DIGITAL TWINS FOR REAL-TIME MONITORING AND OPERATION OF COFFEE VALUE CHAIN AND SUPPLY CHAIN

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Abstract - There has been significant effort and a growing need to develop innovative and cost-effective solutions for real-time monitoring and operation of value chains and supply chains, especially to enhance the predictability and optimisation of complex production systems for a better adaptation to disruptions and market fluctuations as well as improved sustainability. This is particularly important when taking into account the impacts and emerging advancements of smart agriculture, smart manufacturing, Digital Twins, and Industry 5.0, where data-driven solutions and AI-enabled decision-making play an important role for improving real-time monitoring, quality control and management, and operational efficiency. This study presents a conceptual framework for integrating Digital Twins into a smart agriculture platform, focusing on the real-time monitoring and operation of the coffee value chain and supply chain, to demonstrate the potential of Digital Twins in advancing smart agriculture and digital supply chains.

Keywords: Coffee, value chain, supply chain, digital twins, smart agriculture, real-time monitoring, real-time operation, digital transformation, sustainability, Industry 5.0

1. Introduction

There have been emerging needs and huge efforts of investigation of innovative and cost-effective solutions for real-time monitoring and operation of value chains and supply chains, to enhance predictability and optimisation of complex systems which are capable of adapting to disruptions and market fluctuations, especially under the impacts of Smart Manufacturing and Industry 4.0 and 5.0, and Digital Twins (DTs) play a pivotal role in improving real-time monitoring and operational efficiency. A Digital Twin (DT) is a dynamic digital replica of physical assets, systems, or processes, enabling seamless data integration and real-time interaction between the physical and virtual world [1]. Applications of DTs in manufacturing industries have been well-documented, to enable real-time monitoring and operation of production lines and simulate various scenarios for predictive maintenance and process optimisation, leading to improved production scheduling, resource allocation, and operational efficiency, and reduced risks [2,3]. The implementation of DTs has significantly optimised resource utilisation and reduced lead times [4] and allows for rapid response to disruptions and optimisation of production processes. In supply chain management, DTs can be used for real-time monitoring and operations, based on continuous data collection and analysis, proactive decision-making and optimisation, to enhance predictability and resilience of supply chains against unexpected disruptions, which are critical in today's dynamic market environments, especially under the impact of Industry 5.0 that complements and extends Industry 4.0 by specifically putting research and innovation at the service of the transition to a sustainable, human-centric and resilient industry [5]. In addition, DTs facilitate fruitful collaborations and effective decision-making processes across the value chain and supply chain. Real-time monitoring and data sharing among stakeholders ensures that all parties are informed and can respond promptly to changes, and allow for effective planning and optimisation of logistics networks [6], leading to optimised supply chains and value chain, with improved overall performance, quality control and competitiveness, and better demand forecasting, inventory management, and risk mitigation [7]. DTs have been considered as an impactful enabling technology in smart agriculture, especially for precision farming. By integrating data from diverse sources, including sensors, drones, and satellite imagery, DTs enable farmers to monitor crop health, optimise resource allocation, and predict yields with enhanced accuracy [8], leading to more sustainable and efficient agricultural practices, as well as tacking the global challenges of climate change and resource scarcity. Recent studies about the use of DTs in smart agriculture have demonstrated that, with the capability of real-time monitoring of soil moisture, temperature and water, the water use efficiency can be improved up to 15%, the chemical inputs can be reduced up to 20% while maintaining crop yields, and the crop yields can be predicted with accuracy of more than 90%, enabling farmers to make informed decisions about harvesting and market planning [9, 28]. DTs could be used to simulate the impact of climate change scenarios on crop production, allowing for the development of adaptive strategies, and the use of DTs enables farmers to make data-driven decisions that optimise productivity while minimising environmental impact [9, 10].

With the well-documented capabilities of real-time monitoring and operation, as well as traceability and predictability-based data-driven decisions and optimisation, DTs are potential for enhancing various aspects of the coffee industry, including both the value chain and supply chain, to improve quality control and management, efficiency, traceability and sustainability, especially where multiple stakeholders and factors influence the final product quality. DTs can be employed to monitor and optimise various stages of the value chain, taking advantages of innovative precision agriculture solutions. The use of DTs in conjunction with blockchain technology to enhance transparency and traceability in coffee supply chains [11]. The innovative and smart agriculture (INNSA) platform was proposed and developed for improving the coffee value chain and supply chain, focusing on enhancement of quality and values for key elements of the coffee value chain and supply chain in Vietnam [12], with integration of the key enabling digital transformation and smart agriculture technologies, including smart devices and internet of things, big data, artificial intelligence (AI), blockchain and source traceability technologies, and sustainable design and manufacturing. The INNSA platform was designed to collect and analyse farm soil and environmental conditions, with a focus on factors closely linked to crop yields. Based on the real-time data collection, the platform generates detailed reports and offers tailored recommendations to enhance productivity through informed decision-making and AI-based analytics [13], especially the efficient and effective use of agricultural resources, fostering the development of sustainable agriculture via more precise and optimised farming operations.

In this paper, a conceptual framework for integrating DTs into a smart agriculture platform, focusing on the real-time monitoring and operation of the coffee value chain and supply chain is proposed and discussed, with a focus on integration of DTs in the proposed INNSA platform, to demonstrate the potential of DTs in advancing smart agriculture and digital supply chains. The rest of the paper is organised as follows. Section 2 presents an overview of a conceptual framework for the coffee value and supply chain with the integration of DTs. Section 3 demonstrates real-time monitoring and operation of the coffee value and supply chain, based on the framework proposed in Section 2. Finally, Section 4 provides a summary and conclusions.

