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Full length article

Mapping the postharvest life of imported fruits from packhouse to retail stores using physics-based digital twins

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ABSTRACT

Controlling the hygrothermal conditions around fresh fruit and vegetables is vital for their preservation. Therefore, cold chain stakeholders often measure temperature along the supply chain of fresh produce. However, the temperature is typically monitored only in one segment of the entire cold chain, namely from the supplier until the distribution center. Besides, such measured data are rarely used for decision-making because they are not translated into the impact on the quality of the products. We provide a solution by extending the monitoring until the retail stores and upcycling these thermal data into actionable metrics. To do so, we use physics-based digital twins, namely virtual representations of the food products. This study focuses on 331 cold chain shipments of cucumber, eggplant, strawberry, and raspberry imported from Spain to Switzerland. We followed these fruits through pre-cooling, thermally stable conditions at the distribution center, and the temperature ramp-up phase before arriving at the retail store. The temperature performance of each carrier and flow analysis of the shipment enabled us to map the complex logistic system better. The digital twins detected that the fruits lost 43 - 85% of their quality before being displayed at the retail store. This quality loss remains invisible to the retailer. Additionally, we found a strong correlation between fruit quality and shipment duration (i.e., for cucumber $r =$ -0.95 ($P < 0.001$)), which emphasizes the importance of shortening the shipment to prolong the freshness of the fruit. The digital twins have shown a large potential to help further maximize shelf life and uniform product quality.

1. Introduction

In the supply chain of fruit and vegetables, cooling is crucial to minimize quality loss, which eventually leads to food loss (Gustavsson et al., 2011; S. Mercier et al., 2017). This is especially true when long-distance transport is involved, for example, in the international fruit trade. The reason is that the rate of quality-deteriorating biochemical reactions and physical processes in fruits are significantly reduced at lower temperatures (Bron et al., 2005). Lowering the temperature by 10 °C typically doubles or triples the shelf life (Defraeye et al., 2019). In addition to such temperature-driven deterioration, exposure to low temperatures can physically damage the produce, which is so-called chilling or freezing injury (Parkin et al., 1989). Studies have shown that controlling relative humidity reduces not only the mass loss induced deterioration but also the severity of the chilling injury (Yi Wang, 1989; Paull, 1999; Kissinger et al., 2005). Thus, the temperature and relative humidity in the cold chain of fresh produce need to be controlled carefully within a narrow hygrothermal window, particularly for fruit import. Retailers and carriers are taking care of keeping their fresh produce within this range to the best of their abilities from the packhouse to the retail store.

Currently, information about this optimal hygrothermal window based on the fruits' physiology is well known (Table 1). The retailer aims to maintain these conditions in their supply chains to maximize the shelf life, ensure product uniformity, and offer fruits of the highest possible quality to their customers. However, despite these available ideal conditions for postharvest storage of fruits, the temperature history in the cold chain often fluctuates and diverts from these target conditions (Badia-Melis et al., 2018; Wu and Hsiao, 2021). These challenges in meeting the optimal hygrothermal targets are caused by breaks in refrigeration between different stages of the supply chain, bottlenecks in logistics, and the complexity of planning the supply chain as many stakeholders are involved (S. Mercier et al., 2017; Shashi et al., 2018; Ndraha et al., 2018). These diversions from the optimal conditions are,

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Table 1
Optimal temperature and relative humidity (RH) range and estimated shelf life under the optimal environment of the four fruits (Suslow and Cantwell, 1997; (Cantwell and Suslow, 1997); (Mitcham et al., 1996); (Mitcham et al., 1998); (Camelo, 2004). Target temperature shows the targeted range of temperature set by the retailer in their cold chain.

Parameters		Cucumber	Eggplant	Strawberry	Raspberry
Optimal	Temperature	10 – 12 °C	10 – 12 °C	0 °C	-0.5 – 0 °C
	RH	90 – 95%	90 – 95%	90 – 95%	90 – 95%
	Shelf life	10 – 14 days	10 – 14 days	5 – 7 days	2 – 5 days
Retail's target	Temperature	8–12 °C	8–12 °C	2–6 °C	2–6 °C

however, monitored with the use of air temperature sensors, so we can identify where temperature excursions occur. Nevertheless, temperature data are often collected between the packhouse and the distribution center only, and not the entire cold chain up to the retail stores. One reason is that the product goes through different unit operations in the supply chain, and various stakeholders handle the cargo. This situation complicates sensor placement and retrieval, and sensors are often not transferred from one unit operation to another. In addition, not all stakeholders have an incentive for detailed hygrothermal monitoring (Badia-Melis et al., 2018). In short, the sensor technology is available to monitor the postharvest supply chain from packhouse to retail stores, but currently, this is seldom done in a commercial supply chain.

Besides, the measured temperature data are rarely analyzed thoroughly to assess their impact on fruit quality in the supply chain as a whole. We have monitored air temperature data, but cold chain operators cannot quantify to which extent a temperature excursion could damage the fruit and vegetables. The main reason is that the measured data do not directly tell their resulting impact on the remaining life of the products. Thus, for such data to be used for their full potential for decision-making, the data need to be translated into actionable metrics, such as the remaining shelf life. Several studies have shown the importance of such shelf life modeling (Sciortino et al., 2016; Scalia et al., 2019; Hough et al., 2003). However, only a few published studies have combined such modeling with sensor data in commercial operations to investigate and optimize the actual supply chain. There is a lack of studies that utilize the existing temperature data and methods that are robust and applicable in various real supply chains (S. Mercier et al., 2017). Furthermore, the existing temperature data are of the air temperature and do not represent the actual fruit temperature. For shelf life modeling, the fruit temperature is more representative, as this temperature takes heat transfer between fruit and air, and the respiration of fruit into account. In order to overcome these challenges in leveraging the sensor data, digital twins are seen as promising means (Defraeye et al., 2019; T. Defraeye et al., 2021; Moshood et al., 2021; Tao and Qi, 2019). A digital twin virtually represents the real product and reacts physically the same (Moshood et al., 2021; Tao and Qi, 2019; Wagner et al., 2019). In the context of food cold chain, a digital twin of fruit simulates its hygrothermal and physiological behavior in-silico based on measured sensor data in the actual supply chain (Defraeye et al., 2019; T. Defraeye et al., 2021). These fruit twins thereby drift virtually along with the real produce when this moves through the supply chain. The fruit-temperature-based shelf life modeling can be integrated into the digital twins, and they simulate fruits' behavior during the actual commercial operations. Although these points feature the great potential of the digital twins, their concept in the postharvest supply chain of fresh produce emerged only in the past few years (T. Defraeye et al., 2021). The extent to which stakeholders benefit from the digital twins in the food cold chain remains poorly understood.

This study firstly extends the monitoring in supply chains of fresh fruits from the packhouse all the way until the retail stores. Secondly, we upcycled these temperature data via digital food twins to actionable metrics which retailers can use, such as mass loss and remaining shelf life. These twins are based on finite element modeling and thereby calculate the fruit temperature. Our digital twins use this fruit temperature for shelf life modeling and mass loss calculations instead of using only air temperature. The objective of this study is to present how retailers can better utilize temperature data and offer possible solutions to optimize their cold chain with digital twins efficiently. This paper is divided into the following sections. Section 2 (Materials and methods) provides details about the dataset used for analysis and the physics and models integrated to develop the digital twins. In the first parts of the Results and discussion (Section 3.1, 3.2, and 3.3), we analyzed the temperature history and corresponding logistic information along the cold chain of cucumber, eggplant, strawberry, and raspberry imported from Spain to Switzerland. For this analysis, we collected additional air temperature data covering the entire cold chain until the retail stores to have better insights into the current system. In Section 3.4 and 3.5, we utilized the digital twins of the fruits, and translated the measured data into fruit quality, mass loss, and remaining shelf life. We then used these actionable outputs from the digital twins to identify areas for improvement in the supply chain. Section 3.6 provides possible advancements and research in the future to enhance the potential of the digital twins. Finally, in Section 4 (Conclusions), we summarized the primary outcomes from this study.

2. Materials and methods

2.1. Time-temperature monitoring

This study examined the air temperature on the cold chain of four fruits (cucumber, eggplant, strawberry, and raspberry) from Spain to Switzerland. Fig. 1 shows the simplified diagram of the studied supply chain, whereas the shaded area corresponds to the monitored cold chain. As presented in Fig. 1, the fruits are brought from a farm to a packhouse, where pre-cooling is performed. Subsequently, the fruits are transported from Spain by a carrier in a refrigerated truck to a distribution center (DC) in Switzerland and then transported by another carrier to a local retail store in Switzerland.

