Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet

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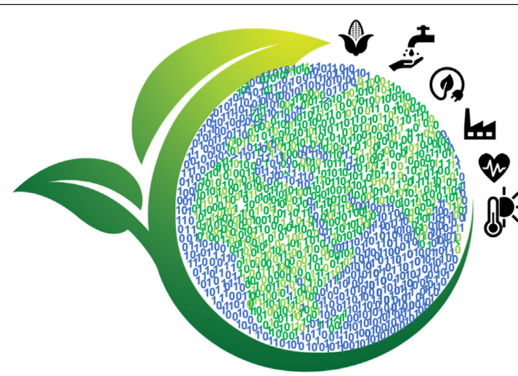
HIGHLIGHTS

- Sustainable development in years to come will capitalize greatly on digitalization.
- Internet of things as essential tool for sustainable food production and planet health
- Artificial intelligence can optimize energy production and water treatment.
- Smart technologies can provide equity access to services and increase wellbeing.
- Digitalization can guide actions to face climate change and protect biodiversity.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 25 April 2021
Received in revised form 14 June 2021
Accepted 15 June 2021
Available online 19 June 2021

ABSTRACT

Digitalization provides access to an integrated network of unexploited big data with potential benefits for society and the environment. The development of smart systems connected to the internet of things can generate unique opportunities to strategically address challenges associated with the United Nations Sustainable Development Goals (SDGs) to ensure an equitable, environmentally sustainable, and healthy society. This perspective describes the opportunities that digitalization can provide towards building the sustainable society of the future. Smart

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https://doi.org/10.1016/j.scitotenv.2021.148539

Keywords:
Digitalization
Food-water-energy nexus
Internet of things
Geographic information system (GIS)
Sustainable development

technologies are envisioned as game-changing tools, whereby their integration will benefit the three essential elements of the food-water-energy nexus: (i) sustainable food production; (ii) access to clean and safe potable water; and (iii) green energy generation and usage. It then discusses the benefits of digitalization to catalyze the transition towards sustainable manufacturing practices and enhance citizens' health wellbeing by providing digital access to care, particularly for the underserved communities. Finally, the perspective englobes digitalization benefits by providing a holistic view on how it can contribute to address the serious challenges of endangered planet biodiversity and climate change.

Contents

1. Introduction

The world is transitioning through the digitalization era in which most of our daily activities are highly dependent on innovative digital and computer technologies. These contemporary technologies have got their applications in socio-economic, environmental, sustainable, and climate research applications to enhance the productivity and efficiency of a given system (Balogun et al., 2020; Ceipek et al., 2020).

Digitalization is the integration of digital technologies into everyday life. Such integration is possible by the digitization of information. Digitization is defined as the process of converting physically collected information (e.g., sensors, written information, etc.) and knowledge into a computer-readable language. The tedious effort of digitizing information gathered over centuries (including paintings, images, and video formats) has given valuable fruits propelled by information technologies. The benefits resulting from digitalization contributed to the development of tools and sensors throughout integrated into the internet of things (IoT) environment. The IoT is a robust network of physical objects connected over internet through embedded sensors, software, and other technologies that enable interchange and collection of data. The convergence of simultaneously developed technologies for real-time analysis, machine learning, and artificial intelligence manages a massive amount of data, also known as big data. The high value of these massive data sets generated is not yet fully exploited but generates unique opportunities to catalyze the transition to more efficient and sustainable smart integrated cities.

Digitalization brings a new set of tools that have to be carefully balanced to ensure smart application and their green character. The capability of making well-informed decisions to use more efficiently resources and services has a significant impact on sustainability and equal access (Appio et al., 2021; Ardito et al., 2018), but several challenges cannot be overlooked to ensure successful achievement of these goals. Development and manufacturing of electronic devices are depleting limited resources and generating e-waste (unwanted electronic products, not working, and nearing or at the end of their "useful life") that is being hardly recycled (Ahirwar and Tripathi, 2021; Dhir et al., 2021). Considering life-cycle and developing e-waste recycling technologies is an urgent need. The necessity of better infrastructure is another challenge that may widen the gap between developed and developing regions instead of narrowing it. There is a need to ensure infrastructure and equal internet access to achieve the holistic goal of reducing inequalities and poverty, aligning with the need to provide digital education to the final users (Habibi and Zabardast, 2020; Lopez-Sintas et al., 2020; Matthess and Kunkel, 2020). Finally, data security is one of the major concerns on big-data sources' wide accessibility and openness. Data security is a sensitive topic that generates debate associated to safety risks and network integrity of these digitalized services (Craig, 2018; Reveron and Savage, 2020). These challenges have to be considered but should not have to be seen as barriers to digitalization's applicability to face sustainable challenges from an applied perspective.

The United Nations (UN) defined in 2015 a roadmap towards equity and sustainable development with a horizon set in 2030 (United

Nations, 2018). These so-called Sustainable Development Goals (SDGs) identify 17 existing challenges that should be overcome to reach this ambitious global goal: (1) No poverty, (2) Zero hunger, (3) Good health and wellbeing, (4) Quality education, (5) Gender equality, (6) Clean water and sanitation, (7) Affordable and clean energy, (8) Decent work and economic growth, (9) Industry, innovation and infrastructure, (10) Reduced inequalities, (11) Sustainable cities and communities, (12) Responsible consumption and production, (13) Climate action, (14) Life below water, (15) Life on land, (16) Peace, justice and strong institutions, and (17) Partnership for the goals. These interlinked SDGs present the urgent needs of our civilization to ensure a sustainable and competitive future. The creative development of digital tools to generate, use, transmit, or source electronic data for organizational activities can be used to achieve SDGs. These tools that contribute to achieving these specific targets could be defined as *digital sustainability*. Digital Sustainability is understood as the effort of developing and deploying smart technologies to secure sustainable economic growth while considering and integrating the SDGs. Modern digital innovations like artificial intelligence and machine learning techniques have seen exponential growth in their value, estimated to add around 14% to the global economy by 2030 (George et al., 2020; Magistretti et al., 2019). In this perspective, we explore how digitalization can pave the way towards sustainable development, which is essential to create a Smart Green Planet that provides resources while protecting the environment and health of all the planet's inhabitants. Fig. 1 summarizes which SDGs can specifically and holistically be addressed by the different sectors.

In this article, we explore how digitalization can assist in attaining SDGs in different sectors such as (i) food-water-energy nexus, (ii) industry, (iii) citizens' health and wellbeing, (iv) climate change and biodiversity protection. Fig. 2 summarizes the different sections of this perspective with emphasis on the specific aspects addressed for the different SDGs. Each big topic is framed to answer a holistic question regarding how digitalization can lead the change towards a more sustainable and balanced society for each challenge. We will specifically discuss digitalization tools implemented in specific areas with the direct aim to benefit said sector and to tackle said SDGs. Even though it is important to remark the tight correlations and interlinks between the different areas that become hard to differentiate. For example, effects resulting from the food-water-energy nexus directly impact the wellbeing of citizens of smart cities. Therefore, it is assessed and discussed how digitalization aids in sustaining the main pillars of our civilization in the food-water-energy nexus, the benefits of industrial manufacturing, and the relevance for human health and wellbeing. The perspective ends with a discussion centered on the benefits of digitalization to protect biodiversity and mitigate climate change.

2. Will digital technologies redefine the future of agriculture and food production systems?

The ever-growing global demand for food, feed, fiber, and clean energy increases pressure on the agroecosystems. Increased stress adversely affects agroecosystems' natural resilience, and it is expected to result in unprecedented environmental changes on a global scale (Okolo et al., 2019). Changing climatic conditions are accompanied by high and low heat stress, altered rainfall pattern, elevated carbon dioxide, increased frequency of extreme weather events like droughts, floods, cyclonic disturbances, and increased saline soils. These effects result in inflation of production costs, pest infestation and disease incidences which collectively add pressure on global agricultural land (Abhilash and Dubey, 2014; Lobell et al., 2012). Owing to the rising demand for food, the stressed supply chains, and diminishing soil carbon levels are depicting a daunting task for future generations to meet the nutritional requirements of 9.7 billion people by 2050. The advent of digital technologies within agriculture is a ray of hope on the horizon. Digital technologies are up-scaling the sustainable management of agricultural land and resources as well as strengthening the associated productivity, services, and livelihood security worldwide as summarized in Table 1. Crop variety, plot, and field-specific sustainable agricultural practices are being developed (Dubey et al., 2019; Okolo et al., 2019) and data generated from promising practices should be maintained and analyzed through digital technologies. Digitalization has made rapid strides within the agricultural sector, making its presence felt in varying dimensions such as land assessment, soil-crop suitability, weather information, crop-growth, biomass and productivity, precision farming, along with the various stages of the agriculture supply chain (processing, packaging, delivery, consumption, and agro-waste management). Digitalization adds multipurpose benefits to global agriculture via real-time monitoring, common fingertip-based smartphones and computers, and satellite and weather information-based consultation. These IoT technologies can alert and allow planning to deal with

Fig. 1. The role of digitalization addressing sustainability from different specific perspectives related to (i) the food-water-energy nexus, (ii) the industry and citizens' wellbeing, and (iii) the climate change and biodiversity protection. It is also considered the holistic, sustainable impacts resulting from the correlated benefits of all these actions.

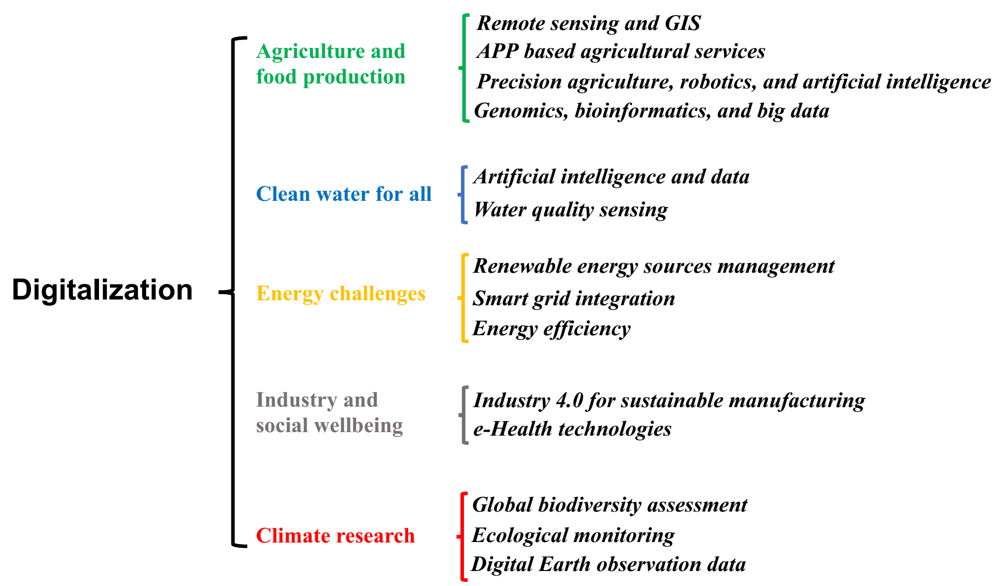

Fig. 2. Summary of the digitalization aspects related to each sustainable development goal addressed in this perspective.

upcoming challenges such as pest infestation and/or disease outbreaks. Digital technologies also help select high yield-oriented optimum practices, precise resource inputs, less production cost with the better nutritional quality of agricultural produces, geo-tagging for precise prophecy, vigorous and elastic farming methods, crop data management, post-harvest services, and agro-based industries. Various technologies like remote sensing, Geographic Information System (GIS), smartphone, robotics, artificial intelligence, genomics, bioinformatics and big data-based digital technologies are being utilized for attaining the target of agricultural sustainability (Basso and Antle, 2020) and the targets of United Nations SDGs (United Nations, 2018) (Fig. 3). Under digitalization, application of various hardware (sensors, ground robot, drones, nursery automation, robotics, robotics-based irrigation, precise fertilization at the base between densely grown crops, automated tractors for crop harvesting), software (geo-mapping, computer imaging technology), and their combination (micro-spraying robots for targeted herbicide application, automated weed uprooting and pruning robotics with computer imaging) are already being employed. Details and implications of the internet of agricultural things-based technologies are described in the following subsections that define promising opportunities enabled by digitalization.

