University *of* Thessaly

Methods for modelling the Water – Energy – Food Nexus and other environmental systems towards resilience and sustainability

Dissertation submitted for the degree of

Doctor of Philosophy

at the University of Thessaly

by

Alexandra E. Ioannou

Supervisor: Professor Chrysi S. Laspidou

Department of Civil Engineering

University of Thessaly

Volos, October 2022

University of Thessaly
School of Engineering
Department of Civil Engineering
Laboratory of Hydrology and Aquatic Systems Analysis

Methods for modeling the Water – Energy – Food Nexus and other environmental systems towards resilience and sustainability

Alexandra E. Ioannou

Seven-member examination committee:

1. **Chrysi S. Laspidou**, Professor UTH, Civil Engineering Department (**Supervisor,** member of the advisory committee)
2. **Theodoros Karakasidis**, Professor UTH, Department of Physics, (member of the advisory committee)
3. **Elpiniki Papageorgiou**, Professor UTH, Energy Systems Department (member of the advisory committee)
4. **Nikitas Mylopoulos**, Professor UTH, Civil Engineering Department
5. **Athanasios Kungolos**, Professor AUTH, Civil Engineering Department
6. **Maria Papadopoulou**, Professor NTUA, School of Rural and Surveying Engineering
7. **Dimitrios Papanastasiou**, Assistant Professor UTH, Department of Environment

Volos
October 2022

Dedicated
to my family

Acknowledgements

By undertaking this PhD, I must acknowledge that I became more mature, experienced and complete not only as a researcher but also as a person and this would not have been possible without the help and guidance I received from some people.

Firstly, I would like to express my deep gratitude and profound respect to my scientific supervising Professor Chrysi Laspidou. She was and always will be my mentor. She guided me through every step of the process, and her positive outlook and confidence inspired me and helped me to build confidence in my abilities. I consider myself fortunate for being able to work with her and experience her extraordinary scientific knowledge and her human qualities. In addition, by involving me in high-level scientific projects I had the opportunity to improve my scientific background, broaden my mental horizons and receive financial support. I would also like to thank her from the bottom of my heart for being by my side through all kinds of difficulties I encountered (personally and professionally) over the years, and being generous, supportive and patient in every way. She taught me, among others, that a woman can succeed in many roles at the same time: as a student, a professional, a wife and a mother.

My thanks and gratitude also go out to the support and guidance I received from Professor Theodoros Karakasidis and Professor Elpiniki Papageorgiou, who provided critical advice towards completing this dissertation.

I am also very grateful to Professors Nikitas Mylopoulos, Athanasios Kungolos, Maria Papadopoulou, and Dimitrios Papanastasiou, for the evaluation of my dissertation as members of the examination committee.

Special thanks to Dr Dimitrios Kofinas, Dr Alexandra Spyropoulou and Dr Nikolaos Mellios who were my close associates in the scientific projects we worked and supported me not only from a scientific perspective but also emotionally to accomplish my dissertation.

Of course, I must express my sincere gratitude to Dr Ioannis Adamos and Mr Stylianos Mimis for their flawless collaboration and support during the time we spent together in our laboratory.

Finally, I would like to thank my dear husband Mr. Eleftherios Moustakas, our beloved son Vatistas and my parents for being so supportive. They always encouraged me to keep trying and never give up. I am sure that they are very proud of me, and my achievements and they will all be very happy when they will see me getting this degree.

Table of Contents

List of Tables

List of Figures

Executive Summary

This dissertation explores the potential of Nexus analysis under the frame of advanced clustering algorithms and system dynamics modeling, to enhance water security at all levels (household-, city-, and national-level) thus contributing to environmental security. When considering the Water-Energy-Food (WEF) nexus and in an effort to identify which sector affects the most the other sectors (most influential) and which sector is affected the most (most vulnerable), other studies (Laspidou et al., 2019) indicate that the Water sector is the most vulnerable one. To this end— efficient water uses through data science, technologies and efficient systems—clustering algorithms and specifically Self-Organizing Maps (SOM), K-means (KM) and Hierarchical Agglomerative Clustering (HAC) are implemented in *matlab* and *RStudio* to detect water consumption patterns at household and consumer level, using different features of the population each time to feed the algorithms. Moreover, a water-energy nexus analysis is conducted quantifying the water-energy nexus at the city level. Then the Greek WEF Nexus system under climate change is simulated using system dynamics modeling implemented in Stella Architect. Next, a system resilience analysis is applied to the same model to examine which proposed policy makes the system more resilient in terms of the size of the disturbance it can absorb and how quickly it recovers to its initial state. Finally, an analysis in terms of quantifying the impact of WEF nexus as a multi-dimensional approach on the 17 Sustainable Development Goals (SDGs) is conducted, aiming to promote integrating planning and policymaking.

In this dissertation, we use several datasets that come from various research projects. The datasets are the following:

1) Water consumption from a single household in Sosnowiec, Poland in various locations, such as kitchen, bathroom sink, shower/bathtub, toilet flushing, dishwasher and washing machine; data had a granularity of 30 sec. This data set came from the EU project ISS-EWATUS.
2) Total household water consumption for Milford, Ohio, USA, for 10 households. Temporal data granularity is not constant here, since there was a recording every time a water use "incident" happened, e.g. every time a faucet was used in the household. This dataset was provided to us via a research collaboration with Prof. Enrico Creaco (Buchberger et al., 2003).
3) Total water consumption for the island of Skiathos, Greece. This dataset came from the Skiathos Water Utility and represents daily amounts of

treated water supplied to households and businesses in Skiathos, with a resolution of one value per day. This dataset came from the EU project ISS-EWATUS.

4) Electricity consumption for the island of Skiathos, Greece divided in 3 uses--domestic, agricultural and commercial--in a monthly time step for 6 years (2010 to 2015). This dataset came from the Public Power Company of Greece.
5) An extensive national level dataset for Greece divided in its 14 River Basin Districts for Water, Energy, Food, Land Use and Climate. The time step is monthly for the year 2010. This dataset came from the SIM4NEXUS project, and it is publicly available at: Mellios and Laspidou, 2020.

The structure of this dissertation is described as follows:

Chapter 2 focuses on how the daily household water consumption can be clustered aiming at water security at household level. Household water consumptions can be grouped into days of the week through specific population characteristics. The features used to discretize the days of water consumption are statistic metrics and (half-hourly) consumption time zone consumption metrics. The time zoning is realized in two ways, the first being the typical morning, noon, afternoon, evening and night and the second considering the local working hour time zones. For the analysis, the *SOM* algorithm is implemented, using some of the selected features. The outcome of this analysis was the self-organization of the Sosnowiec data into groups (clusters) with specific characteristics that essentially differentiate the water consumption of the household on weekdays and weekends. So, the algorithm manages to detect clear consumption patterns, grouping the weekday data (Monday to Friday) into a separate group from that of the weekends.

In chapter 3, an analysis of urban water consumption patterns at consumer level and the estimation of the corresponding water demand for water utility is presented. This study proposes a comprehensive methodology for water managers to achieve an efficient operation of urban water networks, by successfully detecting residential water consumption patterns corresponding to different household needs and behaviors. The methodology uses *SOM* as the main clustering algorithm in combination with *KM* and *HAC*. The objective is to create clusters in a literature dataset that includes water consumption by customer-users. Originally, water consumption data was recorded for every water use incident in the household, while for this analysis, the information is converted to half-hourly water consumption. The consumptions refer to households in Ohio, USA. Individual customers with similar consumption behavior are clustered and water-consumption curves are calculated for each cluster; these curves can be used by the water utility to obtain estimates of the spatiotemporal distribution of demand, thus giving insight into peak demands at different locations. Statistical indices of agreement are used to confirm a good agreement between the estimated and observed water use, when clustering is employed. The resulting curves show a clear improvement in capturing water consumption behavior at household level, when compared to corresponding curves obtained without clustering. This analysis offers residents, water managers, water utilities, and policy makers an innovative solution relying on real time data and using data science principles for optimizing water supply and network operation by successfully detecting residential water consumption patterns corresponding to different residential needs and behaviors.

In chapter 4, a water–energy nexus analysis is conducted in order to achieve a sustainable supply and effectively manage water and energy at city level. Different electricity uses such as domestic, agricultural and commercial are compared and tested on how they correlate with water use. Specifically, time series of water and energy consumption for the island of Skiathos are analyzed using specific distance metrics. The results of the analysis show that water and energy are intimately related. Therefore, domestic electricity use does not correlate with water use. This isolated case is due to the fact that the water on the island of Skiathos is characterized by a high mercury content, thus making the water not eligible for drinking, so its domestic use is limited.

Chapter 5 highlights that climate change impacts the water–energy–food security; given the complexities of interlinkages in the nexus system, these effects may become exacerbated when feedback loops magnify detrimental effects and create vicious cycles. Resilience is understood as the system's adaptive ability to maintain its functionality even when the system is being affected by a disturbance or shock; in WEF nexus systems, climate change impacts are considered disturbances/shocks and may affect the system in different ways, depending on its resilience. Future global challenges will severely affect all vital resources and threaten environmental resilience. In this article, we present a resilience analysis framework for a water–energy–food nexus system under climate change, and we identify how such systems can become more resilient with the implementation of policies. We showcase results in the national case study of Greece. Parametric sensitivity analysis for socio-ecological systems is performed to identify which parameter the model is the most sensitive to. The case study is based on the structure of a system dynamics model that maps sector-specific data from major national and international databases while causal loop diagrams and stock-and-flow diagrams are presented. Through engineering and ecological resilience metrics, we quantify system resilience and identify which policy renders the system more resilient in terms of how much perturbation it can absorb and how fast it bounces back to its original state, if at all. Two policies are tested, and the framework is implemented to identify which policy is the most beneficial for the system in terms of resilience.

Finally, chapter 6 focuses on the cross-mapping of important interactions between Water-Energy-Food nexus indices and the SDGs. Worldwide, many developing countries are making efforts to achieve sustainability through the 17 SDGs and at the same time to contribute to environmental security. The Water-Energy-Food (WEF) nexus aims to enhance this effort through an integrated, multi-disciplinary and multi-domain approach providing a better understanding of the interactions among the Goals, both at and across different scales, to promote equitable access to resources, human wellbeing, and ecological integrity. The Nexus approach will support the implementation of the SDGs especially SDG 2 (Food), SDG 6 (Water), and SDG 7 (Energy), but also most SDGs have elements linked to food, water, and energy in one or more ways, and will benefit from a Nexus approach. The SDGs are designed to be cross-cutting and to be implemented together, which is also reflected in a WEF Nexus approach. In this article, we explore the influence of the WEF nexus on the SDGs by assessing the impact of Water-Energy-Food—the three WEF nexus components—on specific SDG targets by providing scores via a 7-point rating scheme. The goal is to help policymakers to create coherent policies and strategies through a systemic analysis of the many interactions by identifying synergetic or antagonistic effects of WEF nexus policies with the SDGs. Results are showcased through advanced visualization tools that cross-map the WEF nexus on the SDGs to reveal the complex and possibly obscure inter-relationships of the resource nexus with the 17 SDGs. Finally, a Fuzzy Cognitive Map analysis is conducted on the scores in order to identify the most "influential" and most "influenced by" SDGs analyzing the causality in this complex system of positive and negative interlinkages. Through this analysis, specific SDGs are indicated as the most influenced by the WEF nexus, revealing either synergies or trade-offs, while other SDGs are identified as having little interaction with the WEF nexus system.

The novelty of this dissertation relies firstly on a detailed pattern analysis using the SOM algorithm. Daily patterns of water consumption at household level are identified by using specific population characteristics leading to the creation of clusters. An innovative solution for water utilities is proposed, based on real time data and using data science principles to optimize water supply to customers and network operation. Two combined algorithms—Self-Organizing Maps (SOM) – K-Means (KM) and Self-Organizing Maps (SOM) – Hierarchical Agglomerative Clustering (HAC)—were developed to create clusters that include customer water consumption. Then a Water-Energy nexus analysis is performed at the city level in order to quantify their correlation and a WEF nexus approach under climate change combined with systemic resilience and parametric sensitivity analysis at national level is also presented. To simulate and model the Nexus for this analysis, System Dynamics Modelling is used. In this dissertation, the influence of the WEF nexus on the SDGs is also explored, by using Fuzzy Cognitive Maps analysis.

Εκτενής Περίληψη

Αυτή η διατριβή διερευνά τις δυνατότητες ανάλυσης της διασύνδεσης (nexus) των πόρων στο πλαίσιο προηγμένων αλγορίθμων ομαδοποίησης και μοντελοποίησης δυναμικών συστημάτων, στοχεύοντας στη διασφάλιση του νερού σε όλα τα επίπεδα (οικιακό, πόλης και εθνικό επίπεδο) συμβάλλοντας έτσι στην περιβαλλοντική ασφάλεια. Εξετάζοντας τη διασύνδεση Νερού-Ενέργειας-Τροφής (Water-Energy-Food Nexus—WEF Nexus) και σε μια προσπάθεια να προσδιορίσουμε ποιος τομέας επηρεάζει περισσότερο τους άλλους τομείς (αυτός με τη μεγαλύτερη επιρροή) και ποιος τομέας επηρεάζεται περισσότερο (ο πιο ευάλωτος), άλλες μελέτες (Laspidou et al., 2019) καταδεικνύουν ότι ο τομέας του Νερού είναι ο πιο ευάλωτος. Για τον σκοπό αυτό —αποδοτική χρήση νερού μέσω επιστήμης δεδομένων, τεχνολογιών και ευφυών συστημάτων— αλγόριθμοι ομαδοποίησης και συγκεκριμένα Χάρτες Αυτό-οργάνωσης (Self-Organizing Maps), K-means (KM) και Hierarchical Agglomerative Clustering (HAC) εφαρμόζονται στη matlab και το RStudio για τον εντοπισμό προτύπων κατανάλωσης νερού σε επίπεδο νοικοκυριού και καταναλωτή, χρησιμοποιώντας διαφορετικά χαρακτηριστικά του πληθυσμού κάθε φορά για την τροφοδότηση των αλγορίθμων. Επιπλέον, διεξάγεται μια ανάλυση διασύνδεσης νερού-ενέργειας ποσοτικοποιώντας τη διασύνδεση νερού και ενέργειας σε επίπεδο πόλης. Στη συνέχεια το ελληνικό σύστημα WEF Nexus υπό την κλιματική αλλαγή προσομοιώνεται σε δυναμικό μοντέλο συστημάτων χρησιμοποιώντας το Stella Architect. Ακολουθεί μια συστημική ανάλυση ανθεκτικότητας (system resilience analysis) που εφαρμόστηκε στο ίδιο μοντέλο για να εξεταστεί ποια προτεινόμενη πολιτική καθιστά το σύστημα πιο ανθεκτικό όσον αφορά το μέγεθος της διαταραχής που μπορεί να απορροφήσει και το πόσο γρήγορα επανέρχεται στην αρχική του κατάσταση. Τέλος, πραγματοποιείται μια ανάλυση με σκοπό την ποσοτικοποίηση του αντίκτυπου του WEF Nexus ως πολυδιάστατης προσέγγισης στους 17 Στόχους Βιώσιμης Ανάπτυξης (ΣΒΑ), στοχεύοντας στην προώθηση της ολοκλήρωσης του σχεδιασμού και της χάραξης πολιτικής.

Σε αυτή τη διατριβή, έχουν χρησιμοποιηθεί πολλά σύνολα δεδομένων που προέρχονται από διάφορα ερευνητικά έργα. Τα σύνολα δεδομένων είναι τα ακόλουθα:

1) Κατανάλωση νερού από ένα μόνο νοικοκυριό στο Sosnowiec της Πολωνίας σε διάφορες τοποθεσίες, όπως κουζίνα, νεροχύτης μπάνιου, ντους/μπανιέρα, πλύσιμο τουαλέτας, πλυντήριο πιάτων και πλυντήριο ρούχων. Τα δεδομένα είχαν λεπτομερή καταγραφή 30

δευτερολέπτων. Αυτό το σύνολο δεδομένων προήλθε από το ευρωπαϊκό έργο ISS-EWATUS.

2) Συνολική κατανάλωση νερού οικιακής χρήσης για το Μίλφορντ, Οχάιο, ΗΠΑ, για 10 νοικοκυριά. Η ευαισθησία των χρονικών δεδομένων δεν είναι σταθερή εδώ, αφού υπήρχε καταγραφή κάθε φορά που συνέβαινε ένα «περιστατικό» χρήσης νερού, π.χ. κάθε φορά που χρησιμοποιήθηκε μια βρύση στο νοικοκυριό. Αυτό το σύνολο δεδομένων μας παρασχέθηκε μέσω μιας ερευνητικής συνεργασίας με τον καθηγητή Enrico Creaco (Buchberger et al., 2003).
3) Συνολική κατανάλωση νερού για το νησί της Σκιάθου. Αυτό το σύνολο δεδομένων προήλθε από την Ύδρευση της Σκιάθου και αντιπροσωπεύει τις ημερήσιες ποσότητες επεξεργασμένου νερού που παρέχονται σε νοικοκυριά και επιχειρήσεις στη Σκιάθο, με ανάλυση μίας τιμής ανά ημέρα. Αυτό το σύνολο δεδομένων προήλθε από το έργο της ΕΕ ISS-EWATUS.
4) Η κατανάλωση ηλεκτρικής ενέργειας για το νησί της Σκιάθου χωρίζεται σε 3 χρήσεις - οικιακή, αγροτική και εμπορική - σε μηνιαίο χρονικό βήμα για 6 χρόνια (2010 έως 2015). Αυτό το σύνολο δεδομένων προήλθε από τη Δημόσια Επιχείρηση Ηλεκτρισμού της Ελλάδος
5) Ένα εκτενές σύνολο δεδομένων σε εθνικό επίπεδο για την Ελλάδα χωρισμένη στις 14 Περιοχές Λεκάνης Απορροής Ποταμού για το νερό, την ενέργεια, τα τρόφιμα, τη χρήση γης και το κλίμα. Το χρονικό βήμα είναι μηνιαίο για το έτος 2010. Αυτό το σύνολο δεδομένων προέρχεται από το έργο SIM4NEXUS και είναι δημόσια διαθέσιμο (Mellios and Laspidou, 2020).

Η δομή της παρούσας διπλωματικής εργασίας περιγράφεται ως εξής:

Το κεφάλαιο 2, εστιάζει στο πώς μπορούμε να δημιουργήσουμε ομάδες (clusters) χρησιμοποιώντας δεδομένα ημερήσιας κατανάλωσης νερού ενός νοικοκυριού με απώτερο σκοπό τη διασφάλιση του νερού σε οικιακό επίπεδο. Οι οικιακές καταναλώσεις νερού μπορεί να ομαδοποιηθούν σε ημέρες της εβδομάδας, μέσω ορισμένων χαρακτηριστικών του πληθυσμού. Τα χαρακτηριστικά που χρησιμοποιούνται για τη διακριτοποίηση των ημερών κατανάλωσης νερού είναι οι στατιστικές μετρήσεις και οι (ανά μισή ώρα) μετρήσεις κατανάλωσης σε διάφορες ζώνες ώρας. Η χρονική διακριτοποίηση της ζώνης ώρας πραγματοποιείται με δύο τρόπους, ο πρώτος είναι η τυπική πρωινή, μεσημεριανή, απογευματινή, και βραδινή ζώνη και ο δεύτερος λαμβάνοντας υπόψη τις τυπικές ζώνες εργάσιμων ωρών σε κάθε περιοχή. Για την ανάλυση, χρησιμοποιήθηκε ο αλγόριθμος SOM, χρησιμοποιώντας ορισμένα από τα επιλεγμένα χαρακτηριστικά. Αποτέλεσμα της συγκεκριμένης ανάλυσης ήταν η αυτό-οργάνωση των δεδομένων σε ομάδες (clusters) με συγκεκριμένα χαρακτηριστικά που ουσιαστικά διακριτοποιούν τις καταναλώσεις νερού του νοικοκυριού σε καθημερινές και Σαββατοκύριακα. Ο αλγόριθμος δηλαδή καταφέρνει να αναγνωρίσει ξεκάθαρα μοτίβα κατανάλωσης, ομαδοποιώντας τα δεδομένα των καθημερινών (Δευτέρα έως Παρασκευή) σε ξεχωριστή ομάδα από αυτή των Σαββατοκύριακων.

Στο κεφάλαιο 3, παρουσιάζεται μια ανάλυση των προτύπων αστικής κατανάλωσης νερού σε επίπεδο καταναλωτή και η εκτίμηση της αντίστοιχης ζήτησης νερού για την εταιρεία ύδρευσης. Αυτή η μελέτη προτείνει μια ολοκληρωμένη μεθοδολογία για τους διαχειριστές νερού ώστε να επιτύχουν μια αποτελεσματική λειτουργία των δικτύων ύδρευσης, ανιχνεύοντας επιτυχώς πρότυπα κατανάλωσης νερού οικιακής χρήσης που αντιστοιχούν σε διαφορετικές οικιακές ανάγκες και συμπεριφορές. Η μεθοδολογία χρησιμοποιεί SOM ως τον κύριο αλγόριθμο ομαδοποίησης σε συνδυασμό με KM και HAC. Ο στόχος είναι να δημιουργηθούν ομάδες από ένα σύνολο δεδομένων που περιλαμβάνει την κατανάλωση νερού πελατών – χρηστών. Αρχικά, τα δεδομένα κατανάλωσης νερού καταγράφονταν για κάθε περιστατικό χρήσης νερού στο νοικοκυριό, ενώ για αυτήν την ανάλυση, οι πληροφορίες μετατρέπονται σε κατανάλωση νερού ανά μισή ώρα. Οι μεμονωμένοι πελάτες με παρόμοια συμπεριφορά κατανάλωσης ομαδοποιούνται και υπολογίζονται οι καμπύλες κατανάλωσης νερού για κάθε ομάδα. Αυτές οι καμπύλες μπορούν να χρησιμοποιηθούν από την εταιρεία ύδρευσης για να ληφθούν εκτιμήσεις της χώρο-χρονικής κατανομής της ζήτησης, δίνοντας έτσι πληροφορίες για τις απαιτήσεις αιχμής σε διαφορετικές τοποθεσίες μέσα στο δίκτυο. Οι στατιστικοί δείκτες χρησιμοποιούνται για να επιβεβαιώσουν την καλή συμφωνία μεταξύ της εκτιμώμενης και της πραγματικής χρήσης νερού, όταν χρησιμοποιείται ομαδοποίηση. Οι καμπύλες που προκύπτουν δείχνουν μια σαφή βελτίωση στην καταγραφή της συμπεριφοράς κατανάλωσης νερού σε επίπεδο νοικοκυριού, σε σύγκριση με αντίστοιχες καμπύλες που λαμβάνονται χωρίς ομαδοποίηση. Αυτή η ανάλυση προσφέρει στους κατοίκους, τους διαχειριστές ύδρευσης, τις επιχειρήσεις κοινής ωφελείας και τους υπεύθυνους χάραξης πολιτικής μια καινοτόμο λύση που βασίζεται σε δεδομένα πραγματικού χρόνου και χρησιμοποιεί αρχές της επιστήμης δεδομένων για τη βελτιστοποίηση της παροχής νερού και της λειτουργίας του δικτύου, ανιχνεύοντας επιτυχώς πρότυπα κατανάλωσης νερού οικιακής χρήσης που αντιστοιχούν σε διαφορετικές οικιστικές ανάγκες και συμπεριφορές.

Στο κεφάλαιο 4, διεξάγεται μια ανάλυση της διασύνδεσης Νερού-Ενέργειας (Water–Energy Nexus analysis) προκειμένου να επιτευχθεί βιώσιμος εφοδιασμός και αποτελεσματική διαχείριση νερού και ενέργειας σε επίπεδο πόλης. Διαφορετικές χρήσεις ηλεκτρικής ενέργειας, όπως οικιακή, γεωργική και εμπορική συγκρίνονται και ελέγχονται ως προς το πώς συσχετίζονται με τη χρήση του νερού. Πιο συγκεκριμένα, αναλύονται χρονοσειρές κατανάλωσης νερού και ενέργειας για το νησί της Σκιάθου χρησιμοποιώντας συγκεκριμένους δείκτες μέτρησης (distance metrics). Τα αποτελέσματα της ανάλυσης δείχνουν ότι το νερό και η ενέργεια είναι άρρηκτα συνδεδεμένα. Παρόλα αυτά, ως εξαίρεση σε αυτή την περίπτωση μελέτης, συγκεκριμένα η οικιακή χρήση ηλεκτρικής ενέργειας δεν δείχνει να συσχετίζεται με τη χρήση νερού. Η μεμονωμένη αυτή περίπτωση οφείλεται στο γεγονός ότι στο νησί της Σκιάθου το νερό χαρακτηρίζεται από υψηλή περιεκτικότητα υδραργύρου, καθιστώντας έτσι το νερό μη κατάλληλο για πόση, οπότε η οικιακή του χρήση είναι περιορισμένη.

Στο κεφάλαιο 5, υπογραμμίζεται ότι η κλιματική αλλαγή επηρεάζει την ασφάλεια νερού-ενέργειας-τροφής. Δεδομένης της πολυπλοκότητας των διασυνδέσεων σε ένα σύστημα Nexus, αυτό το φαινόμενο μπορεί να επιδεινωθεί όταν οι βρόχοι ανάδρασης μεγεθύνουν τα επιζήμια αποτελέσματα και δημιουργούν φαύλους κύκλους, όπου τα αρνητικά αποτελέσματα φαίνονται ταχύτατα. Στα συστήματα WEF Nexus, οι επιπτώσεις της κλιματικής αλλαγής θεωρούνται διαταραχές/σοκ και μπορεί να επηρεάσουν το σύστημα με διαφορετικούς τρόπους, ανάλογα με την ανθεκτικότητά του. Οι μελλοντικές παγκόσμιες προκλήσεις θα επηρεάσουν σοβαρά όλους τους ζωτικούς πόρους και θα απειλήσουν την περιβαλλοντική ανθεκτικότητα. Σε αυτό το άρθρο, παρουσιάζεται ένα πλαίσιο ανάλυσης ανθεκτικότητας για ένα σύστημα WEF Nexus υπό την κλιματική αλλαγή και προσδιορίζουμε πώς τέτοια συστήματα μπορούν να γίνουν πιο ανθεκτικά με την εφαρμογή πολιτικών. Παρουσιάζουμε αποτελέσματα για την εθνική περίπτωση μελέτης της Ελλάδας. Μέρος της μεθοδολογίας αποτελεί η παραμετρική ανάλυση ευαισθησίας (parametric sensitivity analysis) για κοινωνικό-οικολογικά συστήματα ώστε να προσδιοριστεί ως προς ποια παράμετρο είναι πιο ευαίσθητο το μοντέλο. Η περίπτωση μελέτης βασίζεται στη δομή ενός μοντέλου δυναμικού συστήματος που χαρτογραφεί δεδομένα ανά τομέα από μεγάλες εθνικές και διεθνείς βάσεις δεδομένων, ενώ παρουσιάζονται Causal Loop Diagrams και Stock-and-Flow Diagrams. Μέσω των μετρήσεων μηχανικής και οικολογικής ανθεκτικότητας, ποσοτικοποιούμε την ανθεκτικότητα του συστήματος και προσδιορίζουμε ποια πολιτική καθιστά το σύστημα πιο ανθεκτικό όσον αφορά το μέγεθος των διαταραχών που μπορεί να απορροφήσει και πόσο γρήγορα επανέρχεται στην αρχική του κατάσταση, αν επανέλθει καθόλου. Δοκιμάζονται δύο πολιτικές και εφαρμόζεται το πλαίσιο για να προσδιοριστεί ποια πολιτική είναι η πιο ωφέλιμη για τα διαστήματα ανθεκτικότητας του συστήματος.

Τέλος, το κεφάλαιο 6 εστιάζει στη διασταυρούμενη χαρτογράφηση σημαντικών αλληλεπιδράσεων μεταξύ των δεικτών διασύνδεσης Νερού-Ενέργειας-Τροφής και των ΣΒΑ. Οι χώρες παγκοσμίως καταβάλλουν προσπάθειες για να επιτύχουν βιωσιμότητα μέσω των 17 ΣΒΑ και ταυτόχρονα να συμβάλουν στην περιβαλλοντική ασφάλεια. Η διασύνδεση Νερού–Ενέργειας–Τροφής (WEF Nexus) στοχεύει να ενισχύσει αυτή την προσπάθεια μέσω μιας ολοκληρωμένης, πολυεπιστημονικής και πολυτομεακής προσέγγισης, που παρέχει καλύτερη κατανόηση των αλληλεπιδράσεων μεταξύ των Στόχων, σε διαφορετικές κλίμακες, για την προώθηση της δίκαιης πρόσβασης σε πόρους, την ανθρώπινη ευημερία και την οικολογική ακεραιότητα. Η προσέγγιση Nexus θα υποστηρίξει την εφαρμογή των ΣΒΑ, ιδίως των ΣΒΑ 2 (Τροφή), ΣΒΑ 6 (Νερό) και ΣΒΑ 7 (Ενέργεια), αλλά και οι περισσότεροι ΣΒΑ έχουν στοιχεία που συνδέονται με την τροφή, το νερό και την ενέργεια με έναν ή περισσότερους τρόπους, και θα επωφεληθούν από μια προσέγγιση Nexus. Οι ΣΒΑ έχουν σχεδιαστεί για να είναι δια τομεακοί και να εφαρμόζονται μαζί, κάτι που αντικατοπτρίζεται επίσης σε μια προσέγγιση του WEF Nexus. Σε αυτό το άρθρο, διερευνούμε την επιρροή του WEF Nexus στους ΣΒΑ, αξιολογώντας τον αντίκτυπο του Νερού–Ενέργειας-Τροφής—των τριών συνιστωσών του WEF Nexus—σε συγκεκριμένους ΣΒΑ παρέχοντας βαθμολογίες μέσω ενός σχήματος αξιολόγησης 7 βαθμών. Ο στόχος είναι να βοηθηθούν οι υπεύθυνοι χάραξης πολιτικής, ώστε να δημιουργήσουν συνεκτικές πολιτικές και στρατηγικές μέσω μιας συστημικής ανάλυσης των πολλών αλληλεπιδράσεων, εντοπίζοντας συνεργικές ή ανταγωνιστικές επιδράσεις των πολιτικών δεσμών του WEF Nexus με τους ΣΒΑ. Τα αποτελέσματα παρουσιάζονται μέσω προηγμένων εργαλείων οπτικοποίησης που αποτυπώνουν την επιρροή του WEF Nexus στους ΣΒΑ για να αποκαλύψουν τις περίπλοκες και πιθανώς σκοτεινές διασυνδέσεις του συνδέσμου πόρων με τους 17 ΣΒΑ. Τέλος, διεξάγεται μια Fuzzy Cognitive Map ανάλυση στις βαθμολογίες (scores) προκειμένου να εντοπιστούν οι ΣΒΑ που επηρεάζουν και επηρεάζονται περισσότερο, αναλύοντας την αιτιότητα σε αυτό το πολύπλοκο σύστημα θετικών και αρνητικών διασυνδέσεων. Μέσω αυτής της ανάλυσης, οι συγκεκριμένοι ΣΒΑ υποδεικνύονται ως οι πιο εξαρτημένοι από το WEF Nexus, αποκαλύπτοντας είτε συνέργειες είτε συμβιβασμούς, ενώ άλλοι ΣΒΑ αναγνωρίζονται ότι έχουν μικρή αλληλεπίδραση με το σύστημα WEF Nexus.

Η καινοτομία αυτής της διατριβής βασίζεται πρώτα σε μια λεπτομερή ανάλυση προτύπων κατανάλωσης χρησιμοποιώντας τον αλγόριθμο SOM. Τα καθημερινά πρότυπα κατανάλωσης νερού σε επίπεδο νοικοκυριού προσδιορίζονται χρησιμοποιώντας συγκεκριμένα πληθυσμιακά χαρακτηριστικά που οδηγούν στη δημιουργία συστάδων. Προτείνεται μια καινοτόμος λύση για τις επιχειρήσεις ύδρευσης, βασισμένη σε δεδομένα πραγματικού χρόνου και χρησιμοποιώντας αρχές της επιστήμης δεδομένων για τη βελτιστοποίηση της παροχής νερού στους πελάτες και τη λειτουργία του δικτύου. Δύο συνδυασμένοι αλγόριθμοι—Self-Organizing Maps (SOM) – K-Means (KM) and Self-Organizing Maps (SOM) – Hierarchical Agglomerative Clustering (HAC)—αναπτύχθηκαν για τη δημιουργία ομάδων που περιλαμβάνουν την κατανάλωση νερού από τους πελάτες. Στη συνέχεια πραγματοποιείται ανάλυση του δεσμού (nexus) Νερού-Ενέργειας σε επίπεδο πόλης προκειμένου να ποσοτικοποιηθεί η συσχέτισή τους και παρουσιάζεται επίσης μια WEF nexus προσέγγιση υπό την κλιματική αλλαγή σε συνδυασμό με ανάλυση συστημικής ανθεκτικότητας (systemic resilience analysis) και παραμετρικής ευαισθησίας (parametric sensitivity analysis) σε εθνικό επίπεδο. Για την προσομοίωση και τη μοντελοποίηση του Nexus για αυτήν την ανάλυση, χρησιμοποιείται το System Dynamics Modeling. Σε αυτή τη διατριβή, διερευνάται επίσης η επιρροή του WEF nexus στους ΣΒΑ, χρησιμοποιώντας την ανάλυση Fuzzy Cognitive Maps.

1

Introduction

1.1 Motivation and Objectives

According to the study made by the United Nations (UN) Millennium Ecosystem Assessment, in less than 50 years our planet has experienced a doubling of human population and a shift towards more resource-dependent consumption patterns. Currently, 1.1 billion people survive without clean water, 1.3 billion live without electricity, and 1 billion suffer from hunger (Millennium Ecosystem Assessment, 2015). This trend is expected to worsen soon, as a result of growing resource demand driven by climate change, population growth, economic development, urbanization, changing lifestyles, pandemics, insufficient governance & policies and lack of equitable access to technology & innovation, making the availability and management of resources a priority in political agendas. Research and policy circles have been increasingly recognizing the need for a more integrated approach in planning and management of resources, in order to address the interconnected risks to water, energy, and food security, since each resource "security" implies trade-offs for the security of the others. Growing pressures on natural resources are making the interdependencies and trade-offs between food, water and energy systems, and their interactions with land, climate change and livelihoods, increasingly evident. Understanding their interplay is essential to effectively address sustainability challenges. Furthermore, managing food, water and energy systems is key to achieving the UN Sustainable Development Goals (SDGs) (United Nations, 2018) (specifically SDG 2 for food security, SDG 6 for water and SDG 7 for energy) and requires a better understanding of the interactions between the Goals, both at and across different scales, to promote social equality, human wellbeing and ecological integrity. Providing decision-makers with the multifaceted knowledge needed to seize all opportunities to enhance synergies and minimize trade-offs is, therefore, a major objective for Nexus research. In response to this, the Water-Energy-Food (WEF) Nexus concept highlights the interactions between these systems and provides insights into the cross-sectoral implications of single-sector strategies.