2.1.1. Datasets

Two different datasets were evaluated. The first dataset consists of time-temperature data (dataset A) obtained between the packhouse and the DC (See Fig. 1A) in 2018 and 2019, measured by the retailer on each shipment. The second dataset (dataset B) was collected during the import season between December 2019 and June 2020. This data was obtained to investigate the cold chain at and after the DC, and to evaluate the whole cold chain. Therefore, the monitoring range was extended until retail stores (Fig. 1B). Additional to the air temperature data, dataset B consisted of geolocation data (see Section 2.1.2). Table 2 lists the number of shipment data analyzed for each monitoring campaign. In order to calculate the minimum required data size for the monitored supply chain, we used Cochran's formula with 95% confidence level and ±5% precision. Additionally, we examined the fluctuation of the average temperature values by increasing the sample size to identify the minimum required sample size that stabilizes the average value. From these two analyses considering our dataset's size, 20, 15, 20 and 14 shipments per supply chain for cucumber, eggplant, strawberry, and raspberry, respectively, were found sufficient for this study (See Supplementary material for details).

2.1.2. Sensors

To monitor air temperature during the cold chain between the packhouse and the DC (dataset A), the retailer currently uses TempTale RF® (TTRF) (Sensitech). For additional monitoring over the extended coverage of the cold chain (dataset B), we used TempTale GEO Eagle® (TTgeo) (Sensitech). A TTRF logger has an accuracy of 0.55 °C with a resolution of 0.1 °C, and data was logged at 11.5-minute intervals. The

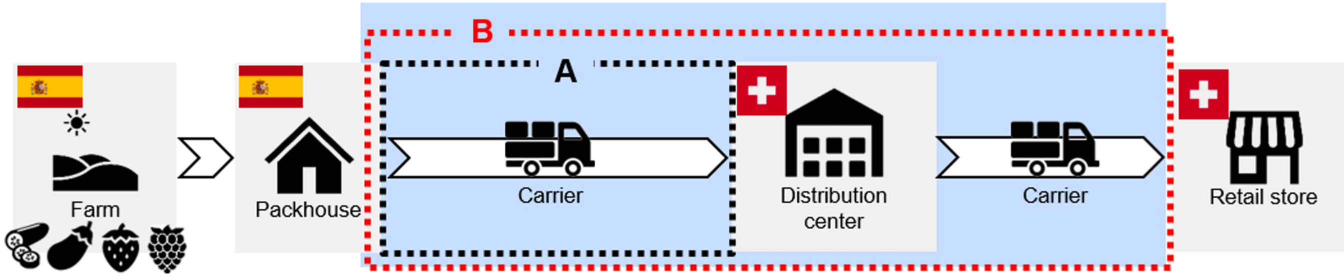

Fig. 1. Food supply chain of the studied system, indicating; cold chain as blue shaded square, (A) current commercial monitoring coverage, and (B) monitoring coverage additionally investigated in this study.

Table 2
Number of studied shipments data (sample size) of the four fruits.

Sample size	Cucumber	Eggplant	Strawberry	Raspberry
Dataset A (Existing monitoring)	57	65	51	63
Dataset B (Extended monitoring)	29	27	23	16

collected data, including time-temperature and logistics metadata, were accessed via the software ColdStream (Sensitech). The logistics metadata consist of the names of the logistical coordinators, packhouse, carrier which is the company organizing refrigerated trucks for transportation, and the DC involved in each shipment. A TTgeo logger contains a temperature sensor with a 0.5 °C accuracy and a resolution of 0.1 °C. Additionally, a geolocation sensor is included in the TTgeo logger, and both temperature and location data were collected at 15-minute intervals. Both TTRF and TTgeo loggers were placed on the upper part of the pallet of the fruit of interest, inside the refrigerated truck, on the pallet that was closest to the door of the truck.

2.2. Digital twin model

Digital twins of the four fruits investigated were developed in a similar way as described by (Defraeye et al., 2019). The key information are given below (Section 2.2.1 and 2.2.2), whereas the extended information of the model are included in the Supplementary material. For the digital twin, we modeled a single fruit that is linked to the real world by receiving air temperature data from the sensor. This digital twin is thus representative of fruit close to the sensor. Note that spatial variations in air temperature can occur in a refrigerated trailer, so our digital twin might not represent each fruit in the shipment. To mitigate this, more sensors can be placed. Dataset B was used as inputs for the digital twins because of its extended monitoring coverage.

2.2.1. Continuum multiphysics model

A continuum multiphysics model was developed to simulate fruit conditions in the cold chain, and we used 2D axisymmetric models. We

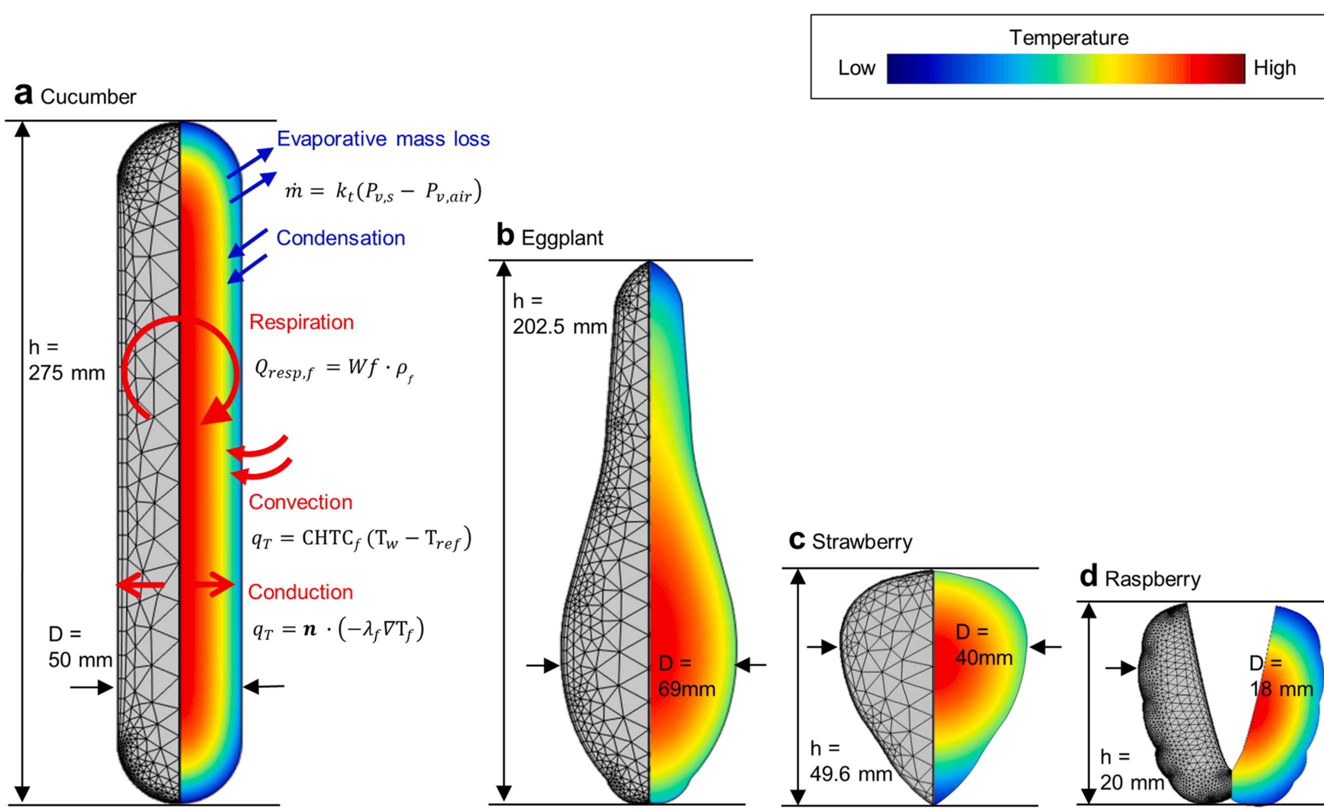

Fig. 2. Computational model of (a) cucumber and designed geometries of (b) eggplant, (c) strawberry, and (d) raspberry with dimensions. Note that the geometries shown are not on the same scale between fruits.

considered heat conduction and respiratory heat for heat transport inside the fruit by solving the energy conservation equation. To account for the heat exchange with the air, a thermal boundary was set at the fruit's surface, and conductive heat flux from the fruit was set equal to the convective heat exchange with the environment. Radiation was not included in this model as its impact was considered limited compared to convection (Defraeye et al., 2019). With these, fruit temperature was calculated for each air temperature input. The computational model is shown in Fig. 2 for cucumber, together with designed geometries for all the fruits.

Additionally, transpiration of the fruit was modeled to calculate a fruit's mass loss. To this end, a mass flux boundary at the fruit's surface was implemented. A difference in vapor pressure at the boundary was considered based on temperatures of air and the fruit surface. Since the airspeed and relative humidity (RH) were not measured along the cold chain, these values were estimated within the model (See Supplementary material for details). The fruit geometry (Fig. 2), initial fruit temperature (set to 20 °C), and thermal properties of the fruit were assumed to be constant.