2.1. Remote sensing and GIS-based technologies for sustainable management of agricultural land

Remote sensing (RS) and GIS techniques offer various solutions starting from crop species identification, farm and landscape-level sustainable management of farming systems, to policy formulation (Basso and Antle, 2020). Thus, increasing agri-productions, resource conservation, above-belowground biodiversity, gender equality, and farmers' empowerment opportunities could be achieved by integrating these modern digital tools. Integration of RS-GIS, Fuzzy-logic, and multicriteria assessment using the Analytical Hierarchy Process generate a superior database and a guide map for effective land-use patterns, crop variety, planning, monitoring of agroecosystem activities, and decision making with several examples summarized in Table 1. These integration techniques have quick and efficient access to a large amount of information, revealing relationships, patterns, and useful trends for combining soil survey information for better land-use suitability assessment (Singha and Swain, 2016). Research has demonstrated the benefits of implementing these techniques as a viable alternative for highly productive and stable agricultural systems over time. Smart integration of GIS-based technology promises better farming systems to production areas with enhanced resilience while mitigating climate change. For instance, GIS-remote sensing tools have been utilized in citrus orchards in China where digital mapping and modeling-based knowledge of area topography, land-use, soil types, climatic conditions, and altitude predicted the suitable area for citrus cropping and their sustainable management from field to end-users (Wu et al., 2011). The RS data helps decipher the spatiotemporal characteristics of the land exceptionally, including the impact of the environment on the growth of crops. According to Al-Gaadi et al., the GIS-RS technology and models (Normalized Difference Vegetation Index, Spectral Reflectance, Fraction of Absorbed Photosynthetically Active Radiation, LandSAT Enhanced Thematic Mapper, Environmental Policy Integrated Climate models, Terra Moderate Resolution Imaging Spectroradiometer) have been explored for improving the sustainability of potato production (Al-Gaadi et al., 2016). The use of advanced multispectral images in RS was highlighted as an effective monitoring tool for determining vegetation dynamics, plant health, and predicting crop yield under different practices (Al-Gaadi et al., 2016). Hence, decisions related to quantitative export and import of the product within the region could be made assuredly to strengthen the net economic benefits to the farming community. Through GIS-RS-based technologies, farm operators are provided with precision maps, information on crops, estimation of fields, and soil characteristics, which are beneficial for producers of the government, as they can provide the necessary projects to support the farmers. Besides, these systems provide better information on climatic parameters for the development of heat and drought-resilient crop varieties via different breeding approaches (Faloon et al., 2015). Also, GIS-RS equipped with Revised Universal Soil Loss Equation models helped explain the susceptibility to severe soil erosion in Syria with a soil loss of more than 109 tons ha^{-1} yr^{-1} by generating a map for soil degradation (Abdo and Salloum, 2017). Around 104–627 kg ha^{-1} plastic materials including synthetic polymers, are being used in agriculture in varied processes like mulching, hail protection, crop protection, shading nets and in irrigation support. Sustainable management of land and crops along-with soil biodiversity sustenance requires the regular removal of these polymers. Here again, readily updatable GIS-based databases and maps have been used to identify the extent of plastic in farms, delineate the place for plastic collection and develop a monitoring and decision-making system for the identification and collection followed by their proper delivery to the recycling companies (Blanco et al., 2018). The involvement of geoinformatics and decision support

Table 1
Application of digital technologies in providing the sustainable solutions to different agricultural problems under different crop type grown across the globe.

Digital technologies	Region of study	Crop spices	Solutions to agricultural problems/key benefits	References
Smart drone based imagery combined with artificial intelligence and deep learning algorithm in Nvidia Tegra SoC	India	Coconut	Pest and disease detection and management	(Chandy, 2019)
IoT (Internet of Things) smart sensors with micro-sprinklers, telemetric autonomous stations for field real time monitoring and data collection	Cyprus	Potato	Eco-friendly, improved farm use efficiency, socioeconomic condition of farmers and pest detection with reduced pest infestations	(Adamides et al., 2020)
Advanced IoT technologies	Greece	Multiple crops	Automated insect surveillance and traps system connected with networks for reporting data at local-global scales	(Potamitis et al., 2017)
Wireless sensor network	India	Apple	Apple disease, micro-climatic monitoring and forecasting systems	(Nabi et al., 2020)
IoT and agricultural unmanned aerial vehicles (UAVs) and wireless sensor networks (WSN)	Global	Multiple crops	Improved irrigation, fertilization, pesticides use efficiency, pest-disease and weed management, plant growth monitoring, and field-level phenotyping	(Boursianis et al., 2020)
Object-based image analysis (OBIA) algorithm combined UAVs and Digital Surface Models (DSMs)	Spain	Cotton	Plant height monitoring, weed detection and herbicide management	(de Castro et al., 2018)
Precision crop monitoring with IoT with smart agri-sensors	India	Okra	Field soil parameters, pests, disease, and nutrient deficiencies monitoring	(Choudhury et al., 2019)
Genome sequencing technologies, quantitative trait loci, gene mapping, genome database development	Global	Wheat, barley, rye and oat	Improvement of plant growth and yield related traits	(Blake et al., 2019)
Genome assisted breeding, high throughput genomics, phenomics, combined with simulation modeling	Global	Range of the legumes	Production of high quality seeds, improved plant stress tolerance, soil health, crop productivity and grain nutritional quality	(Varshney et al., 2018)
Photonics-based plant phenotyping technologies		Rice, wheat and barley	Pest and disease tolerant crop with improved yield and nutritional quality	(Yang et al., 2013)
Deep CNNs combined with UAVs and RGB based imagery	Finland	Wheat and barley	Crop yield monitoring	(Nevavuori et al., 2019)
RS-GIS, Fuzzy-logic, and the multicriteria assessment using Analytical Hierarchy Process	Greece, Iran, Nigeria, Turkey, India, Italy, etc.	Multiple crops	Guide map cum decision making for effective land-use pattern and suitability assessment, crop variety selection, farm activities monitoring	(Singha and Swain, 2016)
GIS-RS (Remote Sensing)	China	Citrus orchards	Knowledge of field area topography, land-use, soil types, climatic conditions, altitude and suitability for sustainable citrus cropping	(Wu et al., 2011)
GIS-RS technology and models (NDVI, Spectral Reflectance, FAPAR, LandSAT, EPIC, SAVI, TerraMODIS)	Saudi Arabia	Potato	Monitoring tool for determining the vegetation dynamics, crop health, and yield	(Al-Gaadi et al., 2016)
GIS-RS-based technologies	Global	Multiple crops	Provide climatic data for the development of breeding based heat and drought-resilient crops	(Faloon et al., 2015)
GIS-RS equipped with Revised Universal Soil Loss Equation models	Syria	Marqya river basin	Predict susceptibility to soil erosion by generating a map for soil degradation	(Abdo and Salloum, 2017)
GIS-based databases and maps	Italy	Multiple crops	Monitoring and decision-making system of agro-plastic waste and recycling	(Blanco et al., 2018)
Food and Agriculture Organization's CROPWAT 8.0 application	Ethiopia	Barley and wheat	Crop-yield estimation model (CROWRAYEM) to evaluate the water requirements	(Eze et al., 2020)
Digital agriculture using ICT based approach: GeoFarmer	East and West Africa and Latin America	Multiple crops	Geographical area specific cheaper ICT-based platform to monitor agricultural production with interactive feedback between the users	(Eitzinger et al., 2019)

systems in precision irrigation plays a significant role in sustainable water management and is crucial for those countries where water is a scarce or highly limited resource and in arid and semi-arid areas. However, this technique requires combining large sets of precise and highly accurate data about land characteristics and water resources. Factors such as the high cost of maintenance and calibration of the sensors make its implementation tiresome, especially in developing countries. Although these technologies are still a challenge for many countries, the availability of open-source geospatial platforms like QGIS and R open up new possibilities for their application in low-income systems. Active stakeholder engagement is further required to highlight the accessibility and feasibility of such GIS software to the rest of the farming community and supply chain members. The world is in an era where online information is becoming more prosperous, with multiple applications for phones, computers, and other devices being launched. Scientific interventions can further boost the integration of emerging digital technologies within agricultural practices, offering several opportunities to significantly improve the social, economic and environmental sustainability of food production systems.

2.2. APP based agricultural services and climate-smart agriculture

Globally, agricultural transformation is proceeding rapidly, with Information Communications Technology (ICT) and digitization being the central players behind this novel transformation. The use of mobile application software by almost all agricultural stakeholders enhances resource use efficiency and equally helps reduce costs associated with production while simultaneously increasing yields and net economic return (Qiang et al., 2011) with several examples collected in Table 1. The use of mobile-based apps by farming, scientific and technical professionals is enabling information access related to climate-smart agricultural (CSA) practices. The integration of digitalized access is assists in decision-making during production and subsequent stages of the supply chain. According to Global System for Mobile Communications Association real-time intelligence data, more than 5.2 billion people (~68% of the world's population) have access to mobile devices worldwide. Globally, the current cellular phone users surpass 3 billion, projected to grow by several hundred million in the next few years. The effectiveness of mobile phones/Apps and

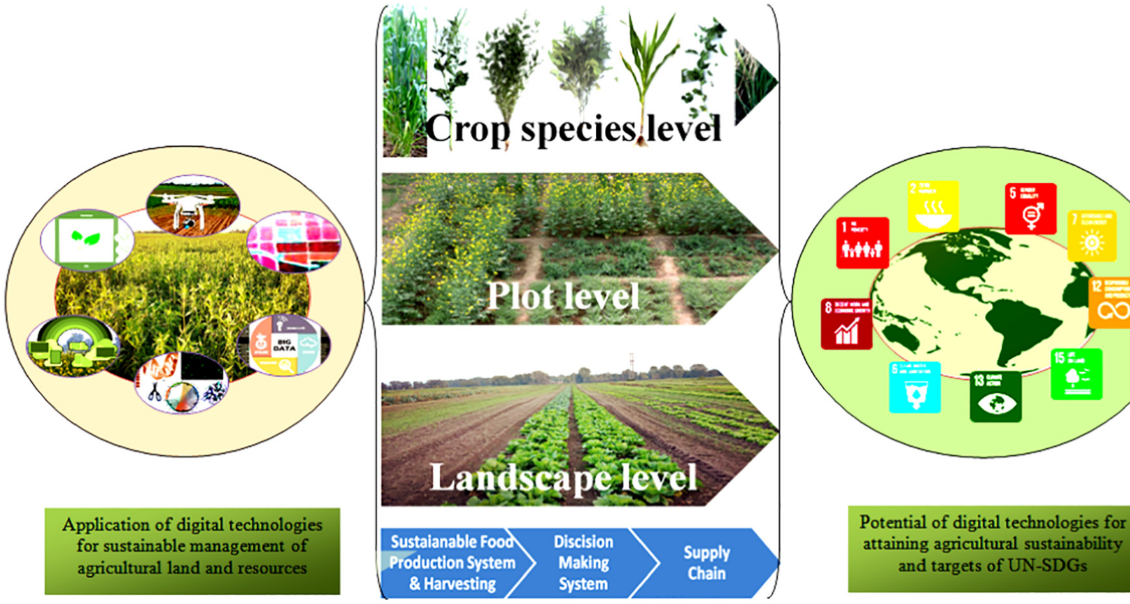

Fig. 3. Framework of digital technologies and their efficacies for improving the global agricultural sustainability, healthy food, people, and planet that help achieve the target of United Nations Sustainable Development Goals (UN-SDGs).