The need to take a Nexus approach that connects these resources has not only been quickly acknowledged by the research community but also in public management. The United Nations, the European Commission and the Food and Agriculture Organization (FAO) of the UN (Flammini et al., 2014) have all acknowledged the importance of dealing with the Nexus between resources in an integrated manner. Hoff (2011) described the process illustrating that the "Nexus" concept provides a new way of thinking that is not limited to just the water, energy and food sectors, while the World Economic Forum launched a report entitled "Water Security: The Water - Energy - Food - Climate Nexus", marking the emergence of the Nexus as we know it today. Other approaches have been described in recent years as well, such as the water-soil-waste Nexus, the water - food - energy - ecosystems Nexus, the water - energy - food - land use - climate Nexus and others. The Nexus approach is also used as a defined area of work under the UN Economic Commission for Europe (UNECE) Water Convention with a strong focus on transboundary aspects, since transboundary water bodies often form the connecting resource for food and energy, while international food trade and regional markets for electricity and energy carriers cross state borders. The strong presence of the Nexus at the World Water Forum and the Rio+20 Conference in 2012 is a proof of the impact that this is an emerging idea worldwide. In few years, the number of books, academic articles and policy reports that refer to the analysis and management of the Nexus have grown exponentially. A large body of academic research on the Nexus concept is available: some are more conceptual, while others focus on quantitative analysis. Liu et al. (2017) and Brouwer et al. (2018) provide recent reviews and references on Nexus research from the technical perspectives of water and energy, respectively, while Weitz et al. (2017) discuss governance across sectors. This proliferation has resulted in the concept being defined by usage, while the variety of perspectives under which the Nexus is assessed, results from its inherent complexity and context specificity.

A recent literature review by Galaitsi et al. (2018) revealed that the WEF Nexus is closely interlinked with economic forces, governance and socio-physical factors. Thus, economic considerations might be those that create and enhance some of the interlinkages within the Nexus and include economic incentives for managing resources and promoting innovations, variable pricing schemes to curb demand, fossil fuel taxation, etc. Sustainable development necessitates the decoupling of economic growth and resource depletion, thus bringing the economy at the heart of WEF Nexus management schemes. If one considers the fact that decision-makers are not resource managers, then it becomes obvious that the WEF Nexus has governance challenges at its core. How can the global community promote an integrated approach to complex trade-offs and challenges in respect of WEF resource security? It can only be achieved with governance processes that engage stakeholders from the Nexus arena and empowers them in analyses and management decisions, thus addressing power and gender imbalances and promoting sustainable and inclusive growth. Raising awareness of the Nexus among actors in governance systems is critical in achieving adequate governance leading to successful strategic vision and efficient resource management. Finally, power dynamics are mentioned by

Galaitsi et al. (2018) as having the key role, as far as social relations are concerned, in determining WEF connections. Institutions, governance processes, technologies and innovations can shape power distribution and can cause particular asymmetries within the Nexus, enhancing its complexity. European policies in the areas of water, energy, food and climate can be qualified as coherent in terms of their design and process. However, policy coherence could still face challenges between objectives, instruments and implementation. This needs to be made explicit and solved at national and regional scales also enabling to exploit synergies across these policy areas. In this dissertation, we address these issues by offering methodologies-solutions to policy makers with the aim to enhance water security at household and customer level in Chapters 2 and 3, while in Chapters 4 and 5 we present a water-energy nexus analysis at city level and a WEF nexus analysis under climate change at national level.

The main challenge is that the WEF Nexus is designed to influence policies, which presupposes that the community is in agreement of what is to be achieved. But how can trust be built by citizens when no standardized method exists, and different methods produce different results? It is difficult to deal with the uncertainty generated through multiple definitions and no standardized methodology, research input, convention, performance indicators, benchmark values, etc. In Chapter 5 of this dissertation, we explore this by looking into the policies and using engineering and ecological resilience measures.

As resource scarcity increases and societies and institutions are getting stressed, especially under the pressure of climate change, abandoning silo-thinking and institutional fragmentation become seven more urgent. Nexus-coherent policies are at the core of achieving the SDGs and securing resources; even though this fact is widely recognized, governments still have a lot of progress to make in that direction, with lack of suitable information, that is easy to comprehend and appreciate probably playing an important role. At first level and considering that Water is the most vulnerable sector of the three nexus sectors (Laspidou et al., 2019), this dissertation offers solutions for enhancing water security at many levels via particular methodologies. Specifically, advanced clustering techniques, such as Self-Organizing Maps (SOM), K-Means (KM) and Hierarchical Agglomerative Clustering (HAC) algorithms were used to address the challenge of water stress (Chapters 2 and 3). Also in this direction, methodologies for analyzing and assessing the Nexus at city (Chapter 4) and national level (Chapter 5) are presented in this dissertation, whereas in Chapter 6, we map the WEF nexus system on the SDGs and we explore how and in what way (positively or negatively) the three Nexus components (Water-Energy-Food), separately and in combination, interact with the 17 SDGs. To simulate and model the Nexus for the analyses presented in this dissertation, System Dynamics Modelling is used. The complexity of a highly interlinked Nexus system, the plethora of data to be considered and the importance of scale make it challenging to communicate modeling outcomes to stakeholders. To this end, in this dissertation, the development of advanced visualization diagrams is used presenting the complex Nexus data coming from robust modeling analysis to stakeholders in a comprehendible manner.

1.2 Original Contributions

The original contributions of this dissertation are described as follows:

1. Through a detailed pattern analysis using the SOM algorithm, daily patterns of water consumption at household level are identified thereby contributing to water security.
2. Specific population characteristics are used to describe daily consumption behavior leading to the creation of clusters.
3. An innovative solution for water utilities is proposed, based on real time data and using data science principles to optimize water supply to customers and network operation, providing tools for the efficient use of water resources.
4. Two combined algorithms—Self-Organizing Maps (SOM) – K-Means (KM) and Self-Organizing Maps (SOM) – Hierarchical Agglomerative Clustering (HAC)—were developed to create clusters that include customer water consumption.
5. A Water-Energy nexus analysis is performed at the city level in order to quantify their correlation.
6. Simulation of a Water-Energy-Food Nexus system under climate change, at the national level, using System Dynamics Modeling in Stella Architect.
7. System resilience analysis framework for a water–energy–food nexus system under climate change is presented, identifying how such systems can become more resilient with the implementation of policies.
8. Parametric sensitivity analysis for socioecological systems is performed to identify which parameter the model is the most sensitive to.

9. The influence of the WEF nexus on the SDGs is explored, by assessing the impact of Water-Energy-Food—the three WEF nexus pillars—on specific SDG targets by providing scores via a rating scheme.
10. Fuzzy Cognitive Maps analysis is used to investigate the influence of the WEF Nexus on the SDGs

2

Data Mining for household water consumption analysis using Self-Organizing Maps

2.1. Introduction

Smart Cities have been defined in many ways. Special focus is given on Information and Communication Technologies (ICTs) as a key driver. Other important aspects of instrumenting the landscape of a smart city would be society, economy, and policies driven by participatory processes. The concept of Smart Cities sets, in the core of urban planning, monitoring, recording, analyzing and transferring in real time all data relative to social activity; thus, enabling social and governmental awareness of all significant design variables. The monitored variables are linked to basic networks and environments such as city services, transport, water and energy (Manville et al., 2014).

Subsequently, the need of collecting and managing great amounts of temporal and spatial high-granularity data becomes of conclusive importance. Great progress in ICTs, social network, and Data Mining (DM) enable new paths of urban planning, empowering the resilience of urban infrastructure and the adequacy of resources and systems (Laspidou, 2014).

DM is an ongoing research area, responding to the presence of large databases in commerce, industry and research (Bishop, 1995). It is a very useful technique in research; because not only can someone extract meaningful information from certain databases, but can also predict changes, discover patterns and relations hidden among the data (Fayyad et al., 1996). In addition, DM is an interactive process that requires the intuition, background knowledge and the computational efficiency of modern computer technology. Clustering techniques can reveal patterns and identify similar trends and components linked to similar behaviors. Clustering visualization is a very important part of DM and can be successfully accomplished, by the use of self-organizing maps (Kaski, 1997).

One of the fundamental urban activities, firmly related to all human well-being aspects, such as public health, is the urban water consumption. The Water Distribution Networks (WDNs) are to be thoroughly monitored in different scales, from an aggregated urban water resources view, down to a household water consumption view, so as to gather all useful data that will enable the improvement of water resources management, through all the available data analysis techniques. The aforementioned DM techniques can realize water consumption forecasting at small scales, by clustering householders in different consumption patterns; thus, enabling water utilities to get more efficient by heading towards more individualized customer services (Beckel et al., 2012, Laspidou et al., 2015). Parallel to increasing resolution at individualized scale, analysis can also enable temporal clustering resolution, identifying different daily consumption patterns. Past research (Arampatzis et al., 2014) has already indicated weekdays/weekends water use particularities at urban level, revealing the potential to further investigate daily patterns at household level. Other studies focus on household water demand management, reviewing approaches to water demand estimation and forecasting over the short- (daily to season) and long-term (years to decade) and note the paucity of studies on weather and climate (Parker and Wilby, 2012), while another study presents a data-driven approach to identify fundamental water and energy demand profiles, cluster buildings into groups exhibiting similar water and energy use, and predict their demand (Frankel et al., 2021).

The aim of the present study is to further advance how specific daily household patterns can be inferred from household water consumption profiles. We make an effort to cluster days of similar water consumption profiles. The automatic classification of days into clusters is accomplished with the application of the SOM methodology.

2.2. Materials and Method

In this paper we develop a methodology for the detection of daily patterns in household water consumption, through a detailed patterns analysis using SOM (Kohonen, 1995). The methodology is a popular neural network algorithm based on unsupervised learning. SOM uses specifically chosen features of a population; then it calculates the Euclidean distances of each unit of the population considering the features as dimensions or components of the input vectors. Lastly, it converts the multidimensional positions of the units into 2-dimensional and maps them. These maps depict all units in a sense that neighboring units correspond to similar features; thus, making clustering of similar units possible. The SOM has proven to be a valuable tool in DM with applications in financial data analysis (Deboeck et al, 1998), in engineering applications, pattern recognition (Kohonen et al., 1996), image analysis, process monitoring and fault diagnosis (Simula et al., 1995). SOM method is widely used to cluster a variety of attributes such as fine-grained electricity consumption, water consumption, etc. (Beckel et al., 2012, Laspidou et al., 2015, Räsänen et al., 2008).

Water consumption is recorded by sensors installed in individual households. Input vectors are produced from water consumption data from a household in Sosnowiec, an industrial city in southern Poland. In this household, sensors were installed in seven different faucets, so we summed all our data in order to have time-series of the total consumption of the house. Water consumption values are recorded every 30 sec and a 445-days sample is used for the analysis. Each day is considered to be a unit of a population of 445 and the analysis aims at clustering days that are linked to similar profiles by mapping them closely. The original data were recorded every 30 seconds, but in order to produce the 13 features, we sum the data accordingly. An indicative timeseries plot of the consumption of the household is presented in Figure 2.1.

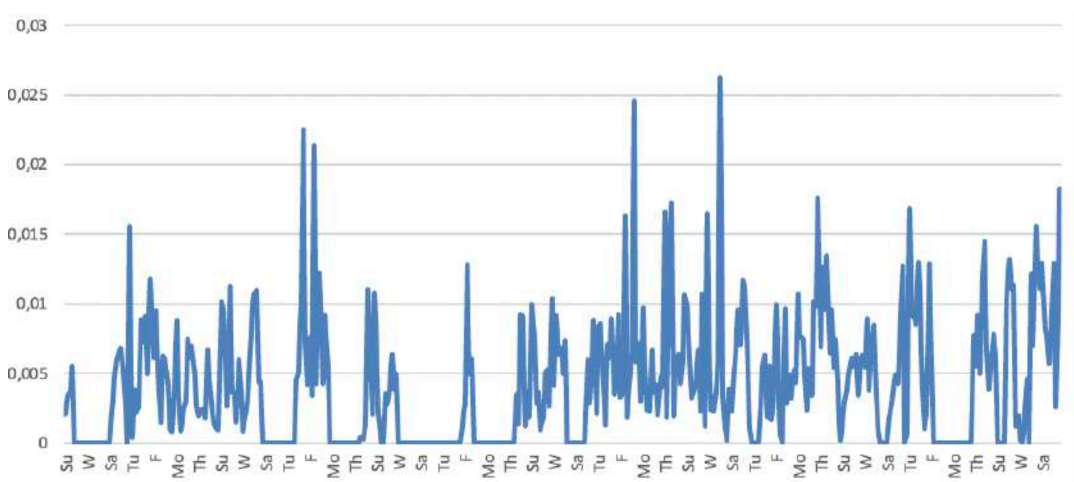


Figure 2.1 Total daily water consumption of the household.

We use 13 features to describe the daily consumption behavior, listed in Table 2.1. The features refer to total daily consumption (feature 1), daily standard deviation (σ) of daily water consumption (feature 6) and partitioning of daily consumption into specifically chosen time-zones (features 2-5 & 7-13). Our data are divided in the following time zones: morning (feature 2), noon (feature 3), afternoon (feature 4), evening (feature 5) and night (feature 7). Another time zone division considers the working hours and rest hours of offices (feature 8 & 10, respectively), banks (features 9 & 11, respectively) and shops (features 12 & 13, respectively). The features are chosen in the sense that total consumption, σ and time zones consumption are suspected to possibly characterize different days' patters. Specifically, the working hours' features are taken into account, because the household is located in an urban environment and most probably its water consumption is directly affected by the working routines. The aforementioned features are combined to create three different dimension sets for the three approaches of our investigation. The features regarded for each approach are listed in Table 2.1.

After the preparation of the data and estimation of the feature table of its single day of consumption, a matlab SOM-toolbox and its scripts are used to preprocess data, initialize, normalize and train SOM and construct the maps (Vesanto et al., 1999). The normalization of data is of great importance for a very specific reason: The estimated features and components of the input vectors of a SOM, due to their different nature, exhibit values of very different magnitude. The feature with the greater magnitude would affect the Euclidean distance unequally to the features with smaller magnitude. With the normalization we achieve, equal partitioning of the features. An overview of the methodology in a step-by-step fashion is shown in Figure 2.2.

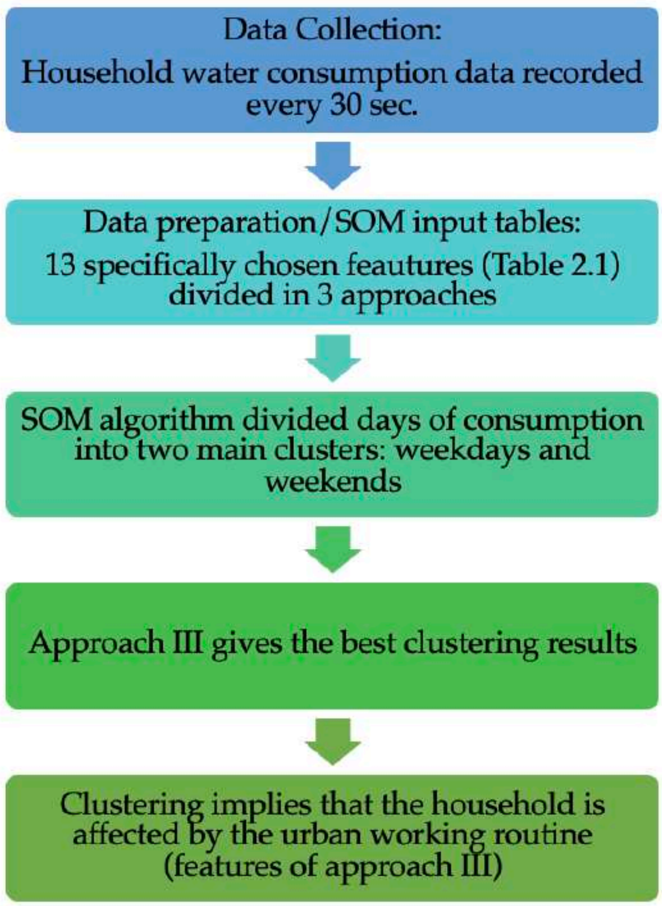


Figure 2.2 An overview of the step-by-step methodology

Another very significant pre-process is that of labeling each feature table after its corresponding day. The purpose of this process is that the maps created are legible and comprehensible and the clusters, possibly created, are easily visualized. This means, that we expect Saturdays, for example, to gather around the same area of a SOM map and this way construct a cluster of similar consumption profile corresponding to that of a typical Saturday.

Table 2.1 Features of daily consumptions used for the 3 different SOM approaches

approach 1	**approach 2**	**approach 3**
1. total daily consumption	7. night consumption *(12am-8am)*	8. consumption at offices working hours *(8am-4pm)*
2. morning consumption *(6am-10am)*	8. consumption at offices working hours *(8am-4pm)*	9. consumption at bank working hours *(8am-6pm)*
3. noon consumption *(10am-2pm)*	9. consumption at bank working hours *(8am-6pm)*	12. consumption at shops working hours *(11am-7pm)*
4. afternoon consumption *(2pm-6pm)*	10. consumption at office rest hours *(4pm-10pm)*	
5. evening consumption *(6pm-10am)*	11. consumption at bank rest hours *(6pm-10pm)*	
6. standard deviation of water consumption (σ)	12. consumption at shops working hours *(11am-7pm)*	
	13. consumption at shops rest hours *(7pm-10pm)*	

2.3. Results and Discussions

The results of the runs are depicted with use of three kinds of SOM maps (Figures 2.1, 2.2 & 2.3). The U-matrix is the 2-dimensional depiction of the multi-dimensional Euclidean distances of all the daily consumption profiles. As we see from top to bottom there is gradation from dark blue, small distances to light yellow, big distances. This means that two units in neighboring cells are closer if the cells are in the blue area than if they were in the yellow area. In the labels map, the location of each unit is presented according to its characterization as a day of the week. This way it can be revealed if same days of the week tend to cluster in neighboring cells; thus, prove to have similar water consumption profiles. At the right side of the figures, the feature matrixes are presented. These maps depict the behavior of each feature separately.

In approach 1 (Figure 2.1), we use features 1 to 6, namely, total daily, morning, noon; afternoon, and evening consumptions and σ. Two main cluster areas, area 1 and area 2, are formed. In the first one, weekends are more frequent, while as, in the second one, weekdays seem to dominate. This clustering of weekdays separately than weekends proves that in the household depicts different water use profiles in working days than in non-working. Moreover, weekend cluster cells are much closer one another than weekday cells. That means that weekend profiles are more uniform than the weekdays. In area 2, three sub-clusters 2a, 2b, and 2c seem to be formed. Sub-cluster 2a includes only Tuesdays, sub-cluster 2b includes only Wednesdays and finally sub-cluster 2c includes only Mondays. The sub-clustering of cluster 2 justifies its looseness, as it seems that throughout the working days, some more specific daily consumption prototypes are formed with some differences. Observing the feature matrixes, we can see that total daily consumption and σ are similar. These two show that weekends in the upper are firmly located, in contrast to weekdays which are more loosely located. This pattern is almost followed by the afternoon consumption feature. On the other hand, morning, noon, and evening consumption features are more uniform in an extended area, with some yellow "gorges" low at the weekdays' area. Subsequently the U-matrix is formed as a combination of the six features degrading top to bottom from blue to yellow.

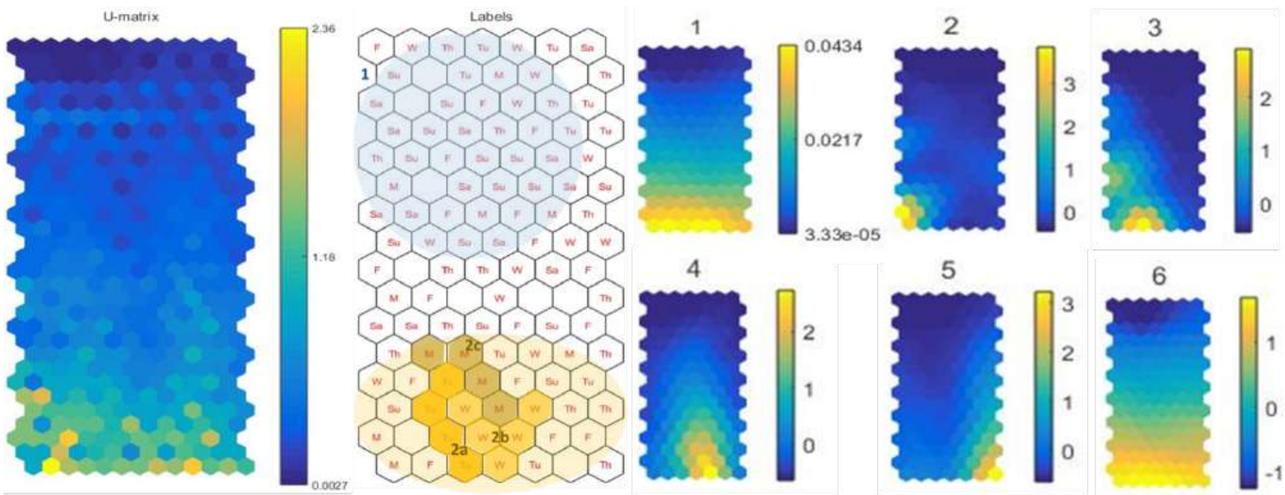


Figure 2.3. It is depicted the SOM map results: U-matrix, Labels, feature 1 total daily consumption, feature 2 morning consumption, feature 3 noon consumption, feature 4 afternoon consumption, feature 5 evening consumption, and feature 6 σ (Approach 1).

In Approach 2 (Figure 2.2), we use features 7 to 13, which refer to the working and resting hours consumptions as well as the night consumption. With this approach, we see that clusters are formed in the same way (weekends upper and weekdays down). However, the clusters appear more discretized and more extended than those of approach 1. This proves that the working and resting hours features are more proper than the typical time zoning of morning, noon, afternoon, and evening features. This could be an indicator that the case study household members follow the prevailing working routine of Sosnowiec (Yang et al., 2017). In contrary to approach 1, two sub clusters, 1a and 1b, are formed in cluster area 1 rather than in area 2. The cluster 1 mostly contains weekends, while its sub clusters 1a and 1b contain exclusively Saturdays and Sundays. The weekdays in this approach don't seem to further sub-cluster discretized. In Approach 3 (Figure 2.3), only three features are used, the working hours consumptions. This improves clustering, since in the weekend area, Saturdays and Sundays rise up to 3 out of 4. In the weekday area, 86 % of the cells are occupied by weekdays. In all approaches, we can see that Fridays are equally distributed in both areas. This indicates that Fridays water consumption profiles are somewhere in between and have characteristics of both weekday and weekend profiles.

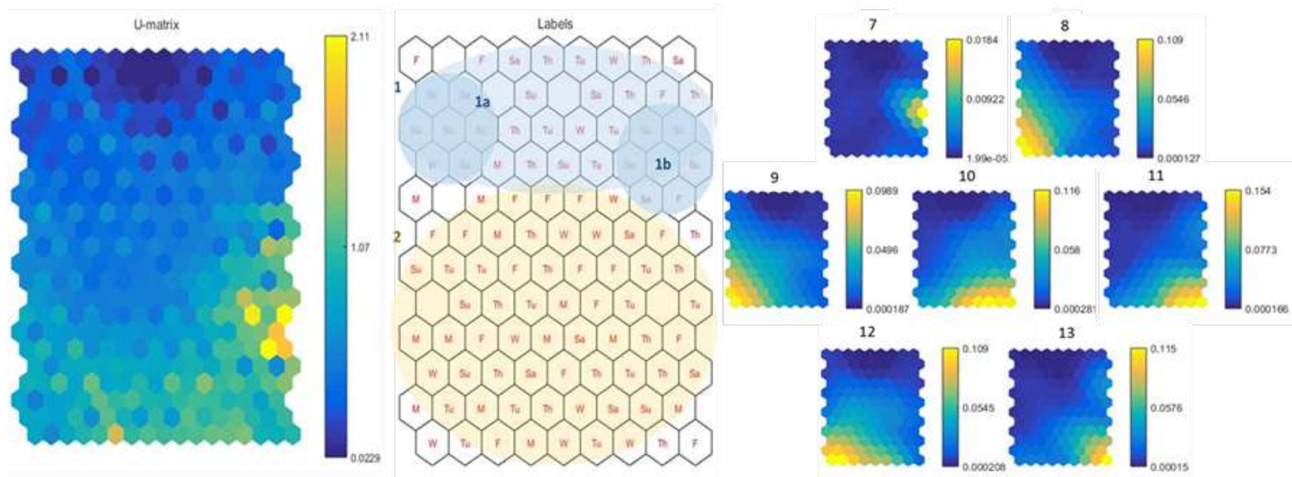


Figure 2.4. It is depicted the SOM map results: U-matrix, Labels, feature 7 night consumption, feature 8 consumption at offices working hours, feature 9 consumption at banks working hours, feature 10 consumption at offices rest hours, feature 11 consumption at banks rest hours, feature 12 consumption at shops working hours, and feature 13 consumption at shops rest hours (Approach 2).

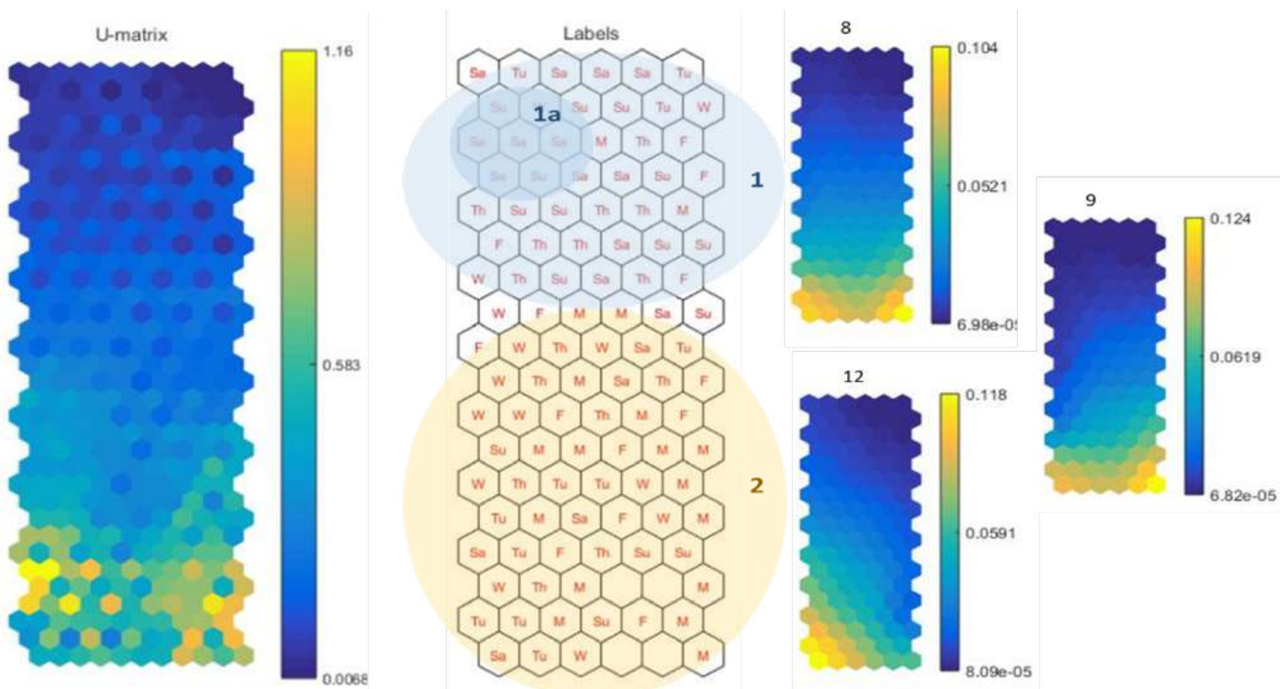


Figure 2.5. It is depicted the SOM map results: U-matrix, Labels, feature 8 consumption at offices working hours, feature 9 consumption at banks working hours, and feature 12 consumption at shops working hours (Approach 3).

Chapter 2 includes parts of the following published work:

Ioannou, A. E., Kofinas, D., Spyropoulou, A., & Laspidou, C. (2017). Data mining for household water consumption analysis using self-organizing maps. *European Water*, *58*, 443-448

- The contribution of **Alexandra Ioannou** involves the conceptualization, the methodology, the software, the formal analysis, the investigation, the validation, the writing—original draft, and the visualization.
- The contribution of **Dr. Dimitrios Kofinas** involves the writing—original draft.
- The contribution of **Dr. Alexandra Spyropoulou** involves the data curation
- The contribution of **Professor Chrysi Laspidou** involves the conceptualization, the methodology, the resources, the scientific supervision, the review and editing, the project administration, and the funding acquisition.

This study was supported by the research project Water4Cities-Holistic Surface Water and Groundwater Management for Sustainable Cities-which is implemented in the framework of the EU Horizon2020 Program, Grant Agreement Number 734409.

3

Exploring the Effectiveness of Clustering Algorithms for Capturing Water Consumption Behavior at Household Level

3.1 Introduction

The United Nations predict that 9.7 billion people will live in cities by 2050 (United Nations, 2015]. Along with the effects of climate change, cities face numerous challenges as their resources and infrastructure are placed under ever increasing levels of strain (European Commission, 2014). As water scarcity becomes more prevalent, the analysis of urban water consumption patterns for consumers and the estimation of the corresponding water demand are expected to be among the top priorities for water companies in the near future. There is a constant need to improve the knowledge of urban water demand and of factors that influence demand patterns in a household; this requires collection and analysis of water consumption data, which can be facilitated by Information and Communication Technology (ICT) systems in a smart city framework. ICTs can help managers in integrating the water sector with other city services and in monitoring their status in real time. This results in several operational benefits that optimize urban water management, including real time demand forecasting and optimization of network devices and of operating costs (Laspidou 2014). On this basis, it is possible to develop better water demand models and new customer-oriented tools to be used for smart metering, smart pricing and tariff planning, water distribution network planning and operation, energy savings in water transfer, and customer service and billing, as well as the real-time management of condition-based tariffs. These goals abide by the European legislation, as described in the EU Water Framework Directive and the Blueprint to safeguard Europe’s water resources (European Commission, 2013) concerning water accounts and ecological flows, water pricing, water trading, and other factors. Furthermore, the recent technological progress in wireless sensors that enable monitoring of water use in individual households, or even in different faucets or appliances inside a single household, can provide detailed information concerning spatial and temporal water use patterns. These data have been collected in the past mainly for research purposes (Kofinas et al., 2018; Rizou et al., 2018; Yang et al., 2017) but are now becoming more common with the diffusion of smart city initiatives, such as the installation of smart water meters (Water World, 2011). In the future, the availability of such information will allow for more accurate billing and customer-specific services, but, more importantly, will increase water efficiency due to a better understanding of the water consumption behavior at household levels for both large and small customers and may help in the reduction of non-revenue water.

In order to assess urban water demand in time and space, a water consumption profile curve is needed. This curve (profile) shows the amount of water a customer uses over the course of time, and it is useful for planning how much water the utility will need to make available for its customers at any given time. Furthermore, water consumption profiles reveal the pattern customers exhibit in using water at different hours of the day, days of the week and seasons of the year, and can specify what the customer's share of the utility's total water consumption is. By analogy with electricity load curves, water consumption profiles can provide estimates of the temporal and spatial distribution of demand, thus giving insight into peak demands at different locations (Rasanen et al., 2010). The major factors affecting the consumption profile are (1) family size and customer water use behavior, as well as residence characteristics and (2) seasonality, i.e., time of day, week, or year. Local climate factors such as temperature, humidity, and solar radiation may play an important role in water consumption patterns, but their effect is captured by seasonality (Kofinas et al., 2014).

Even though it is typical for energy and telecommunication companies to classify their customers into groups with similar consumption patterns taking into account their characteristics and annual demand, such practices are not common for water utilities, maybe because of the relatively low cost of water. The goal of this classification is to assign to each customer a variable estimate of consumption, a sort of a "load curve", in the absence of available meter data. These pre-fixed curves may also be useful for market investigation and distribution management for the utility. Yet, they have flaws as a result of their coarseness, since on the one hand, they may fail to follow actual consumptions, and on the other, they are unable to predict possible changes in people's way of life and/or in their consumption patterns (Bedingfield et al., 2018). It is undisputed that a more thorough description and forecast of water consumption throughout the day, month, and year, capturing seasonality and weekday/weekend patterns in water use can lead to an improved management and planning of demand and distribution, resulting in a potential reduction of costs for the water utility. Understanding customer behavior can lead to a successful categorization based on the recognition of similarities in consumption patterns among consumers. This segmentation would allow water utilities to better tailor pumping, treatment, and network operation, while it can provide useful information on water pricing policies and other incentive-creation strategies (Rodrigues et al., 2003).