Furthermore, to quantify fruit quality evolution in-silico, we added a kinetic rate model, which predicts fruit quality changes over time based on the calculated fruit temperature. A first-order kinetic law model was implemented for this purpose with an assumption that lowing the temperature by 10 °C doubles the shelf life (Defraeye et al., 2019). After arrival at the retailer, no sensor data were available anymore. The remaining quality upon arrival at the retailer was then used to predict the remaining shelf life of the fruit based on the same kinetic rate model. To this end, the digital twin was placed on a virtual shelf at room temperature (set to 20 °C) until the quality fell below a certain threshold. In the Supplementary material, more details such as equations and values of parameters used are given on conservation of energy, hygrothermal boundary conditions, and fruit quality modeling.

2.2.2. Numerical implementation

Physics-based digital twins for cucumber, eggplant, strawberry, and raspberry were developed in COMSOL Multiphysics (version 5.5), a commercial finite-element simulation software. The thermal model was set up and solved in the 'Heat Transfer in Solids' interface to account for heat transfer within the fruit and the heat exchange between the surrounding air and a fruit. The equations were solved for a dependent variable, namely fruit temperature. The mass loss of fruit was calculated in the 'Domain ODEs and OAEs' interface. A kinetic rate-law quality model was also implemented in the 'Domain ODEs and DAEs' interface and calculates quality and remaining shelf life based on the fruit temperature. The solver scheme MUMPS (MUltifrontal Massively Parallel sparse direct Solver) was used. The solver tolerance was set to 10^{-6}, based on a sensitivity analysis. The time step of 900 s was used, which is equivalent to 15 min interval in dataset B. We developed the computational grids based on a grid convergence study for all the fruits (See grid size analysis in Supplementary material for details). The computational grids were refined towards the boundary as the largest gradients exist there. The models had 819, 614, 260, and 3,920 finite elements for cucumber, eggplant, strawberry, and raspberry, respectively, and these computational grids are shown in Fig. 2.

2.3. Statistical analysis

Dataset B was further analyzed together with the outputs from the digital twins. We used Pearson's correlation coefficients (Pearson's r) to determine the correlation between sensor data and outputs of digital twins statistically. To do so, the following time-temperature-based parameters were calculated for each shipment: mean, median, maximum, minimum, and standard deviation (SD) of the temperature [°C]. Additionally, to take the degrees of high temperature and exposure to such high temperature into account, we calculated degree-hour above the optimal temperature [°C hr]. This parameter is a summation of the difference between the measured high temperature and the set threshold temperature (10 °C for cucumber and eggplant, and 2 °C for berries), multiplied by a time interval (See Supplementary material for details). Shipment length [d] was also used as a parameter for calculating Pearson's r. In addition, based on the estimated RH derived from the digital twins, mean, maximum, minimum, and SD of the RH [%] were calculated. Pearson's r of all these parameters against outputs of the digital twins, namely mass loss [%] and remaining quality [%] at arrival at a retail store, were evaluated. The corresponding p-values were calculated with a confidence level of 0.95 to ensure the significance of the correlations. Data processing and analyses were conducted in R (version 4.0.2) (R Core Team 2018) and Microsoft Excel (2016).

3. Results and discussion

3.1. Mapping thermal history in the fruit cold chain

3.1.1. Packhouse to distribution center

Using dataset A (Fig. 1), we first examined the supply chain from packhouse to distribution center (DC) to gain insight into how the fruits' cold chain is maintained when transported with a refrigerated truck from Spain to Switzerland (Fig. 3). For all the four fruits studied, the standard deviation (SD) of temperature among different shipments was 2 °C for 35% of the shipment duration and 3 °C for 91% of shipment duration between the packhouse and the DC (Fig. 3). These little temperature fluctuations suggest that the temperature is controlled relatively well in the current system between the packhouse and the DC. However, concerning temperatures for each fruit, cucumber and eggplant shipments (Fig. 3a and b respectively) had their average temperature lower than the optimal temperature range (see Table 1) for over one day. Thereby, the cucumber and eggplant fruits could have developed a chilling injury, leading to visible fruit damage (Wang, 1990; Saltveit, 2001). The retailer, however, did not observe such damage, which implies that the transport at a slightly lower temperature range did not negatively impact the fruit quality. On the other hand, while the optimal storage temperature range of strawberry and raspberry is 0 °C (Table 1), these berries were transported at temperatures around 5 °C during the shipment. The reason for this is that transport at temperatures close to 0 °C had shown condensation and freezing-related quality problems. Nevertheless, this higher temperature will, to some extent, accelerate the berry quality loss, compared to optimal conditions, as quality decay is exponential with an increase in temperature (Jalali et al., 2020; ASHRAE 2006). As such, there is still some room for improvement for the berries by transporting them at lower temperatures, but then the supply chain needs to be optimized to avoid existing quality problems at these low temperatures.

To further investigate the temperature variability, we analyzed the temperature fluctuation of single shipments (Fig. 4). For cucumber and eggplant, 7% and 12%, respectively, of the studied shipments had their middle 50% (i.e. interquartile range (IQR)) measured temperatures larger than 5 °C (Fig. 4a and b). This suggests that when considering all shipments of cucumber and eggplant, the temperature variations within the same shipments are larger than among different ones. For strawberry, we found that the shipments with the lower temperature range were likely to correspond to those with longer shipment lengths (Fig. 4c). Raspberry shipments had their temperature averages between 2 °C and 8 °C, and 60% of their shipments had their IQR smaller than 1 °C (Fig. 4d). As raspberry is the most perishable product among these fruits (See Table 1), we conclude that, for the current cold chain, the most sensitive products are kept in the temperature range with the smallest variation. The retailer thus refrigerates the most sensitive fruit in the most careful way.

3.1.2. Packhouse to retail store

We analyzed the supply chain from packhouse to retail store (dataset B) to investigate the entire cold chain (Fig. 5). Based on dataset B, we

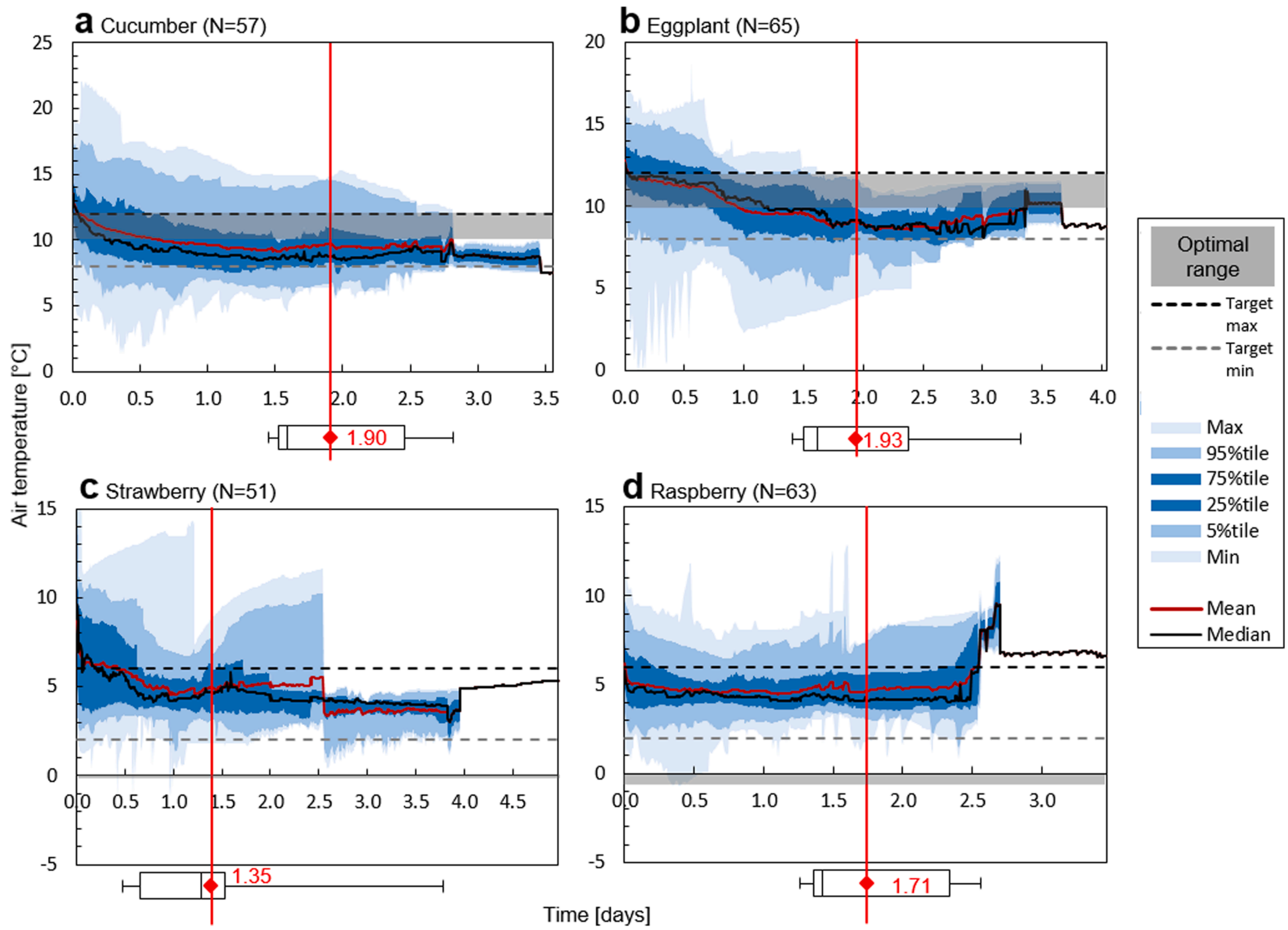

Fig. 3. Time series analysis on dataset A along with the shipment duration in days from the packhouse to the distribution center for (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry. The boxplot shows the shipment duration distribution of all the shipments, including the 25th percentile, median, and 75th percentile, with the whiskers representing the 5th and 95th percentile. Targeted temperature ranges set by the retailer (Table 1) are indicated in dashed lines ('Target max' and 'Target min'). The gray area represents the corresponding fruit's optimal temperature range (see Table 1), and the red vertical lines indicate the average shipment time length.

