SWC(t) - SWC(t-1) \quad (2)$$

where t is equal to the current day. Equation (1) then becomes:

$$SWC(t) = SWC(t-1) + P(t) + I(t) - ET(t) - SR(t) - DP(t) + CR(t) \quad (3)$$

where t + 1 corresponds to the following day and where – except for SWC(t), which is measured in real time – all the values are forecasted. Indeed, as a reminder, ET(t) and P(t) are provided for a sliding window of 1–2 weeks, whereas I(t) is the value to optimise and SWC(t) is the output of the model. Surface runoff, deep percolation and capillary rise

were calculated from the other components using the methods given by Villalobos and Fereres (2016). Eventually, as all values are predicted for n days, replacing predicted SWC(t) with predicted SWC(t), irrigation planning can be foreseen up to t + n days.

If one can predict the SWC with this model, one can establish a parsimonious irrigation optimisation strategy to balance the irrigation volume with the required SWC conditions. To do so, the developed algorithm is based on three SWC thresholds, as follows:

- Comfort threshold: Above this specified SWC value, the plants are in optimal irrigation condition.
- Saturated threshold: Above this specified SWC, the plant receives too much water, leading to water overconsumption and potentially improper phytosanitary conditions.
- Critical threshold: below this specified SWC value, the plant does not have access to sufficient water resources to secure proper maintenance and development.

The threshold values are specified by the user depending on the specific plants' requirements and on the user's local experience with plants' requirements for the specific parcels.

The thresholds are defined as follows:

$$\theta_{PWP} + (1 - AD)(\theta_{FC} - \theta_{PWP}) \quad (4)$$

where θ_{PWP} is the soil volumetric moisture at the permanent wilting point, θ_{FC} is the soil volumetric moisture at field capacity, and AD is the allowable depletion. It allows the description of threshold values independent from the soil volumetric moisture limit values defined previously. For example, a value of AD of 0.2 means that the threshold is equal to 80% of the soil capacity. Here, the selected AD values were 0.2, 0 and 0.4 for the comfort, saturated and critical thresholds, respectively, which are standard values for turf grass (Villalobos & Fereres, 2016).

The optimisation algorithm functions as follows: depending on the authorised/scheduled period where irrigation is authorised (here, days), the algorithm cuts the planning into sub-periods, starting with an authorised irrigation day. Then, for each sub-period, the algorithm uses an initial prediction of the model and increments during the allowed period the release of a fully open 1 min irrigation discharge until the critical threshold is exceeded for all the days of the period. Then, it iteratively increases the irrigation discharge/period until the comfort threshold is exceeded, as long as the saturation threshold is not exceeded for any of the days of the given period.

The considered hierarchy regarding the thresholds can thus be summarised as follows:

- (1) The critical threshold is the one that must be reached absolutely every day.
- (2) Next, the saturation threshold should not be exceeded unless it means being below the critical threshold on any day.
- (3) Finally, the comfort threshold must be exceeded unless this would imply that certain days are above the saturation threshold.

The optimisation algorithm also takes into consideration the existing irrigation schedule constraints which might depend on various external factors such as strategic choice by municipality operators to cope with water cost, water resource-specific availability (e.g. for water reuse during a certain specific time slot constraint, etc.), operators' availability, conflict of usage of the public space, etc.

3. Results

The outcome of the irrigation planning dynamic optimisation method on different inter-seasonal conditions is here assessed. The results are considered successful when:

- (a) in implementing the irrigation plan, the predicted and measured soil moisture are in good

adequation, as close as possible to the defined comfort zone;

- (b) water saving is observed compared to the original irrigation plan;
- (c) vegetation does not suffer any water-induced stress in the parcels.

The results are presented in two parts: (i) during the 1 month dry period, used as a reference, for a sprinkler irrigation sector; then (ii) during the 4 month dry-wet transition period, for a drip irrigation sector.

3.1. Dry period, sprinkler irrigation sector

The irrigation programme recommended by the algorithm and the resulting predicted soil volumetric moisture are presented in Figures 4 and 5.