2. A conceptual framework for coffee value and supply chain with integration of DTs

Figure 1 presents the coffee value and supply chain, highlighting the potential integration of DTs at critical stages, in which smart sensors can be integrated for continuous data collection and analysis, to facilitate real-time monitoring and management of the coffee value and supply chain, especially to optimise operations, enhance efficiency, and ensure quality control throughout the entire coffee value and supply chain. The proposed application of DTs aims to improve the robustness and responsiveness of the coffee value chain and supply chain, ultimately leading to better resource management and more informed decision-making. The key stages of the coffee process chain and value chain include the following: Production – Smart Farming, Processing (Harvest and Post-harvest with wet processing and dry processing), Commerce, Consumption and Recycling.

• *Production – Smart Farming*: DTs are used for real-time monitoring, simulation, optimisation of coffee farms and crop management, and outcome prediction, based on real-time data collected from sensors, drones, and satellites. DTs can model plant growth, soil conditions, and climate impacts, enabling precise irrigation and fertilisation strategies, reducing resource waste, while adapting to climate variability, with data-driven insights and informed decision-making support.

• *Coffee harvesting and processing*: The cherry coffee beans harvested by the farmers are treated to obtain parchment coffee via multiple steps, to remove all external layers of cherry coffee beans to obtain the

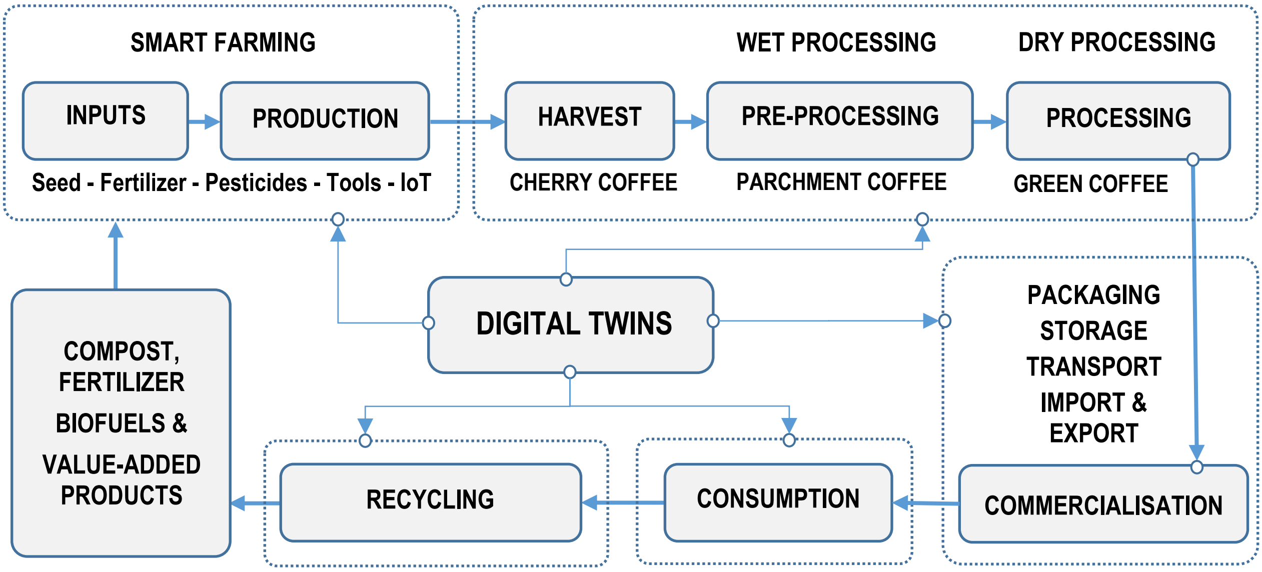

Figure 1. The coffee value and supply chain, incorporating DTs at critical stages for continuous data collection and analysis, facilitating real-time monitoring and management to optimise operations, enhance efficiency, and ensure quality control, with a focus on sustainability and circular economy solutions.

green coffee beans. These include the following main processing steps: wet processing, semi-dry processing and dry-processing [14]. DTs can be used to improve efficiency and quality control of coffee harvesting and processing, via integration with smart sensors, big data analytics, AI and machine learning, to predict optimal picking times and guide selective harvesting strategies, reducing labour costs and improving bean quality. DTs can be used to monitor fermentation parameters, drying conditions, and roasting profiles, enabling precise control and consistency for a better-quality control of coffee processing operations. Recent applications have shown DTs can reduce water consumption in wet processing by up to 30% and energy use in roasting by 15%.

• *Transport, packaging, storage, import and export for commercialisation*: As previously mentioned, DTs can be used to enabling real-time monitoring and optimisation of the supply chains. DTs integrate IoT sensors to track temperature, humidity, and location, ensuring quality preservation during shipment of coffee beans and products. For packaging and storage, DTs simulate optimal conditions, reducing waste and extending shelf life. In import and export operations, DTs facilitate seamless documentation and customs clearance. Besides, blockchain and source traceability technologies can be integrated into DTs to provide transparent and tamper-proof records of coffee origin and processing, and comprehensive supply chain visibility about the farm conditions, processing methods, and transportation [15]. DTs can allow stakeholders to anticipate and mitigate risks, optimise inventory management, and make data-driven decisions throughout the coffee commercialisation process, based on real-time monitoring and informed decision-making.

• *Consumption*: DTs are increasingly being applied to coffee machines to enhance user experience, predict potential issues and detect anomalies, monitor performance in real-time, and take proactive measures to prevent breakdowns. The integration of AI-machine learning algorithms into DTs allows for predictive maintenance, reducing downtime and improving customer satisfaction.

Table 1. The factors that affect coffee quality throughout the entire value chain and supply chain

Stages	Key factors that affect the quality of coffee
Farming	• Environmental and farming conditions: Altitude, soil composition, and climate. • Cultivation practices: Shade management and fertilisation, Fairtrade and organic cultivation.
Harvesting and Processing	• Method of picking, post-harvest processing techniques such as wet processing and dry processing. • Storage and transportation conditions such as exposure to moisture or temperature fluctuations
Consumption	• Roasting methods and conditions: Roasting temperature and time. • Brewing methods and water quality.