were able to see temperature fluctuations at each segment of the cold chain, namely from the packhouse to the DC, at the DC, and the DC to the retail store (Fig. 5). The monitoring of the last two stages was particularly beneficial as we were unable to grasp them from dataset A. At the first 2–3 h of the measured data, there is a temperature drop. This drop is prominent, especially for berries as, on average, their temperature decreased by about 10 °C (Fig. 5c and d). This rapid lowering of the temperature corresponds to pre-cooling conducted just before shipping the produce after placing the sensor at the packhouse. Fig. 5 confirms that pre-cooling is in place and working effectively. For the temperature between the packhouse and the DC, we found that cucumber and eggplant were kept slightly lower than their optimal range (Fig. 5). This observation is in line with the results from dataset A (Fig. 3). This lower range indicates a potential risk of chilling injury, which was, however not observed in practice as the species seem sufficiently resilient. Similar to the findings in Fig. 3, strawberry and raspberry shipments were transported at higher temperatures than their optimal range to secure a robust supply chain and reduce condensation-related quality loss.

At the DC, the temperature stayed stable for cucumber, eggplant, and strawberry as their standard deviation (SD) was 0.8 °C, 0.8 °C, and 1.1 °C, respectively (Fig. 5). On the contrary, the SD of raspberry shipments was 1.9 °C, which was larger than the SD between the packhouse and the DC (SD 1.82 °C). Nevertheless, the temperature was well controlled at the DC (SD $<$ 2 °C) for all four fruits. When the fruits left the DC, an increase in temperature was observed for all fruits. There was an approximately 2 °C increase in 6 h for cucumber and eggplant, followed by a gradual decrease (approx. 2 °C in 12 h). For strawberry and raspberry, there was about 3 °C of a temperature increase in 12 h. This temperature increase is induced by the retailers and is essential for the retailer to avoid condensation on the fruits as they display the fruits at ambient temperature. Fig. 7 reveals that with the ramp-up phase as the fruits approached the retail store, the temperature variability among different shipments became larger, with a temperature spread of over 5 °C. This temperature spread is probably because such a ramp-up is difficult to control.

The temperature fluctuations at each segment discussed above highlight the importance of monitoring the entire cold chain. Overall, our monitoring for dataset B extended the coverage as in time compared to dataset A by 110%, 71%, 125%, and 73% for cucumber, eggplant, strawberry, and raspberry, respectively (Fig. 6). Therefore, dataset B provides a comprehensiveness of the current cold chain and gives a better picture of the environment that the fruits go through until they are displayed at the retail store. Nevertheless, the longest shipment time corresponds to a segment between the packhouse and the DC. Thus, dataset A remains of high importance. This finding led us to further investigate the packhouse - DC segment of the cold chain to identify variations among carriers, which we report in the next section (Section 3.2).

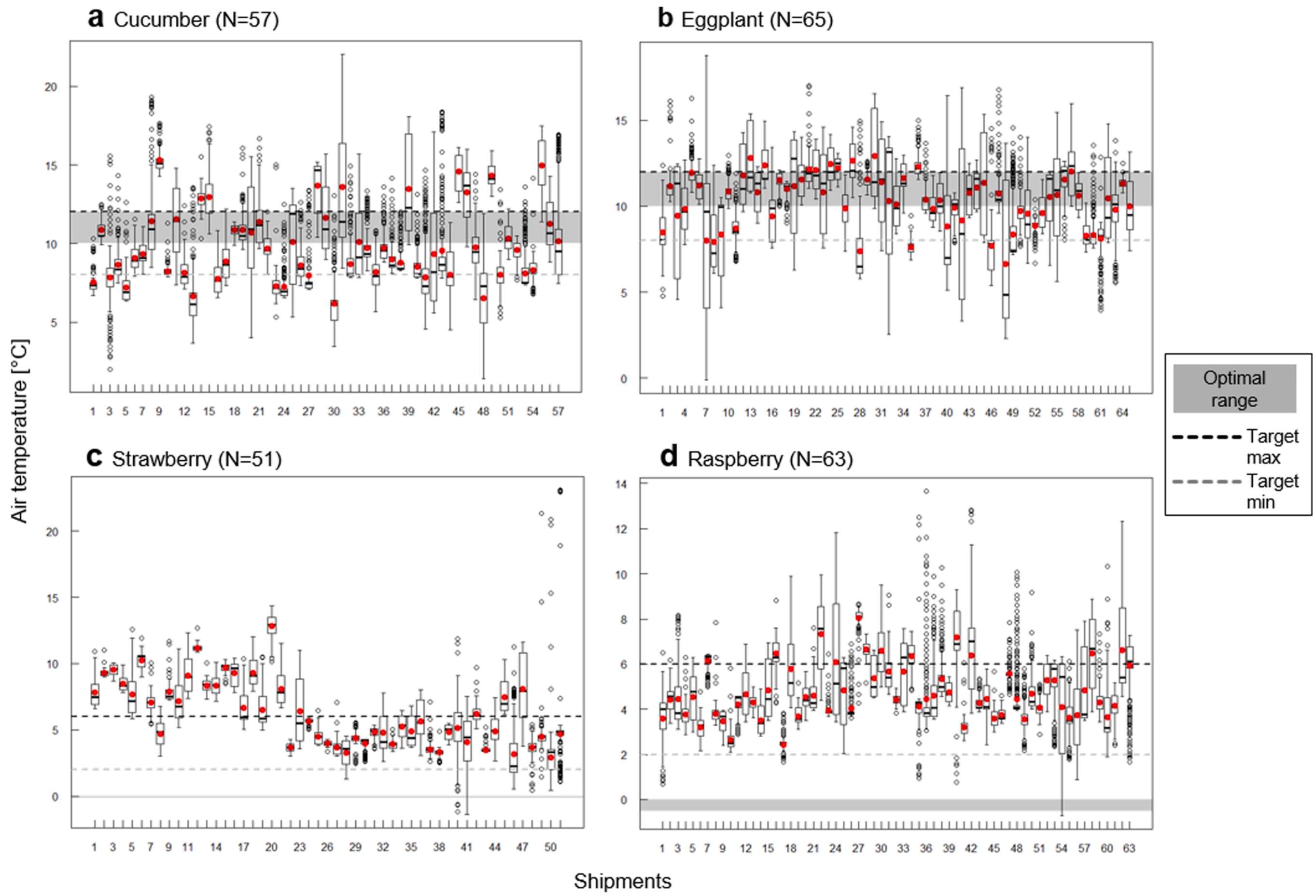

Fig. 4. Temperature distribution of the single shipments based on dataset A for (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry in ascending order of shipment time length. Each boxplot represents one shipment, including the 25th percentile, median, 75th percentile, and mean in the red circle, with the whiskers representing 1.5 times the interquartile range (IQR). White circles represent outliners exceeding 1.5 IQR. Targeted temperature ranges set by the retailer (Table 1) are indicated in dashed lines ('Target max' and 'Target min'). The gray range represents the optimal temperature range for the corresponding fruit (Table 1).

3.2. Temperature condition per carrier

By utilizing the logistics metadata from dataset A, we evaluated each carrier's performance to transport the fruit in the targeted range for the longest segment (packhouse to DC) of the cold chain. Fig. 7 shows how the mean temperature varies among the shipments transported by the same carrier and different carriers. The majority of the shipments with the mean temperature outside the optimal were not registered properly (NA in Fig. 7), which prevents the identification of carriers of inappropriate transport conditions. Nevertheless, this finding emphasizes the importance of improving data completeness. Except for these shipments with the unidentified carriers, the retailer can inform the carriers with suboptimal cold storage conditions, such as excursions outside of the targeted range or a high thermal variability between shipments. In the case of the carriers for cucumber and strawberry (Fig. 7a and c respectively) in particular, one solution for optimization would be to focus on improving the shipping conditions with the carriers who managed the large numbers of shipments outside of the targeted temperature ranges, namely Carrier 24 for cucumber, and Carrier 09 for strawberry. If this is a systematic problem that remains, these data help the retailer choose to redistribute shipments based on the carrier's best performance. Sharing information represented by Fig. 7 with or among carriers could increase transparency in the system and motivate them to optimize the cold chain even more.