Many researchers have shown an increasing interest in Artificial Neural Networks (ANN) to address various kinds of problems in water resources and hydrology (Maier et al., 2000; Govindaraju, 2000a; Govindaraju, 2000b; Dawsonand and Wilby, 2001). Self-Organizing Maps (SOMs) is an ANN algorithm (Kohones, 1982a; Kohonen, 1982b), which has proven to be an excellent tool for clustering, classification, estimation, prediction, and data mining (Alhoniemi et al., 1999; Vesanto and Alhoniemi, 2000; Kohonen, 2001). Kalteh et al. (2008) reviewed a number of successful SOM applications with emphasis on innovative and creative solutions for the analysis, estimation, and prediction of various hydrological processes, such as precipitation (Vesanto, 2002; Hong et al., 2005; Kalteh, 2007), river flow and rainfall-runoff (Abrahart and See, 2000; Hsu et al., 2002; Lin and Chen, 2006), surface water quality (Maier and Dandy, 1996; Maier and Dandy, 1997; Bowden et al., 2005a; Bowden et al., 2005b), and other related disciplines such as climate and environment (Tran et al., 2003; Schutze et al, 2005; Shanmuganathan et al., 2006). SOMs have many applications in signal recognition, organization of large data sets, process monitoring and analysis, and over the last decades, they have increasingly been used for analysis and modeling in the energy domain (Rasanen et al., 2010; McLoughlin et al., 2015; Kameoka et al., 2015; Turncinek et al., 2016). However, only a limited number of articles have been published on domestic water consumption pattern recognition, classifying customers in different segments (Yang et al., 2018; Laspidou et al; 2015; Ioannou et al., 2017).

This study aims to bridge this gap by proposing a comprehensive methodology to residents, water managers, and policy makers, in order to achieve the efficient operation of urban water networks by successfully detecting residential water consumption patterns corresponding to different residential needs and behaviors. This way, households with similar consumption patterns are grouped in clusters. A large dataset taken from the work of Buchberger et al. (2003) and consisting of 7 months of water consumption data recording every instant of water use in the household from 21 customers located in Milford, Ohio, USA, was examined. To the best of the authors' knowledge, residential water consumption data with this granularity have not been analyzed for the purpose of detecting behavioral patterns in water consumption.

The aim of the dissertation is to create more accurate customer-specific water consumption curves using refined measurement data. In this context, we propose a methodology that may be applied in complex and large water consumption time-series, using SOMs as the main clustering algorithm, in combination with K-Means (KM) and Hierarchical Agglomerative Clustering (HAC) to improve performance; this way, we provide a new-estimated water consumption profile for each customer group. The resulting curves that are obtained after clustering customers with similar consumption behavior are compared to the water consumption curves that the water company might use to create timely customer water use estimates without performing clustering. The results indicate that there is a clear improvement when using the newly estimated, data-based water consumption curves after clustering. This analysis offers water utilities an innovative solution that relies on real time data and uses data science principles relevant to a smart city setting for optimizing water supply and network operation and leading to efficient resource use. It creates opportunities to engage citizens while raising their awareness of household water consumption. Therefore, it lays the foundation for developing behavioral change processes for citizens towards more sustainable water use patterns that would reduce their environmental footprint, change their consumption and lifestyle choices, and achieve a climate-neutral way of living.

3.2 Materials and Methods

In order to develop reliable water consumption curves for customers belonging to different classes, large numbers of recorded water consumption values are required—for electricity, it is recommended to have at least 100 customers over a period of 3 years (Lakervi, 1995). For household water consumption, such long datasets are unavailable due to the very recent implementation of smart technologies in the water sector, which is often confined to limited duration of research projects e.g., Yang et al. (2017). In this article, we use the data collected by Buchberger et al. (2003), who carried out an experimental campaign aimed at monitoring residential water demand in the period from April to October 1997 in 21 households in Milford, OH, USA. An electromagnetic flowmeter was installed in the mainline of each household and water discharge data was collected for the 7-month period with a resolution of 1 sec. It should be noted here that only indoor water consumption was included in our data, so even if a household had large gardens, or a swimming pool, it would not make a difference to our dataset. To create a uniform time series for all households, we grouped all water consumption data (210 days) to half-hour slots, resulting in a dataset of 10,080 entries for each household. In Figure 2.1, we show graphs of the consumption dataset for all households—each bar corresponds to the half-hour consumption and there are a total of 10,080 bars in each graph. To show the variation of consumption over weekdays and weekends, in Figure 3.2a, we show, indicatively for household C, average consumptions of all weekday, Saturday, and Sunday consumptions per half-hour time slot throughout the day, for a total of 48 time slots per day. This provides more information on the consumption pattern of each household. In Figure 3.2b, we show for each household, the average total daily consumption for all days and for weekdays, Saturdays, and Sundays. We notice that all households show high average daily water consumptions ranging from 229 liters/day (household F) to 875 liters/day (household T). It should be noted that the low average of household F is a result of many days with zero consumption. 19 households were used for the application of the clustering algorithm, simulating the procedure that the water utility would follow for clustering existing customers; on the other hand, two households, namely households M and N, were set aside and were assigned to clusters later, in order to simulate how well new customers would fit in pre-existing clusters. The number of households that was set aside was kept to a minimum (9.5% of the total data), since a very limited number of households is available in our dataset. Other researchers that have conducted similar analysis with electricity data, e.g., Rasanen et al. (2010), used 5.6% of their data to simulate "new customers", so for our case, the small number of data reserved for validation is deemed acceptable.

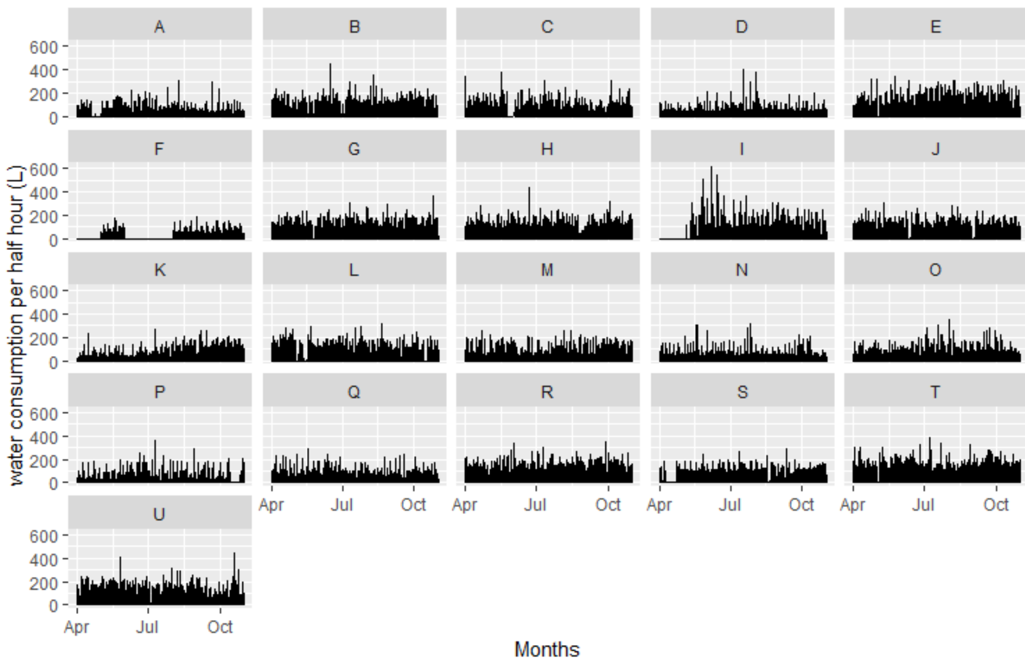


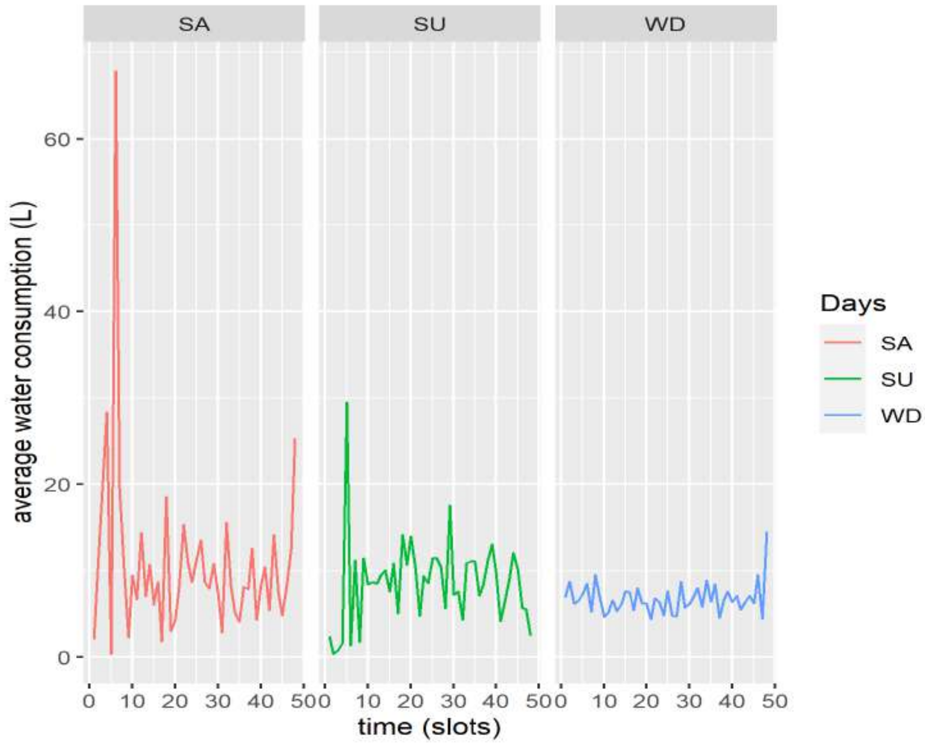
Figure 3.1. Water consumption (in liters) for all households in the case study at the step of half an hour. Households are symbolized by consecutive letters of the alphabet (A through U)—each subfigure shows the water consumption of a different household.

3.2.1. Clustering Methods

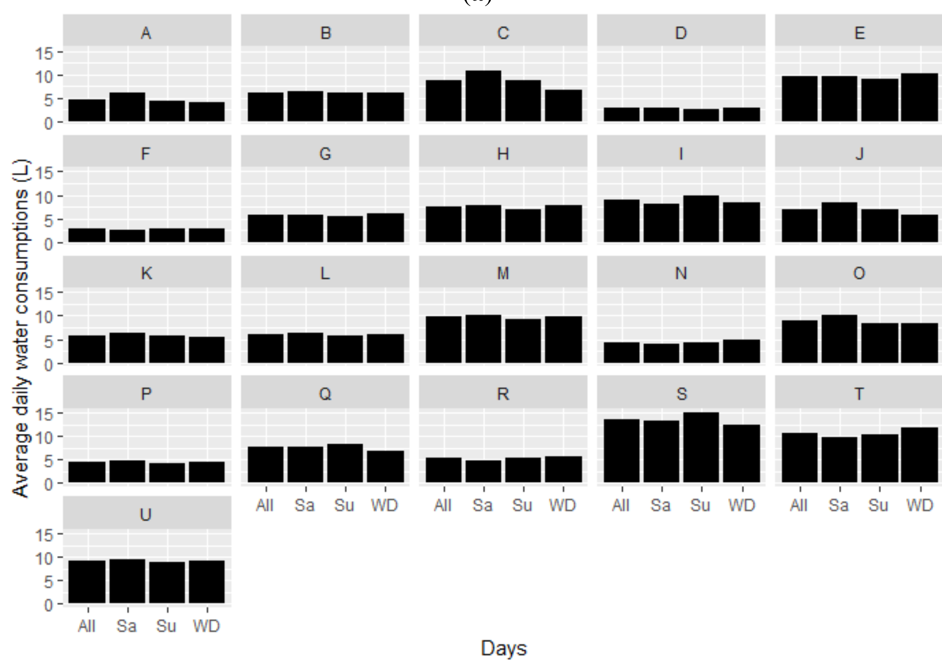
SOMs are well-known unsupervised neural learning algorithms (Kohonen, 1997) and an effective software tool for the modeling and visualization of high-dimensional data. They use unsupervised learning to group input data and produce a low-dimension discretized representation of the input space, i.e., a map. An SOM uses specific features of a population, such as household surface area, income level, age, number of bathrooms, etc. It calculates the Euclidean distance of each population unit, taking into account the features as dimensions or components of the input vectors. It then converts the multidimensional positions of the units into a 2-dimensional space and maps them. These maps (SOMs) depict all units as points in space in a sense that neighboring points have similar features; this way, clustering of similar units is made possible. In this work, an SOMs algorithm was applied as an intermediate step before the clustering process since it reduces the size of the data and makes the computational procedure more efficient. A feature-extraction approach was used to explore the data set and to identify which consumer properties are relevant to be included by the water utility in an automatic classification system (Beckel et al., 2012). In Table 2.1, we list the features that were chosen: they include a statistical property of the dataset (standard deviation) and are based on consumption values of individual days, as well as aggregated over the entire week, over workdays and weekends separately and over seasons. Since our benchmark dataset runs from April to October, we considered separately water use during the summer (June, July, and August) and autumn months (September and October). We used SOMs to calculate the Euclidean distance of the data and to find which households are in the same "neighborhood" or belong to the same cluster. This way, a map emerged consisting of nodes or neurons–in our case, various map sizes were tried, and the 3 × 3 size map was chosen with 9 nodes, since this number of nodes achieved the highest SOM's clustering efficiency (95%). The lattice of the SOM can be either hexagonal or rectangular but hexagonal is preferred for this methodology due to more effective visualization (Kohonen, 2001; Vesanto, 1993). All data were automatically normalized by the SOMs algorithm on a scale 0 to 1. All calculations were performed with RStudio, using the "Kohonen" package.

Table 3.1. Features used to build the input vectors of the Self-Organizing Maps (SOMs).

Features	**Units**
Standard deviation of water consumption	-
Mean daily consumption	L
Mean daily consumption of weekdays	L
Mean daily consumption of weekends	L
Mean morning consumption (6 a.m.–10 a.m.)	L
Mean noon consumption (10 a.m.–2 p.m.)	L
Ratio of mean summer over autumn consumption	-



(a)



(b)

Figure 3 2. (a) Average consumptions (L) for all weekday, Saturday, and Sunday half-hour time slots throughout the day, for a total of 48 time slots/day for household C; (b) Average daily water consumption (in liters) for all households: averages are calculated using all days, only weekdays, only Saturdays and only Sundays to capture variability throughout the week. Households are symbolized by consecutive letters of the alphabet (A through U)—each subfigure shows the water consumption of a different household.

An overview of the methodology in a step-by-step fashion is shown in Figure 3.3.

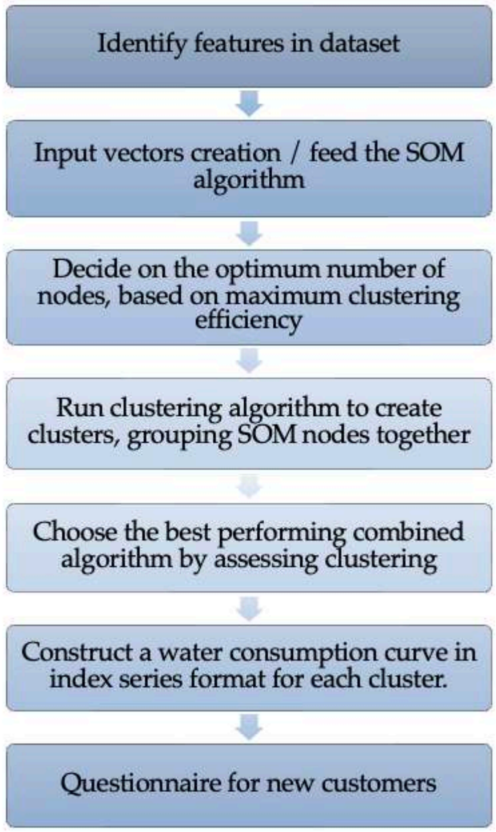


Figure 3.3 An overview of the step-by-step methodology

Once the SOMs algorithm is run and the map is obtained, it can be followed by a second step in which it is combined with other clustering algorithms. The main advantage of using this two-step approach is improved clustering. More specifically, while the SOMs algorithm provides a map of 9 nodes, its combination with other procedures results in fewer clusters (collecting various nodes in larger clusters) with higher accuracy. For this purpose, SOMs were combined with two other clustering algorithms: (1) K-Means clustering (KM) and (2) Hierarchical Agglomerative Clustering (HAC). KM (MacQueen and Some, 1967) is a well-known non-hierarchical clustering algorithm with many applications in different domains. The exact number of clusters was decided by calculating the Within-Clusters-Sum-of-Squares (WCSS) measurement that denotes the total distance of data points from their respective cluster centroids (Makles, 2012). Considering that we have nine SOM nodes, the ideal number of clusters proposed by KM is three, since this number is the closest match to the corresponding number of SOM nodes, when WCSS is calculated, as shown in Figure 3.4.

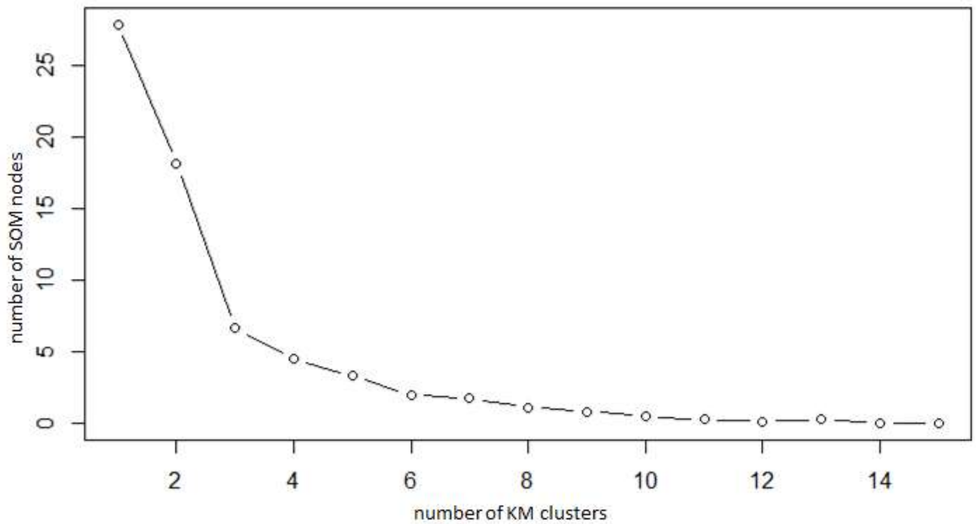


Figure 3.4. Within-Clusters-Sum-of-Squares (WCSS) for number of SOM nodes in our model, used as a basis to decide the number of K-Means (KM) clusters.

HAC is another popular clustering algorithm (Jain et al., 1999). It creates a cluster dendrogram (tree) by grouping several data together over a variety of scales and based on this classification, a clustering scheme emerges. Three clusters were formed from the HAC tree map with this analysis, as shown in Figure 3.5 in grey boxes, which group different SOM nodes, or codebook vectors (shown as V1 to V9). Even though the number of clusters is the same with the two algorithms, the specific SOM nodes grouped under each clustering methodology are different, essentially each one providing a different clustering solution that is separately evaluated for its accuracy.

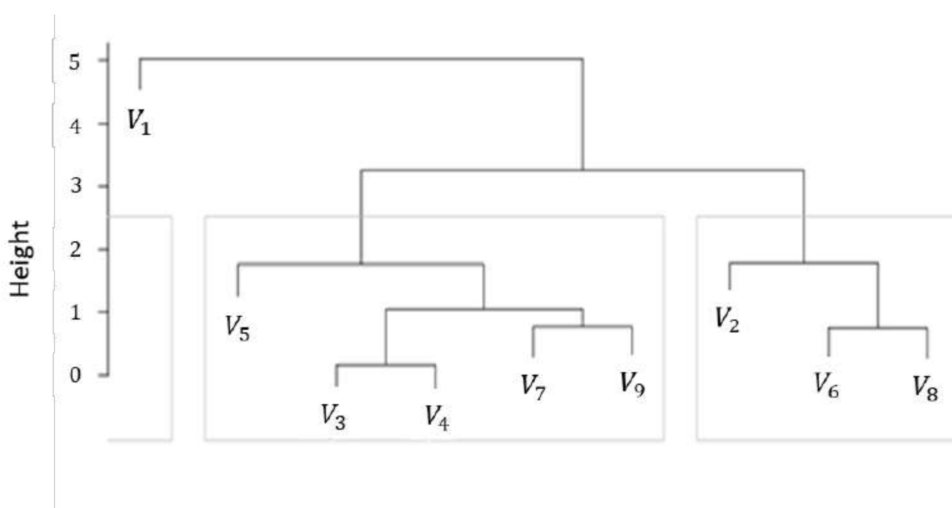


Figure 3.5. Number of clusters decided through cluster dendrogram.

In order to assess the clustering accuracy, we want to know if the features we extracted on water consumption (Table 3.1), actually force households to group together under the same cluster. Ideally, we would use a series of known properties about our households to identify the ones that are particularly relevant, as far as the domestic water consumption pattern is concerned. Examples include size of house and year built, garden and/or swimming pool, number and age of residents, number of appliances/washers, etc. We would then see which of these properties vary significantly among clusters or can likely be discovered from the data. If a property seems to vary across clusters, it will mean that it is a good property to group households by, and that using the set of features we defined in Table 3.1, it is possible to differentiate households by that specific property. In our case, the only household property available for the 21 customers is the number of people per residence; this information is shown in Table 3.2. Naturally, this is a serious limitation in our data set; however, all households came from the same neighborhood in suburban Ohio, so we expect that the houses have some similarities in terms of year built, surface area, amenities, etc. Nevertheless, our only choice is to use number of residents per household to check whether it is appropriate to group households according to it and to calculate clustering accuracy based on this property. We do this only after we confirm that indeed this property varies across clusters, as explained above. Based on the calculation of this accuracy, we decide on the best combined clustering algorithm (SOM+KM or SOM+HAC) and on the final clustering of the households.

Table 3.2. Number of residents per household in the case study.

Households	Number of Residents
A, B, D, F, I, K, L, N, O, P, Q, S	2
C, E, H, J, M	3
G, R, T, U	4

3.2.2. Validation: Estimated Water Consumption Curves and Associated Accuracy

After clustering, the new estimated water consumption curves are calculated for each cluster. These are the curves that would be used by the water utility for all customers belonging in the same cluster, in order to successfully estimate the next customer bill, or plan for the estimated water demand in the network. For comparison purposes, we calculate two types of estimated curves: one for each cluster and one for all households if no prior clustering is performed. The goal is to show that clustering improves estimated water consumption, namely that the index of agreement of customer consumption with the estimated water consumption curves increases when the clustering curve is used. This is done for the two households (M and N) that were set aside for validation, simulating “new customers” not included in the initial clustering; therefore, clustering was done using 19 households and clustering performance is assessed for the two new households.

For the construction of these curves, consumptions are transformed into an index series format, by grouping data in two-week intervals, and transforming the whole time-series into 15 two-week profiles summarizing half hourly data separately for weekdays, Saturdays, and Sundays. Index series format is what the water utility would use to model water consumption for customers, i.e., changing the assumed consumption profile every two weeks, following similar practices already employed for electricity consumption (Rasanen, 2010). In our case, the two-week index series is scaled by taking into account not only the consumption of the two-week period, but also the cluster customers 7-month water use, to calculate the estimated water time-series (Equation (1)) (Mutanen et al., 2011):

$$P_i = \left(\frac{W}{10{,}080}\right) Q_i\, q_i \tag{1}$$

where P_i is the estimated half-hourly water consumption, W is the total 7-month period water consumption for all households in the cluster, Q_i is the average 2-week water consumption of the cluster, expressed in percent of the average 7-month period consumption, and q_i is the half-hourly water consumption expressed in percent of the average 2-week consumption.

The correspondence between customer-specific water demand and the estimated water consumption curves is assessed by the modified Index of Agreement or Willmott Index (WI_{mod}):

$$WI_{mod} = \frac{\sum_{i=1}^{n} |P_i - O_i|}{\sum_{i=1}^{n} (|P_i - \bar{O}| + |O_i - \bar{O}|)} \tag{2}$$

where O_i are the observed values of each customer's water demand, P_i are the corresponding values of each estimated water consumption curve and $\bar{O}$ is the average of observed data. The WI_{mod} is a dimensionless measure, limited to the range [0,1], giving a relative size of the difference between an actual value (O_i) and its estimated/predicted value (P_i). A modified version of the WI was preferred over the original one due to the fact that the original version of the index may lead the user to erroneously select a predicting model that generates poor estimates (Pereira et al., 2018). Values of the WI_{mod} close to one indicate perfect fit, while values close to zero indicate complete disagreement between the observed and estimated values.

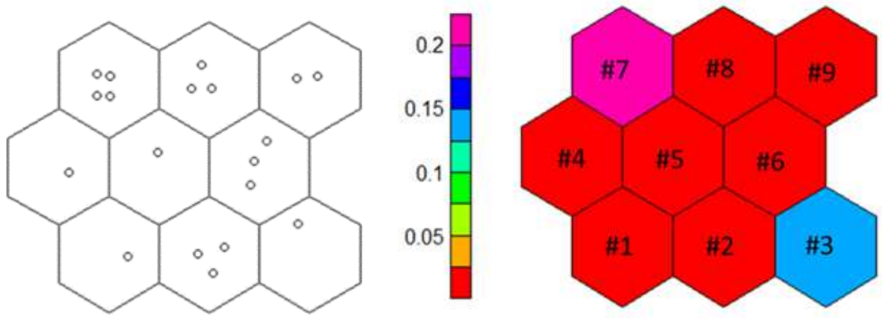
To summarize the methodology that the water utility will need to follow in order to implement this algorithm and benefit from clustering, we are presenting a compact list with all the steps:

1. Identify features in dataset that could potentially identify patterns in the population, in order to lead to data clustering;
2. Create input vectors and feed the SOM algorithm;
3. Decide on the optimum number of nodes, based on maximum clustering efficiency;

4. Run clustering algorithm (KM and/or HAC) to create clusters, grouping SOM nodes together (use WCSS and dendrogram to identify numbers of clusters for SOM-KM and SOM-HAC, respectively);
5. Choose the best performing combined algorithm by assessing clustering accuracy (as described in Section 3); (use WCSS for assessing SOM-KM or dendrogram for assessing SOM-HAC);
6. Construct a water consumption curve in index series format for each cluster. This is the curve that will be used to estimate the consumption of all customers in the same cluster;
7. For new customers, a questionnaire will be filled out by the customer, providing information on the features used initially to classify customers (step 1). Based on the responses, the new customer is assigned to a cluster and the water consumption curve (step 6) is now updated to include this customer's consumption, as soon as it becomes available.

3.3. Results

With the aim of creating more accurate up-to-date customer-specific water consumption curves, refined measurement data per incident, i.e. every time a faucet was used in the household, were used from 21 households in Milford, Ohio, USA. In this context, the SOMs algorithm was applied as the main clustering algorithm and in combination with KM and HAC, optimal clustering was achieved. Specifically, for SOMs clustering, an initial mapping plot was produced, as shown in Figure 3.6a, which includes a number of observations (households) in each node. The observations are spatially distributed and their distance from the node codebook vector—the vector formed with values from the features extracted by the dataset for each node—signifies its relevance. We see that there are no empty nodes, which indicates that the map structure is appropriate for the data. The mapping quality is assessed by the quality plot in Figure 3.6b which shows the mean distance of objects mapped in a node to the codebook vector of that node; thus, values close to 0 indicate good quality of the SOM. Even for the two nodes shown in blue and magenta colors, the mapping quality is still good (0.2 or less), even though not ideal.



(**a**) (**b**)

Figure 3.6. (a) SOMs algorithm map plot showing households per node; (b) mapping quality based on distance of observations from codebook vector for each node. In (b), node number is shown in each node. The color legend corresponds to mapping quality, with values close to 0 indicating good quality of the SOM.

In order to link clustering household characteristics in the dataset and assess clustering accuracy, we test whether the number of people per household varies across SOM nodes. In Figure 3.7, we show the variation of number of people per SOM node, and we see that indeed it varies across nodes. We also see that clustering could be improved, by combining various nodes in a single cluster, which is already an indication that the KM and HAC algorithms can be used to further cluster data to produce fewer and better clusters.

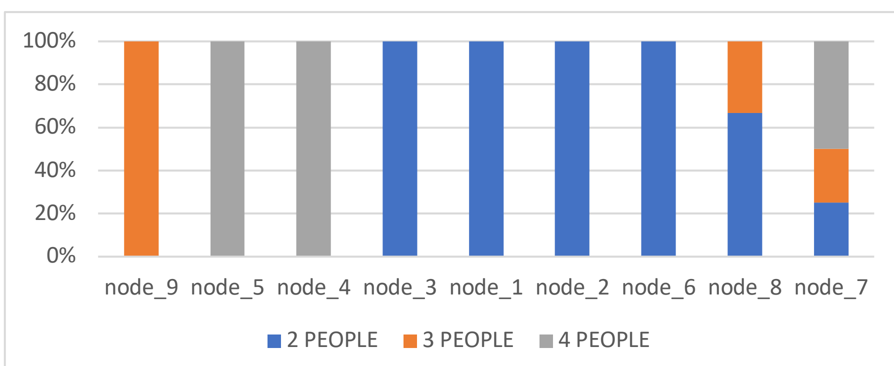
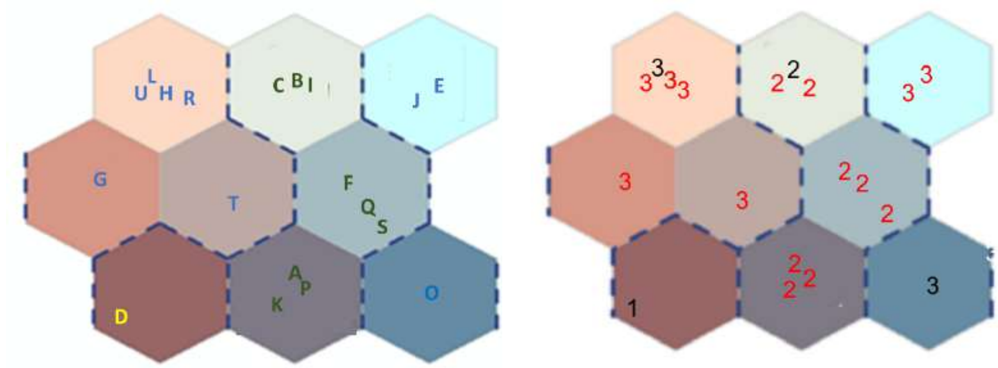


Figure 3.7. Variation of number of people per household across the 9 nodes produced by SOM. The y-axis shows the fraction of households that have the indicated number of people.

To assess the clustering accuracy of the combined algorithms (SOM-KM, SOM-HAC), we provided the number of people per household and examined whether the algorithm would be able to cluster differently the data according to the number of residents per household. Nineteen households were grouped in 3 clusters—different for each combined algorithm. The accuracy results are 73% and 79% for SOM-KM and SOM-HAC respectively, indicating the SOM-HAC as a slightly better and the preferred clustering solution; calculation of the clustering accuracy is explained below. This does not mean that we reject the SOM-KM clustering technique; we simply choose to present one of the two, in the interest of saving space, namely the SOM-HAC technique. The outcome of the SOM-HAC clustering is presented in Figure 3.8a, in which dashed lines group SOM nodes together in larger clusters. This clustering results in the grouping of the codebook vectors or SOM nodes, as shown in the dendrogram in Figure 3.5. Cluster 1 contains a single node (#1 per Figure 3.6b) and a single household (D)—marked in yellow font. Cluster 2 contains 3 SOM nodes (#2, #6, and #8 per Figure 3.6b) and 9 households—marked in green font. Finally, cluster 3 groups 5 nodes (#3, #4, #5, #7, and #9 per Figure 3.6b) and 9 households—marked in blue font. This information is also summarized in Table 3.3. In Figure 3.8b, the algorithm maps the households again, but each entry is represented by its cluster number: therefore, in node #6 for example, instead of showing households F, Q and S (as is done in Figure 3.8a), we show the cluster number that these houses belong to. In other words, we show a series of 2s, since all these households belong to cluster #2. All entries in black font signify the households that should not be classified in that cluster, while red entries are the households that are correctly placed in the specific cluster. Clustering accuracy is the fraction of matches (reds) in each cluster for the combined algorithms. Cluster 2 contains mostly 2 residents per household, while cluster 3 contains mostly 3- or 4-people households. When a household with 3 or 4 people is classified in cluster 2, then it is marked black by the algorithm; the same is true for 2-people households classified in cluster 3. So, household L is classified in Cluster 3, even though it should be classified in Cluster 2 (2 residents in household L, as shown in Table 3.2); thus, the number 3 that corresponds to household L is shown in black in node #7. Cluster 1 contains only 1 household (D), even after employing the HAC algorithm that improves clustering; since clustering analysis has no meaning for a cluster with a single entry, we decide to not consider this cluster further, dropping household D from further analysis, as an outlier.

Table 3.3. Household partitioning in 3 clusters with the combined algorithm SOM-HAC.

Cluster number	Households
Cluster 1	D
Cluster 2	A, B, C, F, I, K, P, Q, S
Cluster 3	E, G, H, J, L, O, R, T, U



(a) **(b)**

Figure 3.8. The SOM-HAC clustering plots—dashed lines signify the clusters. (a) Households are symbolized by consecutive letters of the alphabet (A through U)—households in yellow font belong to Cluster 1, households in green font belong to Cluster 2 and households in blue font belong to Cluster 3. (b) Households appear again, but now instead of letters, cluster numbers are used. Entries in black font: households that should not be classified in that cluster; entries in red font: households correctly classified in the cluster.

3.4. Discussion

The WI_{mod} is used to assess improvement in estimated customer water consumption achieved through clustering. For each of the 18 households, two WI_{mod} values are obtained: one that examines how the actual water consumption time series matches the cluster-estimated curve and one for the no-cluster-estimated curves. The former curve is calculated by including only households in the cluster, while the latter includes all households (no clustering). In Figure 3.9, we see a plot of WI_{mod} for the two cases and we can see that there is an improvement with clustering, which is significant for some households, proving that clustering can lead in obtaining estimated customer water consumption curves that are a closer match to the observed consumptions. Improvement is not observed across the board for all households, and this is something that is expected, due to the very limited number of households and the limited duration of the data set (less than a year). The fact that a significant improvement is observed for some households is important and indicates that the methodology presented in this article is promising.