Figure 4 is representative of a 1 month dry period as precipitation was very scarce (15.7 mm cumulated over the month; no event exceeds 4 mm). In the absence of precipitation, using mostly the soil moisture targeted value, the algorithm still manages to significantly reduce the quantity of water used for irrigation, from 37.6 m³ to 24.1 m³ over that period. This represents a 35% saving on the water resource. Indeed, Figure 5 shows that reducing the irrigation has a very limited impact on the predicted soil volumetric moisture, which stays very high during the entirety of the period (the permanent wilting point for this sector is 0.12 m³/m³). The RMSE between forecasted and

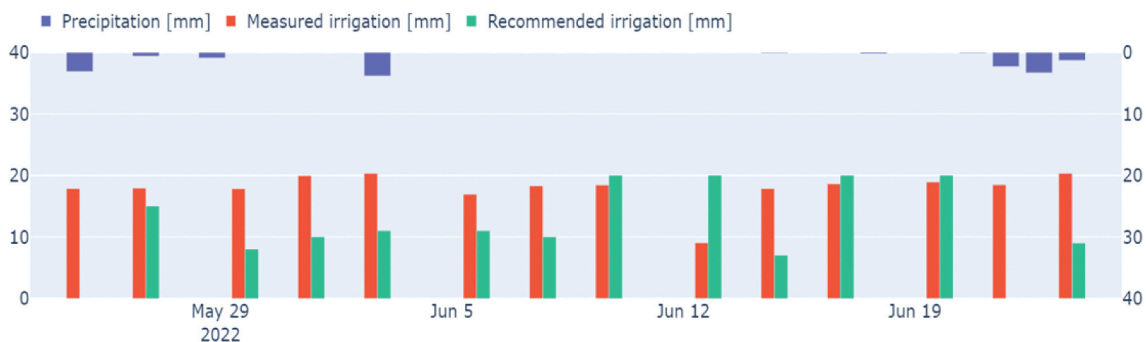


Figure 4. Recommended irrigation, measured irrigation and precipitation during the 1 month dry test period for a sprinkler irrigation sector.

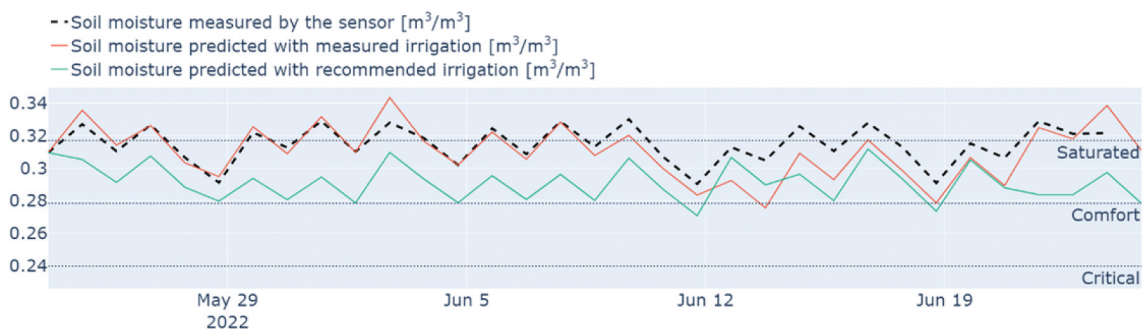


Figure 5. Resulting predictions of soil moisture compared to measurements from the sensor during the 1 month dry test period for a sprinkler irrigation sector.

