Article

Irrigation Distribution Network Design Parameters and Their Influence on Sustainability Management

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Abstract: In 2030, the world population will exceed 8.5 billion, increasing the challenges to satisfy basic needs for food, shelter, water, and/or energy. Irrigation plays a vital role in productive and sustainable agriculture. In the current context, it is determined not only by water availability but also by optimal management. Several authors have attempted to measure the performance of irrigation networks through various approaches in terms of technical indicators. To improve the sustainability in the pipe sizing of the pressurised irrigation networks, 25 different models were evaluated to discuss the advantages and disadvantages to consider in future methodologies to size water systems, which guarantee the network operation but contribute to improving the sustainability. They enable water managers to use them as tools to reduce a complex evaluation of the performance of a system, and focusing on better management of resources and sustainability indicators for agricultural ecosystems are clear and objective values.
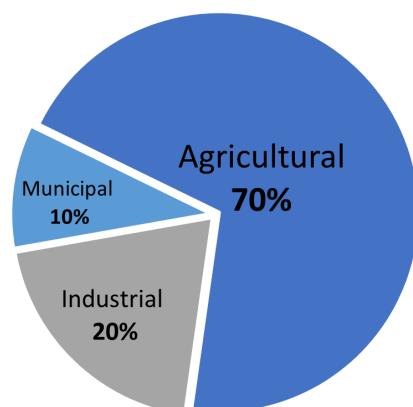
1. Introduction

By 2030, the world's population will be above 8500 million. Over 800 million inhabitants will add to the current quantity in less than ten years [1]. These substantial increases present several challenges for cover inputs, such as food, shelter, water, and energy. To satisfy them, the United Nations Organisation (UN) estimated necessary increases of 35% in the food supply, 40% in water resources, and 50% in energy to prevent the consequences of several human crises [2,3]. Undeniably, access to available resources is crucial in a rising demand scenario to accomplish the required tasks.

According to experts, in terms of quantity, roughly 3% of the total water on the planet is available for human activities [4]. Among these, the agricultural sector remains the largest consumer of freshwater (Figure 1). Its consumption is around 70% of withdrawals and 90% of consumptive usages, compared to 10% required for municipal purposes or 20% for industrial processes [2,5,6]. For example, rice produced requires around 3400 L of water per kilo. Considering daily water requirements per person are about 100 L, this consumption is equivalent to the domestic needs of 34 people [7,8].

Water and energy are inextricably linked; for instance, the water sector is a heavy energy consumer in all life cycle phases: withdrawal, purification, storage, distribution, and treatment. At the same time, the energy generation sector uses extensive amounts of water for all its stages and processes [9,10]. In Europe, an estimated 18% of the total water consumed in energy production is used for cooling [11–13]. With a growing population, urbanisation, and rising living standards in many countries, the future picture implicates increased energy use and water consumption [13]. However, several factors can affect

the predictions, including efficient and renewable technologies and water-smart energy choices, to achieve a more sustainable integrated water cycle [14–16].

Figure 1. World freshwater allocation sectors.

Direct and indirect energy inputs are also crucial for the whole chain in agriculture. Supply agri-food production accounts for 30% of the world's total energy consumption. Irrigated pumping has revolutionised food production, providing 40% of worldwide cereal demand [17]. Nevertheless, despite intensification providing higher efficiency rates, it is directly connected with more energy demands and elevated GHG emissions, putting human mitigation and adaptation aspiration at risk [18,19]. Improving a "climate-smart agriculture" behind and beyond the "farm gate" can achieve substantial savings in water–energy areas, reducing the impact of the food supply system on the environment [18,20,21].

As the environment establishes the initial conditions, societies expand and climate changes; therefore, the vision on energy and water concerns must shift, too. The Paris Agreement and the 2030 Agenda recognise that humanity's long-term development depends on the sustainable management of resources [22,23]. According to the data, considering a 75% population benefit, the irrigation sector is critical in a sustainable goal contributing to the world's GDP and global food security [24].

Irrigation plays a vital role in productive and sustainable agriculture [25]. Currently, it is determined not only by water availability since optimal management from project idea to building is necessary for the entire system life cycle [26]. Increasing knowledge about irrigation systems and underlying internal processes improved our understanding of how new conditions affect the systems and how the systems affect the environment. It can provide detailed information and a solid base for a decision maker to develop smart strategies towards a goal.

1.1. Irrigation Water Use

Agriculture is the way to provide the additional billion tons of food needed for consumption shortly. Irrigation is vital for food security in most crops globally, especially in arid and semiarid areas. Furthermore, artificial rainfall makes it possible to provide the required water, nutrition, and pest control with crop growth [27–29], as well as diminish drought losses, frost hazards, and climate variability [30].

Moreover, irrigation is a crucial component of rural economies, especially in areas that maintain sustainable local small-scale production and the Mediterranean region [31,32]. Figure 2 shows the world's irrigated area divided into three groups: developed, developing, and least developing countries, in which the developing countries have a significant role in food production [33]. Nevertheless, poor management represents a high extraction of freshwater resources and energy investment. Likewise, it carries a process of progressive deterioration of the environment. Pollution of wastewater, groundwater table reduction, eutrophication, soil salinisation, displacement of native diversity, significant greenhouse

gas emissions (GHGs), and micro-residual pollutants, among other consequences, can lead to unsustainability [34,35].
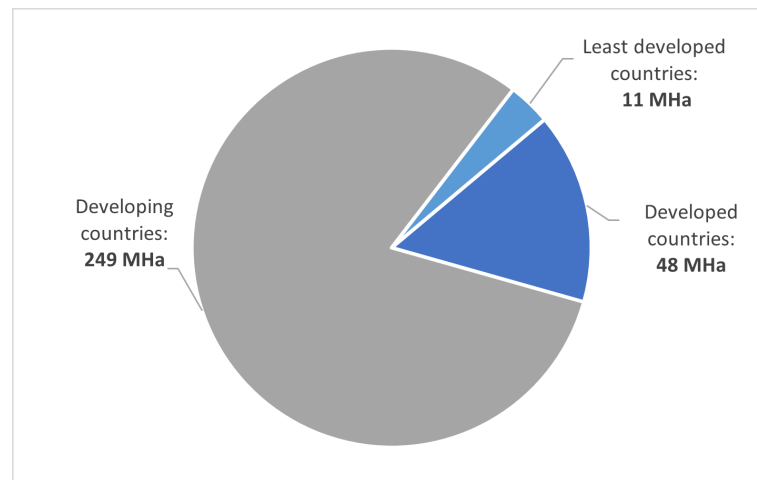
Figure 2. World irrigated area data from 2021 using data from [33].

Figure 3 shows the different uses (i.e., agricultural, industrial, and urban) in the different continents. It shows that agricultural use represents between 20 and 70% of the consumption. Water use and pollution of resources for growing agriculture will reinforce global water competition for municipal and industrial sectors.
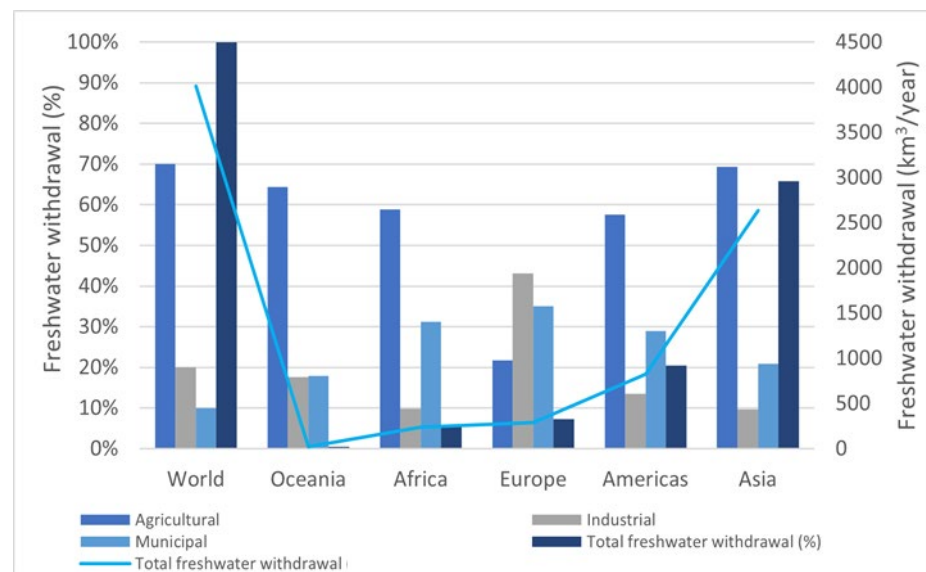
Figure 3. World water withdrawal. Data obtained from [36].