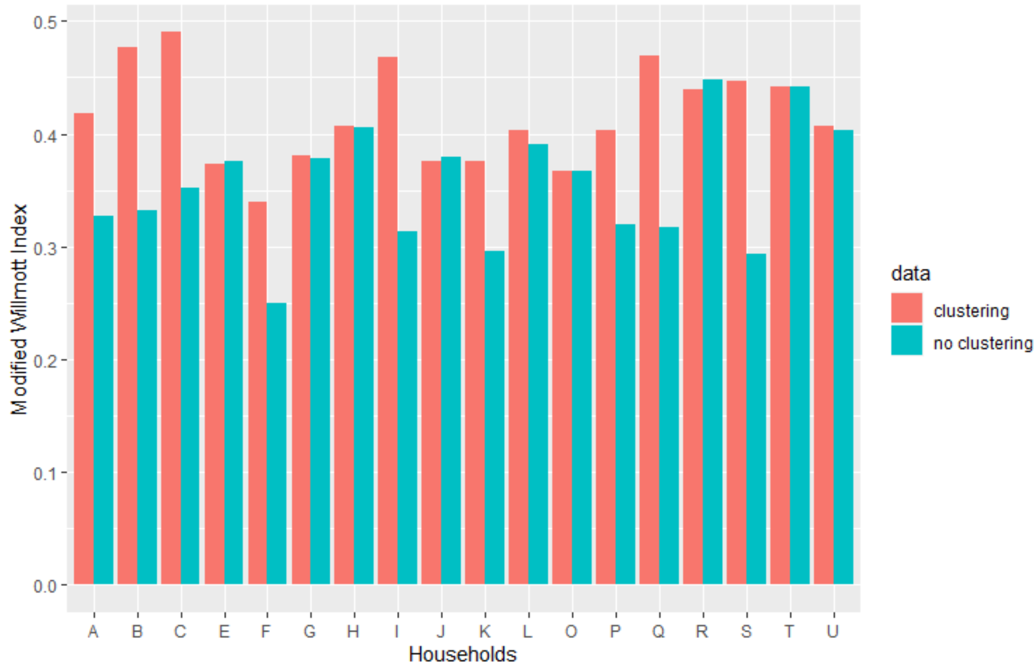
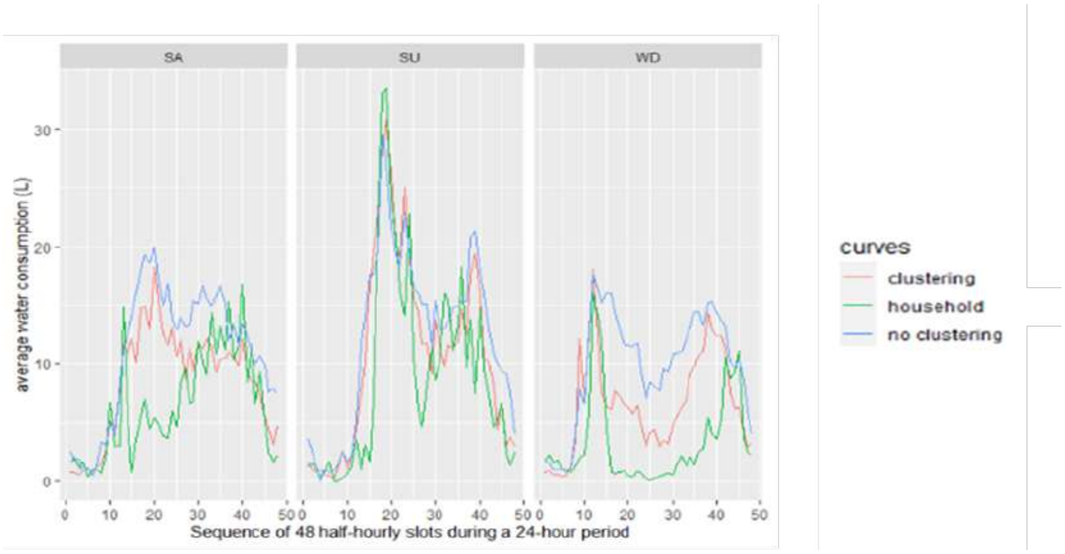
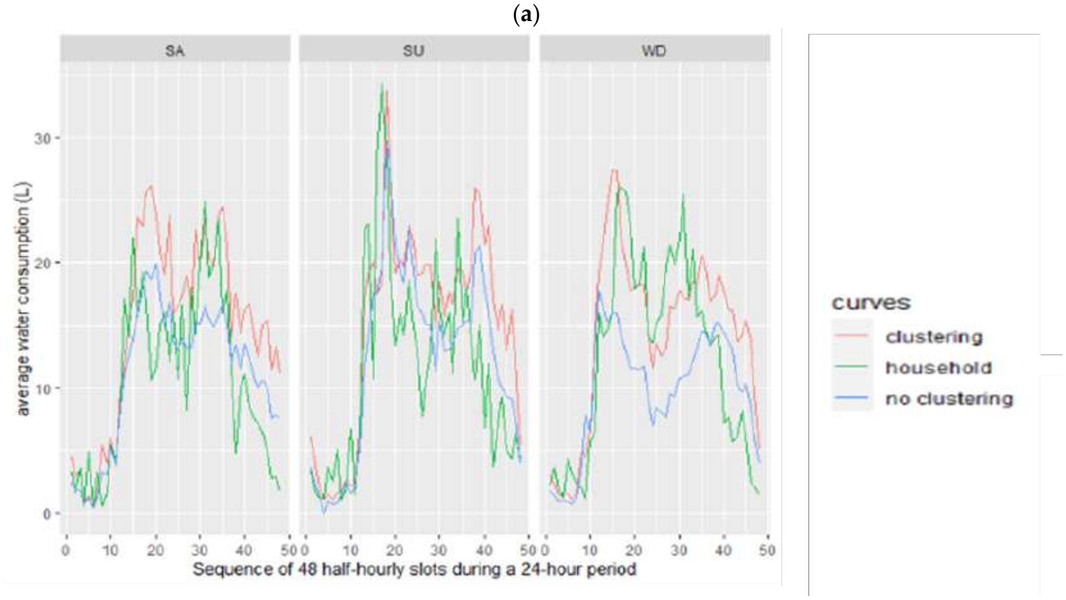


Figure 3.9. The WI_{mod} plot for the two cases; the cluster-estimated curve and the no-cluster-estimated curves.

This analysis would be valid for the water utility on existing customers that are grouped based on their historical consumption data. But what about new customers that come without historical time series? In this case, the utility would classify new customers based on the number of people in the household. We do this for the two households that were set aside for validation, namely households M and N. Since household M has 2 people and N has 3, the former would be classified in cluster 2 and the latter in cluster 3. When we perform the same analysis with the curves, we see that household N has an improvement of almost 40% in the WI_{mod} and household M has about 4% improvement in the same index. In Figures 3.10(a) and (b), we see how the curves of households M and N are comparatively closer to the curves of clusters 2 and 3, respectively, than the curve obtained for all households, thus validating the clustering methodology. Observing the plots in Figures 3.10(a) and (b), one can see that better agreement is obtained on weekday data than on Saturdays or Sundays; this might be a result of more structured activities during weekdays, compared to weekends, when behavior is more stochastic and not characterized by a "typical" schedule that is expected to be followed during work- and schooldays for families. In addition, there are more weekdays than weekends in the dataset, so more data leads to better fitting.



(**a**)



(**b**)

Figure 3.10 Observed and estimated water consumption curves for two scenarios: clustering and no clustering for (a) household N and (b) household M in half hour slots.

Chapter 3 includes parts of the following published work:

Ioannou, A. E., Creaco, E. F., & Laspidou, C. S. (2021). Exploring the effectiveness of clustering algorithms for capturing water consumption behavior at household level. Sustainability, 13(5), 2603.

- The contribution of **Alexandra Ioannou** involves the conceptualization, the methodology, the software, the formal analysis, the investigation, the validation, the writing—original draft, and the visualization.
- The contribution of **Professor. Enrico Creaco** involves the data handling and the review and editing.
- The contribution of **Professor Chrysi Laspidou** involves the conceptualization, the methodology, the validation, the scientific supervision, the review and editing, the project administration, and the funding acquisition.

This research has been conducted within the project Water4Cities. This project has received funding from the European Union's Horizon 2020 Research and Innovation Staff Exchange programme under grant agreement number 734409. This study and the content included in it do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

4

The Water-Energy Nexus at City Level: The Case Study of Skiathos

4.1. Introduction

Water is mankind's most precious resource since there are no substitutes serving the essential functions of life. Human beings consume water directly and also use it in the production of food, for washing, sanitation, and for various industrial and domestic uses. Water supply and demand is affected by many factors such as population growth, increasing urbanization, intergovernmental relations, political and policy choices, social factors, technological growth, and uncertainties of climate. In addition to these issues, water consumption directly affects energy consumption (Plappally, 2012).

Water is an essential element for the extraction, refining, processing and conveying energy and for the operation of hydroelectric and thermal power plants and on the other hand, provision of water for any kind of human activities requires huge quantities of energy (Ziogou and Zachariadis, 2017). Energy is essential to people to run their homes or industries. Population growth, urbanization and climate change exert pressure on water and energy resources worldwide, as global demand increases rapidly. Water and energy are key for satisfying the basic human needs; billions of people however are still lacking access to these resources. The direct interconnection of these two critical resources is easily established, since clean water needs energy to be produced and power plants need cooling water to operate (Wa'el et al., 2017).

On a global basis, water and energy should be affordable for all people. The need to find more efficient ways to use water and energy wisely, in households, in agriculture, and in industry is emerging. Decision makers, researchers and engineers have to recognize the water-energy nexus as a vital one. Using water wisely includes producing potable water and cleaning wastewater with less energy. Pumping water, pressurizing water distribution systems, and pumping wastewater are major energy consumers (Olsson, 2011).

The need for a water-energy analysis is becoming increasingly important as the need for resource efficiency becomes progressively urgent. In a water-constrained world, it is critical to deeply understand the use of water throughout the entire life cycle of electricity production (Schnoor, 2011; Meldrum et al., 2013; Murrant et al., 2015). In all countries the use of water and energy is interconnected. Specifically, in the United States, more than 400 billion gallons of water are withdrawn daily from surface and ground water sources in order to supply various kinds of uses such as domestic, agricultural, industrial etc. Information about the energy that is needed to pump, transport, deliver, and process water is fragmentary and not well documented overall (Copeland, 2014). In a 2002 report, the Electric Power Research Institute (EPRI) estimated that nearly 4% of the nation's electricity use goes toward moving and treating water and wastewater by public and private entities (Goldstein and Smith, 2012).

The main contribution of this chapter is to demonstrate a water–energy nexus analysis, in order to achieve sustainable supply and effectively manage water and energy at city level by comparing the different electricity uses such as household, public, commercial, agricultural, etc., and by showing how they correlate with total water use. The time series that have been analyzed are water and electricity consumption of the island of Skiathos and specific distance metrics are used to check their similarity.

4.2. Materials and Methods

Water and energy consumption time series are analyzed, intending to identify what the correlation of the two resources is. The energy consumption is divided in individual uses such as domestic, commercial, agricultural, industrial and public as well. We used three distance metrics in order to achieve our results. Specifically, we used Minkowski distance which includes Euclidean and Manhattan distance (Miśkiewicz, 2012), and also the Pearson's Correlation Coefficient (PCC).

Our data are time series of water and electricity monthly consumption of the island of Skiathos from 2010 to 2015. For the analysis, we used the total water consumption of the island on one hand, and on the other hand, we used cumulatively agricultural energy consumption, commercial, industrial, and public. Additionally, we investigated how total consumption of water correlate with domestic use of energy consumption. Both water and energy data have been normalized in order to sum to 1. The normalization of the data is essential due to the fact that all data should be of the same measurement unit and so the results can be trustworthy.

The distance measures are very useful techniques that have been used in a wide range of applications such as fuzzy set theory, multicriteria decision making, research, etc. Among the great variety of distances, we can find in literature the Minkowski distance, which can be considered as a generalization of both the Euclidean distance and the Manhattan distance and the PCC as well (Merigó and Gil-Lafuente, 2008; Vadivel et al., 2003).

4.2.1. Minkowski Distance

The Minkowski distance (Euclidean and Manhattan) can be calculated by the equation (1) given
below:

$$D_{MINK} = (\sum_{i=1}^{n} |x_i - y_i|^r)^{\frac{1}{r}} \tag{1}$$

The generic r parameter in Equation (1) can be replaced by the value 2 to yield the Euclidean distance, the value 1 would yield the Manhattan distance, and all the intermediate values in the (1 < r < 2) interval yield an array of Minkowski distances. In this research we will use the values 1 and 2 for the parameter r (Shahid et al., 2009). The values someone can find when calculating the Minkowski distance varies from 0 to 2. To be more specific, the closer to 0 the D_{MINK} is, the more related the two-time series are. On the contrary, the closer to 2 the D_{MINK} is, the more unrelated the two-time series are.

4.2.2. Pearson's Correlation Coefficient

The similarity measure is clearly application-dependent, so here we used also PCC, chosen through the several similarity measures have been proposed, since our data is linear. PCC measures the strength and direction of a linear relationship between two variables X and Y and can be defined as (Liao, 2005; Rodgers and Nicewander, 1998):

$$\left.\begin{array}{r} R = \dfrac{cov(X,Y)}{\sigma_x\,\sigma_y} \\ R = \dfrac{E[(X-\mu_x)(Y-\mu_y)]}{\sigma_x\,\sigma_y} \\ R = \dfrac{E[XY]-E[X]E[Y]}{\sqrt{E[X^2]-E[X]^2}\,\sqrt{E[Y]-E[Y]^2}} \end{array}\right\} \qquad (2)$$

The Statistical Package for the Social Sciences (SPSS) is used for the calculation of the PCC, which are presented in the following section. Below in Table 4.1, the values of PCC and how the two-time series are correlated according to their values, are displayed:

Table 4.1. PCC values and explanations.

Value of R	*Correlation*
$R = \pm 1$	*perfect linear correlation*
$-0.3 \leq R < 0.3$	*no linear correlation*
$-0.5 < R \leq -0.3$ or $0.3 \leq R < 0.5$	*weak linear correlation*
$-0.7 < R \leq -0.5$ or $0.5 \leq R < 0.7$	*average linear correlation*
$-0.8 < R \leq -0.7$ or $0.7 \leq R < 0.8$	*strong linear correlation*
$-1.0 < R \leq -0.8$ or $0.8 \leq R < 1.0$	*very strong linear correlation*

4.3. Results and Discussion

Initially, we had all our data normalized, as aforementioned, in order to have a clear depiction of their actual consumption behavior. Observing the diagrams below, (Figure 4.1) one can see that the total consumption of water approaches the energy consumption—agricultural, commercial, industrial and public use—in a very satisfying way. The reason we summed the 4 uses of energy is due to the fact that they appeared to have a similar consumption behavior.

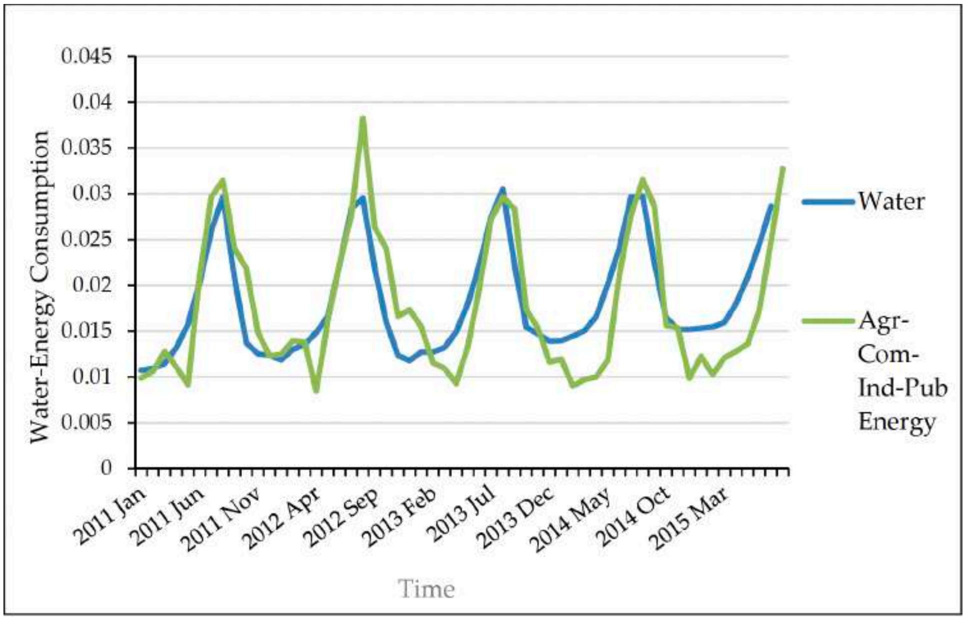


Figure 4.1 The consumption behavior of total consumption of water in relation to agricultural, commercial, industrial and public use of energy consumption.

On the other hand, we notice that total consumption of water and domestic use of energy consumption seem not to have the same consumption behavior (Figure 4.2). We will investigate those two consumptions and try to prove that they are unrelated.

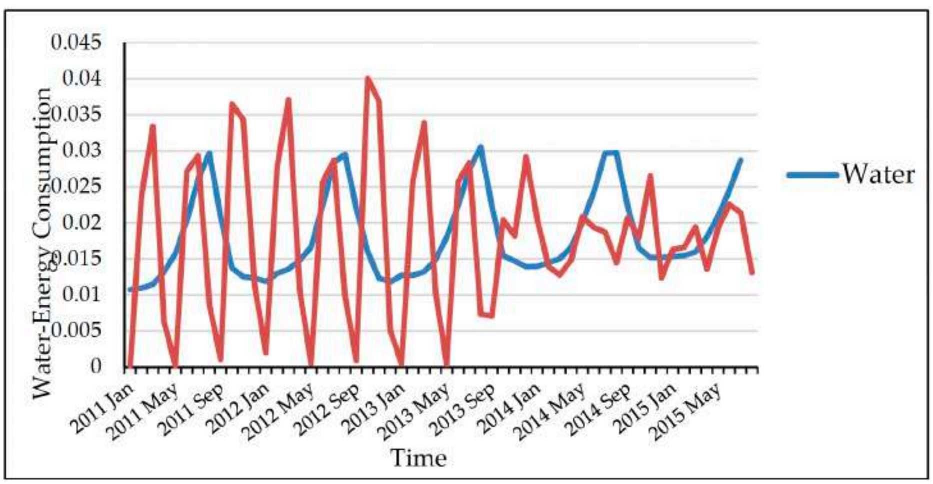
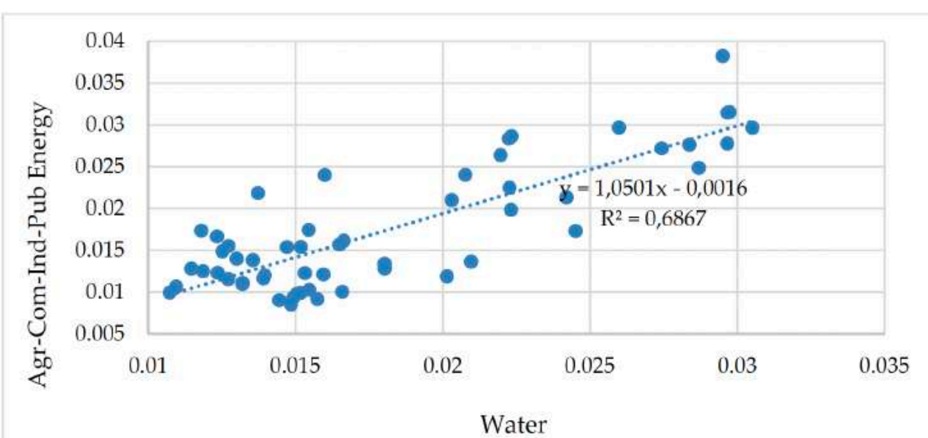


Figure 4.2 The consumption behavior of water in relation to domestic energy consumption.

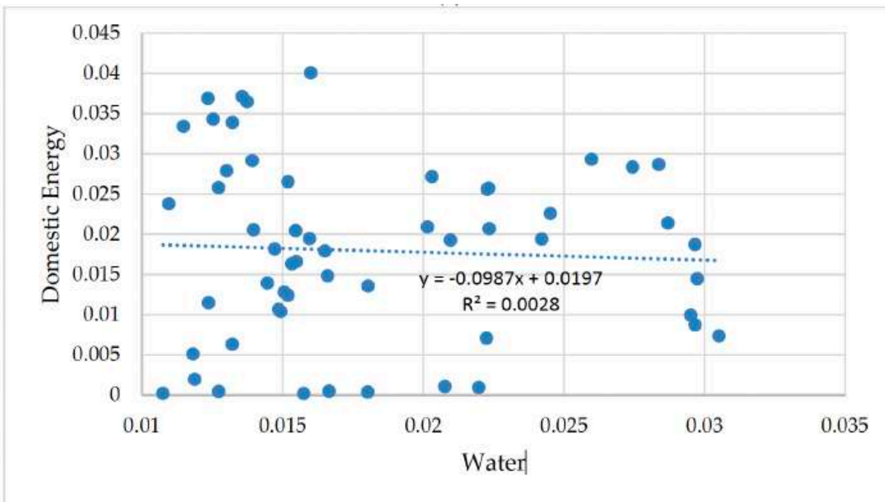
The next step was to calculate the 3-distance metrics and confirm or not the above assumptions. The values of the distance measurements are presented in Table 4.2. The first PCC value (0.829) confirms a very strong linear correlation between the two consumptions (Total Water/ Commercial-Agricultural-Public-Industrial use of Energy), according to Table 4.1, and the variable a, in the third column, indicates that the specific test is significant. In graph (a) in Figure 4.3, this outcome and also their linear function showing the very strong linear correlation they have, is depicted. To the best of our knowledge, this can be explained by the reason that in Skiathos there is agricultural, commercial and industrial activity. The main agricultural products are oil and olives, since 28% of the island is covered by olive trees. In addition, since antiquity, there has been cultivation of a local vineyard from which there is a small production for own consumption. Industrial production includes local food processing industries.

The second PCC value (−0.053) in Table 4.2, reveals that there is no linear correlation between total water consumption and the domestic energy use, even though a small PCC value does not necessarily mean that there is no linear relationship. Furthermore, the variable a, indicates that this test is not significant. The question here arises is why this is happening. Our research concerns the Greek island of Skiathos and according to the Water Utility of the island, the water is not potable due to its high mercury content. This means, that many domestic uses of water, such as cooking, personal hygiene (especially infant hygiene) and drinking water have been replaced by bottled water. That fact might have caused the reduction of water consumption through faucets in households and also created this difference between the two consumptions. Graph (b) in Figure 4.3, visualizes the aforementioned.

Minkowski Distance (Euclidean and Manhattan) is also calculated, and the results are also in Table 4.2. As we can see all four values, for the two groups of consumptions, for both Euclidean and Manhattan distance are closer to 0 rather than to 2. There are some differences in the outcomes of two groups, showing that the first one (water/commercial, agricultural, industrial and public use of energy consumption) contains more correlated consumptions but in general opposes to the result found calculated with the PCC. The error is bigger in values of the second group (water/domestic use of energy consumption), since they appear as correlated consumptions while as in PPC value they have no linear correlation. Considering the above, the Minkowski distance is not the best metric measurement for these data due to the inaccuracy of their outputs. Contrariwise, the PPC seems to be a very good distance metric because its results seem to give better results and can be trustworthy for future prediction of that kind of data set.



(a)



(b)

Figure 4.3 The PCC graphs between water and energy consumption (normalized values): (a) PCC graph for total water and for 4 uses of energy consumption (agricultural, commercial, industrial and public); (b) PCC graph for total water and domestic use of energy consumption.

Table 4.2 Values of PCC, Euclidean and Manhattan Distance

Consumption of Water/Energy	*PCC*	*Variable a*[1]	*Euclidean Distance*	*Manhattan Distance*
Total Water / Commercial – Agricultural – Public – Industrial (Energy)	*0.829*	*0*	*0.069*	*0.375*
Total Water / Domestic (Energy)	*-0.053*	*0.703*	*0.095*	*0.560*

4.4. Conclusions

In this paper, we presented a water-energy nexus analysis for the Greek island of Skiathos. We analyzed the consumptions of different uses of energy—agricultural, commercial, industrial and public—and we concluded that there is a very strong linear correlation with total water consumption. We also examined the correlation of domestic use of energy with total water consumption and the results showed no linear correlation between them. For the results we used PCC and Minkowski Distance (Euclidean and Manhattan) after having all our data normalized at first level. The PCC proved to be the best distance measurement and the Minkowski Distance not a suitable one for our case study.

Through this investigation people could be motivated not only to save energy but also save water as well in order to get financial benefits, because energy is much pricier than water. Residents should be informed at a very early stage,

[1] Variable a defines whether the test is significant or not If $a \leq 0.5$, the test is significant while if $a > 0.5$, the test is not significant.

such as in school for example, in order to save water and energy starting from their households and by achieving that, we could save the environment in general.

Chapter 4 includes parts of the following published work:

Ioannou, A. E., & Laspidou, C. S. (2018). The Water-Energy Nexus at City Level: The Case Study of Skiathos. Multidisciplinary Digital Publishing Institute Proceedings, 2(11), 694.

- The contribution of **Alexandra Ioannou** involves the conceptualization, the methodology, the software, the formal analysis, the investigation, the validation, the writing—original draft, and the visualization.
- The contribution of **Professor Chrysi Laspidou** involves the conceptualization, the methodology, the scientific supervision, the review and editing, the project administration, and the funding acquisition.

The work described in this chapter has been conducted within the project WATER4CITIES—Holistic Surface Water and Groundwater Management for Sustainable Cities—which is implemented in the framework of the EU Horizon2020 Program, Grant Agreement Number 734409. This study and the content included in it do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content. The work described in this paper has been conducted within the project WATER4CITIES—Holistic Surface Water and Groundwater Management for Sustainable Cities—which is implemented in the framework of the EU Horizon2020 Program, Grant Agreement Number 734409.

5

A Resilience Analysis framework for a Water-Energy-Food Nexus system under Climate Change

5.1. Introduction

Economic growth during the last century have positively affected many people, thus providing them with the main essentials resources for living—water, energy and food (WEF) (UNDP, 2016). These accomplishments have adverse effects on environmental assets. Worldwide, aquatic and terrestrial ecosystems have been irreparably affected, natural deposits have been exhausted, some species are facing high risk of extinction, and susceptibility to disturbances has increased (Turner et al., 2003; Vörösmarty et al., 2010; Puma, 2019). Considering the current global situation, GHG emissions projected to increase by 50%, primarily due to a 70% growth in energy-related CO2 emissions (Kitamori et al., 2012). To prevent that, many countries have adopted National Mitigation Actions (NAMAs) to set limits to this increase, aiming at stabilising global temperature increase at 2^{o}C in the future (UNFCCC, 2011). However, if no major interventions are done, the global temperature is expected to rise by 3.5^{o}C by 2035 (IEA, 2010), indicating the need for imperative and drastic implementation of solutions to address the problem in a timely manner. Water security will ensure both the reduction of energy needs for the agri-food sector and the generation of renewable energy supply aiming at stabilizing the GHG emissions.

Both environmental burden and lack of the combined WEF security are expected to deteriorate in the next decades, driven by overpopulation, increasingly resource-intensive lifestyles and susceptibility to disturbances under climate change (Hoekstra and Wiedmann; 2014; Steffen et al., 2018). A WEF Nexus approach seems to be able to set limits to this ongoing problem, since such an approach, can enhance WEF security leading to fewer CO2 emissions, by increasing resource efficiency and integrating management and governance across sectors and scales (Hoff 2011). Applying the nexus approach to policymaking is based on the idea that WEF systems should be addressed collectively and holistically in order to achieve WEF security (WEF, 2011; Bleischwitz et al., 2018). To achieve a sustainable development at national and ultimately at global level, other aspects, such as poverty, hunger, wellbeing, equality, and environment are of equal importance. To this extent, these aspects which constitute part of the 17 Sustainable Development Goals (SDGs) are fully interconnected with WEF nexus under climate change (SDG2-food, SDG6-water, SDG7-energy, and SDG13-climate) since the cross-sectoral management is vital to achieving the SDGs (Flammini et al., 2014). Integrating climate change adaptation strategies into WEF nexus, can obtain efficient resource cooperation, resulting in better environmental resilience (Mpandeli et al., 2018). As the nexus approach becomes more and more popular, a lot of research has been published on the WEF nexus concept (Laspidou et al., 2020; Albrecht, 2018; Finley et al.; 2014, et al. 2015; Stephan, 2018; Ioannou and Laspidou, 2018), or extended

Nexus approaches, such as the Water-Energy-Food-Ecosystem (Malagó et al., 2021), or including Land Use and Climate in the Nexus concept (Janssen et al., 2020; Laspidou et al., 2019), with some articles focusing on the combined WEF security and system resilience (Mguni and van Vliet, 2020; Sukhwani et al., 2019). One of the greatest challenges worldwide, is to provide essential human needs and resources to all, in an environmentally compatible, economically resilient and socially inclusive manner that is capable to contend with disturbances and catastrophes (Sachs et al., 2019).

At the same time, resilience analysis approach arose in scientific debates and evolved from the field of ecology, is firmly linked with sustainability science and global change research (Folke et al., 2010; Scheffer et al., 2012; Anderies, 2015). In a world characterised by uncertainty and complexity, unexpected disturbances and disasters may affect systems in unpredictable ways, reducing system performance (Nyström et al., 2019). Hence, resilience analysis approach accentuates the need to design, develop and manage systems for resilience with the aim to withstand and absorb unavoidable disturbances; either short-term disturbances, such as a pandemic, or long-term disturbances, such as climate change (World Bank, 2013; Hall et al., 2014; Grafton et al., 2019). Resilience literature at its early stage, often uses the metaphor of a stability landscape, where resilience measures the persistence of a system and of its ability to absorb change and disturbance (Holling, 1973). Resilience analysis approach is progressively urged to tackle some of the great disputes of the current century: providing WEF security to all while maintaining natural resource availability at sustainable levels; this is a great challenge, considering the extensive environmental stress caused by exploitation and climate change.

Both nexus and resilience approaches are applicable to science and to policy- and decision-making, but it is still indefinite to what degree they are expected to accomplish what they stand for to make a significant contribution to WEF security goals. In resilience modeling, there is a great deal of diversity in the literature on disturbance conceptualization, methodology, and tools for implementing different approaches. (Grafton et al., 2016; Allen et al., 2019). Similarly for the nexus, while aiming at identifying the WEF system interlinkages under climate change conditions, there are limited advanced analytical frameworks proposed in the literature for integrated WEF policy development (Laspidou et al., 2020; Papadopoulou et al., 2020; Scott et al., 2011; Leck et al., 2015; Albrecht et al.,2018). Therefore, the convergence of objectives and concepts in both contexts led researchers to consolidate the two approaches (Guillaume et al., 2015; De Grenade et al., 2016; Stringer et al.,2018).

System dynamics modeling (Forrester, 1961; Coyle, 1997; Ford, 1999; Kelly et al., 2013) is used with the intention of simulating and analyzing complex systems, thus offering policymakers a valuable tool to comprehend the potential impacts of policy implementation (Bakhshianlamouki et al.,2020). A system dynamics model (SDM) attempts to simulate the real-world system's behavior based on the principal concepts of flows, feedback loops, and time delays. Thus, when aiming at modeling any system, it is critical to develop the model based on the behavior of the system in real-world circumstances and apprehend the interaction of the parameters affecting the system's behavior in accordance with the real system (vanEmmerik et al., 2014; Chen et al., 2016). In this study, the system dynamics modeling approach is adopted to model the WEF nexus interlinkages under climate change due to its adjustability and its ability to focus on the long-term characteristics (Robinson, 1998), and thus propose policies to improve the overall behavior of the system with the aim to enhance its resilience.

In this chapter, we identify and quantify the WEF nexus interlinkages of a system under climate change and develop an SDM that is conceptualized to be used as a framework for nexus system resilience analysis. We focus on the nexus approach at the national level combined with system resilience analysis and parametric sensitivity analysis (SA). We present a study of the systemic reaction to disturbance and quantify different measures of resilience of socio-ecological systems (SESs) (Walker et al.,2006) to climate change for different scenarios/policies for the national case study of Greece. Our goal is to set up a comprehensive resilience analysis framework of the WEF nexus system under climate change through system dynamics modeling and causal loop analysis in order to assess and quantify causality and systemic resilience under environmental stress and shock, simulating extreme events under climate change. This methodology is novel and applicable on systems of various scales and is demonstrated here for the national case study of Greece, but is by no means limited to this application.

This analysis enhances the science-policy interface and translates the complexity of a WEF nexus system in terms that are easy to understand, thus communicating the effects of climate change and leading to informed policy-making. SA is also conducted on a system and sector level to identify variables that the system is most sensitive to. The energy and agricultural policies are modeled, and their effects on system resilience are investigated.

5.2. Materials and Methods

The SDM was implemented in STELLA Architect (www.iseesystems.com/). We used the SIM4NEXUS project dataset (Mellios and Laspidou, 2020) that was developed for 2010 and ran simulations for 100 years (2010–2110) with a yearly time step. We focused on water for the case study of Greece (modeled as available freshwater) since water has been identified as the most vulnerable nexus sector and the one most prominently affected by the other sectors for Greece (Laspidou et al., 2019). In relation to energy, the water–energy interlinkage is monitored through cooling water (CW) since electricity is produced in thermal power plants in the country, requiring large amounts of freshwater. Hydropower is not considered in this study. The water–food interlinkage is presented through the quantities of water for irrigation and available food produced locally, while GHG emissions are produced from fossil-fuel power plants, human activities (transportation, households, services, etc.), and agricultural activity (Figure 5.1). According to the Greek Statistical Authority (ELSTAT), Greece has a population of 10.4 million people (2020), which has been experiencing an ongoing decline since 2010 (Hellenic Statistical Authority, 2020). It is a popular touristic destination amassing over 30 million tourists per year, as was the case in 2019 (SETE, 2019). On the one hand, tourism is a significant factor for the Greek economy, and on the other hand, a demanding resource consumer, affecting resource availability and competing with antagonistic resource uses in the country. Furthermore, the agricultural sector in Greece has always been a reference point for economic and social life, thus contributing to 4% of the GDP, twice as much as in other European countries (Hellenic Statistical Authority, 2018), consuming close to 80% of all national freshwater resources and contributing to 7.84 million tons of GHG emissions (Our World in Data).