Besides, DTs and AI can be used to optimise coffee quality by adjusting brewing parameters based on individual preferences and environmental conditions [16, 27]. Furthermore, by providing comprehensive

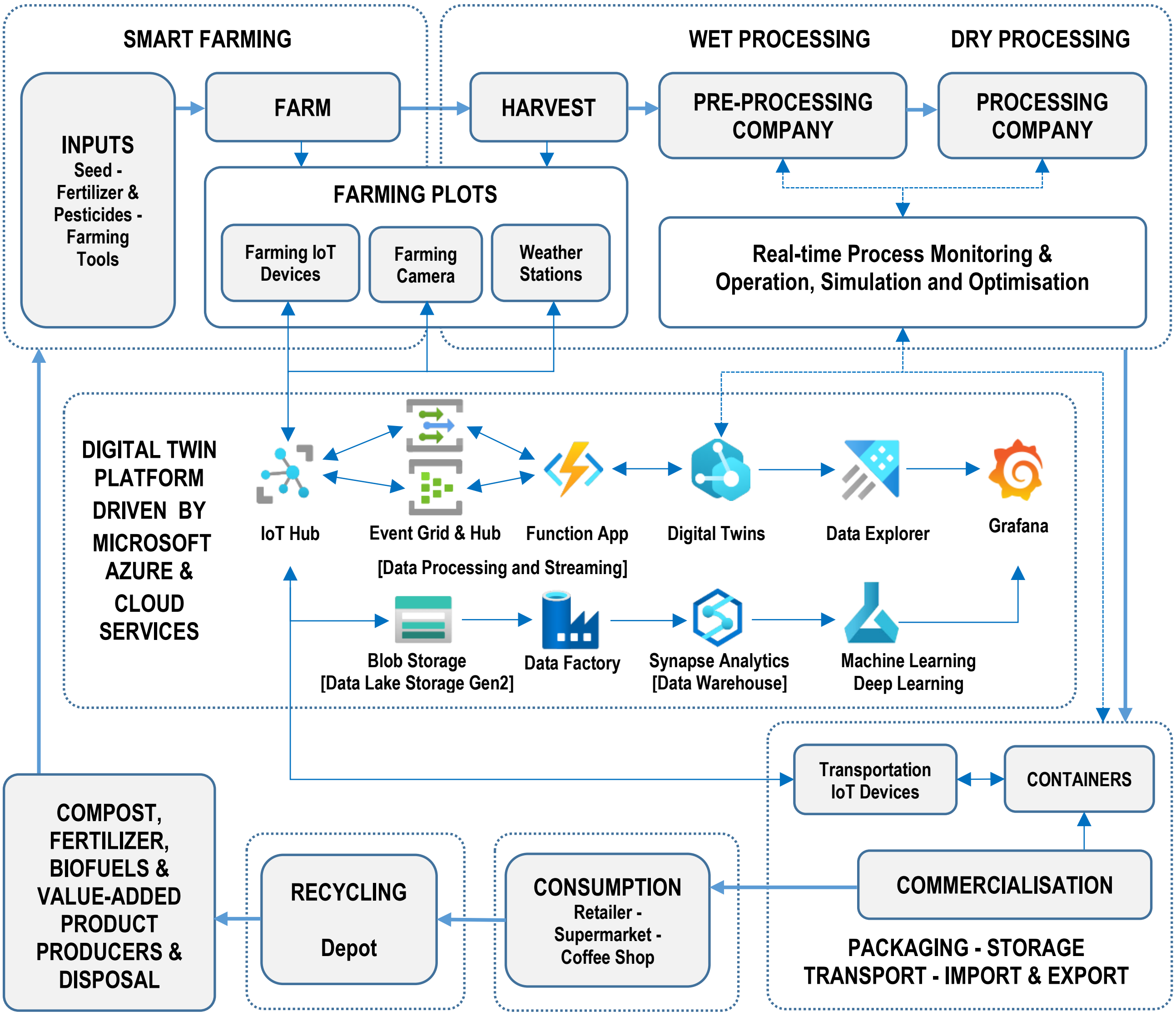

Figure 2. Real-time monitoring and operation of coffee value chains and supply chains: Integrating Microsoft Azure Digital Twins and cloud services as well as simulations and optimisations into a smart coffee farming system and innovative frameworks to optimise operations, enhance efficiency, and ensure quality control of coffee value chains and supply chains.

data on the coffee's journey from farm to cup, DTs facilitate traceability and sustainability efforts, with a better branding and customer satisfactions.

• *Recycling*: DTs can be used to optimise coffee waste recycling processes, offering real-time monitoring and predictive capabilities, including optimisation of processing conditions like temperature, moisture, and aeration, leading to improved quality and speed of compost production from coffee grounds. DTs help in analysing nutrient content and predicting the effectiveness of coffee-based fertilizers in various soil types, and optimise the conversion of coffee waste into bioethanol and biodiesel, improving yield and reducing energy consumption [17].

For coffee recycling to make value-added products, such as activated carbon and biochar, DTs assist in process optimisation and quality control [18]. Finally, DTs can be used to track coffee waste from collection to final product, ensuring efficiency and sustainability [17], with invaluable insights for decision-making and process improvement in coffee recycling.

It is important to note that when designing and implementing DTs, it is necessary to consider the factors that affect coffee quality throughout the entire value and supply chain, as summarised in Table 1.