It is essential to pay attention to discrepancies between low rainfall regions where the water resources are already in sustainable borders, such as Spain's Mediterranean regions and emerging or developing countries with significant water potential [36–38].

Figure 4 shows the high pressure in Mediterranean Europe in the freshwater, especially in Spain.
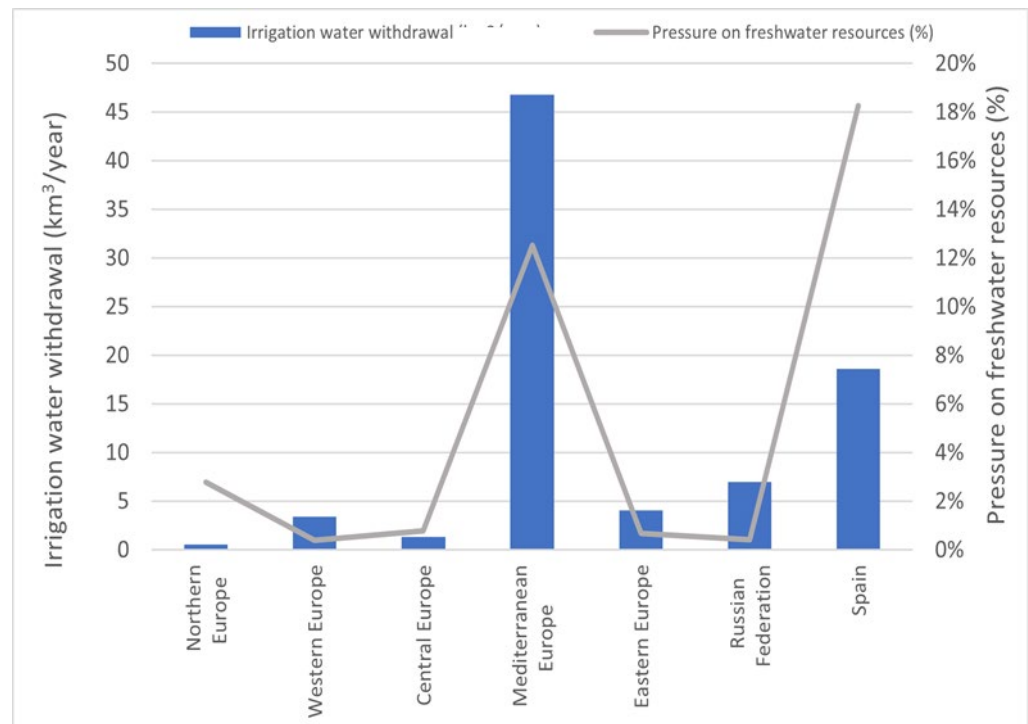
Figure 4. Water withdrawal. Data obtained from Europe [37] and the world [36,39].

In the unclear future, the key to success relies on the availability of the resources to satisfy user's needs—enough demand, disposable energy, and acceptable cost for pumping water—without neglecting the environmental premise, which currently must be at the forefront of all the actors involved, especially water decision makers [40].

1.2. Environmental Implications

As an undeniable reality, climate change accelerated due to the current development model built upon fossil energy consumption [41]. High climate variability (temperatures and precipitation patterns), prolonged episodes of drought, and extreme events are recurrent. Those scenarios increase the insecurity in the future management of crop areas, making it necessary to develop models and tools that allow farm viability within a sustainable use of resources [38].

Considering the high stress on non-renewable resources and crop, classical economic criteria must not be the only performance evaluation parameters [42]. Measuring productivity only as a rate between income benefits and inverted monetary inputs in a food production process keeps the misunderstanding of an integral process where multiple costs and benefits interact with economic, environmental, social, and cultural variables in the short, medium, and long term [43].

Given the impossible dissociation between human beings and their surroundings, the stakeholders should introduce performance monitoring instruments to manage complexity in our new paradigm [44]. Identifying components of food supply challenges within agriculture ecosystems, their relationships and boundaries, and the socioeconomic, environmental, and cultural context lets water managers understand the production process because of multiple interconnected factors [45].

As a tool for reducing a complex assessment of a system's performance, focused on better management of resources, sustainability indicators for agricultural ecosystems are a clear and objective value [46]. Moreover, they also include the correlation between water–energy factors (WF-EFs), the environment (climatic factors (CFs), soil factors (SFs)), socio-cultural factors (SCFs), trade factors (TFs), and gender factors (GFs), among others [18,47,48].

An accurate indicator diagnosis can effectively align exigencies and vulnerabilities, identifying patterns, tendencies, and cause–effect relations in irrigation activities [49].

Indicator benchmarks improve the efficient use of resources, the effectiveness of activities and decisions, equity and the environmental, and the reduction in social impacts. The goal is to ensure long-term resilience systems and sustainable user welfare [50–53].

The global dimension of water–energy management leads to evaluating the environmental footprint in food production and the entire set of negative and positive responses that agriculture systems impose [54]. Special attention to irrigation systems is justified because these are required in more places. However, its non-negligent critical water needs, inherent pollution, and our uncertain context impose clear boundaries [55].

Considering limitations in environmental and sustainable terms, holistic knowledge of irrigation systems brings a framework to reflect the wide margins of water and energy savings in irrigated agriculture. For instance, in Spain, savings have increased by more than 70% in 15 years [56,57]. Quantifying the performance and constraints of irrigation systems provides a global view of a present system condition and the possible further achievements according to the targets and criteria for appraising the improvements within the water–energy–human nexus. It implies the evaluation of the different sustainability indicators based on different targets of the Sustainable Development Goals [58].

Several authors attempted to measure the performance of irrigation networks by several approaches, such as benchmarking analysis [59], flow-driven deliveries and pressure studies [60–62], conventional energy and cost reduction [56], water and energy correlations [63], loss quantification [64], and, finally, water footprint, water use performance, and water savings in environmental and economic viability criteria utilising the effective sustainability irrigation indicators [65–71].

The present investigation is an evaluation of the different existing methods for estimating peak flow rates to address the design of installations. This stage is crucial not only in the investment of infrastructures but it also impacts the estimation of the evaluation of the different targets of the Sustainable Development Goals (SDGs). Also, approaching the estimation of flow rates with different methodologies can lead to differences in the assessment of sustainability indicators and energy audits that address the installation of micro-hydro generation.

2. Evaluation Methodology and Materials

The research methodology is established in different steps, according to Figure 5.

Step I.—Establishment of the parameters. This set is divided into three parts, and a background review is developed to search for the maximum number of proposal models, enabling peak flow estimation. The second step of this block, called I.B analysis review, elaborates a parameter list in which the main variables and characteristics are discretised in the database by indicators or variables (Step I.C).

Step II.—Database development. A database was established using information and data gathered from the consulted bibliographic sources. The indicators utilised in the other examined case studies were chosen to populate the database, encompassing not only measurements and variables but also reference values. It is noteworthy that certain indicators were employed across multiple case studies discussed in the published research. The main variables were peak flow, error between estimation and experimental data, peak period, and type of distribution, among others.

Step III.—This third block constitutes the main block of the research. In the first part (Step III.A), an estimation of the evapotranspiration and possible inputs allowing the development of the different models to determine the peak flow, addressed in Step III.B, was carried out. In this block, a detailed analysis of four different typologies was carried out. A discussion was established evaluating different deterministic, statistical, random, and artificial intelligence models.