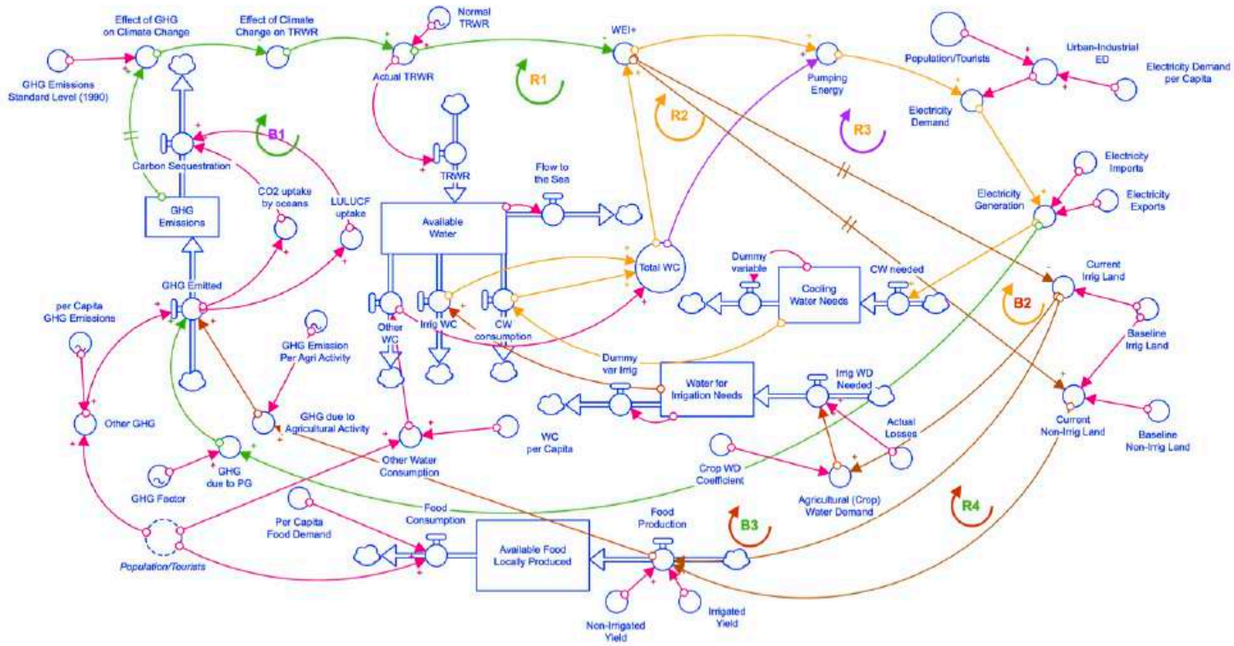


Figure 5. 1. Stock-flow diagram for the national case study of Greece.

5.2.1. System Dynamics Model

System dynamics modeling has broadly been used as a simulator of complex real systems, helping researchers and policymakers to frame and understand the complexities of and interlinkages within the system, while at the same time, it provides information on how the system might evolve over time (Bakhshianlamouki et al., 2020).To conceptualize a complex dynamic system prior to simulation analysis, causal loop diagrams (CLDs) are used to identify the key variables in a system and indicate the causal relationship between the musing links (Randers 1980). CLDs can perfectly describe the flow of the dynamic behavior of complex dynamic systems. A CLD consists of variables connected with links showing their interdependence and corresponding signs on each link that mark the nature of the paired connection—increase or decrease of the dependent variable; the number of increases or decreases defines the nature of the system behavior as a whole—making loops either reinforcing (multiplying the change in one direction) or balancing (breaking the chain, counterbalancing explosive system behavior, and resulting in reduced outcomes) (Lannon, 2012). Balancing or stabilizing feedback loops (Chapin et al., 2009) act by altering variables in the reverse direction to their existing one, neutralizing the effects of the condition on the system (Morecroft,2015). Balancing the feedback loop is crucial because it can contribute to system recovery after a perturbation disappears. Reinforcing or amplifying feedback loops intensify the effects of the perturbations that contribute to destabilizing the system. The policies aiming at enhancing resilience might be used in "vicious" amplifying feedback loops by counterbalancing them to diminish or delay their effects on the outcome function of the system and mitigate the impact of perturbations. Whether loops are reinforcing or balancing, it depends on the number of negative relationships in a feedback loop: an even number of negative relationships indicates that the loop is positive (reinforcing), while an odd number indicates a negative (balancing) loop. Ideally, in each SDM, the existence of both, reinforcing and balancing loops, ensures the overall balance of the system.

As the next step, to quantify the variables in the loop, the stock-and-flow diagram (SFD) is used since SFDs can perfectly capture the stock and flow behavior of a system. Stocks are variables that represent accumulations (Richardson, 2011), and the flow is changing by decisions based on the condition of the system and can be simulated to generate the dynamic behavior of the system. Crucial stocks can enhance system resilience due to the by-default delay created between the disturbance and its effect. Thus, the system outcome function is less affected by the disturbance and saves time for easier recovery. The SFD represents integral finite difference equations involving the variables of the feedback loop structure of the system and simulates the dynamic behavior of the system (Manetsch andPark 1982; Bala et al., 2017).

The SDM (Figure 5.1) starts by simulating the GHG emissions as a stock, so GHGs in the atmosphere are the sum of what is emitted (GHG emitted) minus what is sequestrated (carbon sequestration). The GHG emitted is the sum of GHGs produced due to power generation (PG), GHGs due to agricultural activity, and other GHGs (i.e., urban/household) coming mainly from the population and tourists using the per capita GHG emissions (industrial GHG emissions are excluded from this calculation as they are deemed minor—see Laspidou et al., 2020). Carbon sequestration, on the other hand, depends on land use, land-use change, and forestry (LULUCF) uptake and CO2 uptake by the oceans. As the GHG emissions change overtime, the effect of GHGs on climate change varies accordingly, while the effect of climate change on total renewable water resources (TRWRs) is affected inversely; thus, an increase in GHG emissions leads to a decrease in the TRWR, reflecting the fact that climate change will bring about water scarcity in the long run. The TRWR is the inflow that feeds the available freshwater stock, while its outflows are: flow to the sea, (CW) consumption, the irrigation water consumption (WC) and other WC (household/urban WC). The sum of all these out flows (except from flow to the sea) is the total WC. We use the Water Exploitation Index plus (WEI+) as a measurement of water stress in the country (Casadei et al.,2020). Values greater than 20% indicate water scarcity, while values greater than 40% indicate situations of severe water scarcity (i.e., the use of freshwater resources is clearly unsustainable) (EUROSTAT). WEI+ is affected by both actual TRWR and total WC. The former inversely affects the WEI+ (a delay signal has been used herein, indicating that changes in TRWR will become visible in the WEI+ in the long run), while the latter directly affects the WEI+. When the WEI + increases, It means that we have increasing deficits in freshwater availability, which leads to a drop in aquifer levels and an increase in pumping energy (PE) as we have to go deeper and deeper to find water. In turn, the electricity demand (ED) associated with pumping increases, followed by increased electricity generation to meet demands, which leads to both increased GHG emissions (when fossil fuels are used) and increased demands in CW, and thus in total WC, and a further increase in WEI+, creating a reinforcing loop (R3). An increased WEI+, which is a result of either increased water consumption, decreased TRWR, or both, will in the long run result in farmers switching to alternative crops that do not require irrigation. This is a natural adaptation to climate change practice that farmers will follow. As a result, irrigated land and associated irrigation water demand will decrease and non-irrigated land should increase; this is not expected to be an immediate response to water scarcity; thus, a delay is taken into account in the SDM. Naturally, both irrigated and non-irrigated land affect food production (FP) and GHG emissions due to agricultural activity. Finally, all human consumption is represented and regulated by the population/tourist parameter directly affecting the following quantities in the model: urban–industrial ED, food consumption, other (urban) water consumption, and other (urban) GHG emissions. The CLDs formed in this SDM are presented in the Results section.

An overview of the methodology in a step by step fashion is shown in Figure 5.2.

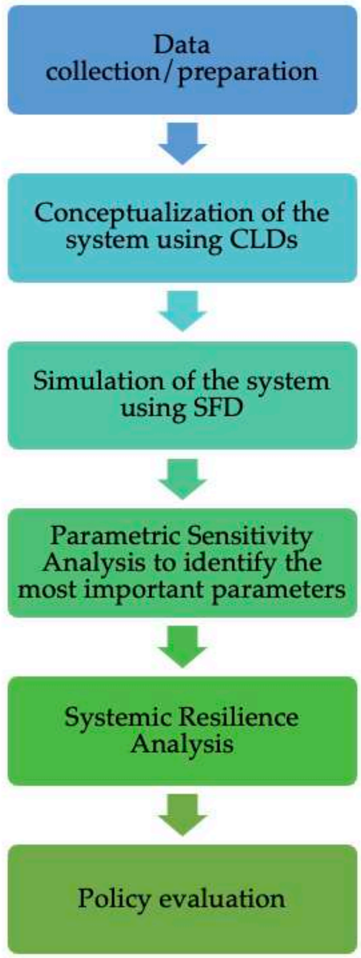


Figure 5.2 An overview of the methodology in a step-by-step fashion.

5.2.2. Sensitivity Analysis

With the purpose of developing confidence and validity in the model and its results, unit consistency and SA were implemented in the developed SDM; this analysis aims to prove that this model is sufficiently accurate for its intended use (Robinson, 2004). To check the unit consistency of our model, each model variable in the SDM was separately selected and either confirmed or amended to ensure that it is correct and in consistent units. In this combined nexus–resilience analysis, we used the SA to identify the most important parameters affecting the basic variables of the system by quantifying the importance of each parameter.

We start by performing sensitivity runs based on Monte Carlo simulations implemented in the SDM for all model parameters. The initial values of the parameters were altered by ±10% to observe the corresponding changes on the variables of the greatest interest in our model. We present the analysis for three important quantities, namely, available freshwater, ED, and GHG emissions. Our interest is to show how these quantities change when all parameters vary by ±10% with a Monte Carlo analysis. For some parameters, we observed almost no change, while for some others, we had significant variability. We show the results for a selected set of seven parameters that our quantities show variable sensitivity to. These are: TRWR (m^3 of water), population/tourists (number), GHG emission factor for PG (kg of CO_2/GWh produced), per capita GHG emissions (kg of CO_2/capita due to human activity—mainly transportation), ED per capita (GWh electricity consumed/capita), irrigated land (m^2 of land), and actual losses in the agricultural irrigation system (m^3 water). All data come from the SIM4NEXUS dataset (Mellios and Laspidou, 2020) and are expressed on a yearly basis.

To quantify sensitivity, we used **Eq. 1**, where $S(p)$ is the estimated sensitivity value of a parameter, x is the selected variable, p is the selected parameter, and Δx and Δp denote the change in the variable and parameter, respectively (Jørgensenand Bendoricchio, 2001). The larger the $S(p)$ value of a given parameter, the more important that parameter is.

$$S(p) = \frac{\frac{\Delta x}{x}}{\frac{\Delta p}{p}} \quad (1)$$

5.2.3. System Resilience Analysis

In the context of implementing SRA, we investigated how our system responds to a disturbance (σ). In our case study, we chose disturbance (σ) to be the reduction of the TRWR (i.e., a drought) as a consequence of climate change. Our outcome function F(x) (i.e., available freshwater) indicates how the system responds to that disturbance. The purpose of this analysis is to investigate whether a system—after being affected by a disturbance(σ)—can recover or not and under which circumstances. More specifically, two things can happen to a system that has undergone shock or a very strong disturbance: it can either absorb the shock and result in maintaining its original behavior (no change) or it can change to a new state. When a system shifts to a new state, it can then either bounce back to its original state (a mechanical equivalent would be that the system "bends") or be forced to a completely new permanent state and never bounce back to its original state (corresponding to the system "braking" according to our mechanical analogy) (Herrera de Leon and Kopainsky, 2019). When assessing system resilience, it is important to identify "when the disturbance forces the system to change its behavior", or in other words, "how big a disturbance needs to be", "under which circumstances and after how long the system bounces back or breaks", and/or "how fast the system can recover", if at all. To address the aforementioned questions, we follow the Herrera (2017) methodology and quantify system resilience by measuring five resilience metrics. To do this, we consider the available freshwater as the outcome function F(x) and quantify the system behavior after being affected by disturbance (σ), which is an extreme drought, expressed as a steep reduction in the TRWR.

Engineering resilience and ecological resilience are both considered here. Engineering resilience is defined as the rate (how fast) at which a system resumes to its original state after a perturbation (Pimm 1984), whereas ecological resilience is defined as the amount of disturbance a system can withstand and not change into a new condition (Carpenter and Gunderson, 2001). As also described by Herrera (2017), for this analysis, we assess engineering resilience by using hardness, recover rapidity, and robustness measures, whereas to assess ecological resilience, we use elasticity and index of resilience measures. To define the aforementioned measures, we consider the following characteristics: δ: magnitude of disturbance, t_c: time when the disturbance starts, t_d: time when the disturbance stops, and t_f: time when the system fully bounces back.

Table 5.1 Whole model's parameter importance in descending order.

Model parameter	**Sensitivity parameter value**
TRWR	0.440
Population/tourists	0.438
Baseline irrigated land	0.297
Electricity demand per capita	0.254
Per capita GHG emissions	0.200
GHG factor	0.184
Actual losses	0.047

Hardness (σ_H) is the system's ability to withstand a disturbance (σ)without presenting a change in the performance of the outcome function F(x). To measure hardness, we increase σ_H to find the smallest value of σ that produces a different outcome function F(x), while keeping t_d and t_c constant.

$$\sigma_H = \delta_H \times (t_d - t_c). \quad (2)$$

Recover rapidity ($\bar{R}$) is the average rate at which a system bounces back to its original situation after a disturbance (σ) (Pimm, 1984; Martin et al., 2011; Herrera 2017). To measure $\bar{R}$, we continue increasing δ ,keeping t_d and t_c steady, and estimate the $F(t_{d_1})$ for the current (original) situation and $F(t_{d_1})$ after the disturbance (σ):

$$\bar{R} = \frac{(F(t_{d_1}) - F(t_{d_2}))}{t_f - t_d}. \quad (3)$$

Robustness ($\bar{\rho}$) is the system's ability to resist big disturbances (σ) without significant loss of performance (Attoh-Okine et al.,2009; Herrera 2017) and is given by Eq. 4:

$$\bar{\rho} = \frac{\sigma}{\left(F\left(t_{d_1}\right) - F\left(t_{d_2}\right)\right)}. \tag{4}$$

Elasticity (σ_E) is the system's ability to absorb a disturbance (σ) without changing to a different permanent state (Holling,1996; Herrera 2017). Elasticity is calculated as the smallest disturbance σ_E that moves F(x) to a different state. The bigger σ_E a system has, the more undisturbed it is

$$\sigma_E = \delta_E \times (t_d - t_c). \tag{5}$$

Index of Resilience (I_{RES}) is the probability of the system to keep its current situation steady (Holling, 1996; Holling and Gunderson, 2002; Martin et al., 2011). High values of I_{RES} indicate low probability of the system changing to a different state.

$$I_{RES} = P(\sigma \leq \sigma_E). \tag{5}$$

5.3. Results and Discussion

5.3.1. Causal Loop Diagrams

For this analysis, the conceptualization of the nexus system is presented through the construction of a CLD. The CLD (Figure 5.3 revealed seven interesting feedback loops–four reinforcing (R1, R2, R3, and R4) and three balancing ones (B1, B2, and B3).

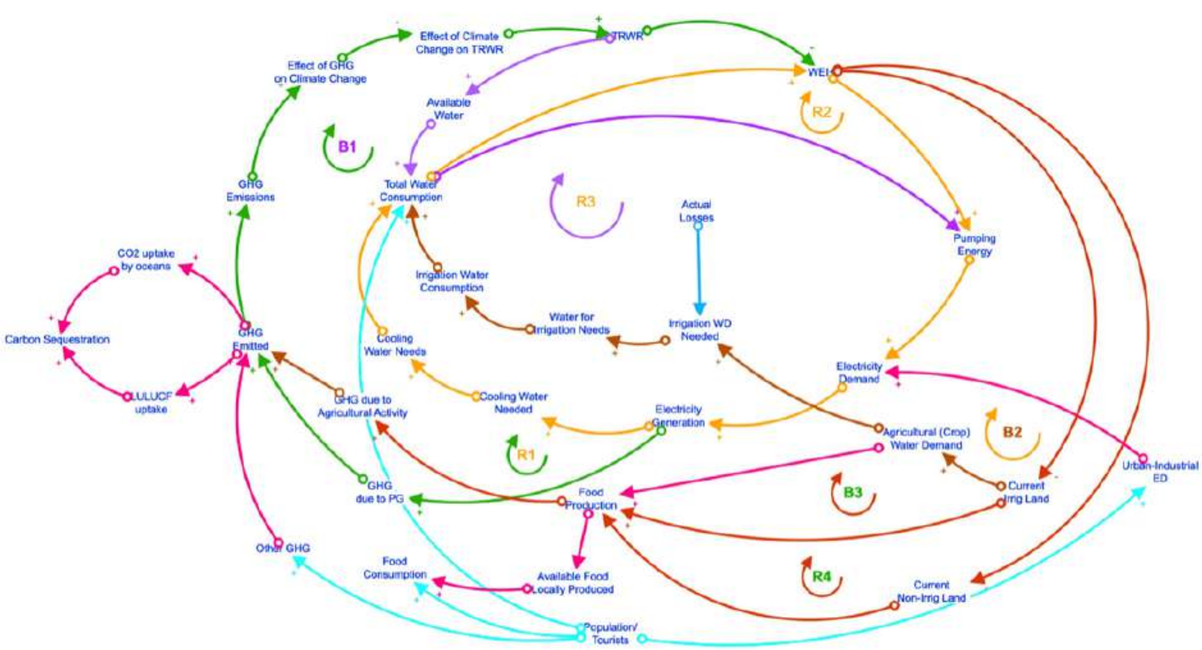


Figure 5.3 Causal loop diagram (CLD) indicating the interconnection of Greece's water-energy-food system under climate change using the SDM.

R1 is a climate–water–energy nexus reinforcing loop starting from the climate sector (Figure 5.4a). When the GHG produced due to PG is dealing with an increase, then the GHG emitted inflow is also increased, which in turn affects the GHG emissions the same way. An increase in GHG emissions causes a delayed increase on the effect of GHGs on climate change, while the effect of climate change on the TRWR is affected inversely, causing a decrease on the TRWR. When the TRWRs are reduced, WEI+—affected by TRWR—faces an increase which intensifies PE, ED, and EG, leading to a further increase in GHG produced due to PG. The R2 loop (Figure 5.4b) indicates the interconnection of total WC, WEI+, PE, ED, EG, and CW, where all are followed by successive increase, thus creating a water–energy nexus reinforcing loop. R3 in Figure 5.4c, is also a water–energy nexus reinforcing loop following the structure of R2, but in this loop, an increase in PE is caused by an increase in total WC due to the emerging need to extract more water to cover water demands (WEI+ is not part of this loop). In the R4 loop (Figure 5.4d), the GHG emissions affect the TRWR and WEI+ in the way described previously for R1. An increase in WEI+ leads to a drop in water supply forcing the farmers to adapt to the new challenge by switching to non-irrigated crops, thus leading to an increase in non-irrigated land and FP. In turn, an increase in FP leads to a GHG emission increase through GHG due to agricultural activity, thus creating a reinforcing climate–water–food nexus loop.

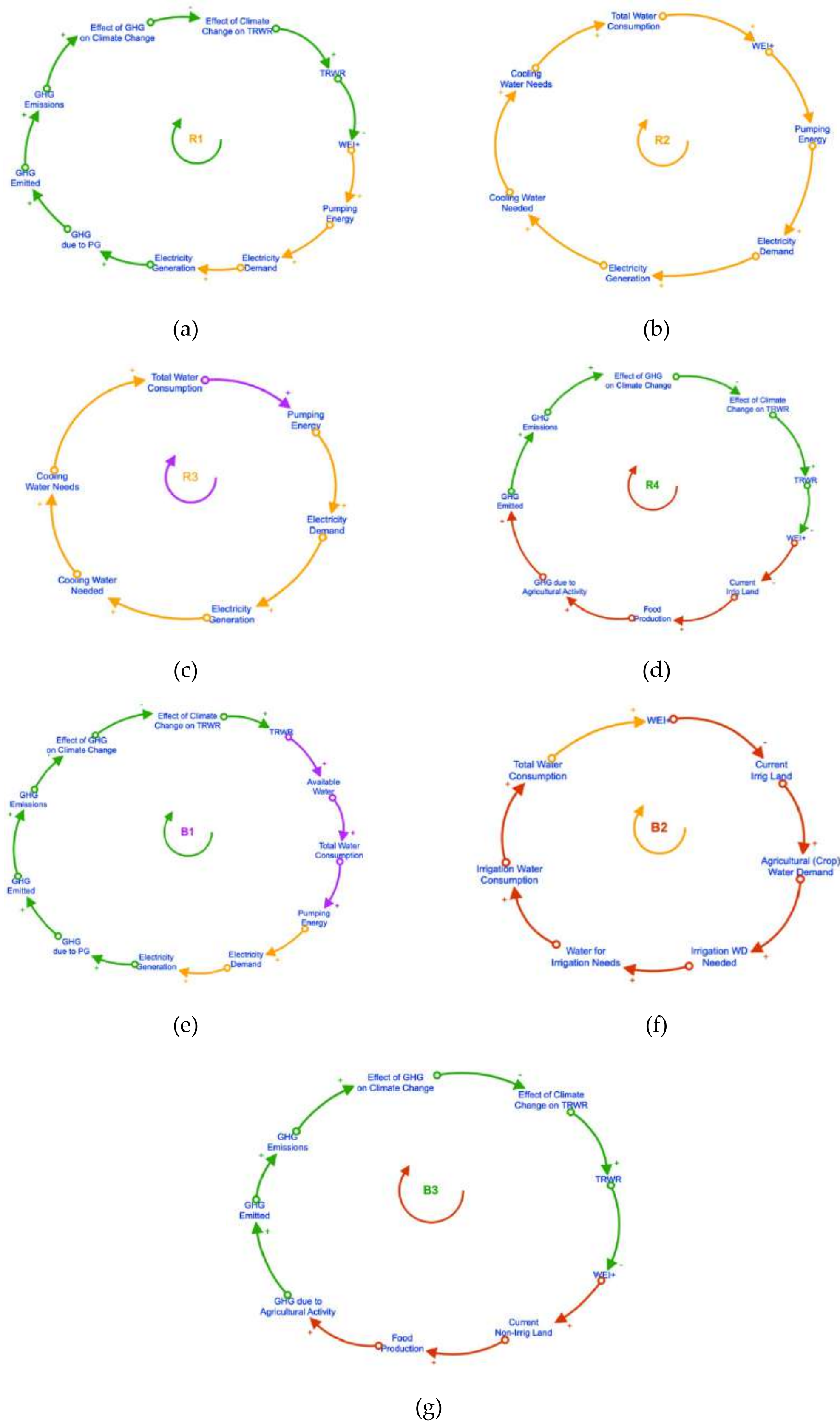


Figure 5. 4. Individual causal loop diagrams (CLDs) indicating the four reinforcing and three balancing loops. (A)Water–energy–climate reinforcing loop, (B)water–energy reinforcing loop, (C)water–energy reinforcing loop, (D) water–food–climate reinforcing loop, (E) water–

energy–climate balancing loop, (F) competitive water uses the balancing loop, and (G) water–food–climate balancing loop.

In the B1 loop (Figure 5.4e), an increase in GHG emissions causes a decrease in the TRWR through the effect of climate change on TRWR; thus, both water availability and WC are also decreased, meaning the energy sector is also facing a decrease contributing to less GHG emissions (through GHG due to PG). Balancing loop B1 contributes to the limitation of climate change effects on the water and energy sector, creating a climate–water–energy nexus loop. In the B2 loop (Figure 5.4f), an increase in total water consumption means that water scarcity is deteriorating, so the WEI+ values increase. When the country faces water scarcity, farmers will adapt to this situation by limiting the cultivation of irrigating crops; thus, the irrigated land, the associated irrigation WD, and irrigation WC will decrease. This behavior sets limits to reckless water use and creates a competitive water use balancing loop.

Table 5.2 Parameter quantified importance/sensitivity for available water, electricity demand, and GHG emissions in a descending order.

Parameters quantified importance/sensitivity for available water		**Parameters quantified importance/sensitivity for electricity demand**		**Parameters quantified importance/sensitivity for GHG emissions**	
TRWR	0.645	ED per capita	0.563	Population/tourists	0.704
Population/tourists	0.313	Population/tourists	0.531	GHG factor	0.509
GHG factor	0.196	Irrigated land	0.199	Per capita GHG emissions	0.423
Per capita GHG emissions	0.181	TRWR	0.175	ED per capita	0.276
Irrigated land	0.163	Per capita GHG emissions	0.090	Irrigated land	0.106
ED per capita	0.119	GHG factor	0.053	TRWR	0.085
Actual losses	0.048	Actual losses	0.034	Actual losses	0.015

In the B3 loop (Figure 5.4g), similar to B2, an increase in WEI + causes a decrease in irrigated land, FP, and GHG emissions through the GHG emitted due to agricultural activity, thus creating a climate–water–food nexus balancing loop. The system comes to a relative balance due to the existence of both kinds of loops–reinforcing and balancing. Following the model's conceptualization, we then proceeded to the system's SFD as depicted in Figure 5.1 to quantify the nexus interlinkages, find the most sensitive system parameters, and quantify system resilience for the three scenarios.

5.3.2. Sensitivity Analysis Results

Table 5.1 reveals the most important parameters that affect the whole system in a descending order based on parameter S(p) (Eq.1). The TRWR and the number of people (population/tourists) seem to be the two parameters that our model is the most sensitive to, while the parameter actual losses in the irrigation network is the one that affects the model the least.

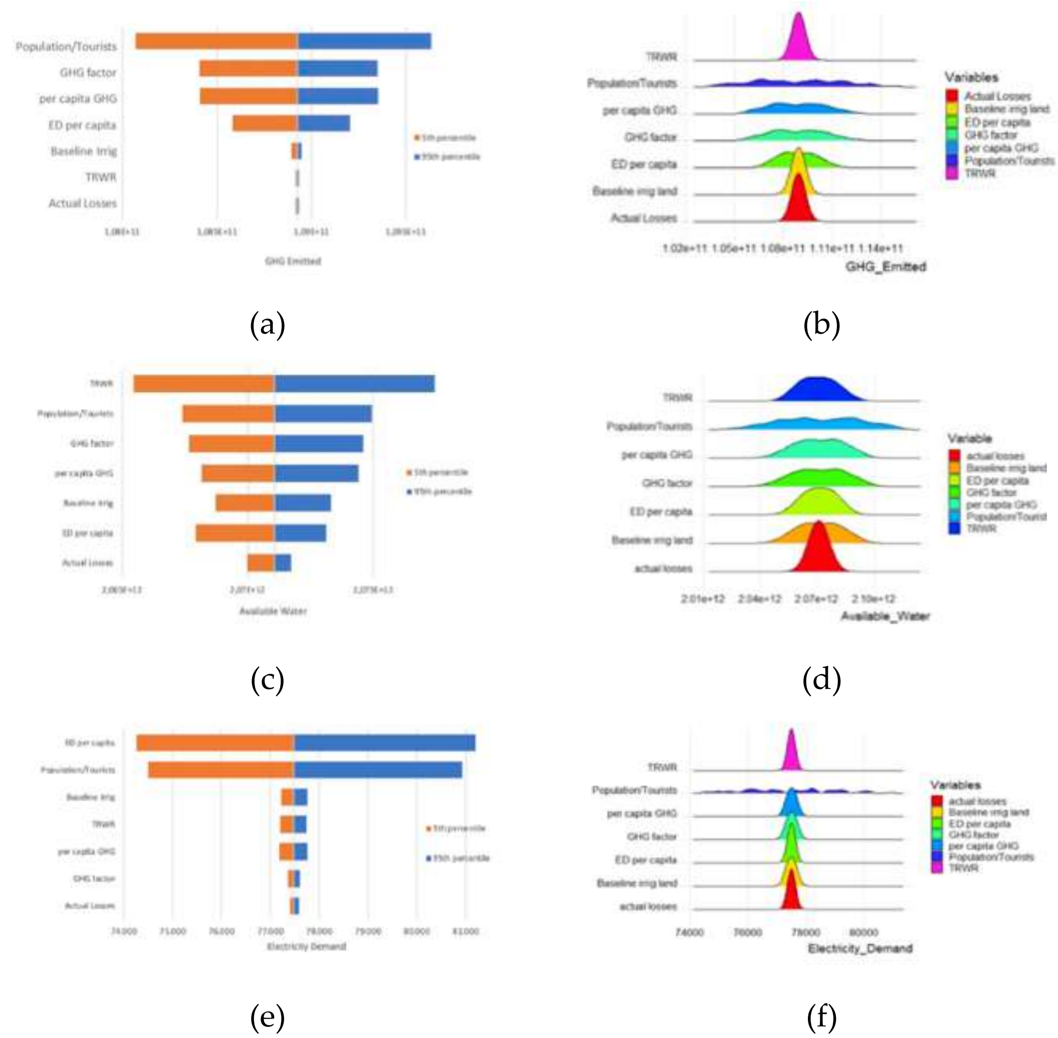


Figure 5.5 Tornado diagrams showing the value of the quantity for the limiting values of the 5th and the 95th percentile of the parameters for: (a) GHG emitted in kg CO_2, (c) available water in m^3, and (e)electricity demand in GWh. Spread diagrams indicating values of the quantities for the whole range of values that the parameter takes in the Monte Carlo analysis for: (b) GHG Emitted in kg CO_2, (d) Available Water in m_3, (f) Electricity Demand in GWh.

To quantify how much these seven model parameters affect the three basic quantities in the model, namely, available water, ED, and GHG emitted, we present a sector-specific SA, in which S(p) is calculated for each quantity, making it possible to compare and contrast the sensitivity of the important quantities to these parameters (Table 5.2). We observe that actual losses are at the bottom of the list, and the number of people (population/tourists) is close to the top of the list for all three quantities.

Next, a percentile analysis is performed. The most sensitive parameters are expected to bring about large variability in the quantities, while small variability indicates that the quantities do not change much, so they are insensitive to the parameters in question. Tornado diagrams are used to visually depict these results, showing the value of the quantity for the limiting values of the 5th and the 95th percentile of the parameter (Howard, 1988; Eschenbach, 1992). To show not only the limiting values but also the values of the quantities for the whole range of values that the parameter takes in the Monte Carlo analysis, we use sensitivity spread diagrams that we reproduced using the "ggplot2" plotting package in R Studio software. These results are shown in Figure 5.5. The climate sector is mostly affected by the population/tourists, GHG factor, and per capita GHG parameters (Figures 5.5a, B). The most important parameters of the water sector are TRWR and population/tourists (Figures 5.4c, d), while the energy sector is proved to be sensitive when ED per capita and population/tourists change (Figures 5.4e, f). Actual losses seem to affect these three sectors (and the whole system) the least.

The spread diagrams indicate the values of the quantities for the whole range of values that the parameter takes in the Monte Carlo analysis for: b) GHG emitted in kg CO_2, d) available water in m^3, and f) electricity demand in GWh.

To validate the results of the model, we used the WEI+ values. We simulated the WEI+ values starting from year 1 (corresponding to actual year 2010), and we compared the two values—simulated and real—for the year 7 (corresponding to actual year 2017). We chose the year 2017 since this is the last value published by EUROSTAT. The actual WEI+ value for the year 2017 is 39.37% (European Environmental Agency (EEA), 2020), while the simulated value is 38.7%, thus validating model results.

5.3.3. Resilience Analysis and Policy Evaluation

To assess SRA for our case study, we study the system behavior and quantify its ability to withstand shock under climate change; in this case, an extreme drought scenario is imposed on the system, and its ability to withstand it is investigated. The ecological and engineering measures of resilience (system resilience analysis) were applied to the developed SDM for the baseline scenario (with no interventions) and also for two suggested policies aiming to enhance WEF security; the implementation of renewable energy systems (RESs) (policy I) and increased stakeholder awareness and education, followed by increased funding to implement advanced irrigation systems with minimal losses in agriculture (policy II).

In Figure 5.6, we show the SFD that includes the implementation of policy I. The outer loop shown with black arrows is reinforcing loop R1, while the balancing loop B1 combines black and blue arrows and goes through the available water stock and through total WC and pumping energy.

For policy I, we add the parameter fraction of RES in total energy generation mix (shown in the box in Figure 5.6), and this way, we reduce the GHG emissions due to power generation by 30% as compared to the baseline scenario. For policy II, we add extra variables in the SDM, and a new loop is formed (reinforcing loop R5). Here, awareness and education is designed to lead to

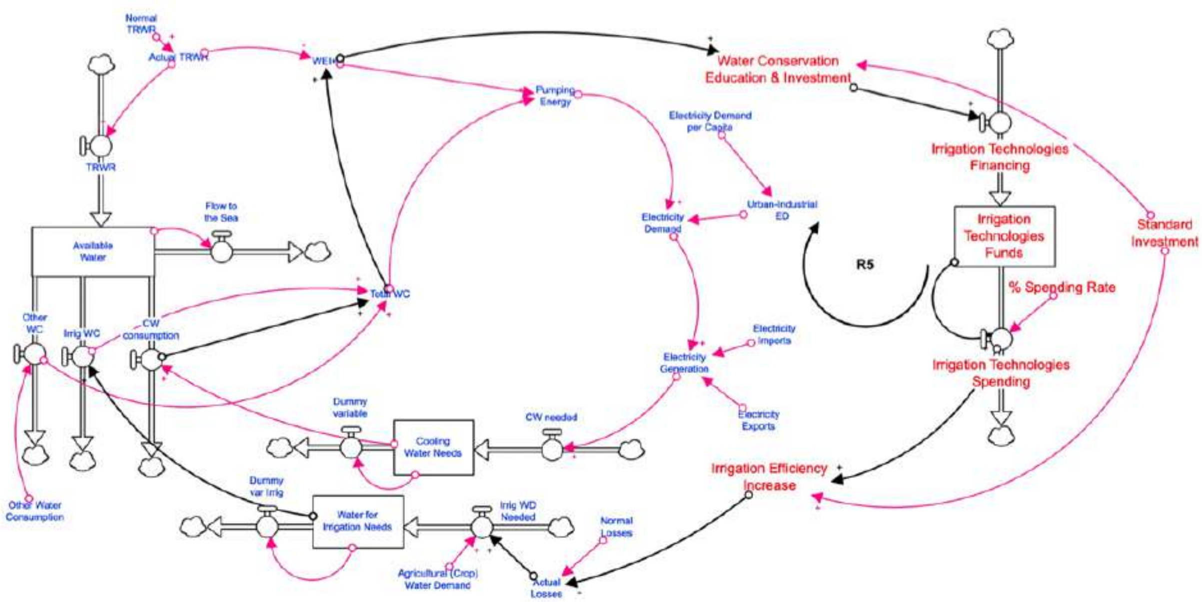


Figure 5.6 Stock – and flow diagram with the implementation of Policy I—renewable energy systems (RES).

stakeholders demanding and obtaining more funding for the implementation of efficient irrigation technologies that will lead to increased irrigation efficiency and reduced actual losses in agriculture (Figure 5.7). We expect both policies to lead to more resilient water systems overall through a WEF analysis; our goal is to compare the two policies in terms of systemic resilience using the metrics presented in the system resilience analysis. Therefore, we simulate and measure the resilience function F(x) (which represents the quantity of choice, depending on our scenario) for the baseline scenario (with no policies yet implemented); in our case, F(x) is available water.