their implication in disseminating agricultural information to farmers have been validated (Mittal and Mehar, 2016). However, the use of ICT in agriculture does not always lead to higher yields and profits for every farmer (Eitzinger et al., 2019). Thus, despite the positive results of mobile applications in improving smallholder agriculture (Tata and McNamara, 2018), many farmers are still left in the "dark" owing to lack of technology access, especially in rural communities of developing countries (Eitzinger et al., 2019). Notably, vital impediments that hinder digitalization in agriculture (i.e., use of mobile phone/Apps and ICT), especially among smallholder farmers in a rural context, include lack of connectivity, missing digital capability, poor usability of ICT applications, and digital illiteracy (Eitzinger et al., 2019; Mittal and Mehar, 2016). Failure to address these shortcomings will eventually lead to farmers facing a new era of digital poverty. More importantly, recognition of the local context of connectivity, user's capacities, synchronization with local dialects, and socio-cultural backgrounds should be focused upon as the new ICT cutting-edge initiatives with the potential to avoid the impending digital poverty among smallholder farmers (Aker et al., 2016; Eitzinger et al., 2019).

Rising agricultural production, food security, and livelihood of millions of people across the globe are being threatened by climate change. Agriculture is a significant contributor to greenhouse gases (GHGs) emissions and global warming (Gebresamuel et al., 2021). Digital technologies-based climate-smart agriculture (CSA) practices that integrated the benefits of sustainable production, climate resilience, and reduced GHGs emissions appear to be very promising and offer a potential solution to existing problems (Abegunde et al., 2020). However, despite the various benefits of CSA technologies, farmers' current adoption rate is relatively low. Factors such as the socio-economic characteristics of farmers, the biophysical environment of a particular location, and the attributes of new technologies influence the adoption of CSA technologies (Bu and Wang, 2019; Deressa et al., 2011). Food systems must undergo significant digital transformation to meet the ever-growing challenges of food security and climate change. From a sustainability perspective, adoption of APP-based agricultural services with location-specific CSA practices could be the major driver of cleaner and greener agriculture, which is also an agenda for global sustainable development.

2.3. Precision agriculture, robotics, and artificial intelligence

Precision agriculture is a farming practice undertaken at an accurate place under specific timing rather than uniform adoption across the field. Lesser ecological risks, higher crop yield (reduced global hunger), and economic gains (reduced poverty) to the farming communities are the fundamental attributes of precision agriculture. Precision agriculture employs robotics, artificial intelligence, and deep learning processes for the next generation and is climate-smart sustainable agriculture practice. Modern unmanned aerial vehicles (UAVs) or drones enabled for providing hyper-class remote-sensing spatiotemporal and spectral records can solve the multifarious problems associated with agroecosystems, farming community and strengthen the path of precision agriculture. The UAVs contain various sensors for predicting the real-time information on drought, soil nutrient, plant growth, yield, disease, pesticide and weed, pest, weather parameters, soil type, moisture content, and spray pesticide and fertilizer (Maes and Steppe, 2019; Vasconez et al., 2019). Thermal imagery, combined thermal with hyper-spectral data, entity-based imaging, and UAVs models could be the better technologies for revealing the drought stress, pathogen, weed, nutrient status, and yield. Artificial intelligence has also proven to improve the impact of precision agriculture. For instance, integration of advanced artificial intelligence models, deep reinforcement learning, information, and cloud technology has the potential to conserve critical agricultural resources while enhancing food production and sustainability (Bu and Wang, 2019). The national governing bodies also adopt the advents of these integrated technologies for the betterment of advisory and data availability to the farming community (http://agricoop.nic.in). In another research, artificial intelligence developed several expert systems for the cotton plant such as COMAX (Cotton Management eXpert) and COTFLEX that provide decision-making information to farmers.

Similarly, SOYGRO and PRITHVI expert system provides information regarding insect attacks and pesticides used for the soybean crop (Jha et al., 2019). Artificial intelligence enabled machine learning technologies and the internet of agricultural things. Wireless communications are increasing the farm knowledge system and decision making for better management of agriculture. Additionally, precision agriculture is growing faster because of rapid research and development of cheaper sensors, better control, and computer imaging systems with evolving artificial intelligence. Consequently, a myriad of semi and autonomous, unmanned ground vehicles or ground robotics are being successfully applied in seedbed grounding, irrigation, spraying, pruning, harvesting, real-time monitoring, and mapping for saving resources, finances, and the environment (Vasconez et al., 2019). In precision agriculture, data expressed in the form of different names such as Digital Farming, Agriculture 5.0 and Smart Farming enhances the accuracy of farm operation and helps in making critical operational decisions. For example, remote sensing technologies such as American Landsat satellites, European Sentinel 2 satellite system, Indian Remote Sensing (IRS) satellites, RapidEye constellation, GeoEye-1 system, WorldView series, and IKONOS provide agricultural information that helps in sustainable planning and management of agriculture. Some other examples of robotic technology such as Vinbot, VineRobot, VineScout, and GRAPE have crop sensing devices and afford multi-season ground-truth justification of vineyards. Furthermore, Naïo Technologies and RowBot Systems LLC are interesting robotics platforms. The first is associated with mechanical weeding, and the latter is used for selective application of fertilizer, mapping crop growth, and other field related tasks. The field-level geographic Information System (FIS) provides satisfactory information for implementation, operational planning, and documentation for the management of farming systems (Saiz-Rubio and Rovira-Más, 2020).

2.4. Role of genomics, bioinformatics, and big data in sustainable food productions

Previously, genomics, bioinformatics, and big data were inclined to explore the elementary processes of the life and biological sciences. However, nowadays, digital technologies-based omics and data science are performing far better in agri-sciences for improving the crop yield, nutritional quality, stress tolerance, and combating the negative impact of climate change. Global projections demonstrate that a one-degree upsurge in global average temperature could reduce the crop-yield of maize, wheat, rice, and soybean by 7.4, 6, 3.2, and 3.1%, respectively (Zhao et al., 2017). Therefore, extensive knowledge of crop genomics is essential to develop climate-smart, resource-efficient and high-yielding crop varieties. Furthermore, multiple draft genomes are being assembled for various cereals (*Oryza sativa*, *Setaria italic*, *Sorghum bicolor*, *Triticum aestivum*, *Zea mays*), legumes (*Cicer arietinum*, *Cajanus cajan*, *Glycine* max, *Phaseolus vulgaris*, *Vigna radiata*), oilseeds (*Brassica napus*, *Camelina sativa*, *Elaeis guineensis*, *Ricinus communis*), vegetables (*Brassica oleracea*, *Brassica rapa*, *Carica papaya*, *Capsicum annum*, *Cucumis sativus*, *Solanum lycopersicum*, *Solanum melongena*, *Solanum tuberosum*) and fruits (*Citrullus lanatus*, *Citrus clementina*, *Citrus sinensis*, *Cucumis melo*, *Fragaria vesca*, *Musa acuminate*, *Phoenix dactylifera*, *Prunus mume*, *Pyrus bretschneideri*, *Vitis vinifera*) (Thottathil et al., 2016) as well as for their wild crop relatives (Chang et al., 2019) and based on their identified genomic traits various crop varieties can be developed with desired traits. Vast volumes of data gathered from the genomics mentioned above, proteomics, and metabolomics are managed through various bioinformatics-based tools and databases that ultimately store all information through computing and cloud technology. Bioinformatics tools are computer-based information technology that decodes the enormous digital data in agricultural sciences. Examples of dedicated databases for improving the crop traits are Integrated Breeding (https://www.integratedbreeding.net/), Wheat Barely and Oat Germplasm (https://triticeaetoolbox.org), Wheat Information System (http://wheatis.org/), Wheat Genome Information (http://www.wheatgenome.info), Rice-Informatics (http://iric.irri.org/), Rice Genome Data (http://rice.plantbiology.msu.edu/), Oryzabase (http://www.shigen.nig.ac.jp/rice/oryzabase/), Rice Genome Annotation Project (http://rice.plantbiology.msu.edu/), Oil-seed Proteomics (http://www.oilseedproteomics.missouri.edu/), Maize Genome Database (http://www.maizegdb.org/), and the International Crop Information System (ICIS) (http://www.icis.cgiar.org), among others. As evident application of genomics, bioinformatics, and big data play a crucial role in improving the crop agronomic traits such as abiotic stress tolerance, insect resistance, herbicide tolerance, higher grain yield, plant height, and weight and crop nutrient content of the crops, which in turn helps in maintaining the food and nutritional security (Batley and Edwards, 2016). Varshney et al. (2020) have proposed 5Gs crop breeding approaches consisting of a crop-specific gene assembly followed by genome and agronomic trait-based characterization of germplasm, gene identification combined with functional annotation, genomic breeding, and gene editing for improving climate-resilient high yielding, nutrient-rich crop varieties. Moreover, in precision genome editing technology, CRISPR-Cas9 helps develop the disease, drought, and herbicide tolerant crops with better plant defense against the virus, bioactive compound production, crop yield, and nutritional quality. In integration, CRISPR-Cas9 with multiple targeting sgRNAs serves as an appropriate genome editing tool that increases nutrient content in wheat, maize, rice, tomato, and sweet orange. The aforesaid mentioned integrated technology had been proven to combat the bean yellow dwarf virus (BeYDV), tomato yellow leaf curl virus (TYLCV), and Beet Severe Curly Top geminivirus (BSCTV) infection by editing the viral genome. Using CRISPR-Cas9 can cause a mutation in TaMLO-A1 and TaMLO-B1 gene of wheat, OsERF922 gene of rice and SIDMR6–1 gene of tomato, increasing the resistance against the powdery mildew, rice blast and *Xanthomonas spp*. in wheat, rice, and tomato, respectively. Similarly, CRISPER based genome editing tool has modified the ARGOS8 gene locus in maize for enhancing the grain yield even under drought stress. Moreover, the mutation in acetolactate synthase genes ALS1 and ALS2 have increased the resistance against chlorsulfuron herbicides in maize (Eş et al., 2019).

These examples highlight the application of information, computing, and cloud-based digital technologies in digging and improving the crop genomic traits for agricultural sustainability. Besides, various computational algorithm-based agricultural system modeling approaches are also being utilized extensively for sustainable land management. These models provide a robust prediction approach for crop yield, soil nutrient cycling, resource use efficiency, GHGs emission, ecosystem services, pest and disease mediated damage, food security, livestock production, agroecosystems responses to global climate change and policy assessment (Holzworth et al., 2015; Jones et al., 2017) across the various global agro-ecological zones and socioeconomic conditions. Further decision-making systems use the knowledge of such models and other computer-based algorithms for enhancing the sustainability of agro-practices at plot, field, agroecosystems, landscape, national, and global scale.