Implementing DTs in the coffee value and supply chain presents several critical technical and economic challenges. Foremost among these is the challenge of data integration, which involves harmonising information from disparate sources across the coffee production lifecycle. Real-time synchronisation poses another significant obstacle, particularly in remote coffee-growing areas where maintaining current data can be problematic. Scalability concerns arise when extending DT implementation throughout the entire coffee chain, necessitating robust computational infrastructure. From an economic perspective, the substantial initial investment required for sensors, software, and personnel training can be a deterrent, especially for smaller coffee producers. Evaluating the Return on Investment (ROI) for DT implementation in the coffee industry remains complex, as quantifying long-term benefits is not straightforward; and there is a risk of uneven distribution of benefits, with larger corporations potentially gaining more advantages from DT adoption compared to small-scale farmers [19, 20].

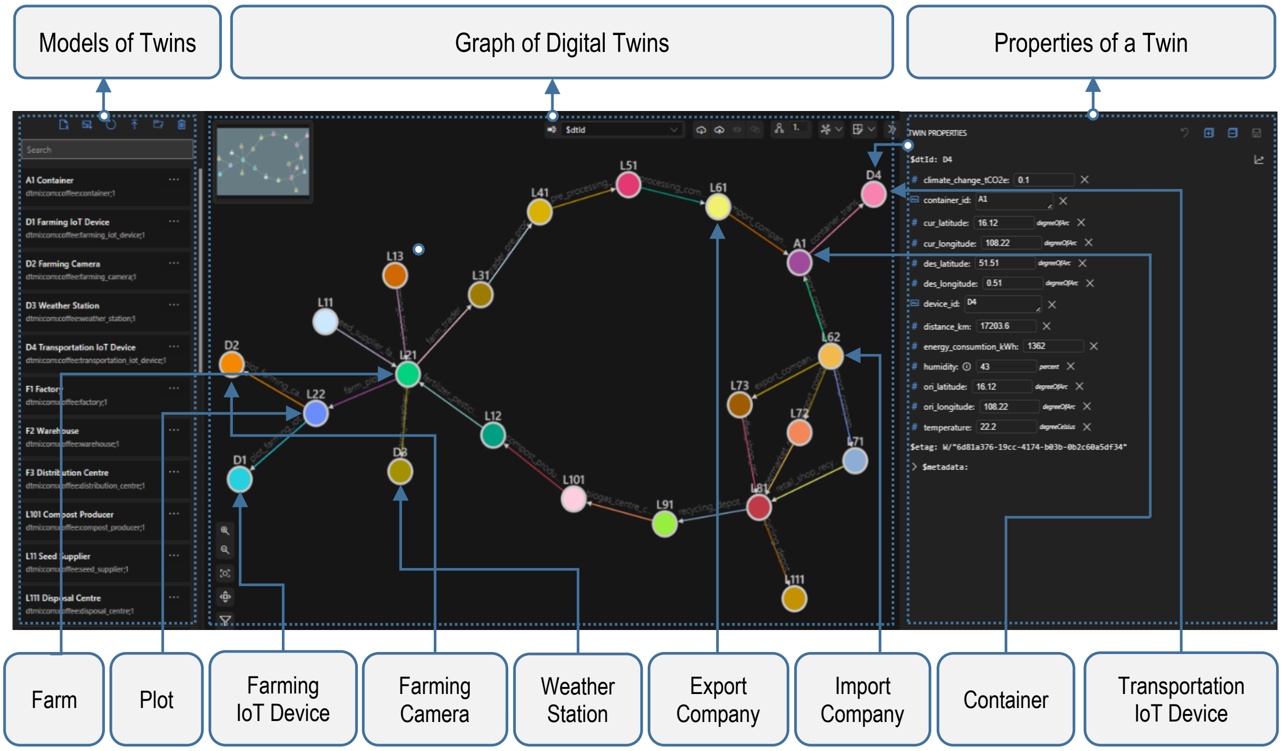

Figure 3. The twin graph of the Iced Coffee case study in the view of Azure DTs, with a focus on physical entities used for demonstrations. The twins or DT here are the circle nodes, which are connected by arrows representing for their relationships. The source nodes at the tail of the arrow have the target nodes at the head of the arrow.

3. Case studies: Real-time monitoring and operation of coffee value and supply chain

A real-world case of a smart coffee farm was used for demonstration of key elements of the proposed conceptual framework for integrating Digital Twins into a smart agriculture platform, with a focus on the real-time monitoring and operation of the coffee value chain and supply chain. A smart farm of 500 m2 of White Lion JSC (Iced Coffee) in Mdrak district, Daklak province, Vietnam, had been used for smart farming demonstration, systematic analysis and evaluation of the coffee supply chain and value chain [18], taking into account the key phases of the whole coffee farming cycle, including smart farming, harvest and post-harvest processing (wet processing and dry processing), as well as commercialisation and consumption.

In this study, there are five main focused objectives for real-time monitoring demonstrations. The first objective (O1) is to obtain real-time simulation and monitoring of environmental and farming conditions, including soil health and weather conditions, based on (1) real-time data of farm soils, which include soil temperature and humidity, CO2 level, pH level, electrical conductivity (EC), salinity, and soil nutrition (N level, P level, and K level); and (2) real-time data of environmental conditions, which include ambient temperature and humidity, light intensity, rainfall, wind speed, and sunshine duration. The second objective (O2) is to obtain real-time simulation and monitoring of the quality of coffee in containers during the transportation processes in the commercialisation stage (import and export activities), taking into account real-time transportation data which include temperature, humidity, and location (latitude and longitude). The third objective (O3) aims to obtain real-time monitoring of levels of maturity of coffee beans by using object detection of five levels of maturity including Dry, Over-ripe, Ripe, Semi-ripe and Unripe. The fourth objective (O4) is to obtain real-time monitoring of the health of coffee trees by using image classification of coffee leaf diseases with six classes of diseases which are composed of Healthy, Miner, Rust, Phoma, Cercospora and Undetermined. Finally, the fifth objective (O5) is to obtain real-time monitoring of the impact on climate change and sustainability of the shipment process by tracking metrics related to carbon footprint - greenhouse gas emissions such as weight of container (metric tonnes), distance (km), mode of transportation (truck, train, airplane and sea ship), energy consumption (kWh) and tonnes of carbon dioxide equivalents (tCO2e).