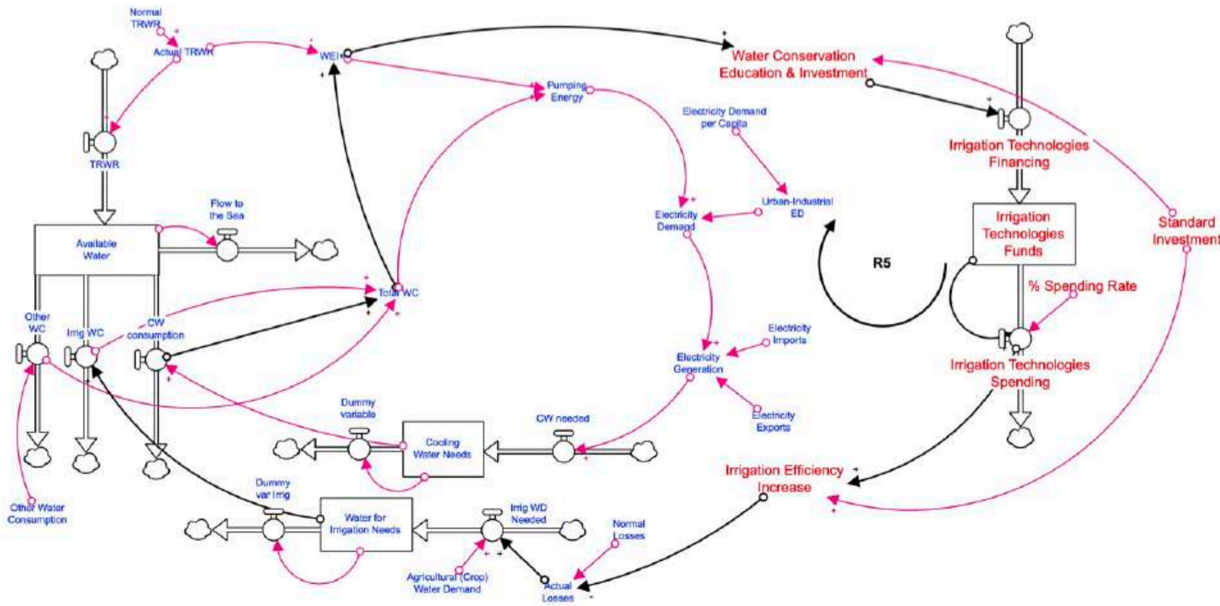


Figure 5.7 Stock – and flow diagram with the implementation of Policy II— funding to reduce water losses in irrigation systems.

As the next step, the two proposed policies are applied separately to the system, and then the respective responses to the system are measured. "Before" and "after" results can then be compared to identify which scenario enhances the system resilience aiming at WEF security under climate change.

We follow a methodology in order to define system hardness (σH) and elasticity (σE). To find system hardness, we keep increasing the magnitude of the system disturbance (TRWR reduction) over a period of 10 years, specifically from 2014 to2024, and we observe how F(x)—available water—changes. The highest disturbance/change in the TRWR that produces the least noticeable change in F(x)is its hardness (σH), the engineering threshold (shown in Table 5.3). We observe that when all scenarios are compared, the baseline is the least resilient system, having the lowest

Table 5.3. Results of engineering and ecological resilience for the three scenarios; the baseline scenario, Policy I—RES, and policy II—irrigation funding.

Engineering resilience				Ecological resilience	
Scenarios	Hardness (σ_H)	$\bar{R}$	$\bar{\rho}$	Elasticity (σ_E)	Index of resilience (I_{RES})
Baseline	2,54·10^9 m^3	0,80·10^9m3/year	0.107	5,08·$10^9$$m^3$	33,4%
Policy I	5,08·$10^9$$m^3$	2,38·$10^9$$m^3$/year	0.108	15,24·$10^9$$m^3$	46,6%
Policy II	4,06·109m3	1,34·109m^3/year	0.108	10,16·$10^9$$m^3$	40%

hardness, while policy I has the highest. With the implementation of policies, the system can withstand bigger changes (higher hardness) in the TRWR, such as extreme droughts caused by climate change, before available water is affected. Variable R shows how quickly the system will recover from the disturbance, and it is the highest for policy I, while in terms of robustness, the two policies appear similarly robust and more robust than the baseline. Ecological resilience is assessed next with the calculation of system elasticity (σE) and Index of Resilience (I_{res}) for the same 10-year period (2014–2024). We now reduce the TRWR even more until the outcome F(x)—available water—changes significantly and to a new state, and we observe whether F(x) bounces back or not.

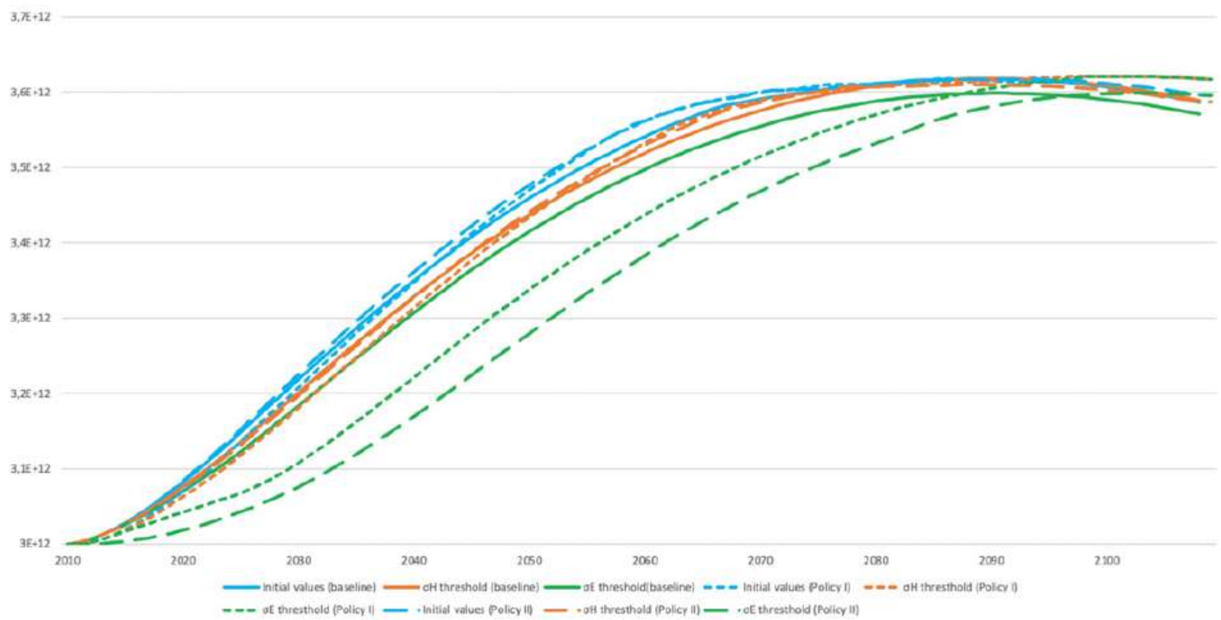


Figure 5.8 Simulated behavior for the available freshwater constituted of initial values of the TRWR (with no disturbance) and system thresholds of hardness and elasticity referring to the three scenarios: baseline scenario, policy I, and policy II.

In a mechanical analog, we speak about the system "bending" and "not breaking", that is, eventually recovering to its original state after some time. Again, policy I seems to perform the best, showing higher system elasticity and a significantly higher Index of Resilience overall. The system shows a higher overall resilience under policy I.

In Figure 5.8, we show graphically the function F(x) for the three scenarios (baseline and policy I and II) along with the initial values (blue), hardness σ_H (orange), and elasticity σ_E (green). The initial values are improved for the two policies, with policy I being slightly better (curve slightly higher than the other blue curves). For hardness and elasticity, we need to compare the difference with the initial values. For hardness, we observe that the biggest difference is found between initial values and policy I, indicating that the system is the "hardest" with policy I. Policy II shows hardness that is improved from the baseline. For elasticity, again, policy I is the most "elastic" with the difference being significantly larger when comparing with policy II and baseline. This means that the system is more resilient, and even when there is a large perturbation, it is capable of “absorbing” it and bouncing back to its original state. When examining the baseline scenario, we observe that the system is capable of absorbing a small disturbance (indicated by hardness curve matching the initial value at 100 years), but it is not able to bounce back to its original state when a larger perturbation occurs. This is indicated when we observe that the green solid line (elasticity for baseline scenario) never meets the blue solid line (initial value, baseline scenario), but even100 years later, it remains lower than the original curve. Thus, without the implementation of any policies, the system suffers a significant blow and never bounces back.

Chapter 5 includes parts of the following unpublished work, that will be submitted for publication:

Ioannou, A. E., & Laspidou, C. S. (2022). Resilience Analysis Framework for a Water–Energy–Food Nexus System Under Climate Change. Frontiers in Environmental Science, 342.

- The contribution of **Alexandra Ioannou** involves the conceptualization, the methodology, the software, the formal analysis, the investigation, the validation, the data curation, the writing—original draft, and the visualization.
- The contribution of **Professor Chrysi Laspidou** involves the conceptualization, the methodology, the resources, the scientific supervision, the review and editing, the project administration, and the funding acquisition.

The work described in this chapter has been conducted within the project NEXOGENESIS. This project has received funding from the European Union's Horizon (2020) Research and Innovation Programme under Grant Agreement No. 1010003881 NEXOGENESIS. This article and the content included in it do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

6

Cross-mapping important interactions between Water-Energy-Food nexus indices and the SDGs

6.1. Introduction

Sustainability is commonly defined by the United Nations Brundtland Commission in 1987 as: “meeting the needs of the present without compromising the ability of the future generations to meet their own needs” (Brundtland, 1987). Nearly 140 developing countries worldwide are trying to find out how to meet their development goals without threatening environmental security. By 2050, the world population is expected to exceed nine billion, while at the same time, a 50% increase in GHG emissions is expected, mainly due to the direct increase of CO2 emissions by 70% related to energy production (Kitamori et al., 2012; Gielen et al., 2019). The economic growth experienced during the last century has been followed by an increase in the use of resources—Water, Energy and Food (WEF) (UNDP, 2016), thus leading to irreversible impacts on aquatic and terrestrial ecosystems and to an alarming rate of natural resource depletion (Vörösmarty et al., 2020; Puma, 2019). At the same time, pressures such as climate change, overpopulation and rapid urbanization are expected to lead to an ever more increasing resource use, while geopolitical instability and crises such as the COVID-19 pandemic showcase weaknesses in the implementation of the UN 2030 Agenda for Sustainable Development (UN, 2015). The 17 Sustainable Development Goals (SDGs) are divided into 169 targets and there are almost 230 indicators intending to achieve the targets. To achieve the SDGs, all relevant stakeholders should collaborate and succeed in managing the synergies and trade-offs across individual management and governance sectors (Stein et al., 2014). However, 'silo-thinking approaches' traditionally implemented to all countries all over the world, seem no longer to be effective enough to address these challenges and there is a need for new integrated and multi- dimensional approaches that will manage to address multiple SDGs, if not all of them (McCollum et al., 2018, Boas et al., 2016).

Managing food, water and energy systems is key to achieving the UN Sustainable Development Goals (SDGs) and requires a better understanding of the interactions between the Goals, both at and across different scales, to promote social equality, human wellbeing and ecological integrity. Providing decision-makers with the multifaceted knowledge needed to seize all opportunities to enhance synergies and minimize trade-offs is, therefore, a major objective for Nexus research. In response to this, the WEF Nexus concept highlights the interactions between these systems and provides insights into the cross-sectoral implications of single-sector strategies. The Nexus approach provides a new way of thinking that is not limited to just the water, energy and food sectors, but promotes an integrated and systems thinking across all sectors. The World Economic Forum launched a report entitled "Water Security: The Water—Energy—Food—Climate Nexus", marking the emergence of the Nexus as we know it today (Hoff, 2011). The WEF Nexus approach focuses on the idea that WEF systems should be addressed in a collective and holistic way in order to achieve WEF security (WEF, 2011; Bleischwitz et al., 2018). WEF nexus is directly linked to 3 out of 17 SDGs, namely SDG 2 (zero hunger), SDG 6 (clean water and sanitation) and SDG 7 (affordable and clean energy), but WEF nexus can indirectly affect more than these three SDGs, positively or negatively through cross-sectoral collaboration. Through the identification of positive synergies and negative trade-offs, WEF nexus approach can contribute to enhance sustainability and at the same time promote higher resource use efficiency (Biswas, 2008), pollution reduction (Li et al., 2012), and more coherent policy (UNCTAD, 2016; Ziliaskopoulos and Papalamprou, 2022; Papadopoulou et al., 2022). Nexus approach can contribute to uncovering synergies and detecting harmful trade-offs among various sectors, scales and regions, revealing unforeseen effects and thus promoting integrating planning and policymaking (Liu et al., 2018).

Several articles have been published addressing fundamental human needs using the WEF nexus approach (Laspidou et al., 2020; Albrecht, 2018; Finley et al.; 2014, Stephan, 2018; Ioannou and Laspidou, 2018), the Water-Energy-Food-Ecosystem Nexus approach (Malagó et al., 2021), the WEF nexus approach under climate change combined with systemic resilience (Ioannou and Laspidou, 2022, Mguni and van Vliet, 2020; Sukhwani et al., 2019), and also the WEF nexus approach including Land Use and Climate (Laspidou et al., 2019; Janssen et al., 2020; Ramos et al., 2022). Additional research focuses on how the SDGs interact with one another (Weitz et al., 2018; Zhang et al., 2022). Almost 700 million people do not have access to clean and safe drinking water, lack of sanitation for 2.4 billion people (WHO, 2015), 795 million people are facing food insecurity (WFP, 2016), and 1.2 billion people still lack access to electricity (IEA, 2015). The three main sectors of water, energy and food are interconnected and thus affect all the SDGs directly or indirectly, so they should not be treated in isolation. The WEF nexus approach seems to offer a holistic framework to policymakers and associated stakeholders to achieve the SDGs (Liu et al., 2018; Weitz et al., 2018; Barbier and Burgess, 2017) and efforts are made on various levels to create and operationalize international Nexus Networks, such as the NexusNet COST Action network (https://www.cost.eu/actions/CA20138/) and the Nexus Community of Practice (Mohtar et al., 2022).

In this chapter, we map the WEF nexus system on the SDGs and we explore how and in what way (positively or negatively) the three Nexus components (Water-Energy-Food), separately and in combination, interact with the 17 SDGs. In a way, we quantify how following a Nexus approach and addressing resource use in a coherent way contributes towards the achievement of the SDGs through synergistic and antagonistic relationships. We choose the three SDGs representing the WEF Nexus (SDG 6, SDG 7 and SDG 2, respectively) and cross-map their relationship to all other SDGs, through two indicative targets for each SDG—for a group of 34 SDG targets in total. A quantified cross-mapping across all SDGs has been conducted by Weitz et al. (2018); we use the same scores but limit the analysis on the three Nexus SDGs. All scores were on a 7-point rating scheme with the most positive scoring +3 indicating that the two targets are highly synergetic ("indivisible") and the most negative scoring −3, indicating that the two targets are highly antagonistic ("cancelling"). By focusing on the three SDGs that are relevant to the Nexus and their interlinkages, we can identify which SDGs are most influenced–either positively or negatively–by the WEF Nexus approach. We postulate that such an approach is highly relevant for working towards the SDGs, since the multi-sector thinking already embedded in the Nexus is a pre-condition for achieving the SDGs. By conducting a systemic analysis of the complex interactions among the WEF Nexus and the SDGs, we aim to identify trade-offs and synergies among the Goals that could help policymakers set investment or political priorities in their agenda. The presented analysis borrows scores presented by Weitz et al. (2018) performed at the national level for Sweden but could be modified to reflect the peculiarities of specific regions, if the scoring is modified accordingly.

6.2. Materials and Methods

6.2.1. Cross-mapping the WEF Nexus indices on selected SDG targets

In this analysis, adapting the procedure of Weitz et al. (2018), we use the selected two indicative SDG targets per SDG as indicated in Table 6.1, to quantify how the WEF Nexus both affects and is affected by the 17 SDGs.

The modified matrix presented in Table 6.2, consists of the impact quantification of the three SDGs representing the WEF Nexus (SDG 2, SDG 6 and SDG 7) over the 17 SDGs in two ways; influencing targets (rows) and influenced by the targets (columns). In other words, the scores show how Water (SDG 6), Energy (SDG 7) and Food (SDG 2) influences all SDGs (presented in the 6 rows—two rows per SDG) and how the WEF Nexus is influenced by all SDGs (presented in the 6 columns—two columns per SDG). Influence could be positive, negative, or zero, if no influence exists. Other than the three rows and three columns that contain scores, the rest of the matrix is filled with zeros.

Table 6.1: The 17 SDGs and the 34 selected SDG targets.

SDGs	**Selected SDG targets**
SDG1: NO POVERTY	*1.3 Social protection*
	1.5 Economic and social resilience
SDG2: ZERO HUNGER	*2.2 Malnutrition*
	2.4 Food production/agriculture
SDG3: GOOD HEALTH AND WELL-BEING	*3.4 Non-communicable disease*
	3.8 Health coverage
SDG4: QUALITY EDUCATION	*4.1 Primary and secondary education*
	4.4 Technical/vocational skills
SDG5: GENDER EQUALITY	*5.4 Unpaid/domestic work*
	5.5 Women's participation
SDG6: CLEAN WATER AND SANITATION	*6.5 Water resources management*
	6.6 Water-related ecosystems
SDG7: AFFORDABLE AND CLEAN ENERGY	*7.2 Renewable energy*
	7.3 Energy efficiency
SDG8: DECENT WORK AND ECONOMIC GROWTH	*8.4 Resource efficiency*
	8.5 Employment
SDG9: INDUSTRY, INNOVATION AND INFRASTRUCTURE	*9.4 Infrastructure*
	9.5 Research/development
SDG10: REDUCES INEQUALITIES	*10.1 Economic equality*
	10.7 Migration
SDG11: SUSTAINABLE CITIES AND COMMUNITIES	*11.1 Affordable housing*
	11.2 Transport
SDG12: RESPONSIBLE CONSUMPTION AND PRODUCTION	*12.1 Sustainable consumption/production*
	12.5 Waste
SDG13: CLIMATE ACTION	*13.1 Climate change adaptation*
	13.2 Climate change policy/planning
SDG14: LIFE BELOW WATER	*14.1 Marine pollution*
	14.4 Fishery
SDG15: LIFE ON LAND	*15.2 Forests*
	15.5 Biodiversity
SDG16: PEACE, JUSTICE AND STRONG INSTITUTIONS	*16.4 Illicit financial/arms flow*
	16.6 Effective institutions
SDG17: PARTNERSHIP FOR THE GOALS	*17.11 Exports from developing countries*
	17.13 Macroeconomic stability

To see the effects of the WEF Nexus to SDG interaction at the SDG level, we proceed with summing the scores of the 2 targets both in rows and columns. The result is a single value per SDG considering the two targets in an integrated form. In Figure 6.1, we show an example of how we get from 4 values per SDG to a single value. Given that the maximum and minimum value per original cell was +3 and -3 respectively, we obtain a Table (Table 6.3) with scores ranging from -12 to +12, since it combines four individual cells in one. We continue by summing the rows and columns for the three Nexus SDGs, to compare the influence among the three Nexus components: row sums indicate the strength of the influence of each component on all SDGs, while column sums indicate which Nexus component is most influenced by the SDGs.

Table 6.2: Modified cross-impact matrix of 6 targets (2 for food—SDG 2, 2 for water—SDG 6 and 2 for energy—SDG 7), and their interactions, adapted from Weitz et al., 2018. The values in the matrix range from -3 (cancelling, dark red) to +3 (indivisible, dark green). Rows indicate targets influencing other targets and columns show how much each target is influenced by other targets.

NEXUS			`	FOOD								WATER		ENERGY																					
	SDGs	1.3	1.5	2.2	2.4	3.4	3.8	4.1	4.4	5.4.	5.5	6.5	6.6	7.2	7.3	8.4	8.5	9.4	9.5	10.1	10.7	11.1	11.2	12.1	12.5	13.1	13.2	14.1	14.4	15.2	15.5	16.4	16.6	17.11	17.13
	1.3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1.5	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FOOD	2.2	0	2	0	0	3	0	1	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	0
	2.4	0	0	0	0	1	0	0	0	0	0	2	2	-1	0	1	0	2	2	0	0	0	0	1	1	2	0	2	3	3	2	0	0	0	0
	3.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3.8	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4.4	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5.4.	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5.5	0	0	2	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WATER	6.5	0	2	0	2	0	0	0	0	0	0	0	3	-1	0	1	0	1	0	0	0	-1	0	1	1	2	1	3	2	1	2	0	1	0	1
	6.6	0	1	0	1	0	0	0	0	0	0	2	0	-1	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2	2	0	0	0	0
ENERGY	7.2	0	0	0	1	0	0	0	0	0	0	-1	-2	0	-1	2	1	3	2	2	0	1	1	0	0	1	3	0	0	-1	-1	1	0	-1	1
	7.3	0	0	0	1	0	0	0	0	0	0	0	0	-1	0	3	0	3	2	0	0	1	2	3	3	0	3	0	0	1	0	0	0	-1	0
	8.4	0	0	1	2	0	0	0	0	0	0	2	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8.5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9.4	0	0	0	1	0	0	0	0	0	0	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9.5	0	0	0	0	0	0	0	0	0	0	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10.1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11.1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11.2	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12.1	0	0	1	2	0	0	0	0	0	0	2	1	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12.5	0	0	0	1	0	0	0	0	0	0	1	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13.1	0	0	1	3	0	0	0	0	0	0	2	3	-2	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13.2	0	0	-2	1	0	0	0	0	0	0	0	-1	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14.1	0	0	0	2	0	0	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14.4	0	0	1	3	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15.2	0	0	0	2	0	0	0	0	0	0	1	3	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15.5	0	0	1	2	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	16.4	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	16.6	0	0	2	2	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	17.11	0	0	0	-1	0	0	0	0	0	0	0	0	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	17.13	0	0	0	2	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

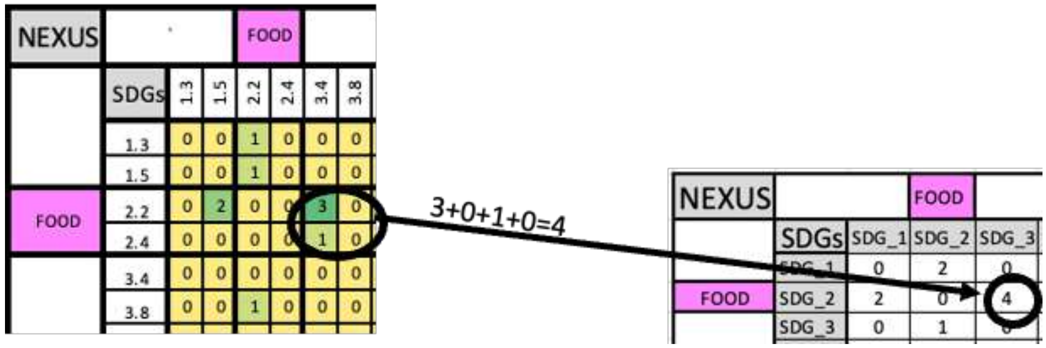


Figure 6.1: An example of how 4 scores between the targets of SDG 2 (rows) and SDG 3 (columns) from matrix in Table 6.2 are summed to constitute the score of how the SDG 2 influences the SDG 3 in total.

Table 6.3: 17×17 cross-mapping matrix with the sums of the target scores and their respective total sums per row and per column.

NEXUS			FOOD				WATER	ENERGY											
	SDGs	SDG_1	SDG_2	SDG_3	SDG_4	SDG_5	SDG_6	SDG_7	SDG_8	SDG_9	SDG_10	SDG_11	SDG_12	SDG_13	SDG_14	SDG_15	SDG_16	SDG_17	SUMS
	SDG_1	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	
FOOD	SDG_2	2	0	4	1	0	4	-1	4	4	0	0	4	4	5	5	0	0	36
	SDG_3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	SDG_4	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	
	SDG_5	0	8	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	
WATER	SDG_6	3	3	0	0	0	5	-2	1	1	0	-1	2	5	5	7	1	1	31
ENERGY	SDG_7	0	2	0	0	0	-3	-2	6	10	2	5	6	7	0	-1	1	-1	32
	SDG_8	0	4	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	
	SDG_9	0	1	0	0	0	2	6	0	0	0	0	0	0	0	0	0	0	
	SDG_10	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	SDG_11	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	
	SDG_12	0	4	0	0	0	5	7	0	0	0	0	0	0	0	0	0	0	
	SDG_13	0	3	0	0	0	4	2	0	0	0	0	0	0	0	0	0	0	
	SDG_14	0	6	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	
	SDG_15	0	5	0	0	0	7	-1	0	0	0	0	0	0	0	0	0	0	
	SDG_16	0	6	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	
	SDG_17	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	
	SUMS		48				40	19											

6.2.2. Fuzzy Cognitive Maps

Fuzzy Cognitive Maps (FCMs) are widely used to analyze causal complex systems, which have originated from the combination of fuzzy logic and neural networks (Papageorgiou, 2013). FCMs usually involve feedbacks, consisting of nodes and directed edges between them. Along these lines, the cross-impact matrix that cross-maps the 17 SDGs with scores on how the targets influence one another and how they are, in turn, influenced by the others has causality and feedback loops making it a good candidate for an FCM of this complex system. In our case, the nodes represent the SDGs, and the edges represent cause-effect relations (influencing / being influenced by) among the SDGs (our scores), creating a causal diagram with closed loops and paths in them. Closed loops show feedback among the SDGs, and they are fuzzy because the scores assigned (Weitz et al., 2018), represented by causal arrows in the diagrams, inherently include fuzziness, or "shades of gray" (Osoba and Kosko, 2019).

Feedback loops in our Nexus to SDG system imply that the system is dynamical and evolves from an initial state, which is defined by the activation vector, which is initially set at 1 for all nodes. The weights of the links (fuzzy causal edges) in the FCM include the fuzzy value of the relative influence which is transformed via a normalization technique from the [-12, 12] range (Table 6.3) to the [-1, 1] range (Table 6.4). Table 6.4 now becomes the causal edge matrix representation **E** for the Nexus-SDG FCM. Each cell shows the fuzzy causal edge value e_{ij}, which signifies how much the i^{th} SDG influences or is influenced by the j^{th} SDG. Once the edge matrix is input, the causal activation iterates in the FCM until the node values reach equilibrium—most FCMs reach it quickly and the equilibrium serves as the system's forward inference from the input.

The algorithm we used for convergence (Papageorgiou 2011, 2014) was based on equation (1) (Kosko's inference) and function *f* is described in (2):

$$A_i(k+1) = f\left(\sum_{j=1, j\neq i}^{N} e_{ji} \times A_j\,(k)\right) \tag{6.1}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{6.2}$$

In equation (1), A_i is the value of each node (SDG), e_{ji} is the strength of the influence between the SDGs and k is the iteration number. Because the algorithm includes e_{ji} (as opposed to e_{ij}), it takes into account columns, not rows. The results are a list of values obtained after convergence for each SDG and denote how the SDGs are influenced by the Nexus (Case A), with 0.5 being the lowest value (indicating no influence) and 1 being the maximum value (indicating the highest possible effect on the SDGs). To assess how the SDGs influence the Nexus, we ran the transpose matrix (Case B) with the same algorithm and produced different results for the SDGs (A_i values). These results are shown in Table 6.5 in the Results section.

Table 6.4: Causal edge matrix representation **E** for the Nexus-SDG FCM. All e_{ij} entries in this FCM are fuzzy values in the [-1, 1] interval. Red values are negative, while zero values denote the absence of causal inference.

NEXUS			FOOD				WATER	ENERGY										
	SDGs	SDG_1	SDG_2	SDG_3	SDG_4	SDG_5	SDG_6	SDG_7	SDG_8	SDG_9	SDG_10	SDG_11	SDG_12	SDG_13	SDG_14	SDG_15	SDG_16	SDG_17
	SDG_1	0	0,167	0	0	0	0,0833	0	0	0	0	0	0	0	0	0	0	0
FOOD	SDG_2	0,167	0	0,333	0,083	0	0,3333	-0,0833	0,333	0,333	0	0	0,3333	0,3333	0,4167	0,4167	0	0
	SDG_3	0	0,083	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	SDG_4	0	0,083	0	0	0	0	0,1667	0	0	0	0	0	0	0	0	0	0
	SDG_5	0	0,667	0	0	0	0,0833	0	0	0	0	0	0	0	0	0	0	0
WATER	SDG_6	0,25	0,25	0	0	0	0,4167	-0,1667	0,083	0,083	0	-0,083	0,1667	0,4167	0,4167	0,5833	0,0833	0,0833
ENERGY	SDG_7	0	0,167	0	0	0	-0,25	-0,1667	0,5	0,833	0,1667	0,4167	0,5	0,5833	0	-0,083	0,0833	-0,083
	SDG_8	0	0,333	0	0	0	0,25	0,25	0	0	0	0	0	0	0	0	0	0
	SDG_9	0	0,083	0	0	0	0,1667	0,5	0	0	0	0	0	0	0	0	0	0
	SDG_10	0	0,083	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	SDG_11	0	0	0	0	0	0	0,3333	0	0	0	0	0	0	0	0	0	0
	SDG_12	0	0,333	0	0	0	0,4167	0,5833	0	0	0	0	0	0	0	0	0	0
	SDG_13	0	0,25	0	0	0	0,3333	0,1667	0	0	0	0	0	0	0	0	0	0
	SDG_14	0	0,5	0	0	0	0,6667	0	0	0	0	0	0	0	0	0	0	0
	SDG_15	0	0,417	0	0	0	0,5833	-0,0833	0	0	0	0	0	0	0	0	0	0
	SDG_16	0	0,5	0	0	0	0,25	0	0	0	0	0	0	0	0	0	0	0
	SDG_17	0	0,083	0	0	0	0	0,0833	0	0	0	0	0	0	0	0	0	0

6.3. Results and Discussion

6.3.1. Analysis and Visualization of the results

To facilitate understanding of the scores shown in Table 6.3, we present them through a Sankey diagram (Figure 6.2), also available in an interactive form through this link: https://rpubs.com/alexioan/931954. We calculate how Water, Energy and Food influences each SDG separately and we post absolute values of influence scores. In total, Energy has the highest influence on the SDGs (if we only take the absolute values), with Water coming second and Food following last. The size of the SDG boxes corresponds to the total influence of the Nexus on them. The third WEF Nexus column sums up the Water, Energy and Food columns, showing the total mapping of the Nexus on the SDGs. SDG 13 (Climate Change) has the highest value, with SDG 9 (Industry Innovation and Infrastructure) and SDG 15 (Life on Land) coming second. SDG 6 (Water) and SDG 12 (Responsible Consumption and Production) come third and the other SDGs follow.

In Table 6.3, we also see that Food provides the highest sum both in rows and columns out of the three Nexus components, showing its high net positive influence, due to its strong interlinkages with water and energy. Surely ensuring sustainable Food production will act in synergy with Water and Energy, making the realization of these targets easier. In terms of the column sum, it makes sense that Food is the highest since it is greatly positively influenced by Water and Energy. Energy is quite a bit lower than the other two, due to negative scores between its own two targets and negative relationship with the other two Nexus components (a discussion on the negative energy scores is presented below). This lower score of Energy indicates that progress in the other SDG targets makes it more difficult to reach the Energy target.

It is important to see that the Nexus is mapped on SDG 13, suggesting that the Nexus offers a sustainable way of addressing the effects of Climate Change and increase resilience. The WEF Nexus includes the main drivers of climate change (water, energy, and food security) and the main sectors affected (water and the environment). Decisions around policy, infrastructure, etc. developed on the basis of WEF Nexus assessments will be suitable as elements of climate change mitigation and adaptation. In fact, it is difficult to imagine solutions to the climate change issue that are not built on a form of Nexus approach. The same is true with the other SDGs that score high, which are all relevant to biodiversity (SDG 15), innovation, infrastructures, sustainable industry (SDG 9), etc. A Nexus approach will clearly benefit all these SDGs that score in the top 3 positions, after our analysis. On the other hand, the lowest score corresponds to SDG 4 (Quality Education), while SDG 5 (Gender Equality) is completely absent. This shows a weakness in the link between WEF Nexus and these two SDGs. To advance the UN Agenda 2030, a strong link between the WEF Nexus and these SDGs should become more evident, as gender equality and quality education lie at the heart of providing equitable access to resources for all.