In addition to genomics and bioinformatics, information, and communication technology uses various massive, heterogeneous, and unstructured data (also known as big data) through the internet and cloud computing. These provide insight into the decision-making aspects of the smart farming system. Computational scripts allow us to analyze such big data in an integrated manner to optimize agricultural productivity and food supply chains. There are multiple robotics systems with heterogeneous nature of data in a single smart farming practice. These data now became accessible to the users through Application Programming Interfaces (APIs) technology.

Similarly, technology and data start-ups-based different datasets can be combined through open standards (e.g., ISOBUS). Farmobile, a recently introduced hardware (passive-uplink communicator) can record all data from robotics; store it in the database, and transmit the data using a wireless system. Another example of big data analysis can be achieved through Open Ag Toolkit (OpenATK) that provides farm management information via cheaper, readily accessible, user-friendly mobiles and stores data on the cloud. Likewise, in Europe, the FIWARE GEs application helps in big data analysis utilizing cloud technology, data collection, and secured information technology that opens up multiple options to identify socio-economic challenges and provide real-time operational decisions, thereby reducing the economic risks involved in the sustainable farming system (Wolfert et al., 2017).

However, although all previously mentioned digital technologies are rapidly gaining influx and witnessing an upsurge in usage within developed nations, they are yet to gain ground within developing countries and could prove crucial in achieving the agriculture related targets of the various SDGs (no poverty; SDG1, zero hunger; SDG2, good health and wellbeing; SDG3, clean water and sanitation; SDG6, industry innovation and infrastructure; SDG9, sustainable cities and communities; SDG11 responsible consumption and productions; SDG 12, climate action; SDG13, life below water; SDG 14, life on land; SDG 15, etc. for global sustainable development) (Dubey et al., 2020; Moomen et al., 2019).

3. Can digitalization catalyze strategies to ensure clean water for all?

3.1. Artificial intelligence and data mining-assisted approaches for optimal design and control of water treatment systems

Water treatment systems (WTSs), such as wastewater treatment plants (WWTPs), drinking water treatment plants (DWTPs), and desalination plants, are complex systems that integrate different processes to remove pollutants, impurities, and salts from target water bodies (Asadi et al., 2017; Heck et al., 2019; Ming-Yang, 2013). The traditional design of WTSs relies on expert knowledge of different treatment processes and cannot be efficiently generalized. Generalization has lead to oversized designs of treatment units and improper selection of treatment processes, which increases capital expenditures and influences the final product water quality. Conventional operation of WTSs employs instrumentation, control, and automation (ICA) techniques, but sometimes fault signals from instruments without regular maintenance may lead to failure responses to the system's control (Qiu et al., 2018). Most of central control systems in WTSs are only capable of acquiring data rather than processing data to guide subsequent actions due to the workforce lacking knowledge in data science (Newhart et al., 2019). The underutilization of the big data in WTSs would lead to the unnecessary increase in operating costs and sometimes inefficient treatment. In recent years, artificial intelligence (AI) technologies have been increasingly applied to translate the passive data into actionable knowledge to improve the WTSs operation and support decision-making (Al Aani et al., 2019; Corominas et al., 2018; Haimi et al., 2013; Li et al., 2021).

The use of the AI approach to optimize the design and control of water treatment systems can be dated back to three decades ago (Krovvidy et al., 1991; Zvi, 1992). An early review outlined the difficulties of the expert system approach, which is based on advanced mathematical techniques and was prevalently used for operational control of WWTP in the early days, in acquiring and representing knowledge of the complex phenomena (Zvi, 1992). It highlighted the advantages of AI techniques particularly the artificial neural networks (ANN) in water and wastewater plant modeling, expert rule extraction, fault detection and diagnosis, plant and instrument monitoring, dynamic forecasting, and robust control (Zvi, 1992). One of the earliest studies using the AI approach to design a water treatment system proposed two phases: the analysis and synthesis phases (Krovvidy et al., 1991). In the analysis phase, an inductive learning algorithm and expert rules are arranged together to evaluate the treatment efficiency of several compounds at different concentrations by an individual treatment process. In the synthesis phase, the sequence of different treatment processes satisfying the treatment targets are obtained using the knowledge rules generated from the analysis phase via the neural network method. This study laid a foundation for the later decision support system (DSS) development to select and sequence water treatment processes, and design treatment facilities (Hamouda et al., 2009). Fig. 4 shows the typical four-stage DSS for WTSs design involving AI techniques, including water treatment problem analysis and interpretation, developing reasoning models, process sequential decision optimization, validating DSS logic, and enhancing user interactivity (Hamouda et al., 2009). In a recent study, the optimization of WWTPs design was realized via the data mining and AI techniques such as artificial neural network and fuzzy logic, following an integral procedure including data collection and cleaning, data warehouse, data mining, and web user interface (Qiu et al., 2018).

Apart from the design of the WTSs, the optimal control and operation of the WTSs are equally important to maximize technical benefits and cost savings. During the treatment processes, vast volumes of data are generated and some are monitored online and collected simultaneously via various sensing technologies. Data-mining techniques are incorporated into sensing techniques to verify process normalcy and create knowledge on plant malfunctioning (Corominas et al., 2018; Haimi et al., 2013). Advanced information extraction and Human-interpretable information extraction based on AI and data-mining techniques are further developed to transform the data into useful information and knowledge for the effective control and optimization of operation of WTSs (Corominas et al., 2018). Newhart et al. summarized the data-driven technologies used in WWTPs for the purpose of fault detection, variable prediction, and advanced automated control to reduce energy consumption, ensure product water quality and prevent system failure (Fig. 5) (Newhart et al., 2019). Li et al. reviewed AI and machine learning for nonlinear relationship analysis and process control for DWTPs (Li et al., 2021). They specifically introduced the current status of these data-driven technologies in each treatment unit from source water quality monitoring and identification to the accurate and efficient control of each treatment unit, such as the control and prediction of coagulation dosage, the analysis of the formation of disinfection by-products, and the advanced control of membrane fouling. Some recent cases were reported on the use of machine learning to develop model soft-sensor for predictive control of WWTPs (Bernardelli et al., 2020; Hernández-del-Olmo et al., 2019). AI and machine learning techniques have also exhibited promise to revolutionize the automation of the desalination process, especially in the renewable energy-driven desalination processes (Al Aani et al., 2019). Cabrera et al. (Cabrera et al., 2018) compared three machine learning techniques, namely artificial neural networks (ANN), support vector machines (SVM), and random forests (RF), in predicting the wind-driven seawater desalination performance (Fig. 6). They found that (1) SVM and RF are significantly better to predict the plant's performances than neural networks, and (2) variable pressure and flow operating mode are more continuous than constant pressure and flow mode. Without focusing exclusively on either AI techniques or a conventional expert system approach, a recent study proposed a hybrid statistical machine learning method to improve the accuracy in predicting ammonia in municipal wastewater treatment (Newhart et al., 2020). This study provided a new perspective to develop new and rigorous treatment models by integrating conventional statistical methods and advanced AI methods.

Despite the promise of AI techniques for predictive and optimal control of WTSs, the utilization of these advanced data techniques is constrained by some conditions. For example, although the data do not need to be linearly correlated or parametrically distributed, those monitored variables must have a high sample frequency and number of historical observations (Newhart et al., 2019). Some challenges for using these advanced techniques are also identified, such as (1) difficulties in the acquisition of useful data in complex environment for screening and identifying targeted contaminants, and (2) challenges on the establishment of a macro intelligence model and decision scheme for entire treatment plants to support the overall management in the water supply system (Li et al., 2021).

3.2. Integration of water sensing to ensure water quality and protect public health

Water of drinking quality is a *fait accompli* that is being placed at stake due to increasing water quality violations (Dettori et al., 2019; "US Water Quality Wake-Up Call: Americans Report Increase in

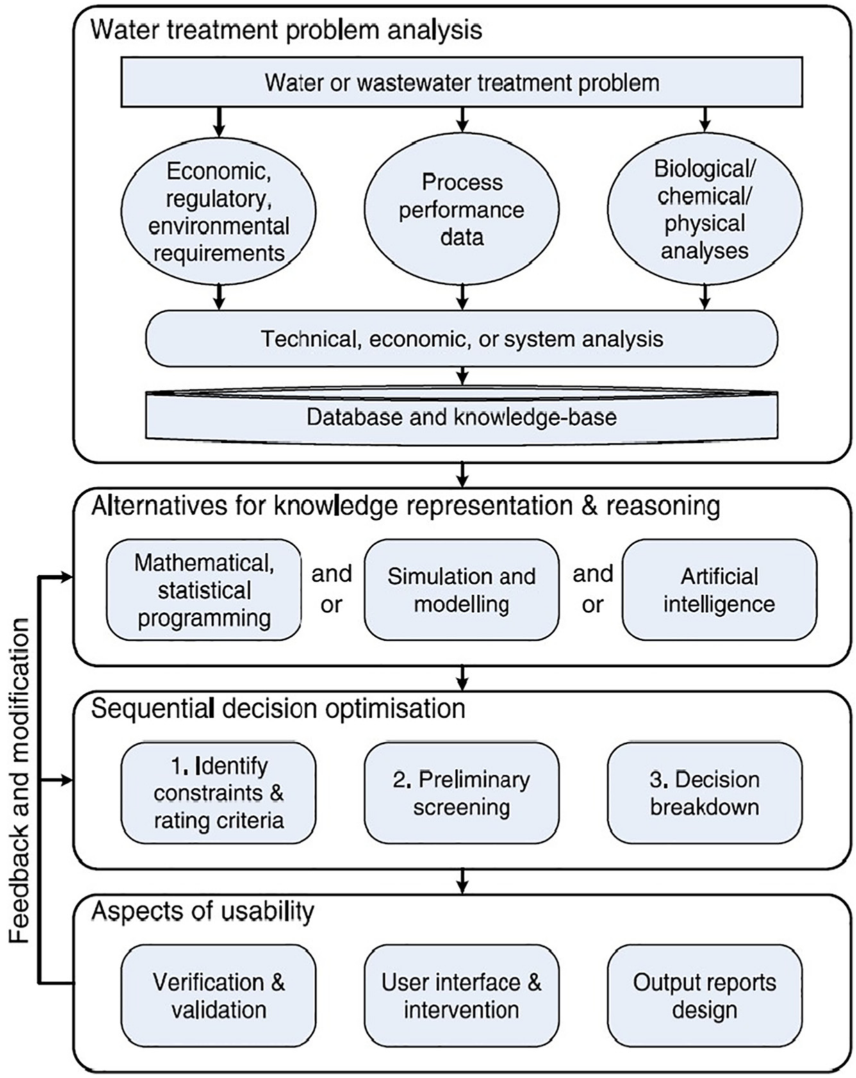

Fig. 4. Stages of developing a water treatment decision support system.
Figure adopted from (Hamouda et al., 2009).

Instances of Water Contamination," 2019). For instance, The American Society of Civil Engineers evaluated America's actual condition of water infrastructure with "D" grade (ASCE, 2017). However, water quality violations are an endemic problem worldwide that becomes more concerning in developing areas. Recent examples of significant quality violations are the Flint water crisis (i.e., lead contamination from aging pipes) (Morckel, 2017), the pressing problems associated with *per*- and polyfluoroalkyl substances (PFASs) in water (Sima and Jaffé, 2021), the high arsenic levels in drinking water sources (Gifford et al., 2018; Rahman et al., 2018), cyanotoxins blooms (Serrà et al., 2021), or water disinfection needs at point of use (Chu et al., 2019; Montenegro-Ayo et al., 2020). The variable water quality arises as a severe health threat for users. Smart cities of the future should warrant accessible water of the highest quality to all their citizens that meets maximum concentration levels defined by the World Health Organization.