The following enabling technologies of Smart Agriculture and Industry 4.0 and 5.0 were applied in the implementation of the demonstrated DT case studies: Cyber-physical System (CPS)/IoT, Big Data Analytics, Source Traceability, Cloud and Edge Computing, and Machine Learning/Deep Learning (ML/DL). These technologies were utilised to achieve real-time simulation, monitoring, and operation of the coffee value chain and supply chain with traceability and predictability. Figure 2 present the workflow for a case study of real-time monitoring and operation of coffee value chains and supply chains, in which Microsoft Azure Digital Twins and related cloud services as well as simulations and optimisations are integrated into a smart coffee farming system and innovative frameworks to optimise operations, enhance efficiency, and ensure quality control of coffee value chains and supply chains.

For the first objective (O1) of obtaining real-time simulation and monitoring of environmental and farming conditions, it is assumed that, a coffee farm is divided into multiple farming plots for flexible and effective management. For each farming plot, one or more farming IoT devices installed for real-time data collection of environmental conditions, including soil temperature and humidity, CO2 levels, pH levels, electrical conductivity (EC), salinity, and soil nutrition (N, P, and K levels). A weather station is used for real-time data collection of environmental conditions, including ambient temperature and humidity, light intensity, rainfall, wind speed, and sunshine duration. Each coffee farm uses more than one weather station. For the second objective (O2) of obtaining real-time simulation and monitoring of the quality of coffee in containers during the transportation processes, it is assumed that, the coffee containers are shipped from Da Nang, Vietnam (VNDAD) to Thames Haven, United Kingdom (GBLGP). A transportation IoT device is installed inside each container for real-time collection of transportation data which include temperature, humidity, and location (latitude and longitude). To obtain real-time object detection of levels of maturity of coffee beans mentioned in the third objective (O3) and image classification of coffee leaf diseases mentioned in the fourth objective (O4), it is assumed that, one or more farming cameras installed in each farming plot for real-time image capturing of coffee beans and coffee leaves. Lastly, data of location collected from the transportation IoT device (Objective O2) can be leveraged and augmented by known shipment information (weight of container, distance, mode of transportation) to estimate the shipment's carbon footprint (energy consumption in kWh and tonnes of carbon dioxide equivalents tCO2e) (Objective O5).

Figure 3 presents the twin graph of the case study in the view of Microsoft Azure DTs, with a focus on physical entities used for demonstrations, in which the twins or DT here are the circle nodes, which are connected by arrows representing for their relationships. Table 2 presents a configuration of physical entities used for demonstrations of a DT in Microsoft Azure DTs.

It is also assumed that a coffee farm has warehouses for storage and inventory purposes. The functional coffee-farming units or companies responsible for coffee pre-processing and processing activities have either factories, warehouses, or distribution centres. In the commercialization phase, there are companies involved in import and export activities, as well as distribution to retail shops, supermarkets, and coffee shops in both domestic and foreign markets. These companies have warehouses and inventory systems for the storage and distribution of coffee products. Regarding the flow of reverse logistics, recycling depots are responsible for collecting and recycling end-of-use (EOU) products and consumption-stage wastes into useful materials for biogas and compost producers. They also release end-of-life (EOL) products to disposal centres. The output of compost production can be materials for fertilizer and pesticide providers in the smart farming stage.

The data stream is designed for real-time data collection, processing, extract, transform, load (ETL) and analytics, leveraging the power of Microsoft Azure DTs in terms of IoT, big data analytics, source traceability, cloud and edge computing and machine learning. The data journey begins in the agriculture perception level [21], where IoT devices which are equipped with microcontroller units (MCUs), sensors, cameras and actuators collect various soil health and environmental parameters such as soil (ambient and inside container) temperature, soil (ambient and inside container) humidity, CO_2 levels, pH levels, electrical conductivity, salinity, nutrient levels, latitude and longitude, as well as, pictures of coffee beans and coffee leaves. These devices transmit data to the edge level via an single board computer (SBC) as IoT Gateways, which aggregates and pre-processes the incoming data streams to ensure efficient transmission and initial data anomaly detection and data recovery. The data is then sent to the cloud level, entering Microsoft Azure platform by beginning with IoT Hub, which acts as a central messaging hub for bi-directional communication between the IoT devices and the cloud infrastructure. A new update or message of data from hardware considered as an event that are published to Event Grid or Event Hub services, triggering Azure Functions that process the raw data and stream the processed data in real-time. These functions perform tasks such as data cleansing, enrichment, and immediate analytics, before updating the Azure DT which comprises of DTs Explorer, twin graph, and 3D Scenes Studio environment that serve as dynamic replicas of the coffee value and supply chain, physical farm and container environment allowing for real-time simulation, monitoring and interaction.

For further analysis and historical data storage, the data is ingested into Data Lake Storage Gen2, which provides scalable and secure data storage. Data Factory orchestrates the ETL processes, moving and transforming data from the Data Lake to Synapse Analytics, which then processes these large datasets, integrating big data and data warehousing capabilities to generate actionable insights. Real-time monitoring dashboards are created using Grafana visualising data from the DT and Data Explorer which facilitates interactive data exploration and analysis to uncover trends and generate detailed reports, enabling stakeholders to monitor key metrics and make informed decisions. For advanced analytics, predictive modelling and forecasting tasks in real-time Grafana dashboard, Azure Machine Learning can be employed to build and deploy models that can forecast environmental conditions and crop yields, optimise resource usage and detect potential issues. Especially, YOLO v8 deep learning model was employed for obtaining Objectives O3 and O4 [22].