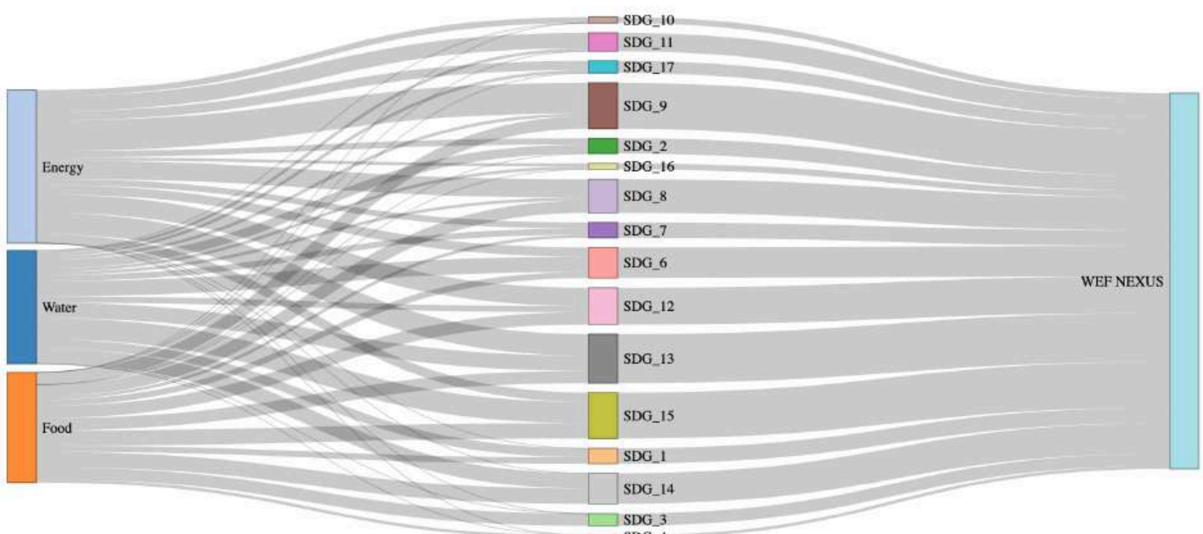


Figure 6.2: The Sankey diagram showing how the three Nexus components Water, Energy and Food both separately and in total (WEF Nexus) affect the 17 SDGs.

Additionally, we plot the same results with a radar chart (Figure 6.3). While in the Sankey diagram we plot influence as an absolute value, thus not being able to distinguish between positive and negative influence, in this plot, we provide this extra information of the sign (plus or minus) of the scores for each SDG. Negative scores correspond to trade-offs, while positive scores correspond to synergies, with some being more intense than others. The most interesting element of this graph is with the link of Energy and SDG 6 and 7. The negative score in SDG 7 stems from the fact that the two targets that were selected were targets 7.2 Renewable Energy and 7.3 Energy Efficiency. These two targets are considered either constraining or counter-active: An increase of renewables in the energy mix will not always lead to an increase in energy efficiency due to the lack of availability of solar or wind power (at least compared to conventional systems), thus we observe the negative score. In terms of the interaction of SDG 6 and 7, we see that hydropower, even though a renewable energy, affects water quality and ecosystem health (Target 6.6).

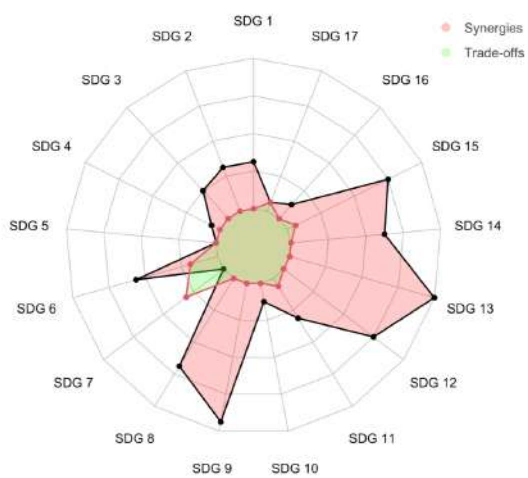


Figure 6.3: The radar chart indicates how the17 SDGs are affected either in a synergistic (positive) or antagonistic (negative) way by the Nexus.

6.3.2. Fuzzy Cognitive Maps results

Figure 6.4 shows the results of the FCM analysis. The arrows indicate the edge values e_{ij} as shown in Table 6.4, with the line width being associated with the magnitude of the value. Red lines indicate negative values. As expected, we see most of the arrows connecting SDGs 2, 6 and 7, but other SDGs show interlinkages as well. Negative interlinkages are shown mostly around SDG 7, as observed also in Figure 6.3, while strong interlinkages are also shown between SDG7 and 9 which are obviously strongly interlinked as energy is at the core of achieving innovative infrastructures and sustainable industries (SDG 9). The sizes of the circles denoting the nodes (SDGs) correspond to the values of A_i, as they converge after a few iterations of the algorithm (k=20 for both cases). Figure 6.4 shows the FCM results in a graphical format for only the first case (how the SDGs are influenced by the Nexus—Case A), while Table 6.5 shows the actual values of the nodes for both Case A and Case B—how the SDGs influence the Nexus.

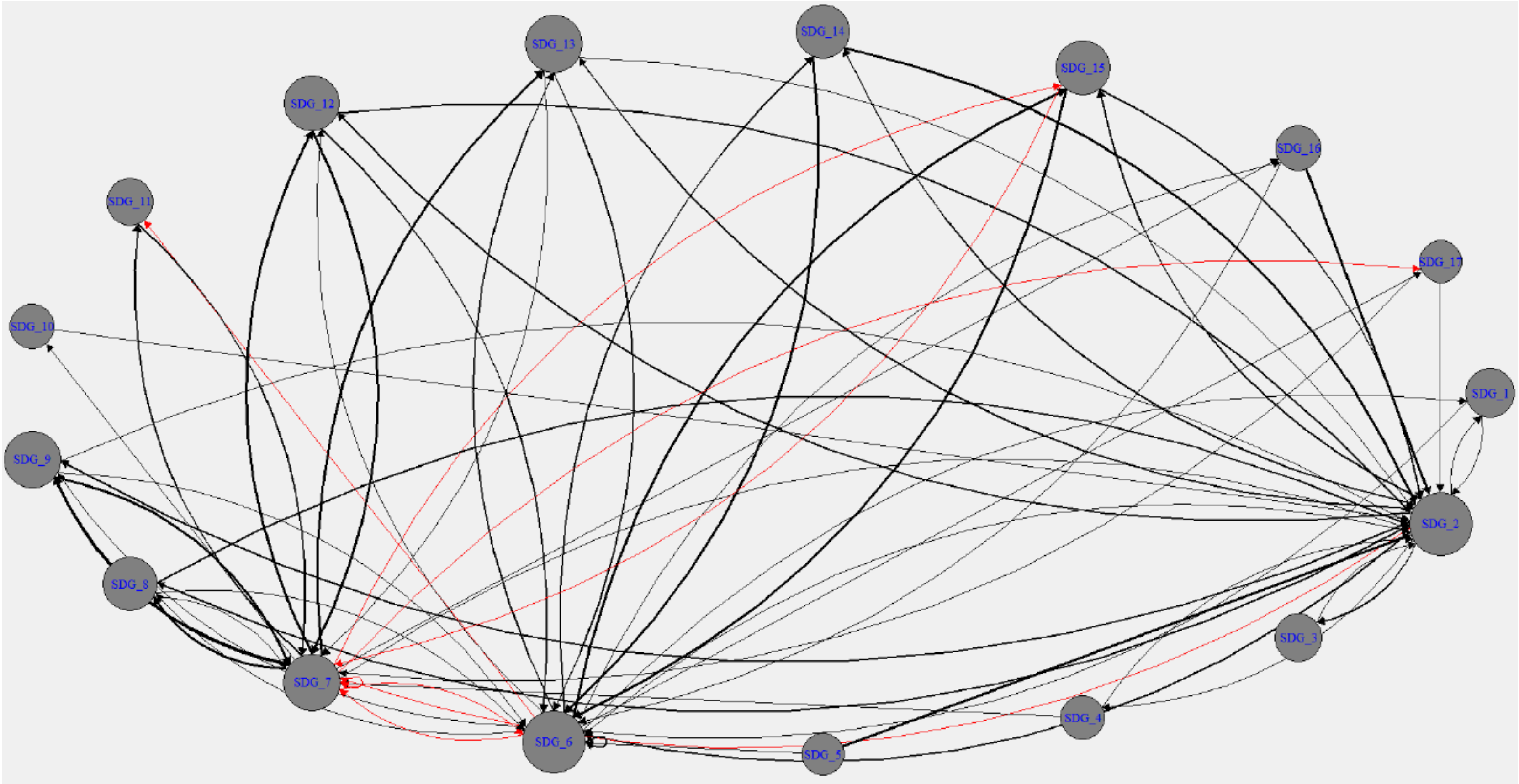


Figure 6.4: Fuzzy Cognitive Map analysis—graphical representation for Case A (how the SDGs are influenced by the Nexus)

Since the analysis focuses on SDGs 2, 6 and 7, we expect to have the largest values for these SDGs in the final FCM results, since these nodes would naturally have most of the interlinkages and influence. However, in Case A we see that SDG13 (Climate Change) takes the 3rd highest value, following SDG 2 (Food) and SDG 6 (Water) and SDG 7 (Energy) comes 5th in place after SDG 13 and SDG 9 (Industry, Innovation and Infrastructure). This is indicative of the strong links already evident with Climate Change, and the availability of resources, thus the Nexus. We see that SDG2 (Food) is the most influential of all SDGs for both cases, with SDG 6 coming 2nd. Through a different analysis that quantified the interlinkages between the Nexus components performed by Laspidou et al (2019), Food was showcased as the one component that was the most influential and Water as the one mostly influenced by the others. So, the strength of the influence of Food has been established elsewhere, since it has strong links mainly with Water, but also with Energy mainly through the water-energy nexus (via pumping). As mentioned before, SDG 5 has the lowest value in Case A showing zero influence by the Nexus (0.5 is the lowest possible value), but has influence on the Nexus, as shown in Case B. It is interesting to see that SDG 3 (Good Health and Wellbeing) has the lowest value in Case B, while it lies in about the middle of the ranking in Case A, indicating that even though SDG 3 is influenced by the Nexus (an obvious link with water quality, energy pollution and food for example), its influence on the Nexus is minimum. Finally, SDG 10 (Reduced Inequalities) ranks at the bottom in Case B and relatively low in Case A, while SDGs 14 and 15 ("Life Below Water" and "Life on Land", respectively) with obvious strong links with the Nexus appear with relatively high values, as expected.

Table 6.5: Fuzzy Cognitive Mapping analysis results after convergence: Node values for all SDGs quantifying their influence in an ascending order; (a) Case A: how the SDGs are influenced by the Nexus and (b) Case B: how the SDGs influence the Nexus

SDGs	Final values
SDG_5	0.5
SDG_17	0.5040
SDG_4	0.5193
SDG_10	0.5301
SDG_16	0.5342
SDG_11	0.5561
SDG_3	0.5767
SDG_1	0.5949
SDG_8	0.6789
SDG_14	0.6835
SDG_12	0.6953
SDG_15	0.7032
SDG_7	0.7249
SDG_9	0.7291
SDG_13	0.7531
SDG_6	0.9194
SDG_2	0.9288

(a)

SDGs	Final values
SDG_3	0.5184
SDG_10	0.5184
SDG_17	0.5360
SDG_4	0.5535
SDG_1	0.5546
SDG_11	0.5701
SDG_9	0.6550
SDG_13	0.6571
SDG_16	0.6588
SDG_5	0.6596
SDG_8	0.6732
SDG_15	0.6904
SDG_14	0.7346
SDG_12	0.7593
SDG_7	0.8471
SDG_6	0.8642
SDG_2	0.8846

(b)

The Nexus approach leads to more integrated and sustainable resource use that goes beyond traditional silos and is applicable at multiple scales. This approach needs to be governed by a coordination mechanism, allowing for the creation of a Community of Practice (Mohtar et al., 2022), where key stakeholders can work towards identifying and prioritizing solutions, benefitting from an overall Nexus perspective. Under Nexus-coherent governance and its linkage with the SDGs, priorities are integrated, compromises are promoted by sometimes adopting decisions that may not be optimal from a single sector policy perspective, but which result in an overall better solution for all sectors involved. This article promotes such thinking and facilitates evidence-based policy making (Carmona-Moreno et al, 2019).

Chapter 6 includes parts of the following published work:

Ioannou, A.E., Laspidou, C.S. Cross-mapping the interactions between Water-Energy-Food nexus indices and the SDGs. [under submission]

- The contribution of **Alexandra Ioannou** involves the conceptualization, the methodology, the software, the formal analysis, the investigation, the validation, the data curation, the writing—original draft, and the visualization.
- The contribution of **Professor Chrysi Laspidou** involves the conceptualization, the methodology, the resources, the scientific supervision, the review and editing, the project administration, and the funding acquisition.

The work described in this chapter has been conducted within the project ARSINOE. This project has received funding from the European Union's Horizon 2020 Innovation Action programme under Grant Agreement No. 101037424 ARSINOE.

7

Conclusions

This dissertation is based on two main parts; in the first one, it is explored how advanced clustering techniques such as Self-Organizing maps, K-means and Hierarchical Agglomerative Clustering can contribute to the detection of daily water consumption behavior at both, household and consumer level while in the second part, a water - energy nexus analysis at city level is presented, and also a resilience analysis framework of the water–energy–food nexus system under climate change at national level is developed to ensure water and environmental security. The use of innovative modelling structures under current methodological frameworks, can be proven crucial towards exploring the ability to deal with complex qualitative and quantitative objectives, from single to multiple water systems and from regional to global scales.

The analysis starts by performing automatic classification of daily water consumption patterns for a household in Sosnowiec, using data collected by sensors. Our investigation is built upon three approaches accomplished with use of the SOM algorithm. Thirteen descriptive features of daily consumption patterns are used for the classification. Approaches 1 and 2, distinguishes two water consumption profiles dividing days of consumption into two main clusters, weekdays and weekends. In approach 3, with use of features partitioning daily water consumption into the time-zones of Sosnowiec working hours, the two clusters get more solid, and the methodology gets more efficient. In all approaches, the clustering of days of consumption into weekdays and weekends implies that the household is affected by the urban working routine. In future scenarios, this investigation could be expanded to more households in order to achieve a further classification, even manage to identify each day of the week. Investigation among households in working areas, or leisure places might indicate different water consumption daily patterns. In all cases the choice of good descriptive features seems to be important. The features have to be customized to better describe daily routines of different types of households. In this dissertation, we have advanced the state of the art in terms of introducing appropriate descriptive features that facilitate the detection of water consumption patterns covering seasonality, behavioral aspects, and socio-economic characteristics of the user.

Next, a novel methodology suitable for handling large datasets of household water consumption is presented. This analysis aims to divide customers into user groups (clusters) based on the similarities of their water use behavior; this way, advanced data-based methods may be employed for creating personalized information about consumer water use. The presented methodology resulted in better estimates of customer water use when clustering was employed, compared to the predictions when clustering was not employed. This powerful information can provide a lot of insight to water companies, as it allows them to have knowledge of water demand in a detailed spatio-temporal granulation, thus promoting good planning and efficient operation. Water companies have better knowledge on what to expect from new customers, by classifying them in pre-existing clusters; they can obtain information on pumping energy needed and they have rich datasets that could be used for modeling the water distribution network, for reducing leakage, for optimizing treatment and pumping, for accurate billing, and for prioritizing investments.

In the second part of this dissertation, a water-energy nexus analysis is presented for the Greek island of Skiathos. The consumptions of different uses of energy—agricultural, commercial, industrial and public— are analyzed and we concluded that there is a very strong linear correlation with total water consumption. The correlation of domestic use of energy with total water consumption is also examined and the results showed no linear correlation between them. According to the literature, a strong correlation between water use and energy consumption is expected (Yu et al., 2018), but our research concerns the Greek island of Skiathos and according to the Water Utility of the island, the water is not potable due to its high mercury content. This means, that many domestic uses of water, such as cooking, personal hygiene (especially infant hygiene) and drinking water have been replaced by bottled water. That fact might have caused the reduction of water consumption through faucets in households thus creating this difference between the two consumptions. For the results we used *PCC* and *Minkowski Distance* (Euclidean and Manhattan) after having all our data normalized at first level. The PCC proved to be the best distance measurement and the Minkowski Distance not a suitable one for our case study. Through this investigation people could be motivated not only to save energy but also save water as well in order to get financial benefits, because energy is much pricier than water. Residents should be informed at a very early stage, such as in school for example, in order to save water and energy starting from their households and by achieving that, we could save the environment in general.

In the 5th chapter, a combined WEF Nexus and Resilience analysis under climate change is presented. New approaches on policymaking relevant to natural resource management need to be applied with the intention to provide essential human needs and resources to all in an environmentally compatible, economically resilient, and socially inclusive manner that can withstand perturbations. SES adaptation to climate change requires a more functional approach of resilience use in policymaking. System dynamic modeling prevails over other simulation techniques by supporting the analysis of system structure and focusing on feedback loop relationships. This study combines WEF nexus analysis under climate change with SA and SRA that are said to have the potential to deliver on these grand development challenges. The proposed methodology describes how to simulate the WEF nexus system under climate change for the national case study of Greece using system dynamic modeling, identify the most important (sensitive) system parameters, and quantify five essential metrics of resilient behavior (for three scenarios), thus providing the policymakers with a quantitative basis to enhance the resilience of SESs. Engineering (σ_H, R, and ϱ) and ecological (σ_E and I_{res}) resilience measures are quantified, and the respective thresholds are also identified. In this study, two proposed policies are compared to decide which one enhances the system resilience best. Evaluating the results, we conclude that the Greek simulated system can withstand an extreme drought event affected for a 10-year period under the allowing circumstances of engineering and ecological thresholds found for the two policies (policy I and policy II); the baseline scenario has little tolerance to such disturbance (reduction on TRWR) and easily breaks when it overcomes the ecological threshold without being able to recover. Policy I proposing the implementation of RES seems to be the most promising scenario as its resilience measures have the highest values, so the system can even recover from the shock for a more severe drought, while policy II is also a good scenario since it contributes to system recovery when affected by drought although having lower resilience measures values by enhancing water security through irrigation funding techniques.

Finally, in chapter 6, the interactions between Water-Energy-Food Nexus and the SDGs are quantified and analyzed. The Nexus approach ensures a more integrated and sustainable use of resources that goes beyond traditional silos and is applicable at different scales. This is particularly relevant in an increasingly globalized world where collaboration becomes essential for societies. By exploring the impact of the WEF nexus over the 17 SDGs and vice versa, and by quantifying that impact, we provide an assessment framework that will help policymakers set priorities in investments. This way, investing in the Nexus might promote synergies and help achieve greater success in associated SDGs that are influenced positively. Since not all SDG targets were considered, but only two targets per SDG, it is important to understand the limitations of the approach, which is dependent on the selected targets and the Case Study under consideration. In this chapter, we provide the framework that allows the users to adjust it to their needs by entering new scores, depending on the peculiarities of each case study; the results of this methodology should be taken into account considering the specific conditions, including socio-cultural aspects and geographical, geopolitical and governance realities, as well as the scale of the case study in question.

Bibliography

Abrahart, R.J.; See, L. (2000). Comparing neural network and autoregressive moving average techniques for the provision of continuous river flow forecasts in two contrasting catchments. Hydrol. Process.2000,14, 2157–2172. doi: 10.1002/1099-1085(20000815/30)14:11/123.0.CO;2-S

Acheampong, M., Ertem, F. C., Kappler, B., & Neubauer, P. (2017). In pursuit of Sustainable Development Goal (SDG) number 7: Will biofuels be reliable?. Renewable and sustainable energy reviews, 75, 927-937. doi: 10.1016/j.rser.2016.11.074

Akter, S., Rutsaert, P., Luis, J., Htwe, N. M., San, S. S., Raharjo, B., & Pustika, A. (2017). Women's empowerment and gender equity in agriculture: A different perspective from Southeast Asia. *Food policy*, *69*, 270-279. doi: https://doi.org/10.1016/j.foodpol.2017.05.003

Albrecht, T. R., Crootof, A., and Scott, C. A. (2018). The Water-Energy-FoodNexus: A Systematic Review of Methods for Nexus Assessment. Environ. Res.Lett.13, 043002. doi: 10.1088/1748-9326/aaa9c6

Alhoniemi, E.; Hollmen, J.; Simula, O.; Vesanto, J. (1999). Process monitoring and modeling using the self-organizing map. Integr. Comput. Aided Eng.1999,6, 3–14. doi: 10.3233/ICA-1999-6102

Allen, C. R., Angeler, D. G., Chaffin, B. C., Twidwell, D., and Garmestani, A. (2019). Resilience Reconciled. Nat. Sustain.2 (10), 898–900. doi: 10.1038/s41893-019-0401-4

Anderies, J. M. (2015). Managing Variance: Key Policy Challenges for theAnthropocene. Proc. Natl. Acad. Sci. U.S.A.112 (47), 14402–14403. doi: 10.1073/pnas.1519071112

Arampatzis, G., Perdikeas, N., Kampragou, E., Scaloubakas, P., and Assimacopoulos, D. (2014). A water demand forecasting methodology for supporting day-to-day management of water distribution systems. In 12th International Conference "Protection and Restoration of the Environment", Skiathos, Thessaloniki, Greece.

Attoh-Okine, N. O., Cooper, A. T., and Mensah, S. A. (2009). Formulation of Resilience index of Urban Infrastructure Using Belief Functions. IEEE Syst. J.3(2), 147–153. doi: 10.1109/jsyst.2009.2019148

Bakhshianlamouki, E., Masia, S., Karimi, P., van der Zaag, P., and Sušnik, J. (2020). A System Dynamics Model to Quantify the Impacts of Restoration Measures onthe Water-Energy-Food Nexus in the Urmia lake Basin, Iran.Sci. Total Environ.708, 134874. doi: 10.1016/j.scitotenv.2019.134874

Bala, B. K., Arshad, F. M., and Noh, K. M. (2017). "Systems Thinking: System Dynamics, "in System Dynamics (Singapore: Springer), 15–35. doi: 10.1007/978-981-10-2045-2_2

Barbier, E. B., & Burgess, J. C. (2017). The Sustainable Development Goals and the systems approach to sustainability. *Economics*, *11*(1). doi: http://dx.doi.org/10.5018/economics-ejournal.ja.2017-28

Bedingfield, S.; Alahakoon, D.; Genegedera, H.; Chilamkurti, N. (2018). Multi-granular electricity consumer load profiling for smarthomes using a scalable big data algorithm. Sustain. Cities Soc.2018,40, 611–624. doi: https://doi.org/10.1016/j.scs.2018.04.006

Beckel, C.; Sadamori, L.; Santini, S. Towards automatic classification of private households using electricity consumption data. In Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Toronto, ON, Canada, 6 November 2012; pp. 169–176.

Bhattacharya, A., Meltzer, J. P., Oppenheim, J., Qureshi, Z., & Stern, N. (2016). Delivering on sustainable infrastructure for better development and better climate. Available at: https://www.brookings.edu/research/delivering-on-sustainable-infrastructure-for-better-development-and-better-climate/

Bishop, C.M. (1995). Neural Networks for Pattern Recognition, Oxford University Press, Oxford.

Biswas, A. K. Integrated water resources management: Is it working? Int. J. Water Resour. Dev.24, 5–22 (2008). doi: https://doi.org/10.1080/07900620701871718

Bleischwitz, R., Spataru, C., VanDeveer, S. D., Obersteiner, M., van der Voet, E., Johnson, C., et al. (2018). Resource Nexus Perspectives towards the United

Nations Sustainable Development Goals. Nat. Sustain.1 (12), 737–743. doi: 10.1038/s41893-018-0173-2

Boas, I., Biermann, F., & Kanie, N. (2016). Cross-sectoral strategies in global sustainability governance: towards a nexus approach. *International Environmental Agreements: Politics, Law and Economics*, *16*(3), 449-464. doi: https://doi.org/10.1007/s10784-016-9321-1

Bowden, G.J.; Dandy, G.C.; Maier, H.R. (2005a). Input determination for neural network models in water resources applications. Part 1 ebackground and methodology.J. Hydrol.2005,301, 75–92. doi: https://doi.org/10.1016/j.jhydrol.2004.06.021

Bowden, G.J.; Maier, H.R.; Dandy, G.C. (2005b). Input determination for neural network models in water resources applications. Part 2. Case study: Forecasting salinity in a river.J. Hydrol.2005,301, 93–107. doi: https://doi.org/10.1016/j.jhydrol.2004.06.020

Brouwer, F., Avgerinopoulos, G., Fazekas, D., Laspidou, C., Mercure, J.-F., Pollitt, H., Ramos, E.P., Howells, M. (2018). Energy modelling and the Nexus concept, *Energy Strategy Reviews* 19, 1-6.

Buchberger, S.G.; Carter, J.T.; Lee, Y.H.; Schade, T.G. (2003). Random Demands, Travel Times and Water Quality in Dead-Ends; AWWARF Rep. No. 294; American Water Works Association Research Foundation: Denver, CO, USA.

Burlig, F., & Preonas, L. (2016). Out of the darkness and into the light? development effects of rural electrification. *Energy Institute at Haas WP*, *268*, 26. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://epic-staging.uchicago.edu/wp-content/uploads/2019/08/WP268.pdf

Brundtland, G. (1987). Report of the World Commission on Environment and Development: Our Common Future. United Nations General Assembly document A/42/427. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf

Carmona-Moreno, C., Dondeynaz, C., & Biedler, M. (Eds.). (2019). Position Paper on Water, Energy, Food and Ecosystems (WEFE) Nexus and

Sustainable Development Goals (SDGs). Publications Office of the European Union.

Carpenter, S. R., and Gunderson, L. H. (2001). Coping with Collapse: Ecologicaland Social Dynamics in Ecosystem Management.BioScience51 (6), 451–457.doi: 10.1641/0006-3568(2001)051[0451: cwceas]2.0.co;2

Casadei, S., Peppoloni, F., and Pierleoni, A. (2020). A New Approach to Calculate the Water Exploitation Index (WEI+). Water 12 (11), 3227. doi: 10.3390/w12113227

Chapin III, F. S., Kofinas, G. P., & Folke, C. (Eds.). (2009). *Principles of ecosystem* stewardship*: resilience-based natural resource management in a changing world*. Springer Science & Business Media. doi: https://doi.org/10.1007/978-0-387-73033-2

Chen, X., Wang, D., Tian, F., and Sivapalan, M. (2016). From Channelization toRestoration: Sociohydrologic Modeling with Changing Community Preferences in the Kissimmee River Basin, Florida.Water Resour. Res.52 (2), 1227–1244.doi: 10.1002/2015WR018194

Copeland, C. (2014). Energy-Water Nexus: The Water Sector's Energy Use; Congressional Research Service: Washington, DC, USA; p. 7-5700.

Coyle, R. G. (1997). System Dynamics Modelling: A Practical Approach. J. Oper.Res. Soc.48 (5), 544. doi: https://doi.org/10.1057/palgrave.jors.2600682

C. S. Holling and L. H. Gunderson (Editors) (2002). Panarchy: Understanding Transformations in Human and Natural Systems (Washington, DC: Island Press). doi: http://hdl.handle.net/10919/65531

Dawson, C.W.; Wilby, R.L. (2001). Hydrological modelling using artificial neural networks. Prog. Phys. Geogr.2001,25, 80–108. doi: https://doi.org/10.1177/030913330102500104

Deboeck, G and Kohonen T. (1998). Visual Explorations in Finance using self-organizing Maps, Springer, London. doi: https://doi.org/10.1007/978-1-4471-3913-3

De Grenade, R., House-Peters, L., Scott, C., Thapa, B., Mills-Novoa, M., Gerlak, A., et al. (2016). The Nexus: Reconsidering Environmental Security and

Adaptive Capacity .Curr. Opin. Environ. sustainability21, 15–21. doi: 10.1016/j.cosust.2016.10.009

Eschenbach, T. G. (1992). Spider plots versus Tornado Diagrams for SensitivityAnalysis.Interfaces22 (6), 40–46. doi: 10.1287/inte.22.6.40

European Climate Foundation 2014 Europe's low-carbon transition: understanding the challenges and opportunities for the chemical sector (The Hague: European Climate Foundation) pp 1–60. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://europeanclimate.org/wp-content/uploads/2020/02/03-2014-europes-low-carbon-transition-understanding-the-challenges-and-opportunities-for-the-chemical-sector-presentation.pdf

European Commission. A Water Blueprint for Europe; Publications Office of European Union: Luxembourg, 2013. doi: 10.2779/12145

European Commission. Directorate-General for Regional Policy. In Cities of Tomorrow: Challenges, Visions, Ways Forward; Publications Office of the European Union: Luxembourg, 2001. doi: 10.2776/41803

European Environmental Agency (EEA) (2020). Development of the Water Exploitation index Plus (WEI+). Copenhagen. Available from: https://www.eea.europa.eu/data-and-maps/daviz/water-exploitation-index-plus#tab-chart_1_filters=%7B%22rowFilters%22%3A%7B%7D%3B%22columnFilters%22%3A%7B%22pre_config_year%22%3A%5B%222017%22%5D%7D%3B%22sortFilter%22%3A%5B%22wei_2017_reversed%22%5D%7D (Accessed November 8, 2021).

European Union's Horizon (2020). European Union's Horizon. Available from: https://ec.europa.eu/info/research-and-innovation/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-2020_en.

Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P., and Uthurusamy R. 1996. Advances in knowledge Discovery and Data Mining, AAAI Press/The MIT Press, California.

Finley, J. W., and Seiber, J. N. (2014). The Nexus of Food, Energy, and Water.J. Agric. Food Chem.62 (27), 6255–6262. doi: 10.1021/jf501496r

Flammini, A., Puri, M., Pluschke, L., and Dubois, O. (2014). Walking the Nexus Talk: Assessing the Water-Energy-Food Nexus in the Context of the Sustainable Energy for All Initiative. Rome: Fao.

Folke, C., Carpenter, S. R., Walker, B., Scheffer, M., Chapin, T., and Rockström, J.(2010). Resilience Thinking: integrating Resilience, Adaptability and Transformability. Ecol. Soc.15 (4), 150420. doi: 10.5751/es-03610-150420

Ford, A. (1999). Modelling the Environment. An Introduction to System Dynamics Modelling of Environmental Systems. Washington, D.C: *Island Press*, 401. doi: **https://doi.org/10.1002/sdr.272**

Forrester, J. W. (1961). Industrial Dynamics. Cambridge, MA: MIT Press. Goldstein, R.; Smith, W. Water and Sustainability (Volume 4): US Electricity Consumption for Water Supply and Treatment: The Next Half Century; Electric Power Research Institute (EPRI): Palo Alto, CA, USA, 2002.

Frankel, M., Xing, L., Chewning, C., & Sela, L. (2021). Water-energy benchmarking and predictive modeling in multi-family residential and non-residential buildings. *Applied Energy*, 281, 116074.

Galaitsi, S., Veysey, J. and Huber-Lee, A. (2018). Where is the added value? A review of the water-energy food nexus literature. SEI Working paper. Stockholm Environment Institute, Stockholm. https://www.sei.org/publications/added-value-review-water-energy-food-nexus-literature/.

Gielen, D., Gorini, R., Wagner, N., Leme, R., Gutierrez, L., Prakash, G., ... & Renner, M. (2019). Global energy transformation: a roadmap to 2050. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.irena.org/DigitalArticles/2019/Apr/-/media/652AE07BBAAC407ABD1D45F6BBA8494B.ashx

Grafton, R.Q., McLindin, M., Hussey, K., Wyrwoll, P., Wichelns, D., Ringler, C., Garrick, D., Pittock, J., Wheeler, S., Orr, S. and Matthews, N., (2016). Responding to global challenges in food, energy, environment and water: Risks and options assessment for decision-making. Asia & the Pacific Policy Studies, 3(2), pp.275-299. doi: https://doi.org/10.1002/app5.128

Grafton, R. Q., Doyen, L., Béné, C., Borgomeo, E., Brooks, K., Chu, L., Cumming, G. S., Dixon, J., Dovers, S., Garrik, D., Helfgott, A., Jiang, Q., Katic, P., Kompas, T., Little, L. R., Matthews, N., Ringler, C., Squires, D., Steinhamm, S. I., Villasante, S., Wheeler, S., Williams, J., and Wyrwoll, P. R. (2019). Realizing resilience for decision-making. Nat. Sustain. 2, 907–913. doi: 10.1038/s41893-019-0376-1

Goldthau, A. (2014). Rethinking the governance of energy infrastructure: Scale, decentralization and polycentrism. *Energy Research & Social Science*, *1*, 134-140. doi: https://doi.org/10.1016/j.erss.2014.02.009

Govindaraju, R.S. ASCE Task Committee on application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology. I: Preliminary concepts.J. Hydrol. Eng.2000,5, 115–123. doi: **https://doi.org/10.1061/(ASCE)1084-0699(2000)5:2(115)**

Govindaraju, R.S. ASCE Task Committee on application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology. II: Hydrologic applications.J. Hydrol. Eng.2000,5, 124–137. doi: **https://doi.org/10.1061/(ASCE)1084-0699(2000)5:2(124)**

Griggs, D. J., Nilsson, M., Stevance, A., & McCollum, D. (2017). *A guide to SDG interactions: from science to implementation*. International Council for Science, Paris. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://council.science/wp-content/uploads/2017/05/SDGs-Guide-to-Interactions.pdf

Grosso, G., Mateo, A., Rangelov, N., Buzeti, T., & Birt, C. (2020). Nutrition in the context of the Sustainable Development Goals. *European journal of public health*, *30* (Supplement_1), i19-i23. doi: https://doi.org/10.1093/eurpub/ckaa034

Guillaume, J. H. A., Kummu, M., Eisner, S., and Varis, O. (2015). Transferable principles for managing the Nexus: lessons from historical global watermodelling of central Asia, Water, 7, 4200–4231. doi: 10.3390/w7084200

Hall, J. W., Grey, D., Garrick, D., Fung, F., Brown, C., Dadson, S. J., et al. (2014). Coping with the curse of freshwater variability, Science, 346, 429–430. doi:10.1126/science.1257890

Hellenic Statistical Authority, 2018. Water use (2000 - 2018). Piraeus, Greece. https://www.statistics.gr/en/statistics/-/publication/SOP07/2000 [Last date assessed: 8/11/2021]

Hellenic Statistical Authority. (2020). Estimated Population and Migration Flows. Piraeus, Greece. https://www.statistics.gr/en/statistics/-/publication/SPO18/. [Last date assessed: 8/11/2021]

Herrera, H. (2017). From metaphor to practice: Operationalizing the analysis of resilience using system dynamics modelling, Systems Research and Behavioral Science, 34(4), 444-462. doi: **https://doi.org/10.1002/sres.2468**

Herrera de Leon, H. J., & Kopainsky, B. (2019). Do you bend or break? System dynamics in resilience planning for food security, System Dynamics Review, 35(4), 287-309. doi: **https://doi.org/10.1002/sdr.1643**

Hoekstra, A. Y., and Wiedmann, T. O. (2014). Humanity's unsustainable environmental footprint, Science, 344, 1114–1117. doi: 10.1126/science.1248365.