According to the review of the background, 45 references were analysed, obtaining 25 different models distributed in Europe, according to Figure 6.
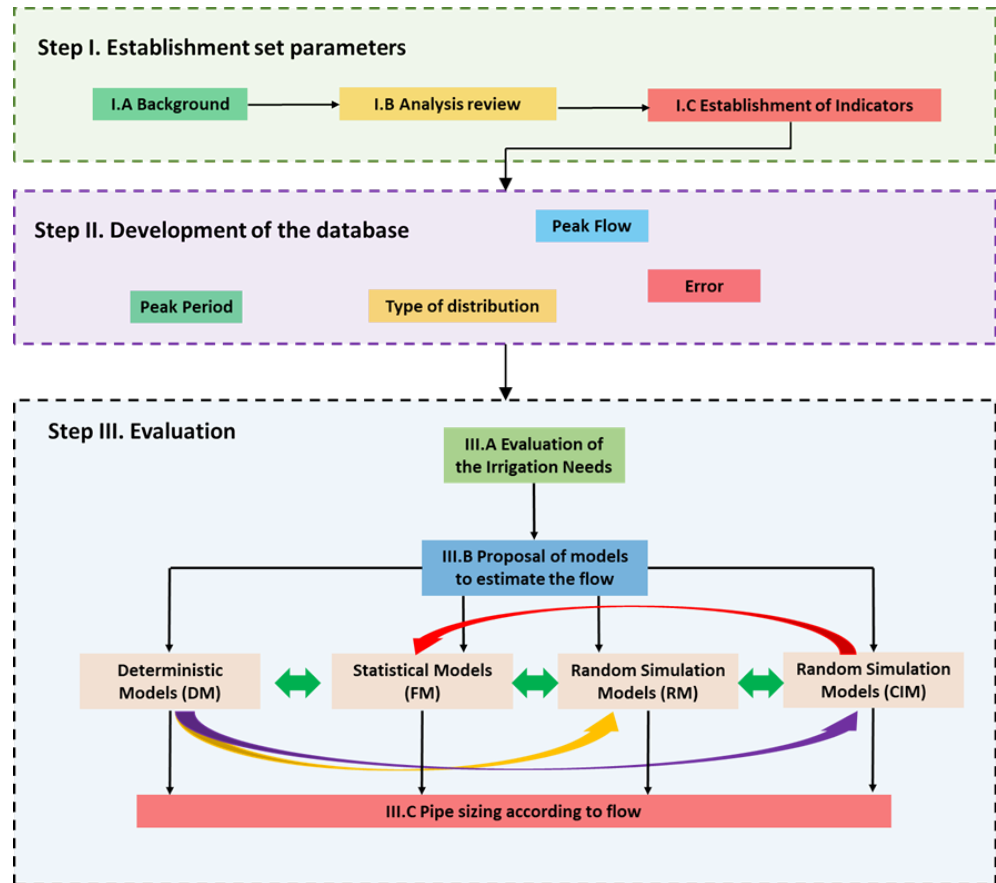
Figure 5. Evaluation methodology of the models to estimate the circulate flow.

Figure 6. Distribution of the different analysed models.

3. Determination of Flows to Design Irrigation Water Networks

Whereas measuring water consumed in the municipal sector is usual in most countries and almost essential in the industrial sector, water control in agriculture is not a strict requirement [72]. Nevertheless, assessing water needs is a fundamental part of sustainable water resource use to avoid losses and obtain "more crop per drop" [73,74]. In addition,

operating losses throughout the life cycle of the network are difficult to identify and quantify [64].

The lack of control, absence, or inaccuracy causes inefficient use of irrigation, affects expected crops, and generates unnecessary environmental expenses. Boosting food production in uncertain conditions calls for effective and sustainable irrigation management and flexible supplies, which means full appraisal of water–energy deliveries. Qualifying the systems and approaching the knowledge about demands initially imposed on the design process can allow for implementation strategies and plans to improve the profit margin of water–energy inversion [75,76].

Flow and pressure in the network are highly variable throughout the day and the operation cycle. Said variations are closely connected to established area limitations of irrigation systems and decision management in the phenological cycle determined by agroclimatic variables and farmers' perceptions. The real flows may differ from prior requirements assumed at the design stage, causing operation problems impacting network capacity, demand forecast, and environmental resilience [77].

3.1. Parameters of Study

A realistic approach to the dynamic interactions between water irrigation and sustainability requires modelling the conditions and relations in a farm [78]. These are relative to the cropping patterns demands over the growing process, hydrant discharges, established network design, environmental conditions and reactions, irrigation technology available, and crop responses, as well as user habits along different temporary and spatial scales [79].

To understand these complex interactions in agricultural, biological, and environmental systems and enhance our ability to make predictions, decision makers should study the interconnected components rather than isolating them [80]. A machine learning approach was developed to represent diverse Earth systems models through mathematical relations and schematic concepts nourished with extracted interpretable information from uncountable data sources [81].

Systems models play a primary role in the development of sustainable agroecosystems. Several crop models with different scales of complexity and limitations are available to understand the interaction between soil–water–plant–atmosphere [82]. Different tools have been developed to estimate yield production and the effects of crops that interact with weather resources and management practices [83]. Scientific and decision/policy makers have underpinned the different approaches for increasing the understanding of growing crop processes and the interaction of soil–water–nitrogen along the life cycle, as well as the impacts of cropping patterns and irrigation distribution under climate variability [77,84–86].

Different issues emerged in agricultural model sciences developed for researchers and decision maker stakeholders, reinforced by the available data, technology and supporting tools, cost–benefit relation, expected results, and specific targets. Purposeful development of the model, increasing scientific tools, and decision/policy support lead to understanding the agroecological systems improve under research questions about processes control and agroclimatic interactions [85]. Description process, understanding relations, and forecast tools motivate the development of models, which target simplifying complex processes where more of the hypothesis and assumptions are not linked with real cases but decrease uncertainty for reasonable results compared with data from the field.

There are models, which consider the soil–water process, reflected in crop water space–time requirements and water balance [87]. They include calculating the inputs and outputs of the system, effective rainfall, evapotranspiration, and crop requirements using soil, climate, and crop data [88]. Soil moisture varies dynamically and at any time in a crop cycle. Therefore, it is crucial to never drop below the wilting point without exceeding the field capacity [89].

The Penman–Monteith and Priestley–Taylor equations for soil–water relation modelling are highly simplified but widely applicable. According to FAO's functional model,

the physically based approach, FAO-56, allows for the soil–water balance to be obtained following Equation (1) [90].

$$r + I + D_d \pm \Delta SM \pm R + W_g - ET_c = 0 \tag{1}$$

where rainfall (r), irrigation (I), and capillary rise (W_g) are the inputs of the system. Surface runoff (R), water loss out of the root due to deep percolation (D_d), and crop evapotranspiration (ET_c) are the outputs that compute the soil moisture change (ΔSM).

Evapotranspiration (ET) is the most important variable in the balance [91]. These phenomenological processes correlate soil evaporation and plant transpiration, which depend on the climate factors, crop characteristics, and water availability in the soil.

In 1998, the FAO-56 ET model was launched. Several definitions and simulation procedures are broadly used following the advances in computing calculation, modern techniques, and tools [92,93].

Climate factors are introduced in this methodology by estimating the daily potential evapotranspiration of a hypothetical parameterised surface—reference evapotranspiration (ET_0)—using Penman–Monteith, described in Equation (2) [90,94].

$$ET_0 = \frac{0.408 \, \Delta \, (R_n - G) + \gamma \, \frac{900}{T+273} u_2 \, (e_s - e_a)}{\Delta + \gamma \, (1 + 0.34 \, u_2)} \tag{2}$$

where detailed energy and aerodynamic data are required, and shortwave radiation at crop surface (R_n), soil heat flux (G), air temperature (T), wind speed (u_2), psychrometric constant (γ), relative humidity by saturation vapour pressure deficit ($e_s - e_a$), the slope vapour pressure curve (Δ) are found in the equation. Although it is currently used and widely implemented for decades, the accuracy of this method depends on the available data.

Other approaches imply evaluating the reference evapotranspiration when lacking in measures required. The Hargreaves method is proposed as an alternative for assessing ET_0 with fewer data, only air temperature, as shown in Equation (3) [95,96].

$$ET_0 = 9.388 \, 10^{-4} R_a \big(T_{avg} + 17.8\big) TD^{0.5} \tag{3}$$

The advantage of this method is that the average daily temperature (T_{avg}) and temperature range (TD) are the only values that require a dataset of measures (maximum and minimum daily temperatures). Extraterrestrial radiation (R_a) is a tabulated value. This method is recommended for use, especially in the absence of existing data or dubious quality [97].

Secondly, for assessing crop evapotranspiration, the FAO-56 method integrates the crop characteristics (crop type and growth phases) via K_c. This is the dual coefficient that combines soil transpiration and crop evaporation along the development stages [90]. This coefficient is mainly connected to the canopy dynamics, leaf area, and ground cover [98]. Although K_c can be evaluated, crop coefficient tables and curves reported in the literature adjusted to local conditions and midseason periods are widely used [99–101].