Water is one of the pivotal components that will define the smart cities of the future. Smart water refers to the holistic approach to manage this resource, related infrastructure, treatment, and delivery (Wu et al., 2020). As cities invest in updating old-fashioned infrastructure, it is the possibility to integrate internet-enabled tools and emerging decentralized smart technologies (e.g., treatment at the point of delivery or point of use). Real-time water quality audits at critical control points can define when decentralized water treatment may be required to operate to ensure public health (Richard et al., 2020). Integrating such neural networks between information technology and modular on/off treatment systems can become a game-changer for ensuring access to water of drinking quality for all. There is an existing need to develop and deploy artificial intelligence systems that identify a water quality issue (e.g., high nitrate levels, bacteria presence, etc.) and activate immediate action for its remediation. Such Smart Actions will ensure sustainable and healthy environments in cities.

4. How can digitalization address energy challenges?

The energy sector faces several challenges that range from well-known old dilemmas, such as overcoming barriers for the grid integration of the ever-fluctuating renewable energy resources, adapting the offer to the demand, or increasing the efficiency of the energy processes in the industry, to facing new foreseeable issues, such as addressing the upcoming increasing energy demands derived from the spread of digitalization worldwide (Coroamă and Mattern, 2019), and the security issues that may be derived from an interconnected energy generation system (Ebrahimy et al., 2018).

Digitalization opens a broad range of exciting possibilities as in any technological revolution but brings, inevitably, a series of concerns. Digitalization is expected to increase the sustainability of our energy systems, spread electricity to remote areas, and improve

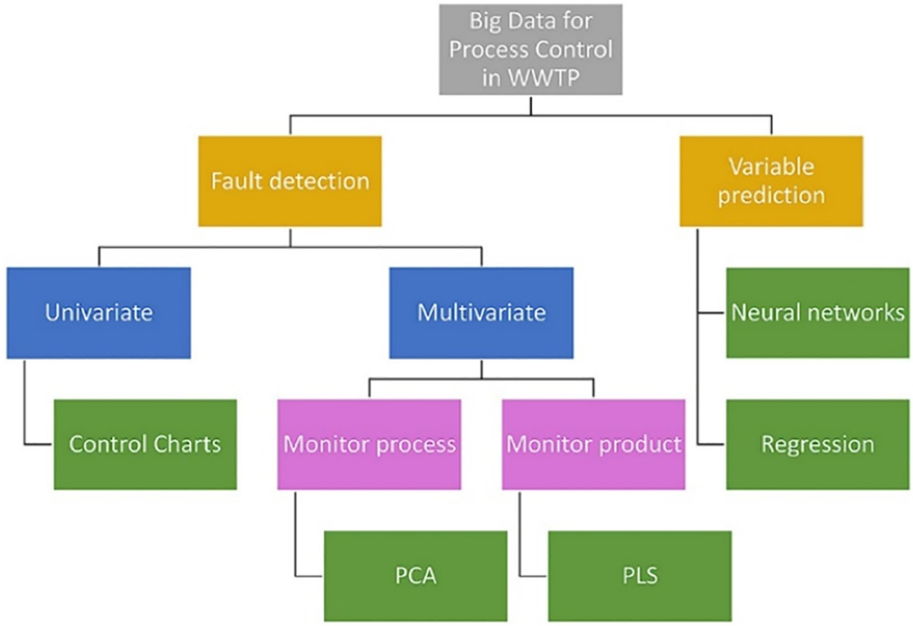

Fig. 5. The data-driven methods identified in green are examples of methods that have demonstrated good performance in WWTP for the purpose indicated by the tree diagram. PCA indicates principal component analysis; PLS indicates partial least squares
Figure adapted from (Newhart et al., 2019).

the way we use it. However, digitalization may also open the door to novel challenges for our energy systems, for which we need to be prepared. In the following sections, we discuss how digitalization will impact the sustainability of energy systems by addressing its role in the integration of renewable resources, its smart management in the complexity of our energy systems puzzles, its use to optimize energy in the ever-insatiable industrial sector, and the needs for storage systems that its use will bring, as an essential part to fulfill the former targets.

4.1. Renewable energy sources and distributed electricity generation

The conventional electricity grid is designed around centralized generation. As such, large power plants are used to generate electricity, typically powered by fossil fuels. Subsequently, the electricity is sent through the transmission lines to consumers, providing, essentially, a one-way flow of electricity in the grid. However, even in this situation, digitalization has been a key for a few years. For example, detailed modeling is performed daily to predict electricity demand based on weather conditions, climatology, or societal habits (i.e., when people come home from work to cook dinner, large events such as football matches, and even advertisement breaks which drive people towards their fridge). As such, and despite few events that may cause over-generation of electricity, supply and demand can be managed with high accuracy.

However, the introduction of scalable renewable energy technologies such as wind and solar have shaken up the system by introducing the concept of distributed energy generation. There are several potential benefits of distributed electricity generation. First, electricity can be generated close to where it is needed. This is particularly the case of rooftop solar photovoltaics (PV), where consumers can generate their own electricity or become electricity generators for other households. Second, it avoids the need to upgrade infrastructure by avoiding transmission losses. Furthermore, some distributed generation sources closely match the demand (e.g., solar with the demand for air-conditioning load on a hot summer day). As such, distributed generation can help reduce one of the biggest costs to electricity networks, which need to have transmission lines over-dimensioned to accommodate the highest demand of the year placed on the overall transmission system. Third, generation only needs to compete against the retail cost of electricity, not the wholesale cost, providing potential savings and investment opportunities for consumers.

Nevertheless, the use of distributed energy systems, intermittent in nature, requires further digitalization of existing systems to accurately model the contribution of individual electricity supplies into the grid, and their dynamics due, for instance, to changing weather conditions. Digitalization, including distributed generators modeling, projections of energy demand, and smart control for energy savings, is therefore needed to help ensure the grid's stability in terms of both voltage and frequency, which is disrupted by the asynchronous nature of the renewable energy systems. Hence, the transition to distributed energy systems that renewable resources bring will imply a more critical role of digitalization.

Moreover, consumers may benefit from increased digitalization of energy systems, as, for instance, the shift to smart digital meters can encourage them to avoid the use of electricity during peak times (Maglakelidze et al., 2019). Additionally, smart energy management can be used for intermittent electricity generation and supply in households, for example, choosing when to heat hot water (i.e., which can be seen as a thermal battery) instead of exporting excess electricity to the grid when it is not needed. Moreover, a grid-wide smart energy system can also decide when that surplus electricity is more valuable being transmitted through the grid for another purpose (e.g., charging electric vehicles or hydrogen generation). This enables the opportunity for peer-to-peer electricity trading, allowing electricity exchanges with neighboring consumers rather than selling it to the electricity provider. For large apartment buildings or micro-grids, this can effectively happen by having the main meter and sub-meters for each individual consumer so that the surplus electricity by one user can be exported to another user within the microgrid, and net surplus or deficits can be exchanged with the main electricity grid. This system may maximize energy savings to the expense of increasing the system and control complexity, for which digitalization of the measuring systems will be crucial.

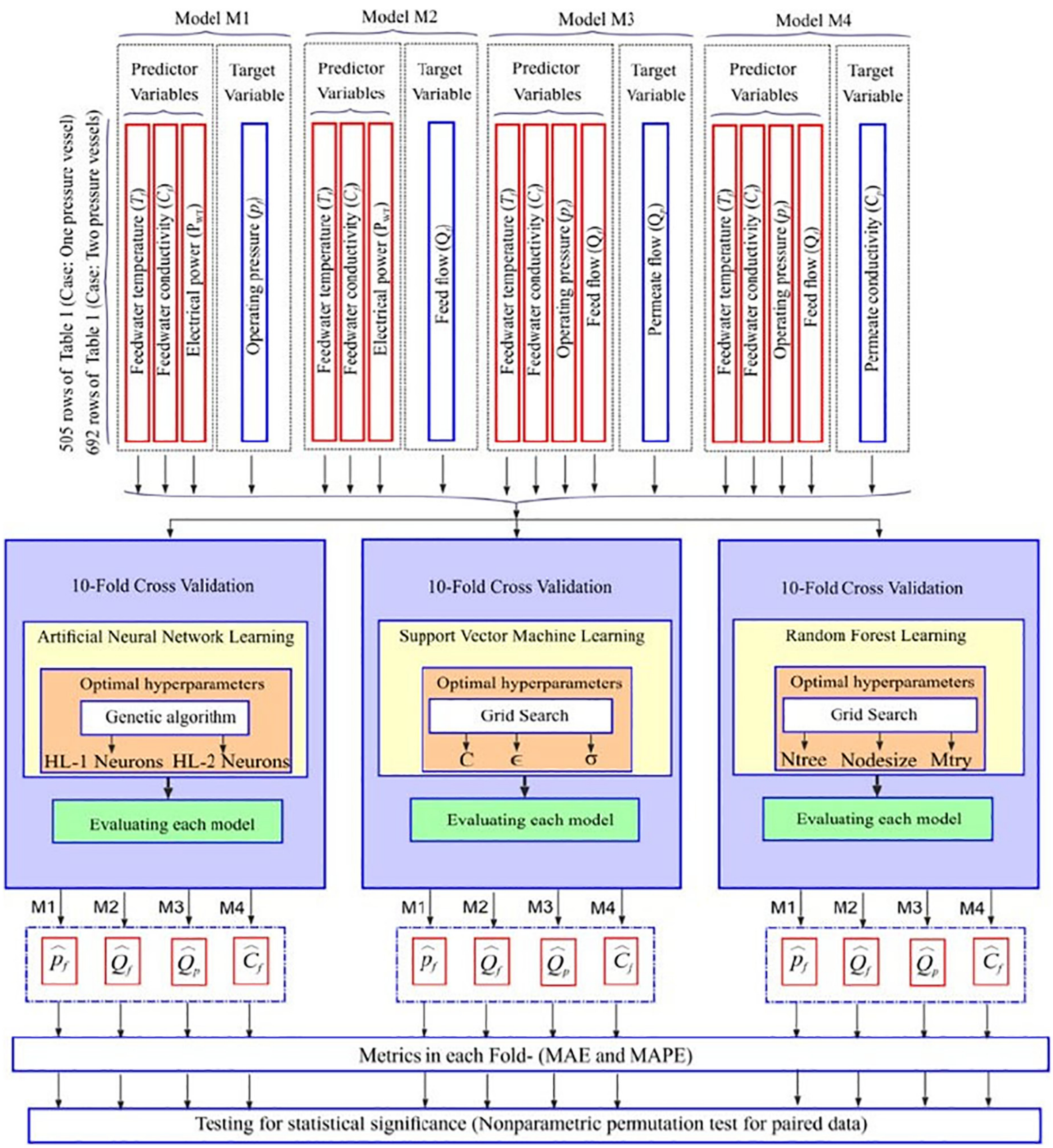

Fig. 6. Schematic representation of the methodology developed to compare the three machine learning techniques in wind-driven seawater desalination plant.
Figure adapted from (Cabrera et al., 2018).

These features, in turn, can be upscaled, allowing the optimal tracking of energy exports and trans-national energy exchanges. The digitalization of large energy distribution systems can also be used to control, manage, and provide grid protection with energy storage or grid stabilization by using large batteries such as in South Australia (Faunce et al., 2018), which can provide urgent stabilization of the grid and avoid a complete network shutdown in the event of an unforeseen shutdown of a major fossil fuel power plant.