3.3. Shipment flow analysis

To further investigate the logistics flow of the individual shipments within the cold chain, we analyzed which stakeholders are involved in which shipments. The Sankey diagram in Fig. 8 represents a flow of the logistical coordinators arranging cucumber shipments to the individual packhouse, and carriers transporting the products from the packhouse to the DC based on dataset A ($N = 562$, see Table S1 in Supplementary material). A high number of stakeholders (> 40) are visible from this diagram for cucumber. For all four fruits, the total number of involved stakeholders was over 70. In particular, the segment involving the highest number of stakeholders corresponds to where the carriers transport the products from packhouse to the DC (where dataset A was collected). In Fig. 8, over 20 different carriers were involved. Note that 259 shipments, which is equivalent to 46% of the shipments in dataset A, did not contain information about their carrier's name. The significance of this missing information was seen as well in Fig. 7, as carriers associated with shipment with the mean temperature outside of the optimal range were often not recorded properly. Despite many carriers involved in this cold chain, the temperatures in most shipments were kept in a narrow range (Section 3.1). Nevertheless, the retailer can utilize this information from Fig. 8, for instance, to investigate their logistics to optimize the number of carriers. The retailer could also propose a protocol to the logistical coordinators, packhouses, and carriers that they interact with one another to achieve uniform product quality. Additionally, this information from Fig. 8 can help look into the cause of missing data on the involved carriers and aim to have a more complete

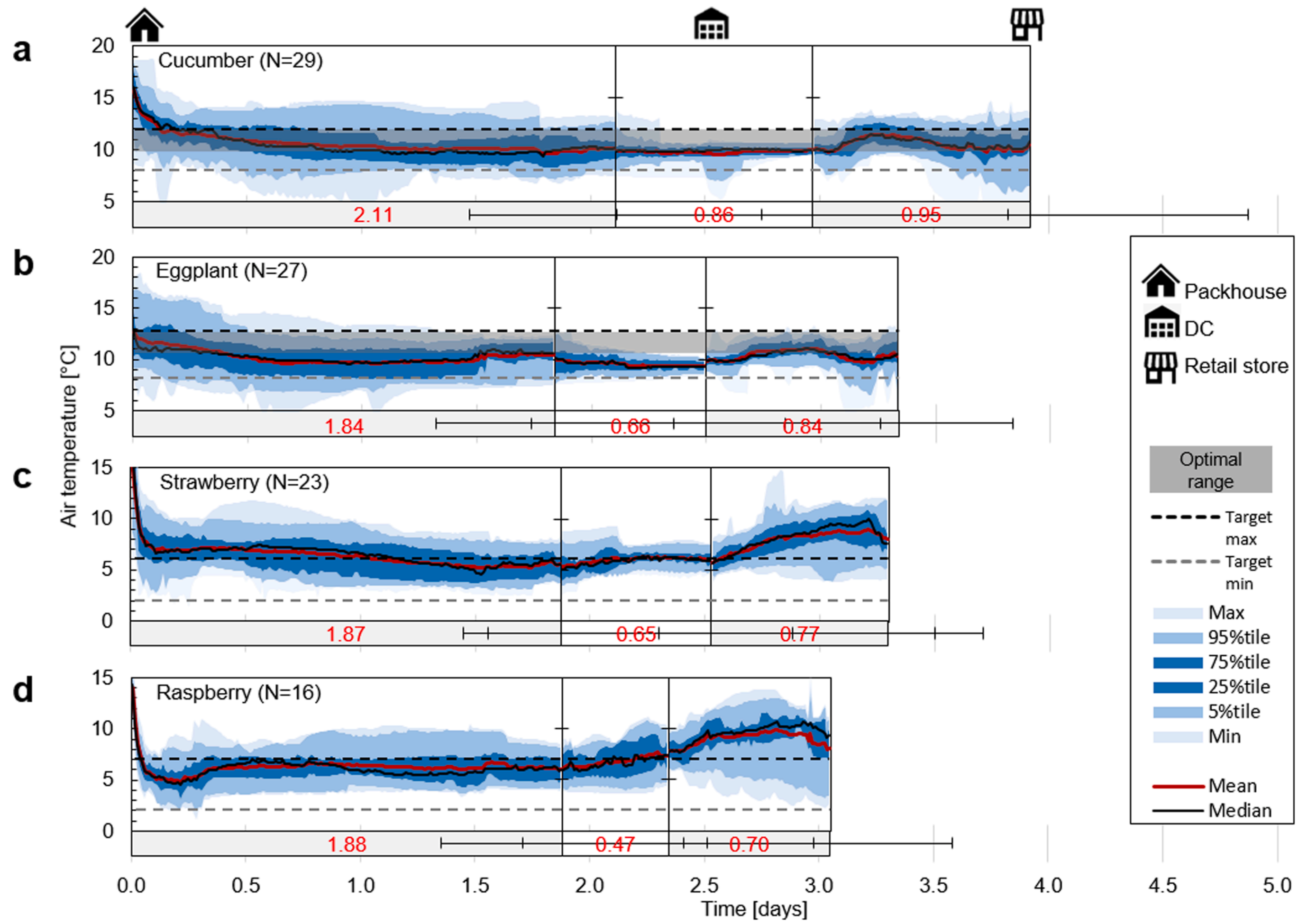

Fig. 5. Time series analysis based on dataset B along with the shipment duration in days from the packhouse to the DC and subsequently to the retail store for (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry. A bar graph shows the average shipment duration, labeled in red, with error bars representing standard deviation. Targeted temperature ranges set by the retailer (Table 1) are indicated in dashed lines ('Target max' and 'Target min'). The gray area represents the corresponding fruit's optimal temperature range (Table 1).

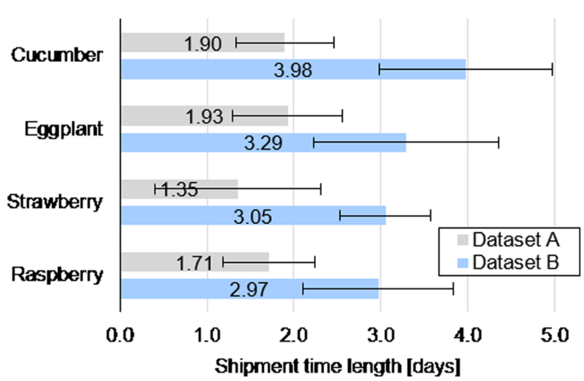

Fig. 6. Average shipment time length comparison between dataset A and dataset B in days. Error bars represent the standard deviation.

dataset in the future. Similarly, the other three fruits also show such complexity of shipments. Their results are shown in the Supplementary material.

Above all, translating dataset A into such a flow diagram enabled the retailer to understand their complex cold chain better and emphasize the importance of transparency in the system. Such logistic metadata was not available for the entire chain (dataset B) as these were custom experiments. The retailer might find it valuable to complement the extended monitoring to include such data in the future to map the flow of the whole cold chain.

3.4. Digital-twin-predicted fruit quality evolution from packhouse to retail store

Following the mapping of the thermal history and the cold chain logistics, we investigated the impact of the hygrothermal history (dataset B from packhouse to retail store and RH calculated within the digital twins) on the resulting fruit quality. To do so, we examined the fruit quality history using the digital twins to identify when, where, and how much of the quality loss occurs along the cold chain (Fig. 9). On average, the digital twins predicted that cucumber, eggplant, strawberry, and raspberry lost 50%, 43%, 70%, and 85% of their quality, respectively, before they reach the retail store. In particular, the most considerable quality loss occurred during the first segment of the cold chain, between the packhouse and the DC, for all the fruits studied. This loss corresponded to 39% of the quality on average. This finding emphasizes the importance of analyzing the temperature performance of each carrier as in Section 3.2 for improving the current system. Meanwhile, the predicted quality loss at the DC was 8% and between the DC and retail store was 9% on average. These quality losses were invisible to stakeholders prior to this study and might have been resulted in food loss. Therefore, this finding can help the stakeholders prioritize a certain segment of the supply chain to improve for optimization and