Thus, it is possible to calculate potential evapotranspiration for a given crop at any moment of its growth following Equation (4).

$$ET_c = ET_0 K_c \tag{4}$$

Another parameter in irrigation that needs quantification is effective rainfall (Pe), a fraction of total valuable rainfall for meeting the water needs to be used by crops, excluding surface runoff, deep percolation, and soil surface evaporation from Equation (1) [102]. FAO-25 describes several approaches for calculating it by the fixed percentage method, the potential evapotranspiration/precipitation ratio method, Renfro equation, empirical relationships, the US Bureau of Reclamation method, and the USDA SCS method [103].

The simplest methodology generally applies a percentage between 70 and 90% of the monthly rainfall. The FAO manual proposes maximum slops in the 4–5% range for Equation (5).

$$Pe = 0.8\,P - 25\,\text{if}\,P > 75\,\text{mm/month} \quad Pe = 0.6\,P - 10\,\text{if}\,P > 75\,\text{mm/month} \tag{5}$$

where rainfall or precipitation, in mm, is represented as (P), and effective rainfall, mm/month, is (Pe).

Equation (6) is used to determine the irrigation net water needs. It shows how these descriptive, empirical, and functional models allow researchers to better understand the relationships between agro-environmental pieces combining physical and biological components and mechanisms, permitting an approach to the possible system's responses due to certain strategies and decisions adopted within simplified scenarios.

$$IN = ET_c - P_e \tag{6}$$

In another approach, dynamic systems can integrate conceptual physical models and mathematical equations with the data collected and provide outputs related to time changes and responses to different externalities, such as climate change or users' practices [104,105]. Sometimes highly complex, although robust, these models need experts to achieve interpretable results and adapt them to specific issues. However, it is not always a straightforward task due to knowledge gaps, and unavailable data add uncertainty to the outputs [70,106]. Examples of such crop models related to irrigation crop water supply, among others, are FAO agronomic models CROPWAT [107], AquaCrop [69], DSSAT [108], CropSyst [109], and software tools [93].

There is extensive experience developing agroecosystem models, science, and analytics tools [110]. The gaps are primarily related to accurately integrating analytical knowledge into the user's decision tools [111]. Moreover, various factors are needed to build an integrative agricultural approach, such as the interactions between crops, farms, socioeconomic, cultural, and landscape context, climatic, environmental, and ecological variables, trades, and agro-economic business on different scales [112].

Food security crises, sustainability concerns, technology and computer advances, open information and data accessibility, interdisciplinary and transboundary science, and user-adapted models summarise a new context that must lead to a new generation model focused on management for sustainability and productivity [113].

Agro-crop modelling under an irrigation environment forecasts the amount of water needed, which determines irrigation scheduling, such as when and how much water quantity is necessary to irrigate [114]. Therefore, it is necessary to have integral knowledge of the internal crop process and system input/output estimable responses to decrease uncertainties. Achieving an accurate system's behaviour characterisation allows the implementation of measures to reduce the water–energy quota invested without the possible detriment of production results expected by farmers.

However, despite the substantial advances in system modelling, the disparity between calculated and real flow demanded is frequently observed. This discrepancy is most often attributable to unpredictable weather conditions, users' practices, and local management in the present new context of uncertainties [77,115].

3.2. Proposed Methods: Forecasting Irrigation Demand Flow

To determine the flow rate in a distribution system, the complexity of the agricultural ecosystems mentioned must be taken into account [116]. Additionally, particular consideration of the relationships between crop pattern, crop growth stage, water and energy requirements, weather conditions, and users' interactions must be given. They are several approaches considered for studying the distribution of water discharges and irrigation scheduling for on-demand irrigation networks [117].

Space–time analysis of the randomness process in irrigation was introduced for the flexibility of use and very low probability for a simultaneous operation of all hydrants in a network, which allowed a mathematical approach for calculating the flow distribution. Of all the methods developed, Clément's first formula (CFF) has had great acceptance since its publication [118].

This formula introduces a statistical analysis for the calculation, implementing a distribution law of probabilities for hydrants' operation in the network. Given the simple application of the algorithm, this methodology has transcended until today. Despite several errors in simulated flow distribution (since the assumed simplifications are not entirely assured), it is the most widely used method [62,119–121]. Nevertheless, the accuracy of these calculations has significant implications for the overall sustainability of the system assessment, such as economic, energetic, hydric budget, flexibility, and safety parameters in all stages, from construction to operation management.

Different approaches have been implemented recently due to technological and computational developments that improve forecasting results. Generally called black box methods, these computational methodologies allow correlating physical parameters with advanced statistical routines to integrate existing uncertainties when correlating inputs and outputs.

Tables 1–4 summarise some of the most significant research work. According to the methodological approach to influence data and involved variables in the circulating flows forecast, with predictive and management purposes, the methods are differentiated into four groups: deterministic models (D), statistical models (F), random simulation models (R) and computational intelligence models (CI).

3.2.1. Deterministic Models (D)

The deterministic conceptual models—empirical, functional, or mechanistic—assume that uncertainties are external to the process [122]. These models aim to establish a relationship between variables and constants that are well known or measurable and aim to produce "accurate" results under specific facts and considerations. Their theoretical approach does not include random methods [123]. This model entirely determines flow rates by inputs and initial and boundary conditions, and since the model does not contain any haphazard approach to the phenomena, it is necessary to understand and define the problem through a vast set of existing information. Moreover, the methodologies described must gather as much information as possible and use complex models to determine those that cannot be measured directly or introduce any uncertainty.

Ref. [124] simulated the flow distribution in the network using the SIMODIS methodology, where remote sensing satellite data worked under techniques of temporal space evaluation of soil–water balance by the numerical soil–water flow model (SWARP). The studied network was in Gromola (southern Italy) using a daily forecast horizon, a one-year temporal dataset and a 33-day peak period. The model assumes that the network's hydrograph is a product of implicit needs and boundaries related to biophysical parameters concerning crop water requirements—vegetation status, crop pattern and stage, potential evapotranspiration rates, surface reflectance, soil properties, groundwater interactions, and hydraulic capacity of the network, among others. Comparing the total irrigation daily values from the irrigation season to the simulated data, the method underestimated the volumes by 9%.

Refs. [125,126] conducted two studies, in 2006 and 2008, in a network in Sicily (Italy) with different goals. In the first, the main goal was to create geohydrological models for improving water management in irrigation. Instead, the latter tried to create a distributed model for the assessment of water in irrigation networks. The irrigation phase is scheduled based on two parameters: soil–water pressure head threshold and soil–water deficit to be refilled. Several exposed case studies were conducted, and the outcomes for a simulated Sicilian district were compiled, resulting in overestimating the modelled flows.

Ref. [120] developed a model centred on water balance, simulating the whole irrigation season by calculating the circulating flows through the network at any time based on the soil moisture deficit. This network was in Santaella, Córdoba (southern Spain), with a daily forecast horizon and two years' worth of data accompanied by a 2-week peak period. Using several climatic and study area characteristics (crop, network, system type, farmer practices) as inputs, the model performs a complete simulation of the irrigation season and provides an hourly consumption on each farm and the operation probability for each event. After evaluating the simulated data and the seasonal volume by year, this method overestimated the demand by 11.6%. The evaluation for each study is summarised in Table 1.

Table 1. Summarised deterministic models articles reviewed.

ID	Reference	Main Results
D.1	[124]	• The temporal variation of water demand at the district level was satisfactorily reproduced. • Irrigation efficiency was evaluated using indicators calculated from the real transpiration rate and irrigation values computed by SIMODIS. • The results of SIMODIS are exceptionally reliable at the primary unit scale while obtaining reliable results at the secondary unit level.
D.2	[126]	• Agrohydrological simulation models and remote sensing can be effectively combined to improve irrigation water management in semiarid regions. • The SIMODIS procedure predicted the water demand satisfactorily at district and secondary levels. • The distributed approach performed better than the lumped one at a large scale to define the upper boundary conditions.
D.3	[120]	• Real demand tends to be concentrated at certain times of the day. • During peak demand periods, water requirements can exceed the design flow. • Demand is not uniform throughout the day; it increases in the morning until peaking, remains constant for several hours, and then decreases at midday. This process is repeated in the afternoon. • To be used in other districts, the gamma model should be applied considering local farmers' practices and network constraints. Human behaviour affects uniform probability prediction.
D.4	[125]	• Differences between simulated and measured irrigation volumes were attributed to different management behaviours. • The threshold value of the soil water pressure head in the root zone (h_m) and the fraction of soil water deficit to be refilled (Δ) can be tuned adequately to reproduce the spatial and temporal evolution of crop water use. • Depends on water availability and farmers' subjectivity to recognise the crop water requirement. • This approach can be effectively used to support the decision-making process in managing irrigation water resources and improving the efficiency of irrigation systems.