Hoff, H. (2011). Understanding the Nexus. Background paper for the Bonn 2011 Nexus conference: The Water, Energy and Food Security Nexus. Stockholm Environment Institute, Stockholm. Available at: https://www.sei.org/publications/understanding-the-nexus/

Holling C. S. (1996). Engineering resilience versus ecological resilience. Engineering within ecological constraints, 31(1996), 32. doi: 10.17226/4919

Holling, C. S. (1973). Resilience and stability of ecological systems, Annual Rev. Ecol. Syst., 4, 1–23. doi: 10.1146/annurev.es.04.110173.000245

Holling, C. S., Gunderson LH (eds). (2002). Panarchy: Understanding Transformations in Human and Natural Systems. Island Press: Washington, DC.

Hong, Y.; Hsu, K.; Sorooshian, S.; Gao, X. Self-organizing nonlinear output (SONO): A neural network suitable for cloudpatch-based rainfall estimation at small scales. Water Resour. Res.2005,41, W03008. doi: **https://doi.org/10.1029/2004WR003142**

Howard, R. A. (1988b). Decision Analysis: Practice and Promise, Management Science 34(6), 679– 695. doi: https://doi.org/10.1287/mnsc.34.6.679

Hsu, K.; Gupta, H.V.; Gao, X.; Sorooshian, S.; Imam, B. Self-organizing linear output map (SOLO): An artificial neural networksuitable for hydrologic modeling and analysis.Water Resour. Res.2002,38, 1302. doi: **https://doi.org/10.1029/2001WR000795**

Hunger statistics. WFP https://www.wfp.org/hunger/stats (2016).

International Energy Agency. (2010) World Energy Outlook. Retrieved from http://sdg.iisd.org/news/iea-releases-world-energy-outlook-2010/ [Last date assessed:8/11/2021]

ILO. 2013a. Sustainable Development, Decent Work and Green Jobs. Report No. 5, International Labour Conference, 102nd Session. Geneva, Switzerland, ILO. http://www.ilo.org/wcmsp5/groups/public/---ed_norm/---relconf/documents/meetingdocument/wcms_207370.pdf

Ioannou A. E. and Laspidou C. S. (2022) Resilience Analysis Framework for a Water–Energy–Food Nexus System Under Climate Change. *Front. Environ. Sci. 10:820125.* doi: 10.3389/fenvs.2022.820125

Ioannou, A. E., Creaco, E. F., & Laspidou, C. S. (2021). Exploring the effectiveness of clustering algorithms for capturing water consumption behavior at household level. Sustainability, 13(5), 2603.

Ioannou, A.E. and Laspidou, C.S. (2018). The Water-Energy Nexus at City Level: The Case Study of Skiathos. In Multidisciplinary Digital Publishing Institute Proceedings (Vol. 2, No. 11, p. 694).

Ioannou, A.E.; Kofinas, D.; Spyropoulou, A.; Laspidou, C.S. (2017). Data mining for household water consumption analysis using self-organizing maps. Eur. Water 2017,58, 443–448. doi: 10.5281/zenodo.2645124

IPCC 2011 Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge University Press). Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.ipcc.ch/site/assets/uploads/2018/03/SRREN_FD_SPM_final-1.pdf

Jain, A.K.; Murty, M.N.; Flynn, P.J. Data clustering: A review. ACM Comput. Surv.1999,31, 264–323. doi: https://dl.acm.org/doi/10.1145/331499.331504

Janssen, D.N., Ramos, E.P., Linderhof, V., Polman, N., Laspidou, C., Fokkinga, D. and de Mesquita e Sousa, D. (2020). The Climate, Land, Energy, Water and Food Nexus Challenge in a Land Scarce Country: Innovations in the Netherlands. Sustainability, 12(24), p.10491. doi: **https://doi.org/10.3390/su122410491**

Jørgensen, S. E., & Bendoricchio, G. (2001). Fundamentals of ecological modelling (Vol. 21). Elsevier. https://www.elsevier.com/books/fundamentals-of-ecological-modelling/jorgensen/978-0-08-044015-6

Kalteh, A.M.; Berndtsson, R. Interpolating monthly precipitation by self-organizing map (SOM) and multilayer perceptron (MLP). Hydrol. Sci. J.2007,52, 305–317. doi: https://doi.org/10.1623/hysj.52.2.305

Kalteh, A.M.; Hjorth, P.; Berndtsson, R. Review of the self-organizing map (SOM) approach in water resources: Analysis, modelling and application.Environ. Model. Softw.2008,23, 835–845. doi: https://doi.org/10.1016/j.envsoft.2007.10.001

Kameoka, Y.; Yagi, K.; Munakata, S.; Yamamoto, Y. Customer segmentation and visualization by combination of self-organizing map and cluster analysis. In Proceedings of the 13th International Conference on ICT and Knowledge Engineering (ICT Knowledge Engineering 2015), Bangkok, Thailand, 18–20 November 2015; pp. 19–23. doi: 10.1109/ICTKE.2015.7368465

Kaski, S. (1997). Data Exploration Using Self-Organizing Maps, Ph.D. thesis, Helsinki University of Technology. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://faculty.runi.ac.il/arik/lodseminar/SOM/kaski97data.pdf

Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005.

Kitamori, K., Manders, T., Dellink, R., & Tabeau, A. A. (2012). OECD environmental outlook to 2050: the consequences of inaction. OECD. doi: https://doi.org/10.1787/9789264122246-en

Kofinas, D.T.; Spyropoulou, A.; Laspidou, C.S. A methodology for synthetic household water consumption data generation. Environ. Model. Softw.2018,100, 48–66. doi: https://doi.org/10.1016/j.envsoft.2017.11.021

Kofinas, D.; Mellios, N.; Papageorgiou, E.; Laspidou, C. Urban Water Demand Forecasting for the Island of Skiathos. Procedia Eng.2014,89, 1023–1030. doi: https://doi.org/10.1016/j.proeng.2014.11.220

Kohonen, T. (2001). Self-Organizing Maps, 3rd ed.; Springer: Berlin/Heidelberg, Germany; pp. 71–104. doi: http://dx.doi.org/10.1007/978-3-642-56927-2

Kohonen, T. (1997). Self-Organizing Maps, 2nd ed.; Springer: Berlin/Heidelberg, Germany. doi: https://doi.org/10.1007/978-3-642-56927-2

Kohonen, T., Oja, E., Simula, O., Visa, A. and Kangas, J. (1996). Engineering applications of the self-organizing map. Proceedings of the IEEE, 84(10), 1358-1384. doi: 10.1109/5.537105

Kohonen, T. (1995). Self-Organizing Maps, Springer, Berlin. doi: https://doi.org/10.1007/978-3-642-97610-0

Kohonen, T. Analysis of a simple self-organizing process. Biol. Cybern. 1982a,44, 135–140. doi: https://doi.org/10.1007/BF00317973

Kohonen, T. Self-organized formation of topologically correct feature maps.Biol. Cybern. 1982b ,43, 59–69. doi: https://doi.org/10.1007/BF00337288

Lakervi, E.; Holmes, E.J. (1995). Electricity Distribution Network Design, 2nd ed.; Springer: Berlin/Heidelberg, Germany; p. 325, ISBN 0863413099. Available at: https://books.google.gr/books?hl=en&lr=&id=HMLBEXay1DUC&oi=fnd&pg=PP13&dq=Lakervi,+E.%3B+Holmes,+E.J.+(1995).+Electricity+Distribution+Network+Design,+2nd+ed.%3B+Springer:+Berlin/Heidelberg,+Germany%3B+p.+325,ISBN+0863413099.&ots=x5AMUzfoWP&sig=FoHG85KozOLFwejLSQSo_T_31zs&redir_esc=y#v=onepage&q=DOI&f=false

Lannon, C. (2012). Causal loop construction: the basics. Systems Thinker, 23(8). Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://thesystemsthinker.com/wp-content/uploads/pdfs/230811pk.pdf

Laspidou, C.S., Mellios, N.K., Spyropoulou, A.E., Kofinas, D.T. and Papadopoulou, M.P. (2020). Systems thinking on the resource nexus: Modeling and visualisation tools to identify critical interlinkages for resilient and sustainable societies and institutions. Science of the Total Environment, 717, p.137264. doi: https://doi.org/10.1016/j.scitotenv.2020.137264

Laspidou, C.S., Mellios, N. and Kofinas, D. (2019). Towards ranking the water–energy–food–land use–climate nexus interlinkages for building a nexus conceptual model with a heuristic algorithm. Water, 11(2), p.306. doi: 10.3390/w11020306

Laspidou, C.; Papageorgiou, E.; Kokkinos, K.; Sahu, S.; Gupta, A.; Tassiulas, L. (2015). Exploring patterns in water consumption by clustering. Procedia Eng.,119, 1439–1446. doi: https://doi.org/10.1016/j.proeng.2015.08.1004

Laspidou, C.S. (2014). ICT and stakeholder participation for improved urban water management in the cities of the future. Water Util. J.,8, 79–85.4. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.ewra.net/wuj/pdf/WUJ_2014_08_08.pdf

Leck, H., Conway, D., Bradshaw, M., and Rees, J. (2015). Tracing thewater–energy–food Nexus: description, theory and practice, Geogr. Compass, 9, 445–460. doi:10.1111/gec3.12222

Li, X., Feng, K., Siu, Y. L. & Hubacek, K. Energy-water nexus of wind power in China: the balancing act between CO2 emissions and water consumption. Energy Pol.45, 440–448 (2012). doi: 10.1016/j.enpol.2012.02.054

Liao, T.W. Clustering of time series data—A survey. Pattern Recogn. 2005, 38, 1857–1874. doi: https://doi.org/10.1016/j.patcog.2005.01.025

Lin, G.; Chen, L. Identification of homogenous regions for regional frequency analysis using the self-organizing map.J. Hydrol.2006,324, 1–9. doi:10.1016/j.jhydrol.2005.09.009

Liu, J., Hull, V., Godfray, H. C. J., Tilman, D., Gleick, P., Hoff, H., ... & Li, S. (2018). Nexus approaches to global sustainable development. *Nature Sustainability*, *1*(9), 466-476. doi: https://doi.org/10.1038/s41893-018-0135-8

J. Liu, H. Yang, C. Cudennec, A.K. Gain, H. Hoff, R. Lawford, J. Qi, L. de Strasser, P.T. Yillia & C. Zheng (2017). Challenges in operationalizing the water–energy–food nexus, *Hydrological Sciences Journal*, 62:11, 1714-1720, DOI: 10.1080/02626667.2017.1353695

MacQueen, J. Some methods for classification and analysis of multivariate observations. In Proceedings of the fifth Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, CA, USA, 18–21 June 1967; Le Cam, L.M., Neyman, J., Eds.; University of California Press: Berkeley, CA, USA, 1967; pp. 281–297. Available at: http://projecteuclid.org/euclid.bsmsp/1200512992

Makles, A. Stata tip 110: How to get the optimal k-means cluster solution. Stata J.2012,12, 347–351. Available at: https://journals.sagepub.com/doi/10.1177/1536867X1201200213

Malagó, A., Comero, S., Bouraoui, F., Kazezyılmaz-Alhan, C.M., Gawlik, B.M., Easton, P. and Laspidou, C. (2021). An analytical framework to assess SDG targets within the context of WEFE nexus in the Mediterranean region. Resources, Conservation and Recycling, 164, p.105205. doi: 10.1016/j.resconrec.2020.105205

Manetsch, T.J. and Park, G.L. (1982). System analysis and simulation with applications to economic and social systems. Department of Electrical Engineering and System Science, Michigan State University.

Manville, C., Cochrane, G., Cave, J., Millard, J., Pederson, J. K., Thaarup, R. K., and Kotterink, B., (2014). Mapping smart cities in the EU. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.europarl.europa.eu/RegData/etudes/etudes/join/2014/507480/IPOL-ITRE_ET(2014)507480_EN.pdf

Maier, H.R.; Dandy, G.C. The use of artificial neural networks for the prediction of water quality parameters. Water Resour. Res.1996,32, 1013–1022. doi: **https://doi.org/10.1029/96WR03529**

Maier, H.R.; Dandy, G.C. Determining inputs for neural network models of multivariate time series. Microcomput. Civ. Eng.1997,12, 353–368. doi:**https://doi.org/10.1111/0885-9507.00069**

Maier, H.R.; Dandy, G.C. Neural networks for the prediction and forecasting of water resources variables: A review of modellingissues and applications. Environ. Model. Softw.2000,15, 101–124. doi: https://doi.org/10.1016/S1364-8152(99)00007-9

Martin S, Deffuant G, Calabrese JM. (2011). Defining resilience mathematically: from attractors to viability. In Viability and Resilience of Complex Systems, Deffuant G, Gilbert N (eds.). Springer: Berlin; 15–36. 4. doi: https://doi.org/10.1007/978-3-642-20423-4_2

McCollum, D. L., Echeverri, L. G., Busch, S., Pachauri, S., Parkinson, S., Rogelj, J., ... & Riahi, K. (2018). Connecting the sustainable development goals by their energy inter-linkages. *Environmental Research Letters*, *13*(3), 033006. doi: https://doi.org/10.1088/1748-9326/aaafe3

McLoughlin, F.; Duffy, A.; Conlon, M. A clustering approach to domestic electricity load profile characterisation using smart metering data.Appl. Energy2015,141, 190–199. doi: https://doi.org/10.1016/j.apenergy.2014.12.039

Meldrum, J.; Nettles-Anderson, S.; Heath, G.; Macknick, J. Life cycle water use for electricity generation: a review and harmonization of literature estimates. Environ. Res. Lett. 2013, 8, 015031. doi: 10.1088/1748-9326/8/1/015031

Mellios, N. and Laspidou, C. (2020), "Water-Energy-Food-Land-Climate Nexus data for the Case Study of Greece: National and River Basin District Scale", Mendeley Data, V1, doi: 10.17632/9x7wn24rrp.1

Merigó, J.M.; Gil-Lafuente, A.M. Using the OWA operator in the Minkowski distance. Int. J. Comput. Sci. 2008, 3, 149–157. doi: doi.org/10.5281/zenodo.1084486

Mguni, P., & van Vliet, B. J. (2020). Rethinking the urban Nexus-Resilience and vulnerability at the urban Nexus of Water, Energy and Food (WEF). An introduction to the special issue. doi: https://doi.org/10.1080/1943815X.2020.1866617

Millennium Ecosystem Assessment (2005). Ecosystems and Human Well-being: Synthesis. *Island Press*, Washington, DC.

https://wedocs.unep.org/handle/20.500.11822/8701;jsessionid=779CD1EAE2596C88C0119B66FC547B7C

Miśkiewicz, J. Analysis of time series correlation. The choice of distance metrics and network structure. Acta Phys. Pol. A 2012, 121, B89–B94, doi:10.12693/APhysPolA.121.B-89.

Mohtar, R. H., Sharma, V. K., Daher, B., Laspidou, C., Kim, H., Pistikopoulos, E. N., ... & Najm, M. A. (2022). Opportunities and Challenges for Establishing a Resource Nexus Community of Science and Practice. *Frontiers in Environmental Science*, 613. doi: https://doi.org/10.3389/fenvs.2022.880754

Murrant, D.; Quinn, A.; Chapman, L. The water-energy nexus: future water resource availability and its implications on UK thermal power generation. Water Environ. J. 2015, 29, 307–319. doi: 10.12693/APhysPolA.121.B-89

Mpandeli, S., Naidoo, D., Mabhaudhi, T., Nhemachena, C., Nhamo, L., Liphadzi, S., ... & Modi, A. T. (2018). Climate change adaptation through the water-energy-food nexus in southern Africa. International journal of environmental research and public health, 15(10), 2306. doi: **https://doi.org/10.3390/ijerph15102306**

Mutanen, A.; Ruska, M.; Repo, S.; Jarventausta, P. Customer classification and load profiling method for distribution systems. IEEE Trans. Power Deliv.2011,26, 1755–1763. doi:10.1109/TPWRD.2011.2142198

Nilsson M, Griggs D, Visbeck M (2016) Map the interactions between sustainable development goals. Nature 534:320–322. doi: https://doi.org/10.1038/534320a

Nilsson, M., Griggs, D., & Visbeck, M. (2016). Policy: map the interactions between Sustainable Development Goals. *Nature*, *534*(7607), 320-322. https://doi.org/10.1038/534320a

Nyström, M., Jouffray, J. B., Norström, A. V., Crona, B., Søgaard Jørgensen, P.,Carpenter, S. R., et al. (2019). Anatomy and resilience of the global production ecosystem, Nature, 575, 98–108. doi:10.1038/s41586-019-1712-3

OECD/FAO (2016), OECD-FAO Guidance for Responsible Agricultural Supply Chains, OECD Publishing, Paris. http://dx.doi.org/10.1787/9789264251052-en.

Olsson, G. Water and energy nexus. Encycl. Sustain. Sci. Technol. 2011, 11932–11946.

Osoba, O., & Kosko, B. (2019). Beyond DAGs: modeling causal feedback with fuzzy cognitive maps. arXiv preprint arXiv:1906.11247. https://doi.org/10.1002/9781119485001.ch25

Papadopoulou, C. A., Papadopoulou, M. P., & Laspidou, C. (2022). Implementing Water-Energy-Land-Food-Climate Nexus Approach to Achieve the Sustainable Development Goals in Greece: Indicators and Policy Recommendations. *Sustainability*, *14*(7), 4100. doi: https://doi.org/10.3390/su14074100

Papadopoulou, C.A., Papadopoulou, M.P., Laspidou, C., Munaretto, S. and Brouwer, F. (2020). Towards a low-carbon economy: a nexus-oriented policy coherence analysis in Greece. Sustainability, 12(1), p.373. doi: **https://doi.org/10.3390/su12010373**

Papageorgiou, E.I. (2014). Fuzzy Cognitive Maps for Applied Sciences and Engineering From Fundamentals to Extensions and Learning Algorithms. *Intelligent Systems Reference Library*. Volume 54. DOI 10.1007/978-3-642-39739-4

Papageorgiou, E.I. (2013). Review Study on Fuzzy Cognitive Maps and Their Applications during the Last Decade. In: Glykas, M. (eds) Business Process Management. Studies in Computational Intelligence, vol 444. *Springer*, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-28409-0_11

Parker, J.M., Wilby, R.L. Quantifying Household Water Demand: A Review of Theory and Practice in the UK. Water Resour Manage 27, 981–1011 (2013). https://doi.org/10.1007/s11269-012-0190-2

Pereira, H.R.; Meschiatti, M.C.; Pires, R.C.D.M.; Blain, G.C. On the performance of three indices of agreement: An easy-to-user-code for calculating the Willmott indices.Bragantia2018,77, 394–403. doi: https://doi.org/10.1590/1678-4499.2017054

Pimm SL. 1984. The complexity and stability of ecosystems. Nature 307: 321–326. doi: https://doi.org/10.1038/307321a0

Plappally, A. K. (2012). Energy requirements for water production, treatment, end use, reclamation, and disposal. Renewable and Sustainable Energy Reviews, 16(7), 4818-4848. doi: https://doi.org/10.1016/j.rser.2012.05.022

Progress on Sanitation and Drinking Water: 2015 Update and MDG Assessment (WHO, UNICEP, 2015). Available at: https://apps.who.int/iris/handle/10665/177752

Puma, M. J. (2019). Resilience of the global food system, Nat. Sustain.2, 260–261.doi:10.1038/s41893-019-0274-6.

Ramos, E. P., Kofinas, D., Brouwer, F., Sundin, C., & Laspidou, C. S. Operationalizing the Nexus approach: insights from the SIM4NEXUS project. *Frontiers in Environmental Science*, 766. doi: https://doi.org/10.3389/fenvs.2022.787415

Randers, J. (1980). Guidelines for model conceptualization. Elements of the system dynamics method, 117, 139. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.albany.edu/faculty/gpr/PAD724/724WebArticles/RandersGuidelinesForConcept.pdf

Rasanen, T.; Voukantsis, D.; Niska, H.; Karatzas, K.; Kolehmainen, M. Data-based method for creating electricity use load profilesusing large amount of customer-specific hourly measured electricity use data.Appl. Energy2010,87, 3538–3545. doi:https://doi.org/10.1016/j.apenergy.2010.05.015

Robinson, C. (1998). Dynamical systems: stability, symbolic dynamics, and chaos. CRC press. Available at: https://www.scirp.org/(S(i43dyn45te-exjx455qlt3d2q))/reference/referencespapers.aspx?referenceid=441980

Robinson, S. (2004). Simulation: The Practice of Model Development and Use. Inglaterra: John Willey and Sons. Inc. Cap, 1(2), 5. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://lmsspada.kemdikbud.go.id/pluginfile.php/123916/mod_label/intro/simulation-the-practice-of-model-development-and-use.9780470847725.21800.pdf

Riehmann, P., Hanfler, M., & Froehlich, B. (2005, October). Interactive sankey diagrams. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005.* (pp. 233-240). IEEE. doi: 10.1109/INFVIS.2005.1532152.

Rizou, S.; Kenda, K.; Kofinas, D.; Mellios, N.; Pergar, P.; Ritsos, P.D.; Vardakas, J.; Kalaboukas, K.; Laspidou, C.; Senožetnik, M.; et al. Water4Cities: An ICT Platform Enabling Holistic Surface Water and Groundwater Management for Sustainable Cities.Proceedings 2018,2, 695. doi: **https://doi.org/10.3390/proceedings2110695**

Rodgers, J.L.; Nicewander, W.A. Thirteen ways to look at the correlation coefficient. Am. Stat. 1988, 42, 59–66. doi: https://doi.org/10.2307/2685263

Rodrigues, F.; Duarte, J.; Figueiredo, V.; Vale, Z.; Cordeiro, M. A comparative analysis of clustering algorithms applied to load profiling. In Proceedings of the International Workshop on Machine Learning and Data Mining in Pattern Recognition, Leipzig, Germany, 5–7 July 2003; Perner, P., Rosenfeld, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2003; pp. 73–85. doi: https://doi.org/10.1007/3-540-45065-3_7

RStudio Team. Available online: http://www.rstudio.com/ (accessed on 25 July 2020).

Sachs, J. D., Schmidt-Traub, G., Mazzucato, M., Messner, D., Nakicenovic, N., and Rockström, J. (2019). Six transformations to achieve the sustainable development goals, Nat. Sustain. 2, 805–814. doi:10.1038/s41893-019-0352-9.

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V.,et al. (2012). Anticipating critical transitions, Science, 338, 344–348. doi:10.1126/science.122524

Schnoor, J.L. Water-energy nexus. Environ. Sci. Technol. 2011, 45, 5065–5065. doi:10.1021/es2016632

Schutze, N.; Schmitz, G.H.; Petersohn, U. Self-organizing maps with multiple input—Output option for modeling the Richards equation and its inverse solution. Water Resour. Res.2005,41, W03022. doi: **https://doi.org/10.1029/2004WR003630**

Scott, C. A., Pierce, S. A., Pasqualetti, M. J., Jones, A. L., Montz, B. E., and Hoover,J. H. (2011). Policy and institutional dimensions of the water-energy nexus, Energy Policy, 39, 6622–6630. doi:10.1016/j.enpol.2011.08.013

Shahid, R.; Bertazzon, S.; Knudtson, M.L.; Ghali, W.A. Comparison of distance measures in spatial analytical modeling for health service planning. BMC Health Serv. Res. 2009, 9, 200, doi:10.1186/1472-6963-9-200.

Shanmuganathan, S.; Sallis, P.; Buckeridge, J. Self-organising map methods in integrated modelling of environmental andeconomic systems.Environ. Model. Softw.2006,21, 1247–1256. doi: https://doi.org/10.1016/j.envsoft.2005.04.011

Simpson G.B., Jewitt G.P.W., Becker W., Badenhorst J., Neves A.R. , Rovira P. and Pascual V. (2020). The Water-Energy-Food Nexus Index, Jones & Wagener <https://www.wefnexusindex.org> doi: 10.31219/osf.io/tdhw5.

Simula, O. and Kangas, J. 1995. Process monitoring and visualization using self-organizing maps, in: Neural Networks for Chemical Engineers, Computer-Aided Chemical Engineering, vol 6, Elsevier, Amsterdam. Available at: https://research.aalto.fi/en/publications/process-monitoring-and-visualization-using-self-organizing-maps

SETE, 2019. Basic Sizes of Greek Tourism. https://sete.gr/el/stratigiki-gia-ton-tourismo/vasika-megethi-tou-ellinikoy-tourismoy/ [Last date assessed: 8/11/2021]

Steffen, W., Rockstrom, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D.,et al. (2018). Trajectories of the earth system in the anthropocene. Proceedings of the National Academy of Sciences, 115(33), 8252-8259.Proc. doi:10.1073/pnas.1810141115.

Stein, C., Barron, J., Nigussie, L., Gedif, B., Amsalu, T., & Langan, S. J. (2014). Advancing the water-energy-food nexus: social networks and institutional interplay in the Blue Nile. *WLE Research for Development (R4D) Learning Series*. doi: 10.5337/2014.223

Stephan, R. M., Mohtar, R. H., Daher, B., Embid Irujo, A., Hillers, A., Ganter, J. C., Karlberg, L., Martin, L., Narizi, S., Rodriguez, D. J., & Sarni, W. (2018). Water–energy–food nexus: a platform for implementing the Sustainable Development Goals. Water International, 43(3), 472-479. doi: https://doi.org/10.1080/02508060.2018.1446581

Stringer, L. C., Quinn, C. H., Le, H. T. V., Msuya, F., Pezzuti, D. R., Dallimer, M., Afiomis, S., Berman, R., Orchard,. S. E., and Rijal, M. L. (2018). A New framework to enable equitable outcomes: resilience and Nexus approaches combined. Earths Future 6, 902–918. doi:10.1029/2017ef000694

Sukhwani, V., Shaw, R., Mitra, B. K., & Yan, W. (2019). Optimizing Food-Energy-Water (FEW) nexus to foster collective resilience in urban-rural systems. Progress in Disaster Science, 1, 100005. doi: https://doi.org/10.1016/j.pdisas.2019.100005

Tran, L.T.; Knight, C.G.; O'Neill, R.V.; Smith, E.R.; O'Connell, M. Self-organizing maps for integrated environmental assessmentof the Mid-Atlantic region. Environ. Manag.2003,31, 822–835. doi: https://doi.org/10.1007/s00267-003-2917-6

Turcinek, P.; Motycka, A. (2016) Exploring Consumer Behaviour by Classification Methods.J. Appl. Econ. Sci.,1, 148–151.

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., et al. (2003). A framework for vulnerability analysis insustainability science. Proc. Natl. Acad. Sci. U. S. A.100, 8074–8079. doi:10.1073/pnas.1231335100.

UNCTAD (2016). Development and globalization: facts and figures. UN Avalable at: http://stats.unctad.org/Dgff2016/partnership/goal17/target_17_14.html

UNDP. (2016). Human development report 2016—human development foreveryone, New York, NY: United Nations Development Programme. Available at: https://www.undp.org/publications/human-development-report-2016

UNFCCC, 2011. Compilation of information on nationally appropriate mitigation actions to be implemented by Parties not included in Annex I to the Convention. United Nations Framework Convention on Climate Change. Available at: http://unfccc.int/resource/docs/2011/awglca14/eng/inf01.pdf.

United Nations (2018). The Sustainable Development Goals Report. New York.

United Nations. World Population Prospects. In The 2015 Revision: Key Findings and Advance Tables; United Nations: New York, NY, USA, 2015; pp. 2–3. Available at: https://www.un.org/en/development/desa/publications/world-population-prospects-2015-revision.html

United Nations (UN) (2015). Transforming Our World: The 2030 Agenda for Sustainable Development. United Nations, New York. Available at https://sustainabledevelopment.un.org/post2015/transformingourworld/publication

UNSD (United Nations Sustainable Development). 1992. Agenda 21. United Nations Conference on Environment and Development, Rio de Janeiro, Brazil, 3 to 14 June 1992. Available at: https://sustainabledevelopment.un.org/content/documents/Agenda21.pdf

Vadivel, A.; Majumdar, A.K.; Sural, S. Performance comparison of distance metrics in content-based image retrieval applications. In Proceedings of International Conference on Information Technology (CIT), Bhubaneswar, India, 20–22 December 2003; pp. 159–164. Available at: https://www.researchgate.net/publication/308953711_Performance_comparison_of_distance_metrics_in_content-based_image_retrieval_applications

van Emmerik, T.H.M., Li, Z., Sivapalan, M., Pande, S., Kandasamy, J., Savenije, H.H.G.,et al., (2014). Socio-hydrologic modeling to understand and mediate the competition for water between agriculture development and environmental health: Murrumbidgee River basin, Australia. Hydrol. Earth Syst. Sci. 18 (10), 4239–4259. http://dx.doi.org/10.5194/hess-18-4239-2014.

Vesanto, J.; Alhoniemi, E. Clustering of the self-organizing map.IEEE Trans. Neural Netw.2000,11, 586–600. doi: 10.1109/72.846731

Vesanto, J. Data Exploration Process Based on the Self-Organizing Map. Ph.D. Thesis, Helsinki University of Technology, Espoo, Finland, 16 May 2002. Available at: https://aaltodoc.aalto.fi/handle/123456789/2178.

Vesanto, J., Himberg, J., Alhoniemi, E. Parhankangas, J. 1999, November. Self-organizing map in Matlab: the SOM Toolbox. In Proceedings of the Matlab DSP conference (Vol. 99, pp. 16-17). Available at: https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.97.179

Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., et al. (2020). Global threats to human water security and river biodiversity, Nature 467, 555–561. doi:10.1038/nature09440

Yang, A.; Zhang, H.; Stewart, R.A.; Nguyen, K. Enhancing Residential Water End Use Pattern Recognition Accuracy UsingSelf-Organizing Maps and K-

Means Clustering Techniques: Autoflow v3.1.Water2018,10, 1221. doi: **https://doi.org/10.3390/w10091221**

Yang, L.; Yang, S.H.; Magiera, E.; Froelich, W.; Jach, T.; Laspidou, C.S. Domestic water consumption monitoring and behaviour intervention by employing the internet of things technologies. Procedia Comput. Sci.2017,111, 367–375. doi: https://doi.org/10.1016/j.procs.2017.06.036

Yu, M., Wang, C., Liu, Y., Olsson, G., & Bai, H. (2018). Water and related electrical energy use in urban households—Influence of individual attributes in Beijing, China. *Resources, Conservation and Recycling*, *130*, 190-199.

Vesanto, J. SOM-based data visualization methods. Intell. Data Anal.1993,3, 111–126. doi: 10.3233/IDA-1999-3203

Wa'el A.H.; Memon, F.A.; Savic, D.A. An integrated model to evaluate water-energy-food nexus at a household scale. Environ. Model. Softw. 2017, 93, 366–380. doi: **http://doi.org/10.1016/j.envsoft.2017.03.034**

Walker B, Gunderson LH, Knizig A, Folke C, Carpenter S. 2006. A handful of heuristics and some propositions for understanding resilience in social-ecological systems. Ecology and Society 11(1): 13. doi: 10.5751/ES-01530-110113

Water World. Available online: https://www.waterworld.com/international/article/16209217/smart-water-meters-fornationwide-grid-in-malta (accessed on 18 September 2020).

Watts, N., Adger, W. N., Ayeb-Karlsson, S., Bai, Y., Byass, P., Campbell-Lendrum, D., ... & Costello, A. (2017). The Lancet Countdown: tracking progress on health and climate change. *The Lancet*, *389*(10074), 1151-1164. doi: https://doi.org/10.1016/S01406736(16)32124-9

WEF. (2011). Water security: the water–food–energy–climate nexus. Washington DC: World Economic Forum. Available at: https://www.weforum.org/reports/water-security-water-energy-food-climate-nexus/

WFP. Hunger statistics. https://www.wfp.org/hunger/stats (2016).

Weitz, N., Carlsen, H., Nilsson, M., & Skånberg, K. (2018). Towards systemic and contextual priority setting for implementing the 2030 Agenda. *Sustainability science*, *13*(2), 531-548. doi:10.1007/s10784-016-9321-1

Weitz, N., Strambo, C., Kemp-Benedict, E. and Nilsson, M. (2017). Closing the governance gaps in the water-energy-food nexus: Insights from integrative governance. *Global Environmental Change* 45, 165–73.

World Bank (2013). World development report 2014: risk and opportunity—managing risk for development. Washington, DC: World Bank. Available at: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/273251468336570194/world-development-report-2014-risk-and-opportunity-managing-risk-for-development-overview

World Energy Outlook 2015 (International Energy Agency (IEA), 2015). Available at: https://www.iea.org/reports/world-energy-outlook-2015

WSSD (World Summit on Sustainable Development). 2002. Plan of Implementation of the World Summit on Sustainable Development. Adopted at WSSD, Johannesburg, South Africa, 26 August-4 September 2002.
http://www.un.org/esa/sustdev/documents/WSSD_POI_PD/English/WSSD_PlanImpl

WWAP (United Nations World Water Assessment Programme). (2016). The United NationsWorld Water Development Report 2016: Water and Jobs. Paris, UNESCO. Available at: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.unescap.org/sites/default/files/2016%20UN%20World%20Water%20Development%20Report-%20Water%20and%20Jobs.pdf

Zhang, J., Wang, S., Pradhan, P., Zhao, W., & Fu, B. (2022). Mapping the complexity of the food-energy-water nexus from the lens of Sustainable Development Goals in China. *Resources, Conservation and Recycling*, *183*, 106357. doi: https://doi.org/10.1016/j.resconrec.2022.106357

Ziliaskopoulos, K., and K. Papalamprou. (2022). A Bilevel Linear Programming Model for Developing a Subsidy Policy to Minimize the Environmental Impact of the Agricultural Sector. *Sustainability* 14, no. 13: 7651. https://doi.org/10.3390/su14137651

Ziogou, I.; Zachariadis, T. Quantifying the water–energy nexus in Greece. Int. J. Sustain. Energy 2017, 36,972–982. doi: https://doi.org/10.1080/14786451.2016.1138953