The publicly available BRACOL dataset and Coffee Fruit Maturity datasets were respectively utilised for training pre-trained weights obtained from YOLO v8 model with the task of Oriented Bounding Boxes (OBB) Object Detection (Objective O3), and the task of Image Classification (Objective O4) [23, 24]. The Adam optimiser was utilised with an initial learning rate of 0.01, a weight decay of 0.0005. The training processes were conducted using an NVIDIA A100 GPU with 40GB of memory and trained in 100 epochs with 640x640 image size. New weights generated from the training processes are saved in Azure Machine Learning and used for the inference processes. This integrated and multi-layered approach of data stream ensures that the coffee value and supply chain can be real-time simulation and monitoring with data-driven insights guiding agricultural practices for improved productivity, resilience and sustainability. Importantly, as recommended by the user community, Azure services that are related to IoT applications operates well with the 4 seconds sampling time, so we designed the IoT devices and gateways to read and send data every 4 seconds. Further information about these Azure services can be referred at Microsoft learning platform [25].

Figures 4 and 5 presents the results of demonstration of real-time simulation and monitoring of (1) soil health and environmental conditions, (2) levels of maturity of coffee beans, and (3) types of coffee leaf diseases at the smart coffee farm. There are three physical entities that are considered.

Table 2. A configuration of physical entities of a digital twin used for demonstrations in Microsoft Azure

Physical entity	ID in twin graph	Attributes for real-time simulation & monitoring	Demonstration Objectives O1 to O5
Weather Station	D3	device_id, latitude, longitude ambient_temperature, ambient_humidity, light_intensity, rainfall, wind_speed, sunshine_duration	O1 - Real-time monitoring of environmental conditions
Farming IoT Device	D1	device_id, plot_id, latitude, longitude soil_temperature, soil_humidity, co2_level, pH_level, electrical_conductivity, salinity, n_level, p_level, k_level	O1 - Real-time monitoring of soil health and farming condition
Farming Camera	D2	device_id, plot_id, latitude, longitude maturity_percent	O3 - Real-time monitoring and detection of levels of maturity of coffee beans
		device_id, plot_id, latitude, longitude, disease_type	O4 - Real-time monitoring and classification of coffee leaf diseases
Transportation IoT Device	D4	device_id, container_id, cur_longitude, cur_latitude, ori_longitude, ori_latitude, des_longitude, des_latitude, temperature, humidity	O2 - Real-time monitoring of quality of coffee in containers and tracking location of the containers
		device_id, container_id, cur_longitude, cur_latitude, ori_longitude, ori_latitude, des_longitude, des_latitude, climate_change_tCO2e, distance_km, energy_consumption_kWh	O5 - Real-time monitoring of carbon footprint for the shipment process, which includes energy consumption and tCO2e

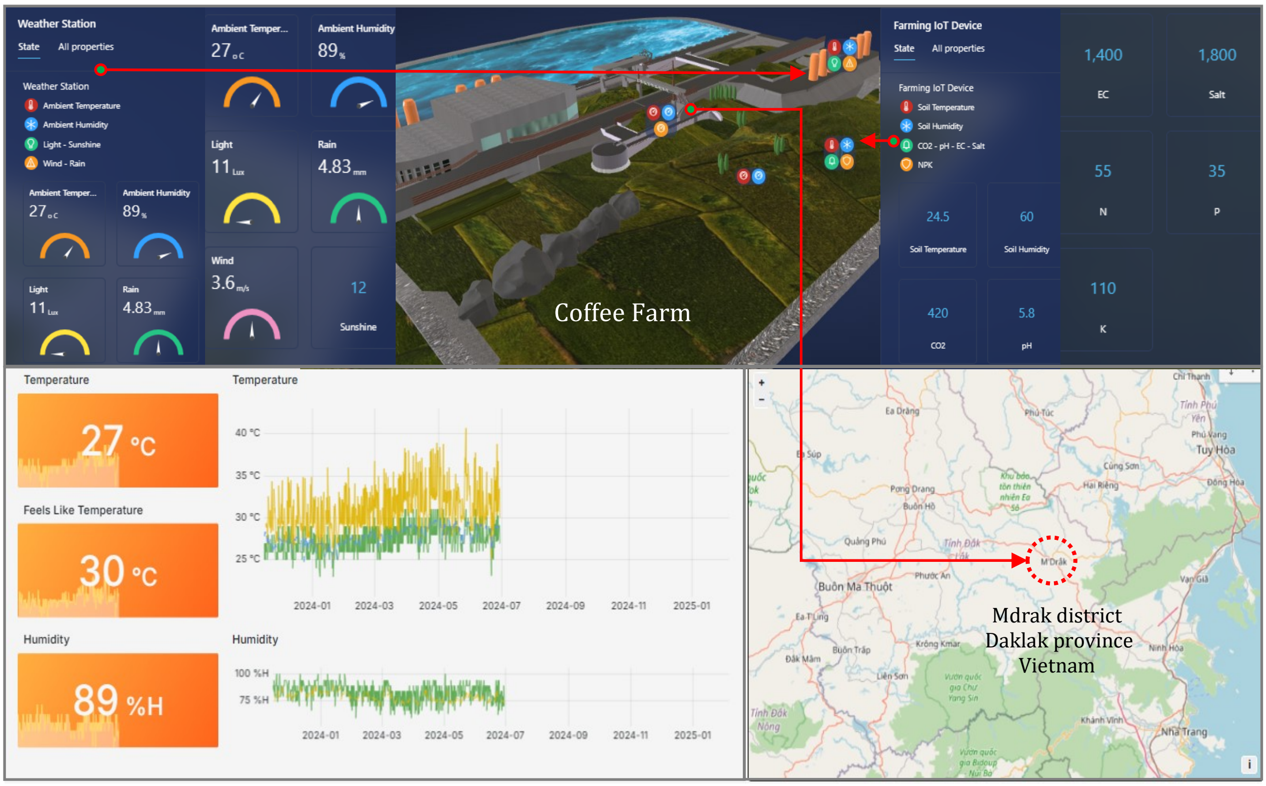

Figure 4. Demonstration of the smart coffee farm in Mdrak district, Daklak province, Vietnam. The dashboards show the real-time simulation and monitoring of soil health and environmental conditions which are viewed in Azure Digital Twins and Grafana.