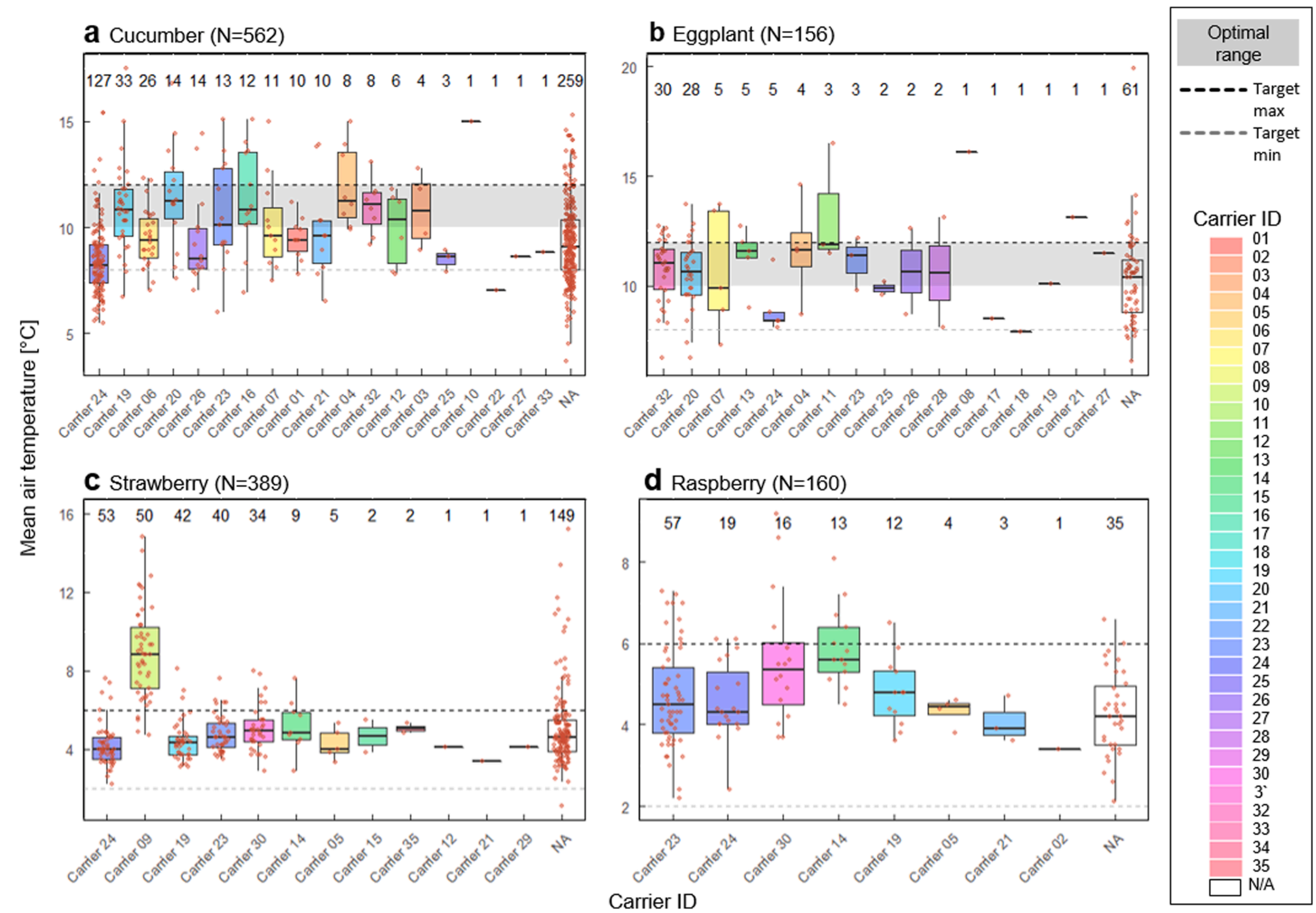

Fig. 7. Distribution of mean temperature for each shipment categorized by the different carrier who delivered (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry in dataset A. Each red dot in the boxplot is the mean temperature of one shipment conducted by a corresponding carrier, with the whiskers representing 1.5 times the interquartile range (IQR). For each plot (a), (b), (c), and (d), carriers are in descending order based on the number of shipments, which are indicated in the upper part of each boxplot. Note that the same Carrier ID is used in Fig. 8. Targeted temperature ranges set by the retailer (Table 1) are indicated in dashed lines ('Target max' and 'Target min'). The gray area represents the corresponding fruit's optimal temperature range (Table 1).

subsequently reduce food loss. In the case of this study, the segment from the packhouse to the DC corresponds to where fruits were transported from Spain to Switzerland, and it was typically the most extended cold chain segment (Fig. 5). On average, the shipment time length was 1.94 days from the packhouse to the DC (56% of the whole shipment time length), 0.68 days at the DC (20% of the whole shipment time length), and 0.83 days from the DC to retail stores (24% of the whole shipment time length). This finding proves that there is a strong correlation between fruit quality and shipment duration.

Despite the higher quality loss in the segment of the supply chain from packhouse to the DC, we found that the management at the DC and during the transport from the DC to the retail store also had significant influences on the quality (Fig. 10). For instance, in the case of cucumber shipments, shipment 3, 8, and 12 in Fig. 10a resulted in lower quality than that of shipment 1 by the time the cucumbers reached the retail store. Similarly, shipment 20, and 23 had less quality decline in the end than that of shipment 29, while shipment 29 had a better quality when it reached the DC. As the shipment length was previously identified as a major factor of quality loss of fruits, it is most likely that shipments with large-quality loss at the DC correspond to the longer stays at the DC. To understand the current system and identify the points for improving the supply chain, these differences among different shipments need to be considered.

3.5. Suggested areas of improvements identified by correlating cold chain parameters

We examined the correlation among different cold chain parameters to identify the factors influencing the fruits' quality. Fig. 11 shows the correlations among time-temperature-related parameters and the digital twins' outputs, which are fruits' mass loss and remaining quality upon arrival at a retail store (shown as 'mass loss' and 'remaining quality' in Fig. 11, respectively). The results show that the digital twins' outputs are strongly correlated to shipment time length (i.e., for cucumber: mass loss ($r = 0.61$, $P < 0.001$), and remaining quality ($r = -0.95$, $P < 0.001$)). This correlation confirms the relationship between fruit quality and shipment time length discussed in Section 3.4 and suggests quantitatively that supply chains should be as short as possible. Besides, the mass loss has strong correlations with the remaining quality (i.e., cucumber: $r = -0.81$ ($P < 0.001$)). For berries, both mass loss and remaining quality show a strong correlation with degree-hour above the optimal [°C hr] ('Degree-hour' in Fig. 11) (i.e., strawberry: $r = 0.93$ ($P < 0.001$), and $r = -0.94$ ($P < 0.001$) respectively). Thus, this finding with berries highlights the sensitiveness of berries to the exposure to high temperatures.

In addition, Fig. 11 shows that the correlation between the remaining quality from the digital twins and temperature related parameters is low. For instance, food quality is only weakly correlated with the maximal or minimal temperature ('Temp max' and 'Temp min' in Figure 11b, respectively). One reason for such low correlations could be