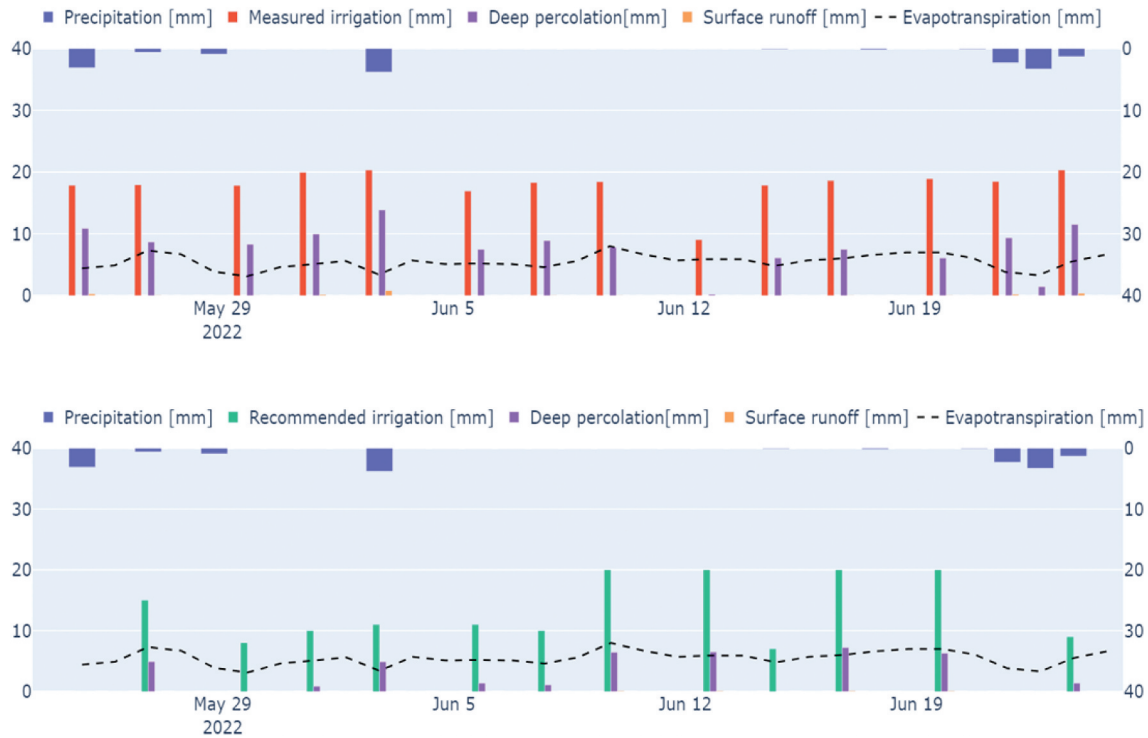


Figure 6. Water balance model components comparing measured (top) and recommended (bottom) irrigation during the 1 month dry period.

measured soil moisture is 3.4%, indicating a satisfying reliability of the water balance model. Thus, using the algorithm in this test dry period allows the improvement of irrigation efficiency. It also led to figuring out that here, 35% of the volume of water was lost due to deep percolation and surface runoff (Figure 6).

3.2. Wet period, drip irrigation sector

For this period, the irrigation programme recommended by the algorithm and the resulting predicted soil volumetric moisture are presented in Figures 7 and 8, respectively. Over the 4 month period, the first 2 months (September–October) still had an elevated temperature and vegetation with high physiological activity, favouring evapotranspiration, and a few significant rainfall events: two events with more than 10 mm per 24 h each (Figure 7). Over that period, the recommended irrigation planning allowed water savings mostly in October. The algorithm used the forecasted rainfall events to reduce the irrigation volume 7 days in advance, while allowing the maintenance of soil moisture around the comfort zone (Figure 8). For this sector, RMSE between forecasted and measured soil moisture is 5.6%. It should be noted that for the month of September, which corresponds to the tail end of the dry season, the recommended irrigation did not differ from the standard irrigation scheme as the soil moisture was far below the critical threshold. Thus, even though a rainfall event was forecasted, no irrigation cut has been planned until the soil moisture critical threshold is surpassed.

The second 2 month sub-period (November–December) had a relatively lower temperature, with declining vegetal physiological activity and with rainfall events becoming more regular (Figure 7). The irrigation was then cut in response to the predicted rainfall, while maintaining an optimal soil moisture level (comfort zone).

Over the 4 month period, for these sectors, the recommended irrigation volume has been reduced from 19.95 m³ to 6.5 m³. This represents a 67% water saving for these two parcels. However, this important saving percentage will be moderated as the initial irrigation programme has not been modified, and it is likely that under normal operation procedure, the municipality would have reduced the irrigation frequency starting from November.

4. Conclusion and perspectives

The benefits of technical implementation of public green space optimised irrigation planning relying on hydroinformatics components are here demonstrated. Smart sensors, water balance models, optimisation algorithms, and weather forecasts are combined, and the operational capability of the system is displayed. Irrigation plan optimisation led to a 35% water saving during the dry season and more than 60% water saving during the dry–wet season transition period. The open-source standard technology and approach used here can be included in the