Figure 5. Demonstration of the smart coffee farm in Mdrak district, Daklak province, Vietnam. The dashboards show (a) the real-time detection of levels of maturity of coffee beans, and (b) real-time classification of coffee leaf disease types, which are viewed in Azure Machine Learning Studio.

The first physical entity is the weather station (Weather Station in Figures 2 and 3), which is equipped with smart sensors to collect and monitor the following data: ambient temperature (°C), humidity (percentage), light intensity (Lux), rainfall (mm), wind speed (m/s) and sunshine duration (hours). The second physical entity is the farming IoT device (Farming IoT Device in Figures 2 and 3), which is equipped with smart sensors to collect and monitor the following data: soil level (pH unit), EC (µS/cm), salinity (mg/L), soil temperature (oC) and humidity (%), CO_2 level (ppm), pH, and nutrition (N level, P level and K level) (mg/kg). The third physical entity is the farming camera (Farming Camera in Figures 2 and 3), which is equipped with smart cameras to capture the photos of coffee beans and coffee leaves in coffee trees.

For every 4 seconds, data in the properties of the twin of Weather Station, Farming IoT Device and Farming Camera are updated in Azure DTs. With the uses of native cloud services such as Azure Function and event triggering and propagation services such as Event Grid and Event Hub, whenever data of a twin in the twin graph was updated based on IoT device, the downstream services would be accordingly updated. It is noted that, the twin in Azure DTs, 3D digital replica in Azure Scenes Studio and real-time dashboard in Grafana are regularly refreshed and updated. In the 3D simulation environment, the visual rules for visualising behaviours of Weather Station and Farming IoT Device are designed by using common icons, dynamic gauges and text boxes. In Figure 4, the real-time dashboard can be shown in the 3D simulation environment. The map of the area where the smart coffee farm is located can be viewed. It is noted that, the machine learning models such as Random Forest and XGBoost can be used to generate weather forecasting information about temperature and humidity by using Azure Machine Learning based on historical time-series data. Besides, the photos of coffee beans and coffee leaves can be regularly captured and stored directly in Data Lake, then manually inferred to understand the optimal