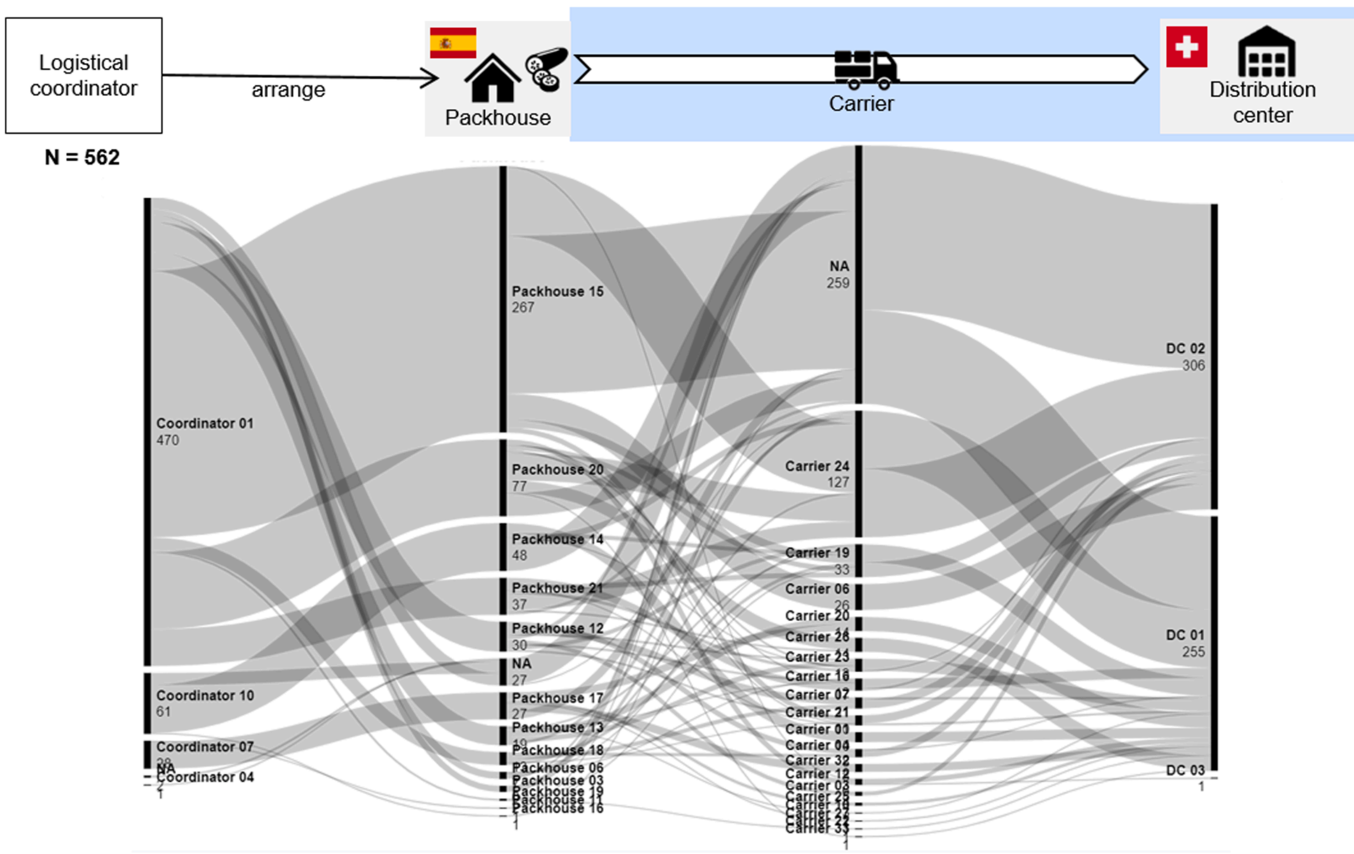

Fig. 8. Sankey diagram displaying stakeholders (logistical coordinator, packhouse, carrier, and distribution center (DC)) configuration for all cucumber shipments in dataset A ($N = 562$, see Table S1 in Supplementary material). The flow thickness is proportional to the number of corresponding shipments, and NA represents the shipments with missing information. The blue shaded area in the diagram above indicates the cold chain. Carrier ID corresponds to that of Fig. 7.

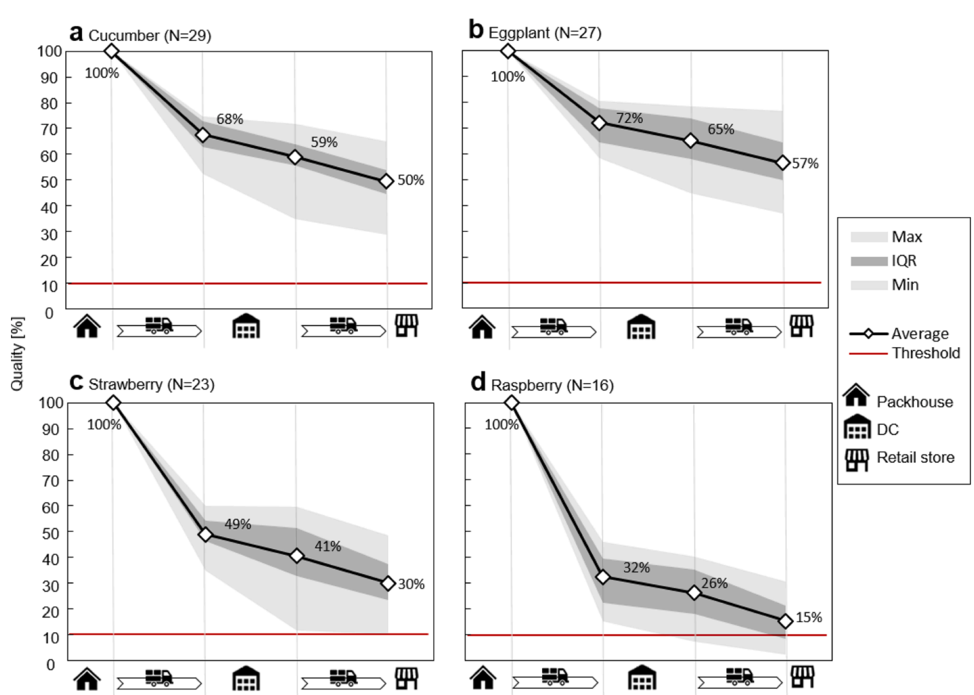

Fig. 9. Quality decay distribution at different stages along the cold chain for (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry. The fruit quality of 100% was assumed when leaving the packhouse. The quality distribution at arrival at and departure from the distribution center (DC) and the arrival at retail stores are shown.

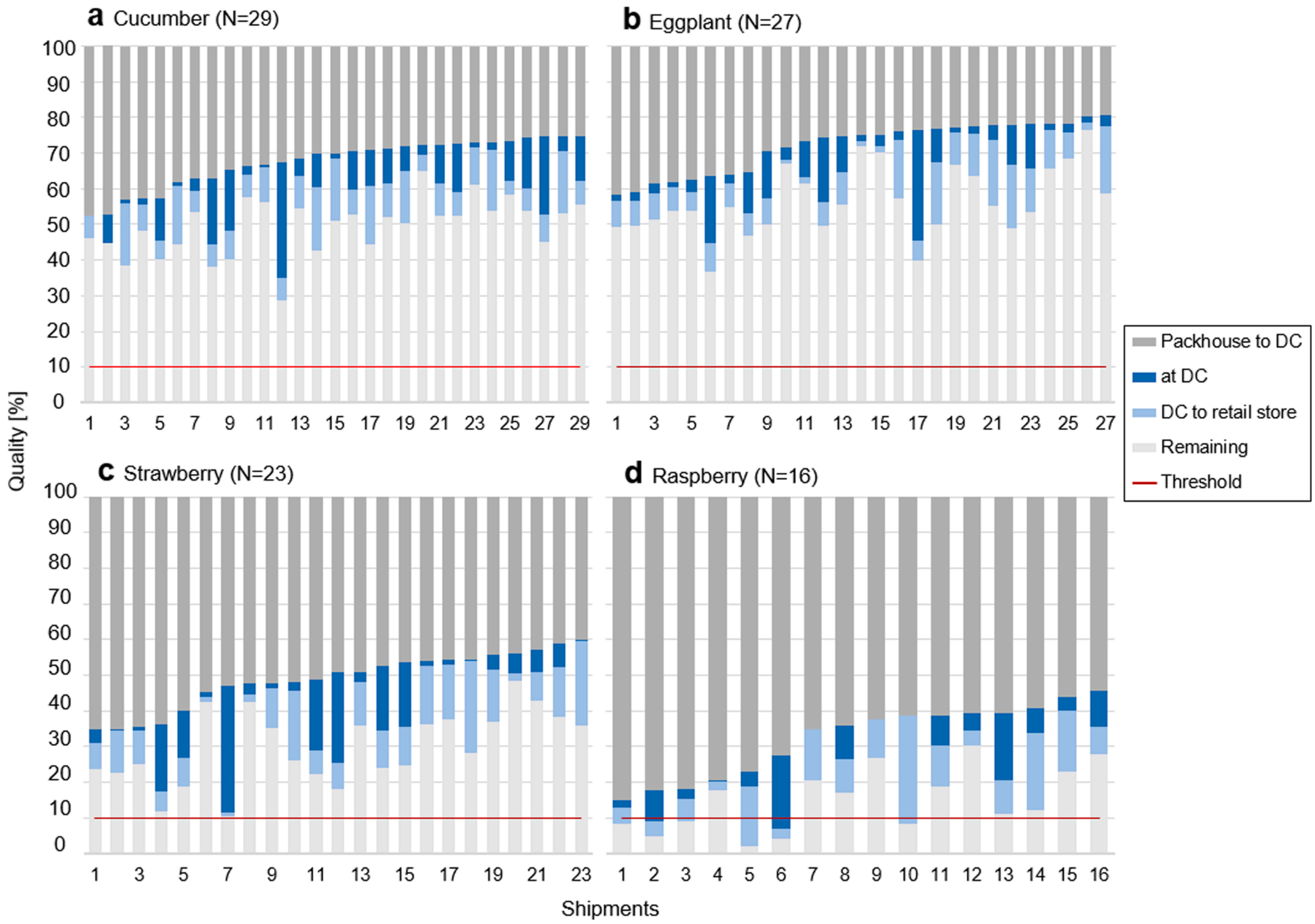

Fig. 10. Identification of quality loss of (a) cucumber, (b) eggplant, (c) strawberry, and (d) raspberry at a corresponding segment of the supply chain, namely from packhouse to the distribution center (DC), at DC, and from DC to a retail store, in each shipment, ordered by the quality loss between packhouse and the DC.

that a difference between fruit temperature and air temperature. Fruit temperature was derived by considering heat exchange between air and fruit (See Section 2.2.1 and Supplementary material for details). Our digital twins calculated fruits' quality based on the fruit temperature, as it is more representative to evaluate the quality of fruit. Nevertheless, this low correlation shows that the peaks or valleys are not a direct indication of quality loss or retention, although they might seem intuitively bad for a person evaluating the temperature monitor output. Currently, only such temperature related values based on dataset A are looked at by the retailer. This finding highlights the impact of temperature fluctuation throughout the cold chain and use of the digital twins. To emphasize these points, Fig. 12 shows, for each shipment, the remaining shelf life calculated by digital twins and compares that of time-temperature based and average-temperature based (Fig. 12a and b respectively). Although Fig. 12a and b are representing the same shipment, thus the same dataset (cucumber shipments in dataset B), the calculated remaining shelf life are different. For instance, a shipment with the longest shelf life (6.34 days) in Fig. 12a does not correspond to the longest shelf life in Fig. 12b and has only 5.03 days remaining. This difference comes from the delayed response of the fruit to fluctuations in air temperature and the nonlinear kinetic rate law model. Such a difference indicates the importance of using time-temperature data and using fruit temperature in the quality model. It is thus emphasized that fluctuation of temperature affects the quality of the fruits. By translating the time-temperature dataset into actionable metrics by calculating the effect of temperature and humidity on the fruit's characteristics by integration, the digital twins add values to the monitoring.