Distributed energy systems offer, therefore, the path towards sustainable energy systems, and their development requires parallel development of their digitalized control and modeling. Nevertheless, it has to be mentioned that despite notable advances in digitalization in the last few years, the main driver and accelerator in the shift to distributed energy systems has been the drop in photovoltaic systems cost, which has gone below that of other renewable and fossil-based resources, as shown in Fig. 7. In fact, as of today, the low payback times for solar-generated electricity at the residential level, and even large solar plants, can be cheaper than the generation cost of coal-based electricity. Thus, the current situation is the best possible, and digitalization offers the key solution to the biggest challenge for distributed renewable energy systems, which is the supply and demand management for intermittent generation technologies. It is up to the development of digitalization technologies to catch up and make the most of it.

4.2. Smart grid integration of different energy sources

It is clear that the modernization of power systems brings a number of benefits to all energy stakeholders. However, these advantages are

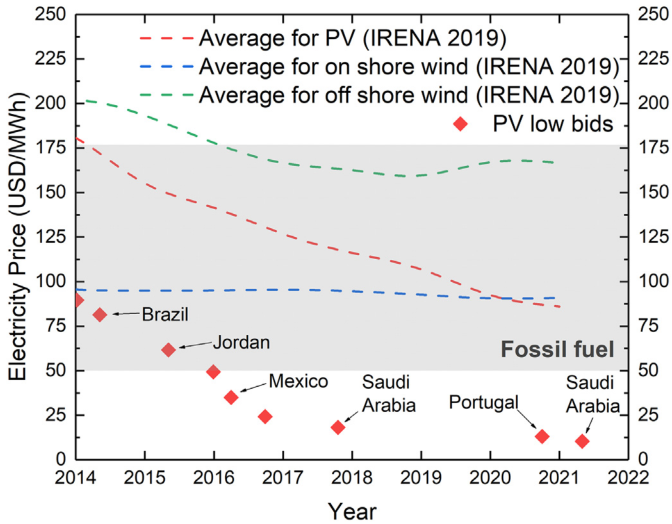

Fig. 7. Rapid cost reduction of electricity generation from solar photovoltaic systems of low-cost international electricity auctions, compared to that of other energy sources.

challenged by the system transit to the new technology and system innovation. Nevertheless, despite the high level of complexity that integrated and distributed energy systems may imply, the concept of smart grid technologies offers a solid platform for a safe, stable, and sustainable transition.

The conceptual framework of smart grids, which can be represented as in Fig. 8, consists of (i) the application of intelligent strategies to effectively allow the coordination of the energy flow between generation and the consumption of power (Bansal, 2019; Mbungu et al., 2020, 2019); (ii) the coordination of diverse energy resources by encouraging maximum use of renewable energy resources; (iii) the integration of distributed and diverse energy storage systems; (iv) energy management policies through which the relationship between the consumer and the supplier is coordinated.

In order to become a reality, smart energy systems need the development of optimal control schemes from the production sites to the consumption sites. Currently, energy management strategies use smart grid technologies to guarantee optimal energy coordination into the electrical system. The features that the smart grid technologies offer provide the electrical system with the opportunities of having a digitalized system with diverse possibilities to optimally coordinate several energy resources. Contrary to traditional energy networks, smart grids are adaptive, distributed, and have smart metering sensors that allow two-way communication, providing pervasive control, self-monitoring, and remote checks in a real-time and dynamic environment.

The development and deployment of smart grids will define the implementation perspective of the future electrical. One of the greatest challenges will be to guarantee a better relationship of the energy trilemma (Mbungu et al., 2019), which consists of solving the equilibrium aspect of the equilateral triangle where the sides are energy equity, energy security, and environmental sustainability. Therefore, in the future perspective of power systems, we will not only be looking for affordable and green and clean energy generation, but also secure and reliable energy resources. And to this purpose, the novel approach of smart grid will need to integrate the concepts of energy internet and the internet of energy (IoE).

4.3. Energy efficiency in industries and transportation

Distributed generation and smart grids are thus the keys for a greener energy supply, but a crucial factor that may impact the energy use sustainability to the same or even greater extent as its efficient

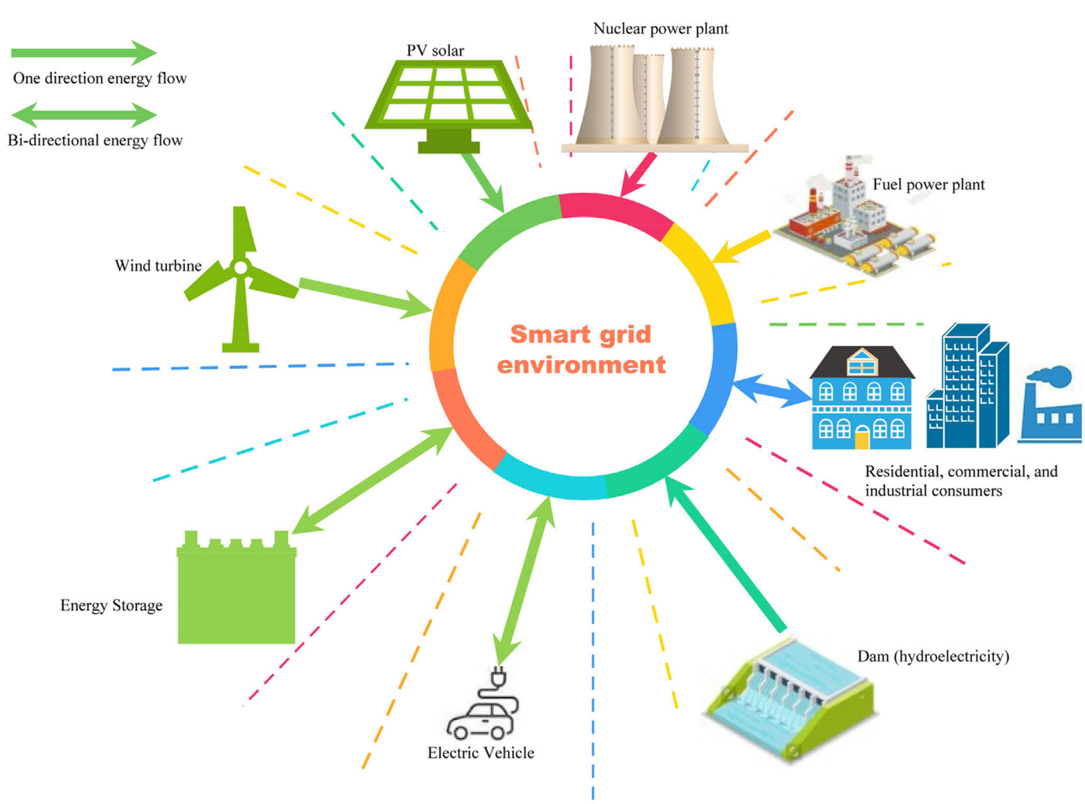

Fig. 8. Overview of intelligent energy system (Mbungu et al., 2020).

use. When it comes to energy use, the industrial and transport sectors represent more than half of the total energy consumption in the world (Taylor et al., 2010). A great majority of processes consuming energy in these sectors require high temperatures, which are achieved, mostly through the combustion of fossil fuels, therefore contributing to most of the greenhouse gas emissions on the planet (Panayiotou et al., 2017). These processes, have efficiencies between 45% (i.e., Diesel engines) to about 85% (i.e., gas boilers), meaning that around 15–55% of the energy provided by fossil fuels is wasted in the form of residual heat. This heat represents a significant waste of energy resources, which in turn contributes to global warming, exposing these sectors' incapacity for using the valuable resources in a smart way.

The standardization of inline sensors for processes metering and the popularization of logging systems and connectivity (Halstenberg et al., 2019), conforming the concept of the internet of things in the industry, will soon provide extensive datasets for process optimization that may allow for energy savings of up to 20% in industry (Kagermann, 2015). Beyond static operation, the continuous availability of processes data will allow a rapid adaptation of the processes configurations in combination with autonomous control systems, which in turn, may self-learn daily from the generated data by using neural network-based systems (Han et al., 2016).

This new capability may be easily extended to the transport sector, especially the one concerning the shipping of goods by air, sea, and road (i.e., trucks), which are the three main contributors to the CO_2 emissions from transport (Dray et al., 2012). Data logging onboard ships and trucks have become a reality in recent years, where many companies initially motivated to reduce the economic stress of ship owners by reducing fuel consumption, have found their side contribution on cutting down emissions (Fruth and Teuteberg, 2017). Similarly, the road transport sector is taking up the baton, as digitalization is currently claimed as the main driver for change in the sector (Noussan et al., 2020; Schiller et al., 2016). Interconnected devices between trucks and supplier centers may allow dynamic route optimization, ensuring better capacity utilization and fuel savings. Equally, individual systems that monitor each driver's style, and the maintenance needs for each vehicle (e.g., wear on components) may be used to dynamically optimize the operating parameters to save fuel, reduce emissions, and increase the truck's lifetime.

Nevertheless, it should be kept in mind that increased energy efficiency from the user side may bring with it the so-called induction effect, by which more optimized energy systems may create new energy demands. For instance, it has been claimed that the evolution of autonomous cars may increase the amount of users that, because of special mobility needs, may not be using cars before or were using the 'greener' public transport (Coroamă and Mattern, 2019). Moreover, the forecasted gains in efficiency may be more than outweighed by the increase in energy consumption due to new digital services, therefore resulting in a counterproductive effect. It is therefore in our hands, and those of the future generations, to investigate the impact of different aspects of digitalization in our energy systems, aiming at define which digital technologies and services may foster more environmentally friendly and sustainable energy production technologies, and which may only result in a rebound effect (Coroamă and Mattern, 2019).

5. Does digitalization hold the key to catalyze changes on industry and social wellbeing?

5.1. Industry 4.0 towards sustainable manufacturing and infrastructure

Industrial production of goods and services is undergoing significant changes in the last years evolving rapidly as digital technologies improve communication among the actors along the value chain (Correani et al., 2020). The term Industry 4.0 was coined to address the fact that the fourth industrial revolution will rely on digitalization rather than only automation as the third did, and that future production will be modular within factories consisting of "smart" objects. This trend is given by an application pull that requires standardization of systems, short development periods, individualization on demand (batch one manufacturing), flexibility, setting safe and secure production environments, resource efficiency, and decentralization for decision-making. Simultaneously, there is a technology push that will enable increased automation and mechanization, networking of elements leading to completely digitalized environments and an increasing degree of miniaturization (Lasi et al., 2014; Oztemel and Gursev, 2020).

Industry 4.0 conceives an integration of the entire product life-cycle ranging from the raw material acquisition stage all the way to the end of life of the product. In between there are manufacturing (and intermediate transformation) steps and the users, which also requires transportation (see Fig. 9) (Ardito et al., 2019; Stock and Seliger, 2016).