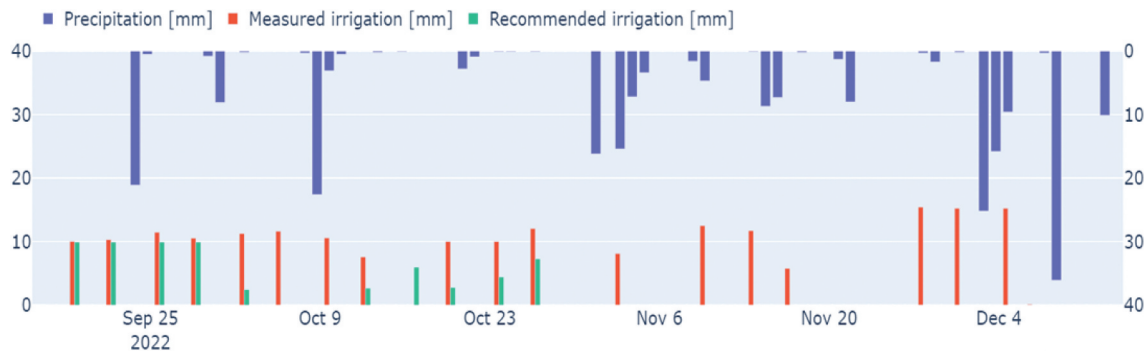


Figure 7. Recommended irrigation, measured irrigation and precipitation during the 4 month dry-to-wet period transition for the drip irrigation sector.

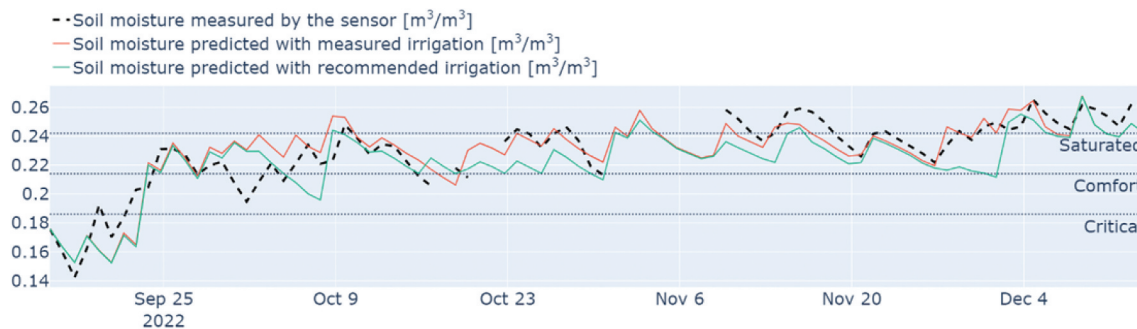


Figure 8. Resulting prediction of soil moisture compared to measurements from the sensor during the 4 month dry-to-wet period transition for the drip irrigation sector.

municipality hypervisor without any key technical challenge to fit with an orchestrated implementation of the smart city/smart water concept. Indeed, relying on the FIWARE framework, the developed hydroinformatics-based method uses common and popular smart-city/software conventions, rendering the proposed work maintainable and interoperable from the perspective of software engineering. Limitations are those depending on the quality of the entry data (measured and forecasted). Also using a small number of sensors with respect to the number of parcels means that the irrigation of non-instrumented parcels is driven by the soil moisture feedback of a different parcel. This can induce some undetected drift and requires particular on-field attention. The implications of scaling such an application to an entire city would therefore require particular attention, especially in the instrumentation and drift control strategies. Other types of sensors could be tested for this application, such as tensiometers, which are used for irrigation scheduling (Intrigliolo & Castel, 2004) but are less compatible with the presented water balance model. The optimisation can be further improved to upgrade to a multivariate problem such as crop growth status requirements, water restriction or water reuse programming constraints, etc., in the irrigation planning optimisation.

5. List of hardware and software

	Type	Availability
Hardware	Sensecap temperature and volumetric sensor	https://www.seeedstudio.com/SenseCAP-Wireless-Soil-Temperature-VWC-EC-Sensor-LoRaWAN-AU915-MT20-p-4995.html
Hardware	Flowmeter	Proprietary
Hardware	Control valve	Proprietary
Data source	External weather API	Any API
Communication protocol	Lorawan	https://www.enless-wireless.com/fr/lor/
Software	Stellio Context Broker	https://www.github.com/stellio-hub/stellio-context-broker
End-user interface	Grafana dashboards	https://grafana.com/grafana/dashboards/
Program language	Python	https://www.python.org/
Standards	NGSI-LD	https://fiware-datamodels.readthedocs.io/en/stable/ngsi-ld_howto/

Disclosure statement

The authors report there are no competing interests to declare.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