3.2.2. Statistical Models (F)

More extended statistical models aim to find a relative frequency associated with different flows during the irrigation season [127]. Through the assumption of certain hypotheses and, despite the random behaviours of some variables, it is possible to arrive at a particular degree of accuracy by utilising an adequate problem definition [128].

These models focus on finding hydrants' operation probability at a given period, often during peak periods, in the function of maximum crop requirements and own parameters of the probability distribution that describe the system's behaviour to meet a determined water demand for a given supply [129].

Granados [130] made a detailed description of principal statistical methodologies: Clément, [118,131], de Boissezon and Haït, [132], and Mavropoulos, [133]. Also, he summarised various research works where authors contrast mathematical flows and calibrate parameter implications with real or simulated flows in real irrigation networks.

Clément proposed that flows circulating into the network follow the normal distribution when the number of outlets is significant enough by associating farmers' activities

with hydrant usage as a binomial variable in a Bernoulli experiment, assuming uniform open probability and uniform nominal flow rate downstream of a line section [118,131].

According to Clément's first formula (CFF), it is possible to determine the downstream flow for a study section using a standardised outlet flow under a service guarantee, as shown in Equation (7).

$$Q_{Clem} = \sum p_i d_i + U \sqrt{\sum p_i d_i^2 (1 - p_i)} \tag{7}$$

where the variables are flow to forecast (Q_{Clem}), fixed flow assignment of an outlet (d), probability operation hydrant (p), and guaranteed service level (U). The subscript i indicates the group of outlets with the same flow assignment and probability.

Mavropoulos [133] changed the perspective and described the system's performance by defining the oversaturation of the network based on the rate of recurrence of demands in the network, for instance, how unusual or recurrent demand requests are.

The time between two successive irrigation calls, defined as a random variable (r.v.), follows an exponential distribution and is associated with the flow discharged at any time during a peak period using a Weibull distribution. This distribution was selected due to its high flexibility, making it possible to adapt in several flow distribution cases. Equation (8) shows the generalised formula proposed by Mavropoulos and Lotidi [134].

$$Q = \sum_i Q_i = \sum_i n_i p_i c_i + 0.5284 \sum_i n_i p_i q_i c_i \sqrt[\alpha_W]{t_i} \tag{8}$$

The equation considers variables such as the number of outlets with the same assigned flow (n), open hydrant probability (p), shape parameter of the Weibull distribution related to available time use of the network (α_W), outlet flow assignment (c), the time between two demands (t), and i = index that groups uniform population outlets.

Between the articles that pursue the analysis, validation, and contrast of these equations, the results that evaluate the theoretical hypothesis assumed for the models are crucial for future developments.

An entirely random variable is not a precise definition for an open hydrant demand because external factors can influence it. Pulido-Calvo et al. [119] analysed energy tariff constraints that affect farmers' decisions in the township of Cordoba located in Southwest Spain, using data from 8 years. Their work shows that the probability of outlet operation cannot be the same over the day and defines different probabilities according to different energy cost rates.

Monserrat et al. [121] analysed the CFF model's hypothesis in networks located in the Ebro River basin (northeast Spain), concluding that only the independent operation of the outlets is satisfied. Setting the daytime irrigation as a preference rejects the random probability. As a result, the calculated flow was underestimated compared to the observed data; a higher standard deviation than calculated in real data, especially connected with human irrigation preferences, is observed.

Ref. [120] also concluded that human behaviour affects predicted probability and shows a more significant deviation in distribution flows due to a greater probability of higher flows. The normal distribution is only shown in a peak period, not according to CFF. Furthermore, after simulating a complete irrigation season in a case study, the gamma distribution was proposed as a better fit with elevated suppleness.

The same appreciation was established by [135] in the network and peak period analysed, where a larger hydrant group operated during weekends in contrast with low cumulative operation on weekdays. This behaviour is justified due to a higher time availability for the farmers and lower energy costs; also, a variable hourly probability operation avoided costly and high evaporation periods.

For Mavropoulos' method validation, the author published the verification through a real network with registered data for monthly peak irrigation. Despite the good fit found with Weibull's asymmetric distribution, the uniform probability assumed in the model

could not be corroborated. Therefore, introducing λ3, a correction factor, is necessary, representing the non-random farmer's behaviour and other uncertainties [134].

Unsuccessful demand forecasting and the assumed hypothesis for CFF are also disclosed in the work of Soler et al. [136]. The authors also mention that the flow rate cannot be assumed as a random variable if the number of outlets is not large enough or the operating conditions are not homogeneous.

Ref. [137] conducted various tests to compare CFF's calculated distribution with observed flow data compiled from a real system. The results showed that the expected normal distribution did not match the observed data in any month of the analysis period. The records had a strong right skew, showing that other distribution functions, such as GEV, could be a better fit. Farmers' behaviour and preferences like duration, quantity, and hourly and weekly trends can explain the gap between data. As exposed by Pérez-Sánchez et al. [138], human influence determines irrigation patterns, and it is unreasonable to consider uniform probability as a valid hypothesis for forecasting irrigation flows.

Table 2. Summarised statistical models articles reviewed.

ID	Reference	Type	Main Results
S.1	[119]	Statistical	• Probability operation is not a constant due to cost energy discrimination. Farmers prefer low- and medium-cost hours and avoid high-price hours. • Human behaviour is influenced by time discrimination rate costs. • The recommendations of optimum pump combination produced significant reductions in energy costs.

S.2	[121]	Frequentist	• Hypothesis 1: only two possible states of the hydrants (open/closed). Not fulfilled. CV = 25%.
			• Hypothesis 2: Uniform hydrant opening throughout the day.
			• Not fulfilled. CV = 5.7% daily and CV = 13% hourly.
			• Hypothesis 3: The hydrants function randomly and independently.
			  - Random functioning is rejected since the Kolmogorov–Smirnov p-value = 0.
			  - Independent operation is fulfilled.
			• The normal distribution hypothesis is not fulfilled.
			Moreover, the model with Clément's first formula seems robust enough in the conditions studied, so using more complicated models is unnecessary

S.3	[120]	Deterministic	• The generated distribution tends towards a normal distribution only in the peak demand month (July) and will not coincide with Clément's distribution. • Because the standard deviation is higher, a greater probability of higher flows exists. • Although most of Clément's hypotheses were not fulfilled, his formula is a valid design criterion. • The formula used to determine Clément's design flow adjusts better to demand behaviour than Mavropoulo's does, particularly for a small number of outlets.
S.4	[134]	Statistical	• The validity of the probability theory in on-demand irrigation networks was largely verified on the study network. • The goodness of fit test results shows that the same crop in a plain area with the same climate, and general slope and high territorial homogeneity can significantly alter the irrigation water demand, favouring the randomisation of demand over time.
S.5	[135]	Random Simulation	• Normal distribution fit hypothesis: the Kolmogorov–Smirnov test with a p-value lower than 0.05. Therefore, it cannot be assumed to be a better approximation to a gamma distribution for 2003 and a Weibull for 2004. • Daily and hourly opening hydrant probability hypothesis: The analysis of a variance p-value was lower than 0.05. Thus, it is concluded that there are significant differences between the peak period days for each season. • In the peak period week of the first season, farmers used weekends to irrigate because they had more time and lower costs. In the following one, the behaviour of the network was not the same, which may be due to some breakdown in the network or weather conditions. The underestimation caused by the Clément methodology is due to using the average opening hydrant probability concept.
S.6	[137]	Statistical	• Data were not distributed in the network under CTD (in which the mean and standard deviation were calculated under Clément's parameters) in any of the months of the year. • Normal distribution does not satisfactorily explain the behaviour of the random variables. • Other distributions were proposed, obtaining a better fit for distributions of the observed flows in each month.

3.2.3. Random Simulation Models (R)

Random simulation models focus on system behaviour analysis through a random approach. The target is a model configuring the relations between variables associated with the portion of the irrigation problem that cannot be known accurately, thus introducing uncertainty to the results.