The vision of Industry 4.0 perfectly aligns with the concept of lean manufacturing (LM) since both approaches pursue improvements in quality, productivity, seek a reduction of waste, and are customer-oriented. With its historical origin in the Toyota Production System, LM has been a paradigm that has pushed industrial practice to operational excellence for years. It is based on five main guidelines, namely: the identification of value, map the value stream, creation of continuous flow between production steps, introduce pull between

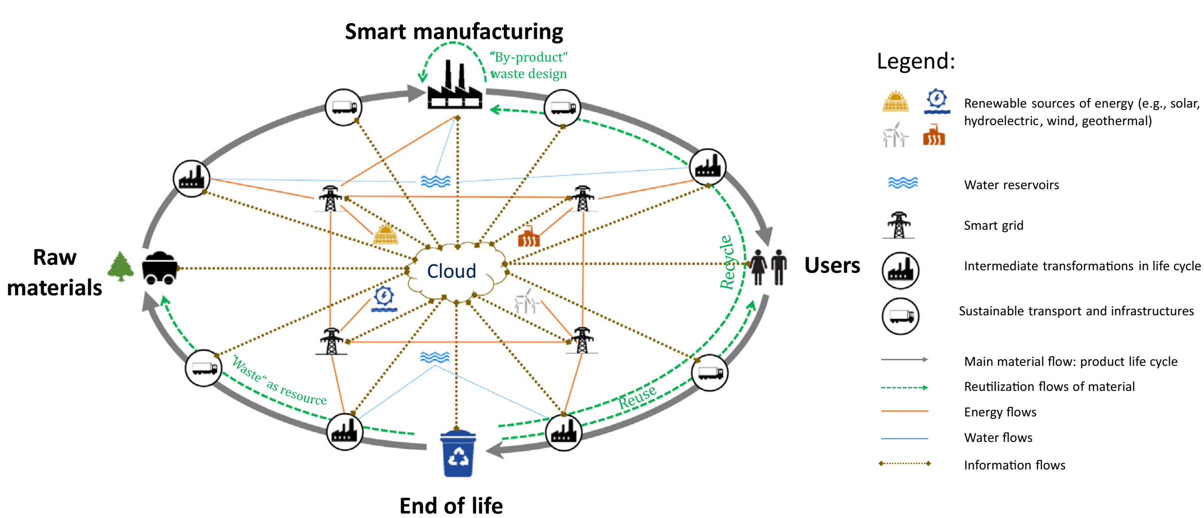

Fig. 9. Vision of the product life cycle in Industry 4.0 integrated with material, energy and information flows through digital technologies.

these steps, and, finally, seek perfection in the performance (D'Ippolito et al., 2019; Womack and Jones, 1996).

The reutilization of material flows is indeed a point of paramount importance in LM practice and, obviously, Industry 4.0 and must be emphasized. In this sense, the principles of both concepts are coherent with the perspective of a green chemical sector of the future, whereby industry would need to consider and implement "waste design." This philosophy deals with how production should be readapted to design processes that (a) avoid as much as possible waste creation and subsequent management and (b) make by-products in the processes useful raw materials (Zimmerman et al., 2020). In the end, this will lead to the creation of value by reutilization throughout the supply chain contributing to a circular economy, which is crucial to consider sustainable manufacturing decisions (de Sousa Jabbour et al., 2018). Another consideration is that the transportation of completed or intermediate goods demands the use of the most sustainable infrastructure to connect the different stations of the value chain, optimizing costs while minimizing emissions and safety issues (Dev et al., 2020). As for energy flows, originating from renewable sources, they will go into smart grids to which each smart factory is connected to manage the demand or supply of energy.

The core of the manufacturing process would be the smart factories (also referred to as "dark factories," "lights out factories," or "unmanned factories"). Smart manufacturing aims to optimize concept generation and production by employing computer control and high levels of adaptability hence promoting self-organization and decentralized decision-making. For this, it takes advantage of advanced information and manufacturing technologies to enable flexibility in physical processes to operate in dynamic global markets (Oztemel and Gursev, 2020). In turn, smart factories are heavily reliant on machine-to-machine communication through cyber-physical systems (CPSs). CPSs are one of the key aspects of Industry 4.0, and they encompass a network of objects and systems communicating with each other over the internet and a virtual environment created by computer simulation of objects and behaviors in the real world. Cloud computing becomes essential for the interconnection of CPSs as it enables data mining and determining responses to be given by the self-organized systems. Within smart factories, virtual manufacturing (VM) allows the simulation and optimization of operations and processes of the different modules with different technologies like computer-aided process design, product life cycle management, virtual or augmented reality, or 3D modeling, to name a few. VM technologies, in the end, are key elements to the individualization of the production, which in the end will be realized by additive manufacturing, such as 3D or 4D printing (Kamble et al., 2018; Kerin and Pham, 2019; Oztemel and Gursev, 2020).

In contrast with Industry 4.0 and considering its prior establishment, the LM philosophy can be regarded as a relatively low-tech approach whose excellence stems from its simplicity and the consideration of humans as a foundation to sustain continuous improvement of practices. Although this may represent a potential conflict from the standpoint of the involvement of manpower, given the similarity of many of the objectives of LM and Industry 4.0, it is more than arguable that positive associations between the two exist (Tortorella and Fettermann, 2018). A recent study by Pagliosa et al. covered precisely the potential synergies and the application of Industry 4.0 technologies that can overcome difficulties that directly concern LM (Pagliosa et al., 2019). After identifying a total of 9 Industry 4.0 technologies and 14 LM practices and analyzing their pairwise interactions, it was realized that very positive associations exist with a very high potential to achieve higher operational performance. A total of 24 relationships were suggested for prioritization, such as the relationship between CPSs and value stream mapping. Likewise, some technologies were also deemed a lower priority, such as advanced robotization, as they did not pose a definitive advantage to several LM practices. Another conclusion of the study is the highlight of the opportunities in research related to the area of Industry 4.0 and LM, which include the obvious need for validation of the synergies proposed, a categorization of technologies and LM practices in different levels of the value stream and the examination of the effects of the proposed relationships on operational performance (Pagliosa et al., 2019). Integration of life cycle assessments for decision-making is still underexplored and undoubtedly necessary to consider material and energy flows (Jose and Ramakrishna, 2018), which can help establish concepts like zero-waste manufacturing. This idea advocates for an industrial transformation that will reduce the designing for zero waste, smart auditing and collecting of any waste generated, subsequent waste to resource conversion, and establishing collaborative platforms for industrial symbiosis (Kerdlap et al., 2019). While it appears that the development of environmental and economic impacts of Industry 4.0 is promising, and several projects are already running (Oztemel and Gursev, 2020), the societal impact will have to be thoroughly assessed. Artificial intelligence technologies will enable autonomous vehicles and lights-out manufacturing, whereby the presence of operators will be minimal. These will reduce hazards by avoiding the presence of workers in the corresponding factories or transport infrastructures but could also lead to significant job losses.

In the current context of ongoing rapid changes, the definition of the fifth industrial revolution is starting to take shape. Industry 5.0 would represent an extension to Industry 4.0 evolving into manufacturing practices that focus on the personalized demands of individual customers. Therefore, the application of human intelligence is key to the development of this concept. Thus, many efforts are being put into tools to increase personalization, including virtual reality or holography among which capitalize on the human-machine interaction (Javaid and Haleem, 2020).

5.2. Use of e-Health technologies to promote wellbeing and quality of life

Digitalization is revolutionizing healthcare facilitating access to health services and addressing significant challenges in aging, mental health, and other costly and complex health care needs, overcoming the shortage of workers, and providing care to remote locations. e-Health is a critical area to expand and support as eHealth has the potential to provide affordable, sustainable, and quality health care (Bucci et al., 2019; Krick et al., 2019; Ossebaard and Van Gemert-Pijnen, 2016).

Digital health includes different technological advances such as telehealth and telemedicine. Telehealth is the use of electronic information and telecommunication technologies to support and promote long-distance clinical health care, patient and professional health-related education, public health, and health administration. Whereas, telemedicine refers to connections at a distance with professional providers to obtain treatment via videoconferencing (Weinstein et al., 2018). However, the World Health Organization uses the term e-health to encompass all these different aspects related to the internet of health things (IoHT) that are advancing healthcare during the Digital Age (Larson et al., 2018; Ossebaard and Van Gemert-Pijnen, 2016; WHO, 2019).

The reliance on IoHT has increased over the years, but it has gained more popularity during the COVID-19 Pandemic as an efficient alternative to access health services while respecting social distancing measures. Telemedicine brings solutions to consumers regarding their location and provides equal access to health, increasing health services at a lower price (Weinstein et al., 2018). Telemedicine is a helpful tool for reaching outpatients in rural areas to provide equal access to healthcare. With federal legislation increasing demand for medical services already in short supply, telehealth and telemedicine are often seen as more efficient methods for people to receive care. Eliminating traveling implies a series of savings, reduce hassles in many homes, and saves time, especially in rural areas (Larson et al., 2018; Rupert et al., 2017).

Furthermore, telemedicine offers the opportunity to support persons of different ethnicities, cultures, and languages by facilitating access to health care providers that are culturally competent and offer translator services (Larson et al., 2018). Despite improvements in high-speed internet in developing countries, there are many barriers to overcome to implement telehealth from the part of organizations (e.g., cost), patients (e.g., age, level of education, computer literacy), and providers (e.g., technically challenged staff, resistance to change) (Scott Kruse et al., 2016). The IoHT is still in its infancy but a promising public health tool with the potential to significantly increase access to health care for medically underserved populations of different backgrounds and ethnicities. Furthermore, there is a widespread belief that IoHT can reduce healthcare costs and improve health outcomes overall (Bashshur et al., 2016).

Wellbeing is one of the SDGs gaining importance worldwide. Digital tools play a vital role in promoting wellbeing and improving quality of life as these facilitate access to health care. Quality of life is an individual perception of physical, mental, and social wellbeing state even in the presence of a disease. Mobile phone apps and computers are resources for the population to communicate in different ways (phone call, video conference, email, app), allowing patients to meet and follow up with their providers. Implementation and normalization of eHealth enable the person to self-manage their health condition, improve their wellbeing, and prevent future health problems (Ossebaard and Van Gemert-Pijnen, 2016; Weinstein et al., 2018). Some examples are apps for promoting positive mental health strategies, physical activity, better management of diabetes, and heart control, among others (Weinstein et al., 2018). These IoHT applications have demonstrated that digital tools improve the overall quality of life of patients with chronic conditions while helping them manage their health from the comfort of their homes. Persons engaged in e-health achieve the same positive health outcomes as those who have the usual care at the clinic or hospital (Larson et al., 2018). Some examples of the use of telehealth and other digital sources to improve quality of life are: (i) telemonitoring to assist in the care and management of diabetes (Lee and Lee, 2018), (ii) use of telemedicine to help to control asthma (Chongmelaxme et al., 2019), (iii) telemedicine to help individuals with heart failure (Lin et al., 2017), (iv) telehealth to assist Cancer patients (Larson et al., 2018), and (v) telemonitoring for individuals with chronic obstructive pulmonary disease or COPD (Tupper et al., 2018). Telemedicine can reduce the number of admission and length of stays in the hospital. Preventive measures have demonstrated to delay mortality (Lin et al., 2017). All these aspects diminish the use of medical resources and positively impact the healthcare system and accelerate care attention.

Emerging technologies such as virtual reality (VR), augmented reality (AR), and videogames that induce the participant to exercise (also known as exergaming) present opportunities to improve our community's wellbeing and quality of life. VR/AR offer quasi-naturalistic and real-life experiences that might not perform in a safe environment for the person. VR/AR allows treating, stimulating, and improving the patient's wellbeing by training physical and cognitive abilities (Zucchella et al., 2018). VR reality can make dull activities more entertaining and increase adherence (Schröder et al., 2019; Slater and Sanchez-Vives, 2016). For example, adding VR to a stationary bike contributes to increasing the person's motivation for training by making the stationary exercise more attractive (Slater and Sanchez-Vives, 2016). In rehabilitation, VR offers a safe home-training environment to improve mobility (Schröder et al., 2019). Additionally, VR interventions improve cognition (memory) and psychological functioning, such as alleviating anxiety, impacting the wellbeing of persons with neurocognitive disorders such as Alzheimer's, stroke, and mild cognitive impairment (Moreno et al., 2019).