References

- Aldegheishem, A., Alrajeh, N., García, L., & Lloret, J. (2022). SWAP: Smart Water Protocol for the irrigation of urban gardens in smart cities. *IEEE Access*, 10, 39239–39247. <https://doi.org/10.1109/ACCESS.2022.3165579>
- Alves, R. G., Maia, R. F., & Lima, F. (2023). Development of a digital twin for smart farming: Irrigation management system for water saving. *Journal of Cleaner Production*, 388, 135920. <https://doi.org/10.1016/j.jclepro.2023.135920>
- Augusto, B., Roebeling, P., Rafael, S., Ferreira, J., Ascenso, A., & Bodilis, C. (2020). Short and medium-to long-term impacts of nature-based solutions on urban heat. *Sustainable Cities and Society*, 57, 102122. <https://doi.org/10.1016/j.scs.2020.102122>
- Benedict, M. A., & McMahon, E. T. (2002). Green infrastructure: Smart conservation for the 21st century. *Renewable Resources Journal*, 20(3), 12–17.
- Castellar, J. A., Torrens, A., Buttiglieri, G., Monclús, H., Arias, C. A., Carvalho, P. N., Galvao, A., & Comas, J. (2022). Nature-based solutions coupled with advanced technologies: An opportunity for decentralized water reuse in cities. *Journal of Cleaner Production*, 340, 130660. <https://doi.org/10.1016/j.jclepro.2022.130660>
- Dicks, H. (2015). Penser le nouveau paradigme de l'hydrologie urbaine: Biomimétisme, éco-phénoménologie, et gestion intégrée. *La Houille Blanche*, 5(5), 92–98. <https://doi.org/10.1051/lhb/20150060>
- Domene, E., & Sauri, D. (2006). Urbanisation and water consumption: Influencing factors in the metropolitan region of Barcelona. *Urban Studies*, 43(9), 1605–1623. <https://doi.org/10.1080/00420980600749969>
- Dorst, H., Van der Jagt, A., Raven, R., & Runhaar, H. (2019). Urban greening through nature-based solutions—Key characteristics of an emerging concept. *Sustainable Cities and Society*, 49, 101620. <https://doi.org/10.1016/j.scs.2019.101620>
- European Commission. (2019). *The European Green Deal. COM (2019) 640 final. 11 December 2019, Brussels*. https://ec.europa.eu/info/sites/info/files/european-green-deal-communication_en.pdf
- FIWARE. (2020). *Fiware catalogue*. Retrieved January 7, 2023, from <https://bit.ly/3G0P1Sx>
- Gourbesville, P. (2016). Key challenges for smart water. *Procedia Engineering*, 154, 11–18. <https://doi.org/10.1016/j.proeng.2016.07.412>
- Gourbesville, P., & Ma, Q. (2022). Smart river management: What is next? *River*, 1(1), 37–46. <https://doi.org/10.1002/rvr2.13>
- Holz, K. P., Cunge, J., Lehfeldt, R., & Savic, D. (2014). Hydroinformatics Vision 2011. In P. Gourbesville, J. Cunge, & G. Caignaert (Eds.), *Advances in hydroinformatics* (pp. 545–560). Springer Hydrogeology. https://doi.org/10.1007/978-981-4451-42-0_44
- Intrigliolo, D. S., & Castel, J. R. (2004). Continuous measurement of plant and soil water status for irrigation scheduling in plum. *Irrigation Science*, 23(2), 93–102. <https://doi.org/10.1007/s00271-004-0097-7>
- IPCC. (2022a). Summary for Policymakers. In P. R. Shukla, J. Skea, R. Slade, A. Al Khouradajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley (Eds.), *ClimateChange 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 2029). Cambridge University Press.
- IPCC. (2022b). Climate change 2022: Impacts, adaptation, and vulnerability. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegria, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.), *Contribution of Working Group II to the Sixth Assessment report of the intergovernmental panel on climate change* (pp. 3056). Cambridge University Press. <https://doi.org/10.1017/9781009325844>
- Lewis, G., Snider, B., Vamvakieridou-Lyroudia, L., Chen, A., Djordjević, S., & Savić, D. (2023). Developing water monitoring solutions with FIWARE defining, creating, populating, and extending digital twins. *IOP Conference Series: Earth and Environmental Science*, 1136, 012003. <https://doi.org/10.1088/1755-1315/1136/1/012003>
- Monteiro, L., Cristina, R., & Covas, D. (2021). Water and energy efficiency assessment in urban green spaces. *Energies*, 14(17), 5490. <https://doi.org/10.3390/en14175490>
- Monzon, A. (2015). Smart cities concept and challenges: Bases for the assessment of smart city projects. In *2015 International Conference on Smart Cities and Green ICT Systems (SMARTGREENS)* (pp. 1–11), IEEE.
- Morote-Seguido, A. F., & Hernandez-Hernandez, M. (2016). Green areas and water management in residential developments in the European Western Mediterranean. A case study of Alicante, Spain. *Geografisk Tidsskrift-Danish Journal of Geography*, 116(2), 190–201. <https://doi.org/10.1080/00167223.2016.1211483>
- Nouri, H., Borujeni, S. C., & Hoekstra, A. Y. (2019). The blue water footprint of urban green spaces: An example for Adelaide, Australia. *Landscape and Urban Planning*, 190, 103613. <https://doi.org/10.1016/j.landurbplan.2019.103613>
- Oral, H. V., Carvalho, P., Gajewska, M., Ursino, N., Masi, F., Hullebusch, E. D. V., Kazak, J. K., Exposito, A., Cipolletta, G., Andersen, T. R., Finger, D. C., Simperler, L., Regelsberger, M., Rous, V., Radinja, M., Buttiglieri, G., Krzeminski, P., Rizzo, A., Dehghanian, K., & Zimmermann, M. (2020). A review of nature-based solutions for urban water management in European circular cities: A critical assessment based on case studies and literature. *Blue-Green Systems*, 2(1), 112–136. <https://doi.org/10.2166/bgs.2020.932>
- Pereira, L. S., Paredes, P., & Jovanovic, N. (2020). Soil water balance models for determining crop water and irrigation requirements and irrigation scheduling focusing on the FAO56 method and the dual Kc approach. *Agricultural*