Some parameters influenced by uncertainties are defined randomly within established assumptions and scopes. Often used for performance analyses of existing networks, these models propose considering stochastic flow variability due to farmers' management strategies. Defined by the users' decisions related to the perception of crop stage, the number and location of open hydrants define the complete system performance [139]. Also, the flow rate is a product of a random computer simulation, a random variable within a sample space of possible events, which can include potential combinations satisfying the corresponding constraints and integral network spatial–time variability.

After considering the CFF model, Soler et al. [136] proposed calculating the flow rate distribution as a non-normalised random variable; they implemented two random methods based on the number of downstream outlets of the section analysed. Thus, the first step was to create a complete sample space of irrigation events. Associates knew the constant operation probability for each hydrant, the corresponding nominative discharge with a randomly generated vector, and the operational state of the hydrant (on/off) configured by 1 or 0, respectively.

When the number of hydrants is sufficient, the authors used the Monte Carlo approach to build an incomplete sample space according to known probability and discharge rates.

$$k^j = \left(k_1^j, k_2^j, \ldots, k_{n_1}^j \right) \rightarrow Q_I^j = \sum_{i=1}^{n_1} k_i^j \cdot q_i \rightarrow P\left[Q = Q_1^j \right] = \prod_{i=1}^{n_1} f\left(k_i^j \right) \forall\, j = 1, \ldots, m_I \quad (9)$$

where the jth-event on/off vector is $\left(k^j \right)$, the total number of event vectors is (m_I), the probability for the event is $(P[Q = Q_i])$, the nominal flow rate is (q_i), and the index for each hydrant is (i).

$$Q = \begin{cases} Q_I^1 \\ \cdot \\ Q_I^j \\ \cdot \\ Q_I^{m_1} \end{cases} ; f(Q) = \begin{cases} P\left[Q = Q_I^1 \right] \\ \cdot \\ P\left[Q = Q_I^j \right] \\ \cdot \\ P\left[Q = Q_I^{m_1} \right] \end{cases} ; F(Q) = \begin{cases} P\left[Q = Q_I^1 \right] \\ \cdot \\ \sum_{i=1}^j P\left[Q = Q_I^j \right] \\ \cdot \\ \sum_{i=1}^{m_1} P\left[Q = Q_I^{m_1} \right] \end{cases} \quad (10)$$

where Q is the discrete random variable flow vector, $f(Q)$ is the probability density function, and $F(Q)$ is the cumulative distribution function.

On the other hand, Labye [140] introduced it as part of the design process considering the temporal variability of flows circulating through the network and the importance of Several Flow Regimes (SFR approach). Likewise, as opposed to the "only a single flow", Lamaddalena et al. [141] provide a Random Generated Model (RGM) for obtaining different combinations of hydrants simultaneously open among the total of hydrants in the network, satisfying a given discharge and considering an upstream demand hydrograph at the end of the network as an input.

The flow circulating in a specific section is calculated by adding the discharges withdrawn from the downstream open hydrants. This tool serves different purposes, such as analysing an existing network or designing a new one while computing the upstream end demand input by a CFF-based model.

In a different approach, without considering an average operation probability, Moreno et al. [135] assumed a random starting opening time for the hydrants and the irrigation set time for each one according to the cropping requirements and the crop yield characteristics.

The method builds vast Random Daily Demand Curves through a dataset of open hydrants and the operation time of the network.

Adding these open hydrants makes it possible to calculate the total demand upstream of the study section in a determined time. Obtaining the main line flow associated with an operational quality service is possible. The case study provides a good fit between measured and calculated data.

Table 3. Summarised random models.

ID	Reference	Conclusions
R.1	[141]	• A good fit exists between the theoretical Gaussian curve and the histogram of frequencies obtained using field data. This means the population of the discharges during this period is well represented by CFF. • The r coefficient should be intended only as a calibration coefficient aiming to understand the farmer's behaviour. • Using field calculations, the Clément operation quality corresponded to 97.6% (exceeding the designed value of 95%). This implies a lower probability of exceeding the maximum discharge.
R.2	[142]	• The IRDEMAND model was able to generate hourly discharge hydrographs of pressurised irrigation systems operating on demand. • This methodology considers the deterministic component (crop irrigation requirements) and the uncertainty associated with farmers' decisions on crops, farm irrigation systems, seeding dates, irrigation performances, and scheduling.
R.3	[143]	• The comparison has shown good correspondence, particularly for daily withdrawn volumes. • A stochastic approach simulated the farmers' management strategy. • The simulated hourly discharges showed, sometimes, hourly peaks higher than the measured ones. • Model results show good agreements between the registered and simulated values for both the daily and hourly irrigation volumes.
R.4	[135]	• RDDC has a better fit with the measured data compared to the Clément methodology. • Considering a normal flow distribution in each line, Clément's underestimation is due to the use of opening hydrant probability. • The proposed methodology avoids the problem of using average opening hydrant probability.
R.5	[144]	• The HydroGEN model was conceived based on a methodology consisting of deterministic and stochastic components. • The model's short approach cannot simulate the hourly configurations of hydrants in simultaneous operations. • The model applicability varies from system design and redesign to the analysis of operation and evaluation of the performance of on-demand irrigation networks.
R.6	[136]	• The alternative methods proposed work well in the analysed scenarios, mainly because the normality hypothesis is not required. • The programs allow the applicability of Clément's method to be checked and provide two alternative solutions when the CFF fails.
R.7	[145]	• DESIDS module (Decision Support for Irrigation Distribution Systems) • The model proved to be a crucial tool for decision making, providing information, flexibility, and the ability to predict PID operation.

Hybrid models exposed by Khadra et al. [139,141], Calejo et al. [142], Zaccaria et al. [144], and Fouial et al. [145] are a combination of deterministic and random stochastic models. They assume the presence of variables within the model requiring random treatment due to wider spatial–temporary variability, higher uncertainty contribution in the process, and low viability to assess an accurate soil–water balance.

Deterministic components, water budget, and crop requirements are estimated utilising the soil–water balance at the plot irrigated level. Uncertainties and variability of some parameters, such as those introduced by the farmers' management decisions—seed day, irrigation depths, irrigation efficiencies, and starting irrigation time—are modelled by a stochastic approach.

Similarly, Pérez-Sánchez et al. [138] proposed a new methodology for determining flow allocations, crop water demand, and consumption patterns, which are considered

by a deterministic approach. Assuming indeterminate irrigation farmers' habits are the stochastic part, and the model included weekly and hourly trends and the irrigation duration using information about users' behaviour obtained from farm interviews.

3.2.4. Computational Intelligence Models (CI)

Fourthly, some proposals face the complex problem of flow distribution in the networks in a varying and uncertain environment under the influence of knowing computational intelligence models. Focused on understanding systems' behaviour through the design of "intelligent agents" that represent real problems, these models propose applications that exhibit an ability to learn from historical data and adapt it to predict new data, inspired by the biological and organisational models [146,147].

The branches composing the computational intelligence that promotes efficient forecasting solutions include fuzzy logic, decision trees, neural networks, and evolutionary algorithm models [148].

Krupakar et al. [149] performed a comparative analyses of a broad spectrum of methods regarding the performance and accuracy of predictions. Some of the analysed methods are summarised below.

A Computational Neural Network, CNN, is a non-linear mathematical structure that tries to reproduce the human brain's performance to solve problems and its ability to replicate complex non-linear problems, finding patterns and correlations. Learning from the relations between inputs and outputs allows it to apply the knowledge acquired to solve different situations in a new context [150,151].

The performance of CNN models in predicting water irrigation demands was presented by Pulido Calvo et al. [152], taking past and present data on water demands and climatic and crop parameters as inputs.

In a four-layer feed-forward CNN structure (i.e., in a model where the previous information travels only in one way from the input to output layers and with hidden layers), a learning–training algorithm to determine the interconnecting weights between the nodes and neurons of each layer is implemented.

Activation functions were linear, and sigmoidal non-linear functions were used for the output layer and hidden layers, respectively. The controlled index chosen for the model was the determination coefficient (R_t^2).

Fuzzy logic rules (FL) introduce the mathematics of fuzzy theory [153], which allows one to study and describe the systems within a scale that includes partial values, such as the Boolean logic of zeros (0) and ones (1), gaining knowledge of the information that involves a certain degree of uncertainty.

This alternative to the binary systems resembles the human decision procedure that can make a choice based on the information with much imprecision, such as "it is warm" or "it is wet", traducing it in clear values through the assigned relation functions [154]. Genetic algorithms (GAs) are used to find the optimum solution to complex problems. This approach is inspired by natural selection and heritage principles, where through crossovers, selection, and mutation rules, the initial populations defined "evolve" to better individuals as a better solution, improving their characteristics generation after generation.