6. Can digitalization tools assist us in climate research?

In climate research, multi spatial-temporal climatic data form a baseline to understand climate variability and future projections. Digitalization of historical climate data and availability of real-time climate data revolutionized the prediction of extreme climate events, and developed strategies for their mitigation and adaptation (Munang et al., 2013). The open-source data policy, robust storage and processing infrastructure, advanced algorithms, less cost and time, and participatory scientific forums have enthused global researchers from interdisciplinary fields to work in sustainability research at different scales. This section focuses on the role of digital solutions as a way forward to comprehend more about the prospect of digital solutions for climate actions to attain ecological sustainability. The key areas of our interest are the application of digitalization in biodiversity research, earth observation, and climate action.

6.1. Digitalization in Global Biodiversity Assessment

Since the beginning of the Anthropocene epoch, human-induced impacts on the environment, including urbanization, pollution, globalization, Green House Gases (GHG) emission, and climate change, are ever-increasing. Quantifying such impact based on available data is a big debate since there is a question on delimiting the onset of the Anthropocene still prevails (Lewis and Maslin, 2015). The practice of collecting and availability of historical and real-time biodiversity data in digital format has evidently increased worldwide from the beginning of the twenty-first century. The Global Biodiversity Information Facility (GBIF) is an intergovernmental organization that hosts an online interoperable network of biodiversity databases from biological surveys and collections done at different geographical realms. The GBIF holds nearly one billion biodiversity occurrences records, of which nearly 150 million were based on a preserved specimen from natural history collection (Edwards, 2004; Yesson et al., 2007). However, estimates suggest that only 10% of specimen samples are available in digital format (Ball-Damerow et al., 2019). Online public participation has the potential to further accelerate the digitalization of biodiversity research specimens through three stages: transcription, geotagging, and specimen annotation. There are concerns over the data quality during the incorporation of citizen science data. But, this could be overcome by data quality control efforts such as standardization of transcription, spatial data accuracy, targeted training, development of pliable and multistage database management systems, practicing appropriate statistical procedures, and data validation protocols (Ellwood et al., 2015). It is conclusive that digitalization of collection-based research helps to derive and assess biological baseline to evaluate the impact of climate change, land use (biophysical characteristics of land) and land cover (anthropogenic utilization of land) change, invasive species, and anthropogenic induced impact on global biodiversity (Hedrick et al., 2020).

6.2. Ecological monitoring to evaluate land and marine ecosystems

The need for studying the long-term impact of climatic and anthropogenic factors on the environment is much needed to assess biodiversity loss and its implications on biogeochemical cycles and global food security (Shiklomanov et al., 2019). Environmental monitoring procedure incorporates processes such as background investigation, scheme determination, distribution optimization, field sampling, experimental analysis, data collection, and analysis complexion. Traditional data collection methods collect field samples on environmental change and pollution, which is now augmented through the intervention of the Internet of Things (IoT) technology. The vast amount of such scattered, unstructured and data collected worldwide could be connected through telecommunication and the internet for a single-point access. Big data analysis and cloud computing have enabled mining of such a vast amount of data to extract useful information to frame environmental management strategies (Li, 2014). Recent advancements in the sensing and communication infrastructures with storage infrastructure, flexible and interoperable geodatabase, cloud processing, and advanced algorithms have made the digital data inevitable input for continuous mapping and spatiotemporal monitoring of the land and marine ecosystems. Contemporary earth observation sensors such as multispectral, hyperspectral, microwave, and LiDAR provide high spatial and spectral resolution data utilizing diverse wavelength regions of the electromagnetic spectrum. The archived and real-time data from these sensors provide a plethora of information that could be effectively combined with ground-based information to understand the spatiotemporal dynamics of earth's ecosystems. The IoT technologies enable us to build and deploy the communication of interconnected sensors to avail continuous real-time data (Abraham et al., 2017). The latest developments in the open-access interactive tools and frameworks for processing such a massive volume of data using LiMES (Live Monitoring of Earth Surface), and xROI helps even a non-expert in remote sensing to analyze and derive useful products out of raw data (Giuliani et al., 2017; Seyednasrollah et al., 2019). Furthermore, the integration of social sensing data through mobile technologies in participatory environmental management programs suggests that the participation of stakeholders enhances mapping and provides new information on the socio-ecological system (Brammer et al., 2016; Dong et al., 2019).

6.3. Digital earth observation data for the assessment of essential climate variables

Geospatial information infrastructure consists of technological, semantic, organizational, and legal components which enable the user to discover, share, and utilize geospatial data to assess the rapidly changing climate and its implications on our physical environment. The multi-source, multi-band, multi-variable, and multi-scale earth observation data combined with auxiliary data has inherent 4 V qualities (volume, variety, veracity, and velocity) of big data, which could valuably contribute to the effective monitoring of 34 Essential Climate Variables (ECVs) as identified by UNFCCC at multiple scales (Guo et al., 2015). Time series satellite data for understanding the temporal dynamics in vegetation (Measho et al., 2019), deltas and estuarine wetlands (Kuenzer et al., 2019), alpine wetlands (Wang et al., 2020), snow line changes (Hu et al., 2019), polar ice cover (Eythorsson et al., 2019), urban impervious surface (Kuang, 2019), urban microclimatic regions (Bechtel et al., 2019), marine phytoplankton (Dutkiewicz et al., 2019), and sea surface temperature (Merchant et al., 2019) in response to the global climate change have proven the application potential of geospatial data in different domains of environmental monitoring. Recent digital advances, including IoT, big data, cloud computing, machine learning, and deep learning techniques together can handle a massive number of datasets generated from synchronous satellite-aerial-ground-based observation systems for the continuous monitoring of atmosphere, hydrosphere, lithosphere, and cryosphere. From these observations, accurate, comprehensive, and diverse information on essential climate variables, extreme climate events, and global environmental change could be derived to further investigate spatiotemporal dynamics of climate change indicators from regional to global scale (Jia et al., 2020).

7. Conclusions

The United Nations defined in 2015 the sustainable development goals (SDGs) to roadmap research and social needs towards equity and sustainable development of our society. The advent of digital technologies is a ray of hope on the horizon that can guide and catalyze the change towards achieving all the holistic 17 SDGs. The role of digitalization and the technologies associated with the internet of things (IoT) have been discussed for their potential to solve big challenges in the food-water-energy nexus, and enabling Industry 4.0, improving social wellbeing, and reducing the effects of climate change.

The ever-growing global demand for food is one of the greatest challenges of this century, aggravated by the unequal access to food resources. Digital technologies are up-scaling sustainable agricultural land and resources management and strengthening the associated productivity, services, and livelihood security worldwide. For example, the use of remote sensing and GIS techniques is increasing agri-productions. The use of data is mapping and guiding effective land-use pattern, defining crop variety, and monitoring agroecosystem activities. The early implementation of various hardware (e.g., sensors, drones, precise fertilization, etc.) combined with geo-mapping leads the new agriculture revolution, given the prediction capabilities to magnify production yield and improve sustainable agriculture. The use of mobile application software provides unique opportunities for connectivity with agricultural stakeholders and farmer independence. Furthermore, applications position the farming communities as the essential attributes of precision and sustainable agriculture while ensuring economic gains (reduced poverty).

Smart cities of the future should ensure accessible water of the highest quality for all of their citizens. Big data and digitalization play an essential role in meeting these goals. The underutilization of big data in water treatment systems may be leading to an unnecessary increase in operating costs and sometimes inefficient treatment. Artificial intelligence technologies can translate passive data into actionable knowledge to improve operation and lead decision-making. Digitalization can lead to an optimized design of water treatment plants. Optimized control and operation through efficient data management can maximize technical benefits and result in cost savings. Data-mining techniques are incorporated into sensing techniques to verify process normalcy and create knowledge on plant malfunctioning to respond faster. Advanced automated control through digitalization holds the promise to reduce energy consumption, ensure product water quality and prevent system failure. Integration of internet-enabled tools and emerging decentralized smart technologies (e.g., treatment at the point of delivery or point of use) for-real time water quality audit at critical control points can define when decentralized water treatment may be required to operate to ensure the public health and facilitate equal access to safe water for all.

Digitalization can enhance energy efficiency and provide sustainable alternatives. Modeling electricity usage based on data is used to predict demand based on weather conditions, climatology, or societal habits. These data-driven strategies can be translated to decentralized energy systems based on renewable sources (e.g., photovoltaics). Smart management in the complexity of our energy systems puzzles is an extraordinarily complex matter that can be dealt with through integration on the internet of things. Energy management strategies based on digitalization tools can contribute to managing with high accuracy supply and demand for a more efficient and sustainable generation and use of energy. It has been suggested that smart use of datasets for process optimization may allow up to 20% energy savings. Similar energy benefits can be observed in transportation systems where interconnected devices between trucks and supplier centers may allow dynamic route optimization. These strategies will ensure better capacity utilization and fuel savings while decreasing CO_2 emissions associated to transportation.

Sustainable manufacturing is one of the key aspects of Industry 4.0 that conceives an integration of the entire product life-cycle. Digitalization and material selections become an essential element to improve green manufacturing approaches considering the entire product life and its reusability/recyclability. Furthermore, smart manufacturing integrates computer and internet of things aid strategies to optimize industrial yield. Computer control and machine-to-machine communication through cyber-physical systems have shown high adaptability and demonstrated optimized self-organization and decentralized decision-making.

Healthcare and equal access to health are being revolutionized by digitalization. Reliance on the internet of health things has increased over the years, but it has gained more popularity during the COVID-19 Pandemic as an efficient alternative to access health services while respecting social distancing measures. Telemedicine has been indispensable to bring solutions to consumers regardless of their location and income. Digital tools play a vital role in promoting wellbeing and improving quality of life through facilitating access to health care.

Implementation and normalization of e-Health enable the person to self-manage health conditions, prevent them, monitor chronic needs, and improve citizens' wellbeing and quality of life.

The interconnection of SDGs is undeniable. Sustainable approaches have demonstrated synergies that can mitigate climate change and its effects. Digitalization and artificial intelligence support low carbon energy systems with the integration of highly efficient renewable energy that can also monitor and model responses of climate and biodiversity over time. In climate research, multi-spatial-temporal climatic data form a baseline to understand climate variability and future projections. Digitalization of historical climate data and availability of real-time climate data have revolutionized prediction and provided a framework for understanding the current climate events and impacts on biodiversity. The recent implementation of Internet of Things technology has drastically improved collection methods and on-time big data analysis, which could favorably contribute for the effective monitoring and solutions deployment. There is a clear need for studying the long-term impact of climatic and anthropogenic factors on environment and biodiversity. Digitalization is a game-changing tool to assist the scientist in this race against time to stop climate change.

Digitalization defines the path towards a smart Green Planet by providing solutions and assisting sustainable development. Integration of IoT, big data management, and artificial intelligence have already demonstrated a myriad of benefits. Special attention should be paid to implications of inequal data access that can result in digital poverty and hence increase inequalities instead of reducing the gap. Cybersecurity of strongly interconnected systems through the cloud should be reinforced. However, the benefits of big data integration in our daily lives can promote quality of life and drastically assist humanity towards the sustainable challenges to ensure human, biodiversity, and earth resilience.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors gratefully acknowledge the Green Talents prize awarded by the Bundesministeriums für Bildung undForschung (BMBF) of the German Federal Government. In memoriam of Dr. Maria E. Mondejar for inspiring and leading this collaborative work. We acknowledge the Green Talents award funded by the Bundesministeriums für Bildung und Forschung (BMBF) of the German Federal Government. However, this is not specific funding.

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