- Water Management*, 241, 106357. <https://doi.org/10.1016/j.agwat.2020.106357>
- Probst, N., Bach, P. M., Cook, L. M., Maurer, M., & Leitão, J. P. (2022). Blue Green Systems for urban heat mitigation: Mechanisms, effectiveness and research directions. *Blue-Green Systems*, 4(2), 348–376. <https://doi.org/10.2166/bgs.2022.028>
- Qi, Y., Chan, F. K. S., Feng, M., Griffiths, J., Hutchins, M., O'Donnell, E., Thorne, C., Liu, L., Zhang, C., & Li, X. (2023). Developing a “Sponge Catchment Management Plan(SCMP)” framework at the catchment scale: The case of Guiyang, SW China. *River*, 2(1), 109–125. <https://doi.org/10.1002/rvr.2.33QIETAL.125>
- Qtaishat, Y., Hofman, J., & Adeyeye, K. (2022). Circular water economy in the EU: Findings from demonstrator projects. *Clean Technologies*, 4(3), 865–892. <https://doi.org/10.3390/cleantechnol4030054>
- Rocha, A. D., Vulova, S., Meier, F., Förster, M., & Kleinschmit, B. (2022). Mapping evapotranspirative and radiative cooling services in an urban environment. *Sustainable Cities and Society*, 85, 104051. <https://doi.org/10.1016/j.scs.2022.104051>
- Sammis, T., Sharma, P., Shukla, M. K., Wang, J., & Miller, D. (2012). A water-balance drip-irrigation scheduling model. *Agricultural Water Management*, 113, 30–37. <https://doi.org/10.1016/j.agwat.2012.06.012>
- Santana, M. V., Cornejo, P. K., Rodríguez-Roda, I., Buttiglieri, G., & Corominas, L. (2019). Holistic life cycle assessment of water reuse in a tourist-based community. *Journal of Cleaner Production*, 233, 743–752. <https://doi.org/10.1016/j.jclepro.2019.05.290>
- Singh, J., Lo, T., Rudnick, D. R., Dorr, T. J., Burr, C. A., Werle, R., Shaver, T. M., & Muñoz-Arriola, F. (2018). Performance assessment of factory and field calibrations for electromagnetic sensors in a loam soil. *Agricultural Water Management*, 196, 87–98. <https://doi.org/10.1016/j.agwat.2017.10.020>
- UNDP. (2017). *Human development reports database*.
- Villalobos, F. J., & Fereres, E. (eds). (2016). *Principles of agronomy for sustainable agriculture*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-46116-8>
- Zebiri, A. (2020). Estimation de la dynamique à partir de l'assimilation d'images radars multi-échelles: application à la prévision des taux de précipitation à courte échéance, à partir des images radars [Ph. D. thesis, Sorbonne université]. <https://doi.org/10.1017/9781009157926.001>