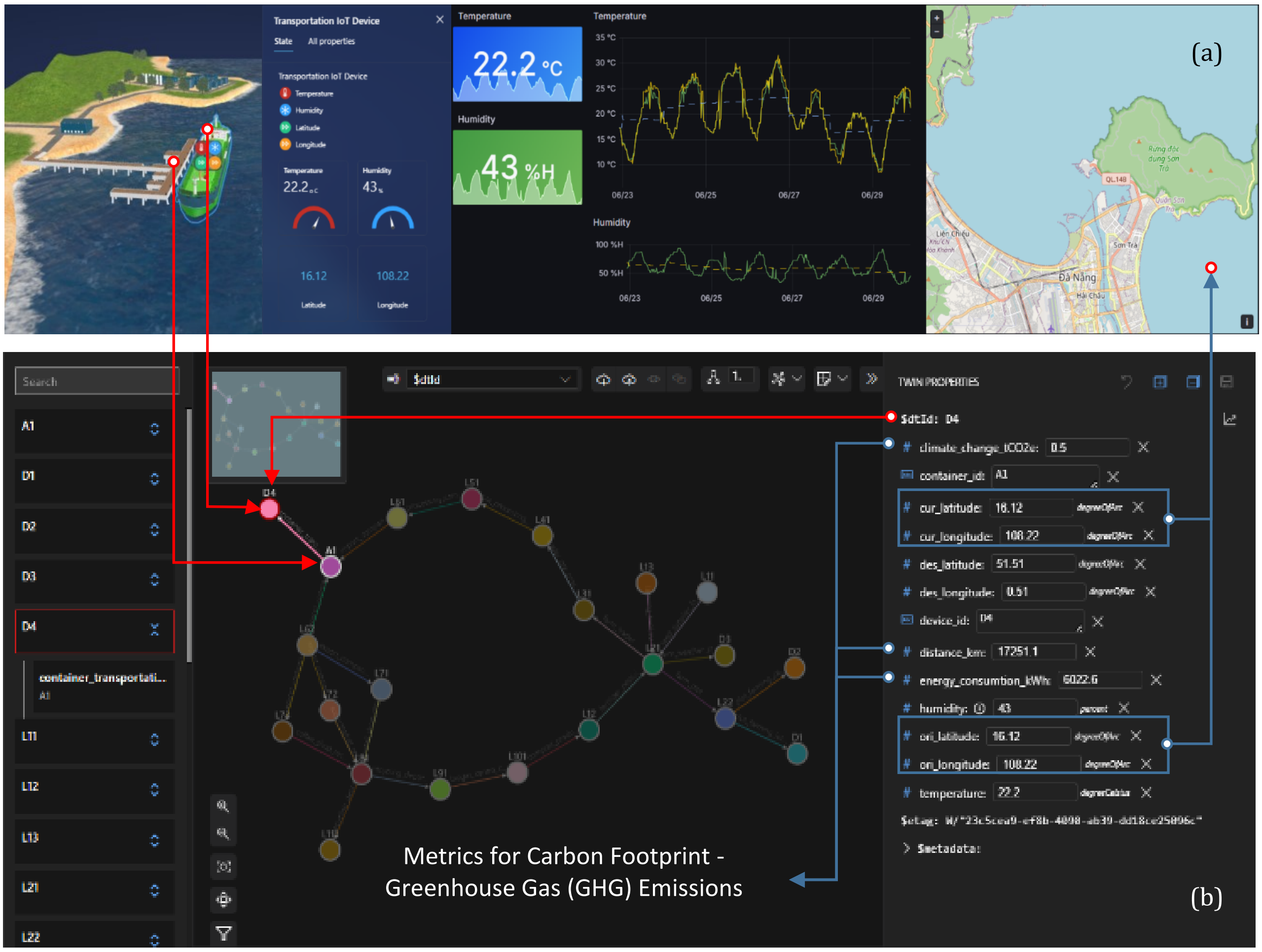

Figure 6. The results of demonstration of real-time simulation and monitoring of the quality of coffee in the container and impact on climate change of the shipment during the transportation processes in the commercialisation stage, taking into account (a) real-time transportation data which include temperature, humidity, and location, and (b) real-time tracking of carbon footprint - GHG emissions which include distance, tonnes of carbon dioxide (CO_2) equivalent and energy consumption. The real-time 3D simulation and monitoring dashboards are viewed in Azure Digital Twins and Grafana.

harvest time and the health of coffee trees using the trained YOLO v8 models which were saved in Azure Machine Learning Studio as shown in Figure 5.

Figure 6 presents the results of demonstration of real-time simulation and monitoring of the quality of coffee in containers during the transportation processes in the commercialisation stage (import and export activities), taking into account real-time transportation data which include temperature, humidity, and location (latitude and longitude), and carbon footprint using metrics such as location, distance, tCO2e and energy consumption. The transportation IoT devices (Transportation IoT Device in Figures 2 and 3) are used to collect and monitor the temperature, humidity, and location of the container to ensure that the cargo ship's routing and internal environment do not damage the quality of the coffee. This includes the timely control of the container's air conditioner. It is noted that the real-time dashboards are designed to keep track of temperature, humidity, and location. Additionally, the predictive capability for monitoring temperature and humidity can be implemented via the use of Azure Machine Learning. Location data generated from Transportation IoT Device can be collaborated with shipment information such as destination, transportation mode, weight and distance to calculate tCO2e and energy consumption based on the methodology reported in [26]. The downstream Azure services can be timely and precisely updated whenever the IoT device changes. The behaviours of 3D digital replica of transportation IoT devices in the 3D simulation environment and real-time dashboard of time-series insights can be visualised, including the historical and predictive data of temperature and humidity inside the container as shown in Figure 6(a). The information about the location of the container can be shown in the map with the real-time dashboard for viewing, including the location of Tien Sa port in Da Nang city, Vietnam. Finally, machine learning models such as Random Forest and XGBoost can be applied to generate predictions for temperature and humidity, keep track of any abnormalities, and promptly inform about detections and diagnoses of air conditioner failures based on historical time-series data.

4. Summary and conclusions

With growing competition in the global coffee market, significant effort is required to facilitate real-time monitoring and management of the coffee value and supply chain, especially to optimise operations, enhance efficiency, and ensure quality control throughout the entire coffee value chain and supply chain, especially under the impacts of smart agriculture, regenerative agriculture and circular economy, as well as Industry 4.0 and 5.0. In addition, there is an emerging need for data-driven solutions and AI-enabled decision-making, which play an important role in improving real-time monitoring, quality control and management, and operational efficiency.

In this study, a conceptual framework for integrating Digital Twins into a smart agriculture platform is proposed and discussed, with case studies to demonstrate the potential of DTs in advancing smart agriculture and digital supply chain, based on the emerging technologies and platforms of DTs such as Microsoft Azure. This study is a part of our effort in development of innovative and smart agriculture platform for improving the coffee value chain and supply chain [12], with integration of key enabling digital transformation and smart agriculture technologies, including smart devices and IoT, big data analytics, AI, ML/DL, Cloud and Edge Computing, blockchain and source traceability technologies, and sustainable design and manufacturing.

The demonstrated case studies show the potentials of DTs in real-time monitoring and management of the coffee value and supply chain. However, there are some challenges that need to be taken into account. The first challenge is related to the real-time integrity and synchronisation of data in remote farming areas, as it is heavily dependent on the reliability of the sensors and network connectivity. These potentially affect the timeliness and accuracy of the real-time monitoring and control system. The second challenge is related to the complexity and the cost-effectiveness of implementation in practices. For the cases of larger and more diverse farming areas, it requires substantial computational and infrastructural investments, complex logistics and technical efforts, as well as the high associated costs of setting up and maintaining the smart technologies and IoT infrastructure. The initial cost of setting up IoT devices and integrating them into the DT platform can be high, leading to limited accessibility for smaller-scale farmers and small and medium enterprises (SMEs) in developing countries.

For future phases and studies, it is aimed to demonstrate and integrate AI and ML/DL tools, real-time simulation, and optimisation systems with the capabilities of unmanned aerial vehicles (UAVs) into the proposed DT platforms for coffee quality control and management. This integration includes UAVs equipped with lightweight deep learning models that can be effectively run on edge devices (edge layer) rather than cloud infrastructure. These systems will be capable of real-time video recording and simultaneous identification of maturity levels, insect detection, and plant disease recognition. Additionally, emerging tools and eco-systems of AI and ML/DL will be employed for more accurate prediction of weather conditions and soil moisture levels, cost-effectively supporting regenerative and precision agriculture practices. Additionally, it is necessary to fully develop proof-of-concept prototypes of cost-effective and innovative INNSA platforms to improve the coffee value and supply chains. These platforms will enhance the quality and value of key elements in the coffee value chain and supply chain, taking into account the emerging applications of smart technologies and AI-powered robotic systems in harvesting and post-harvesting activities, as well as source traceability and blockchain technologies, to enhance the efficiency of pre-processing, processing, inventory and transportation phases; and these directly and indirectly improve the quality and flavours of final coffee products.

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