A defined objective function evaluates the fitness of each new individual generated, and a constraint set penalises those who violate them [155].

Multiple regression models are used to obtain a linear equation that explains the phenomena targeted to predict dependent variables by knowing independent variables and the assigned contributions of each one to these estimations [156].

Pulido-Calvo et al. [157] implemented multiple regression for predicting daily water consumed as a dependent variable in irrigation models. In a best-proposed model, the water demand of the previous two days was recorded on a farm by a telemetry system installed as input knowing variables. Equation (11) shows the linear equation obtained for a calibrated analysis period for olive crop farms.

$$\hat{Q}_t = 4.01 + 0.91 Q_{t-1} - 0.18 Q_{t-2} \tag{11}$$

where $\hat{Q}_t$ is the estimated consumption on day t and Q_{t-1} and Q_{t-2} are the observed demands at one and two days before t, respectively.

Large amounts of information and variables can complicate any model and reduce the precision due to high correlations between its components. Wang et al. [158] implemented a regression analysis method to face this problem using Principal Component Analysis (PCA) methods to identify the main factors influencing water demand, keeping as much information as possible while reducing the large amounts of inputs in a multiple-factor irrigation space.

Results show that the contribution of precipitation and irrigated areas have the strongest influence among the analysed factors. Both are used in a linear regression method in addition to a water-saving coefficient (α) representing the human influence on irrigation demand.

This coefficient includes planting structure adjustment and water-saving technologies, which can change the water demand required year by year. Equation (12) represents the function of the water demand for irrigation.

$$W = \frac{a + b * P + c * F}{\alpha^{(t-t_0)}} \tag{12}$$

where W is the predicted amount of water, P is the precipitation, F is the irrigation area, α is the annual average water saving coefficient, t is the forecasting year, and t_0 is the data series corresponding to the first year.

To capitalise on the strength of several models and enhance their entire performance, combining them to create hybrid models is possible. Ref. [151] developed a model combining different paradigms from CI, such as a feed-forward CNN, fuzzy logic, and genetic algorithms, to forecast daily irrigation district demands, taking only the historical data series as the input. According to the authors, the predictive capacity of this model is explained by its remarkable ability to extract the highly variable and unstable underlying patterns of the time series data.

In further work, Ref. [159] opted for the Evolutionary Robotic method (ER), which obtains the best CNN and integrates the capacity of the GA to improve precision. This method created an optimal ANGN (Artificial Neuro-Genetic Network) for a short-term (daily) forecast of irrigation demands at the district level. A GA was used to achieve the optimal parameters that structure the CNN to forecast with maximal accuracy and minimal error estimation.

After correlation analysis, the model reduced the data to twenty-seven possible weather inputs and daily historical water register data and selected seven of the best inputs to achieve the singular water demand output.

Although the model has excellent performance, matching observed and simulated data with small datasets and simulation time shows that for the peak demands, the lack of accuracy is present for the three best CNNs. The article refers to various reasons, such as a lack of adequately trained patterns with extreme values.

In another hybrid method, Ref. [160] predicted the amount of water applied on a farm. Likewise, this work combines the three methodologies (CNN, FL, and GA). Fuzzy logic was used to select relevant inputs from the vast irrigation space information and to model farmers' behaviour related to local practices, empirical thermal sensation, or holiday appreciation. Genetic algorithms were implemented to optimally split the linguistic universe for each variable (e.g., "it is warm") to be transformed in a range of mathematical inference sets.

Input variables that directly correlate with applied water forecast were, for this work, irrigation depth water from the previous and two previous days; the thermal sensation can also condition farmers' irrigation decisions. Trained with three different crops in an irrigation district, the analysis model shows that cultural and local practices defined for users' demands can differ for each crop, even when the irrigation system stays the same.

Accenting the relations between dataset attributes inputs and expected forecast outputs, decision tree models (DT) are structures with internal and external nodes, decision functions, and terminal data results, connected by branches that search for understanding logic rules between them.

Ref. [161] used the DT model to focus attention on when the irrigation event occurs at the farm level. As a binary occurrence problem capable of better-replicating farmers' behaviour, a DT was built starting with an irrigation process input vector, which included weather, phenological plant state, local practices, and daily hydrant operation, and was explicitly selected for a case study and split into two main classes.

A multi-objective GA selected the optimal tree structure. The accuracy of predicted event occurrences for the best DT designed was very high, between 90 and 100% of irrigation events in a real network.

Table 4. Summarised computer intelligence models articles reviewed.

ID	Reference	Model Type	Conclusions
CI.1	[152]	Computational Neural Networks (CNNs)	• The CNN model predicted daily water demand better than multiple regression and univariate time series analysis. • The best results were obtained when inputting the water demands and maximum temperatures from the two previous days. • The model is well suited for real-time operations when the system's state is continuously monitored.
CI.2	[157]	Linear Regressions and Computational Neural Networks (CNNs)	• The best demand predictions were obtained when using the water demands from the two previous days as inputs. • Results could indicate that rainfall factors and other climatic variables are implicitly considered in water demand observations. • The CNN performed better than the regressions when water demand and climatic variables were considered as input data. • Short-term demand modelling can be used as input in real-time methods and/or programs for managing water delivery systems.
CI.3	[151]	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	• The hybrid methodology was designed to forecast one day ahead of daily water demands at irrigation districts. • Fuzzy inference was used to estimate the correction of forecasts obtained from an autoregressive neural network to find the optimal values of the parameters of the fuzzy system. • This model, with not very large data requirements, can be very suitable for decision-making strategies in networks.
CI.4	[159]	Artificial Neuro-Genetic Networks (ANGNs)	• The model was applied to predict water demand one day ahead in the network. • The genetic algorithm was used to find the optimal neural network settings to explain the maximum water demand variance with minimal error estimation. • Without an extended dataset and time requirements, the model can be a powerful tool for developing management strategies.
CI.5	[158]	Principal Component Analysis (PCA) + Regression Analysis Methods	• The irrigation water demand forecasting method, considering multiple factors, can achieve higher modelling accuracy. • The PCA method was used to identify the main influencing factors (precipitation, irrigation area, water-saving technology) • The water-saving improvement coefficient (α) concept is introduced into the water demand forecasting model based on the dual characteristic of "artificial-natural". • The predicted irrigation water requirements of the Haihe River basin are lower than the present situation at the moment of the study.
CI.6	[160]	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	• Farmers' behaviour and cultural practices differ depending on the crop, even when the irrigation system is the same for different crops. • When several crops were trained together, the model's representativeness and accuracy were worse than those trained independently. • Irrigation district managers can determine the amount of water to apply at each hydrant beforehand, thus making it possible to manage the pumping station in advance and maximise its efficiency. • In the event of a pumping station failure, these models allow scheduling repairs and managing the time required to fix pumps, repair equipment, and purchase materials.
CI.7	[161]	Decision Trees + Genetic Algorithm (DTs + GA)	• DTs were successfully used as classification models to forecast when farmers irrigate. • The model focuses on the prediction of when irrigation events occur. • The optimal classification model predicted between 99.16% and 100% for the given dataset. • The model also allows the user to know each operational zone of the irrigation network one day ahead.

3.3. Flow Pipe Sizing: Indicators

The use of the different methodologies, as well as the study of opening probabilities as a function of the flow assessment and the estimation model, allows water managers to obtain different flow distributions over time. These distributions, which are different according to the chosen method (different colours), are represented schematically in Figure 7. Defining the design value and the best estimate is crucial in the design and subsequent management of water infrastructure.
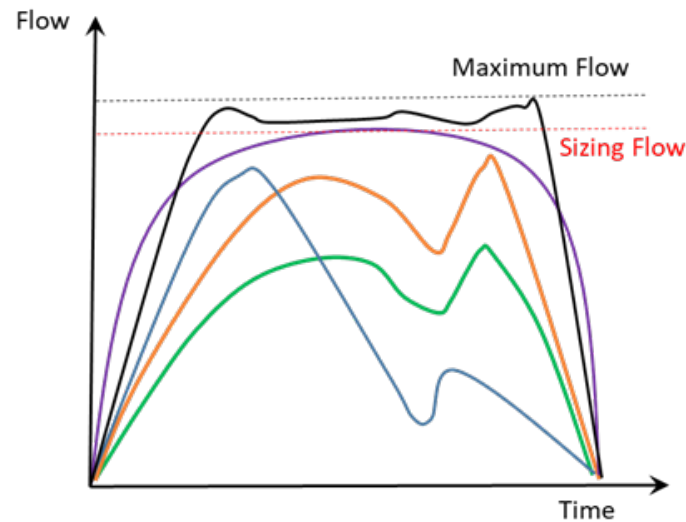

Figure 7. Distribution of flow over time.

As shown in Table 5, which includes 20 different distribution networks, the uniqueness of the network and its topology implies that the values of flow, leakage, and energy consumed (and thus CO_2 emitted) are different. Therefore, the analysis of flow distributions is crucial to address the design and subsequent management of distribution systems.

Flow distributions not only involve energy consumption and CO_2 water footprint, but the construction of the network itself involves CO_2 emissions for each metre of pipeline installed when taking into account the creation, excavation, transport, and execution of the irrigation system works, as shown in Figure 8, which shows that the variation of CO_2 emitted varies between 50 and 150% as a function of the diameter and the material.
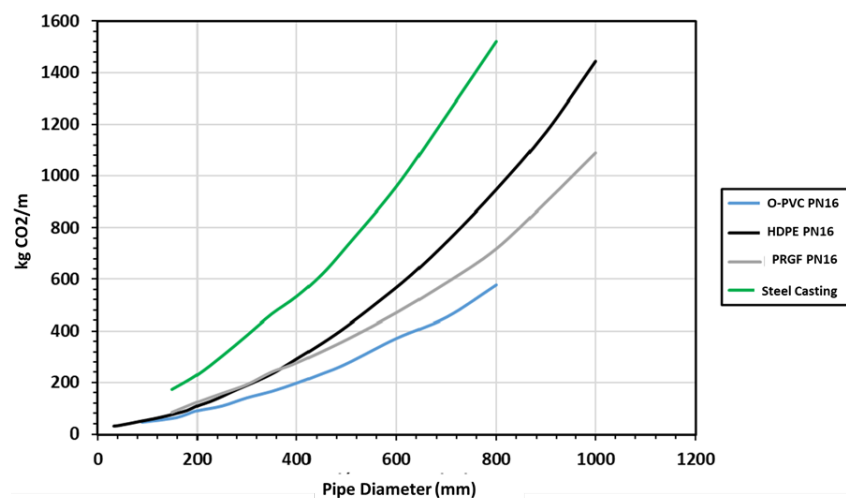

Figure 8. Distribution of the different analysed models.

Table 5. Variation of the flow, leakage, and annual consumed energy in irrigation networks.

No.	Reference	Country	Average Flow (L/s)	Average Leakage (L/s)	Annual Energy Consumed (MWh)	Annual Carbon Emission (TnCO$_2$)
1	[162]	Portugal	17.36	3.47	139.09	257
2	[163]	Spain	31.17	6.23	2949.01	2.98
3	[138]	Spain	29.34	5.87	2776.28	2.81
4	[164]	Spain	4012	802.40	379,567.30	383.97
5	[165]	Italy	1200	240.00	113,529.60	114.85
6	[166]	Spain	17.81	3.56	1685.21	13
7	[167]	Spain	10	2.00	946.08	0.96
8	[168]	Spain	479.8	95.96	45,392.92	1140.2
9	[168]	Spain	1428	285.60	135,100.22	136.67
10	[169]	Spain	221.80	6.76	20,984.58	21.23
11	[169]	Spain	0.036	0.01	1245.95	1.26
12	[169]	Peru	250	50.00	23,652.00	23.93
13	[170]	Spain	76.27	2.32	7215.78	7.3
14	[171]	Greece	774	154.80	73,226.59	74.08
15	[172]	Uzbekistan	619.61	123.92	58,620.00	59.29
16	[173]	Spain	4800	960.00	454,118.40	459.39
17	[174]	India	6.3	1.26	596.03	0.6
18	[175]	Spain	120	24.00	11,352.96	11.48
19	[176]	Jordan	520.8	104.16	49,271.85	49.84
20	[177]	Italy	215.04	43.01	20,345.10	20.58

4. Conclusions

To accurately forecast irrigation demands, agronomic variables have a key role. Moreover, relationships between crop patterns, crop group stage, water and energy requirements, weather conditions, and user interactions should be considered. Various approaches have been developed, resulting in different methodologies showing the different methods to estimate the maximum flow to size the different pipes of water irritation networks.

This paper shows some of the most important articles supporting different methods for forecasting irrigation demand. Based on the variables involved, the methods are classified into four groups: (i) deterministic models (D), in which it is assumed that uncertainties are external to the process, and they need to gather as much information as possible, and (ii) statistical models (F), which aim to determine the relative frequency corresponding to different flows during the irrigation season. The main goal is obtaining the operation probability of the hydrants at a given period. (iii) Random simulation models (R) consider a random approach of variables by creating and assuming relationships with the components associated with the portion of the irrigation that cannot be known accurately. They be influenced by uncertainties or within established assumptions and scopes. (iv) Computational intelligence models (CI) can learn from historical data and use them to predict new values based on patterns and series inspired by the biological and organisational models. The comparison of the different methods was focused on the adjustment of the function and a better definition of the maximum flow rate that allows the design flow rate to be established. Addressing and/or knowing the best flow frequency distribution function according to statistical function settings can lead to improved irrigation network design and management methods in terms of sustainability and investment.

Computer intelligence science is implemented in many fields and transforming water management concepts. Progress in this area and data collection technology allow modelling variables, such as human behaviour, thus finding relationships between expected water

demands and weather conditions, water applied in previous days, and even the users' thermal sensations.

It is powerful to learn from experience and quickly adapt to new information. Moreover, it is used to create robust models for getting into advanced irrigation management, saving considerable water volumes and energy and leading to better planning for each irrigation season and day-to-day operation time.

A study of the influence of flow distribution in distribution networks, considering its influence on energy consumption, the possible installation of micro-hydraulic generation systems, and its sustainability in terms of infrastructure implementation and operation, is necessary to address sustainable management of irrigated agriculture.

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Abbreviation

List of acronyms and abbreviations used in this article.

CFF	Clément's first formula
CNNs	Computer Neuronal Networks
DESA	Department of Economic and Social Affairs
DESA	Department of Economic and Social Affairs
FAO	Food and Agriculture of the United Nations
EEA	European Environmental Agency
ICID	International Commission on Irrigation and Drainage
IPCC	International Panel on Climate Change
IWMI	International Water Management Institute
RGM	Random Generated Model
SFRs	Several Flow Regimes
UN	United Nations
UN	United Nations
WEF	World Economic Forum
WWAP	United Nations World Water Assessment Programme
WWDR	World Water Development Report
α_W	Shape parameter of the Weibull distribution
α	Annual average water saving coefficient
ΔSM	Soil moisture change
Δ_{ET_0}	Slope vapour pressure
γ_{ET_0}	Psychrometric constant
c_i	Outlet flow assignment of group i
D_d	Water loss out of the root due to deep percolation
d_i	Fixed flow assignment of outlet group i
ET_c	Crop evapotranspiration
ET_0	Reference evapotranspiration
$e_s - e_a$	Relative humidity by saturation vapour pressure deficit
F	Irrigation area
$F(Q)$	Cumulative distribution function (*cdf*)

$f(Q)$	Probability density function
G	Soil heat flux
I	Irrigation
IN	Net irrigation water needs
K_c	Crop coefficient
k^j	Vector representing the jth event
m_I	Total number of vectors analysed
n_i	Number of outlets with the same assigned flow at group i
P	Precipitation; rainfall
Pe	Effective rainfall
$P[Q = Q_i]$	Probability of Q being Q_i
p_i	Probability of the operation of hydrant group i
Q	Discrete random variable flow vector
$\hat{Q}_t$	Estimated water demand in day t
Q_{Clem}	Flow to forecast (Clément's first formula)
Q_{t-1}	Observed water demand in day $t-1$
Q_{t-2}	Observed water demand in day $t-2$
q_i	Nominal flow rate of vector i
R	Surface runoff
R_a	Extraterrestrial radiation
R_n	Radiation at crop surface
r	Rainfall
T	Air temperature
TD	Temperature range
T_{avg}	Average daily temperature
t	Forecasting year
t_0	Data series corresponding to the first year
t_i	Time between two demands in group i
U_i	Guaranteed service level of group i
u_2	Wind speed
W	Predicted amount of water demanded
W_g	Capillary rise

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