3.6. Outlook

This study showcases how to better utilize the monitored data in the cold chain by using digital fruit twins. The use of the digital twins with sensor data enables us to identify where and how much the fruits lose their quality in the supply chain. This information can be beneficial to optimize the cold chain system effectively and efficiently. To further enhance such advantages of monitoring and using the digital twins of fruits, there are some areas for improvement.

First, several critical environmental parameters are currently not measured in the cold chain. These data include relative humidity and ambient fruit temperature at harvest. Having these values will increase accuracy when predicting fruit quality and mass loss using the digital twins, which will facilitate understanding the current system. The second point for improvement concerns a lack of transparency and communication in monitoring. One solution would be to share sensor data among all the stakeholders to encourage uniformity and higher completeness of data collection in the system and motivate the stakeholders for monitoring. A preferred option can be the use of blockchain or a customized platform. Mapping the shipment flows (Fig. 8), and showing each stakeholder's performance as in Fig. 7, could further increase transparency among stakeholders and educate them on the importance of monitoring.

Regarding the digital twins, they should be upgraded by using real-time data as input. With this upgrade, risk for quality loss can be identified before fruits decay and become no longer marketable. By doing so, food loss can be even more reduced (T. Defraeye et al., 2021). These real-time data fed twins could be used to grade the quality of the fruit

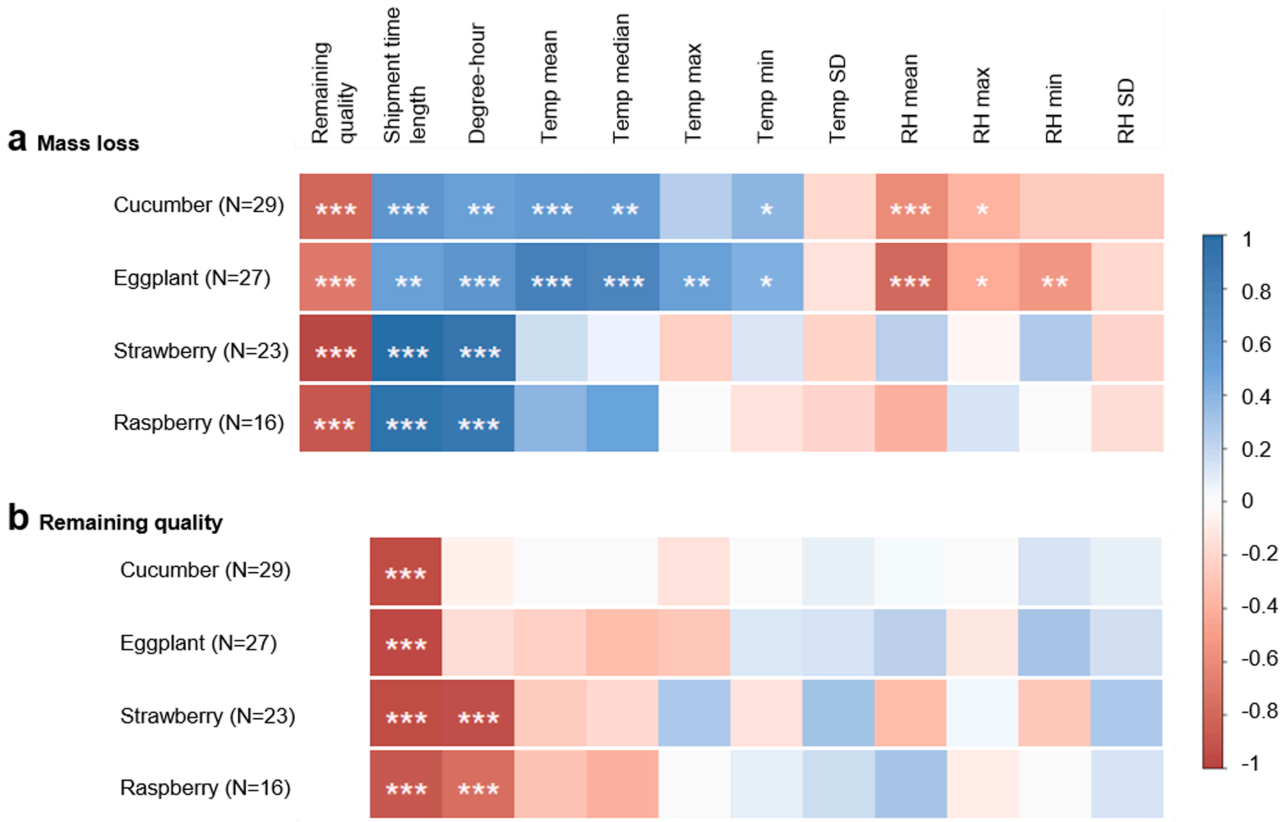

Fig. 11. Pearson's correlation coefficients of cold chain parameters and (a) mass loss and (b) remaining quality of each fruit at arrival at a retail store, obtained from the digital fruit twins. Degree-hour refers to the degree-hour above the high limit of optimal temperature range [°C hr]. The positive (blue) and negative (red) correlation are indicated, and the color gradient features each correlation's strength. White asterisks represent p-value as *** for $P < 0.001$, ** for $0.001 \leq P < 0.01$, and * for $0.01 \leq P < 0.05$.

upon arrival at the distribution center. In this context, a strategy such as First-expired-first-out (FEFO) practice can be integrated into the food supply chain (T. Defraeye et al., 2021; Scheer, 2006; Jedermann et al., 2014). Another example of utilizing digital twins would be to parametrically run virtual experiments to test different cold chain scenarios before the retailer implements these changes in their logistics. Such experiments in the cold chain system can be costly and time-consuming due to the placement of the sensors and the possible partial loss of the shipment. If these experiments turned out to be suboptimal, there could be an increase in food loss. Therefore, digital twins' applications prior to engaging in a commercial pilot can be more economical and time-efficient (Wagner et al., 2019). The digital twins developed in this study calculates fruits' quality using the first-order kinetic rate model. This model is based on the derived fruit temperature and does not take damage from exposure to lower than the optimal temperature into account. Thus, the digital twins can be extended by including biophysical processes such as chilling injury, freeze damage, occurrences of condensation, microbiological decay, the incidence of pests, and the diffusion of gasses (e.g., CO_2, O_2, ethylene), amongst others. The outputs from such a comprehensive and dynamic digital twin would predict the fruit quality, more preciously and quantitatively, bringing benefits to all the stakeholders.

4. Conclusions

In this study, we quantified for retailers (1) how the temperature from packhouse all the way to the retailer store looks like, and (2) how this temperature history impacts the quality of their produce. As a result of this, we helped to identify areas for improvement in their supply chain. We analyzed 331 shipments of cucumber, eggplant, strawberry, and raspberry and visualized the complex logistic system and quality decay with the fruit digital twins. The temperature monitoring of the entire cold chain with geolocation presented variations in temperature fluctuation patterns in different cold chain segments. We identified that pre-cooling at the packhouse was appropriately done, the stable temperature was maintained at the distribution center, and a gradual temperature increase before the arrival at the retailer store was successfully implemented. Mapping the cold chain logistics and the temperature data identified that some data were still incompletely documented, and the specific carriers had a suboptimal performance. These findings emphasize the benefits of utilizing the dataset and the potential advantage of sharing them among stakeholders to increase the transparency and traceability in the system. Overall, the temperature was maintained stable with small fluctuations for the studied cold chain (SD < 3 °C for 91% of the shipment time duration), despite a large number of stakeholders (> 70) involved. In addition to understanding the fruits' thermal history, temperature data of the entire cold chain was used as an input for a digital twin, a virtual representation of fruit. Based on fruit temperature, the outputs of mass loss, fruit quality, and the remaining shelf life of each product were obtained. By using these actionable metrics, the fruits' quality decay evolution was visualized. We identified that a segment between the packhouse and the distribution center corresponds to 39% of quality loss on average. Furthermore, a strong correlation between shipment duration with fruit quality was identified (i.e., cucumber: r = -0.95 ($P < 0.001$)), emphasizing that shipment should be as short as possible to enhance the fruit quality at the retail store. The impact of this study lies in the fact that the retailers can use this information to optimize their logistics with stakeholders they work with and sharpen the temperature goals that different carriers should reach. In addition, retailers now see how much difference in shelf life they receive

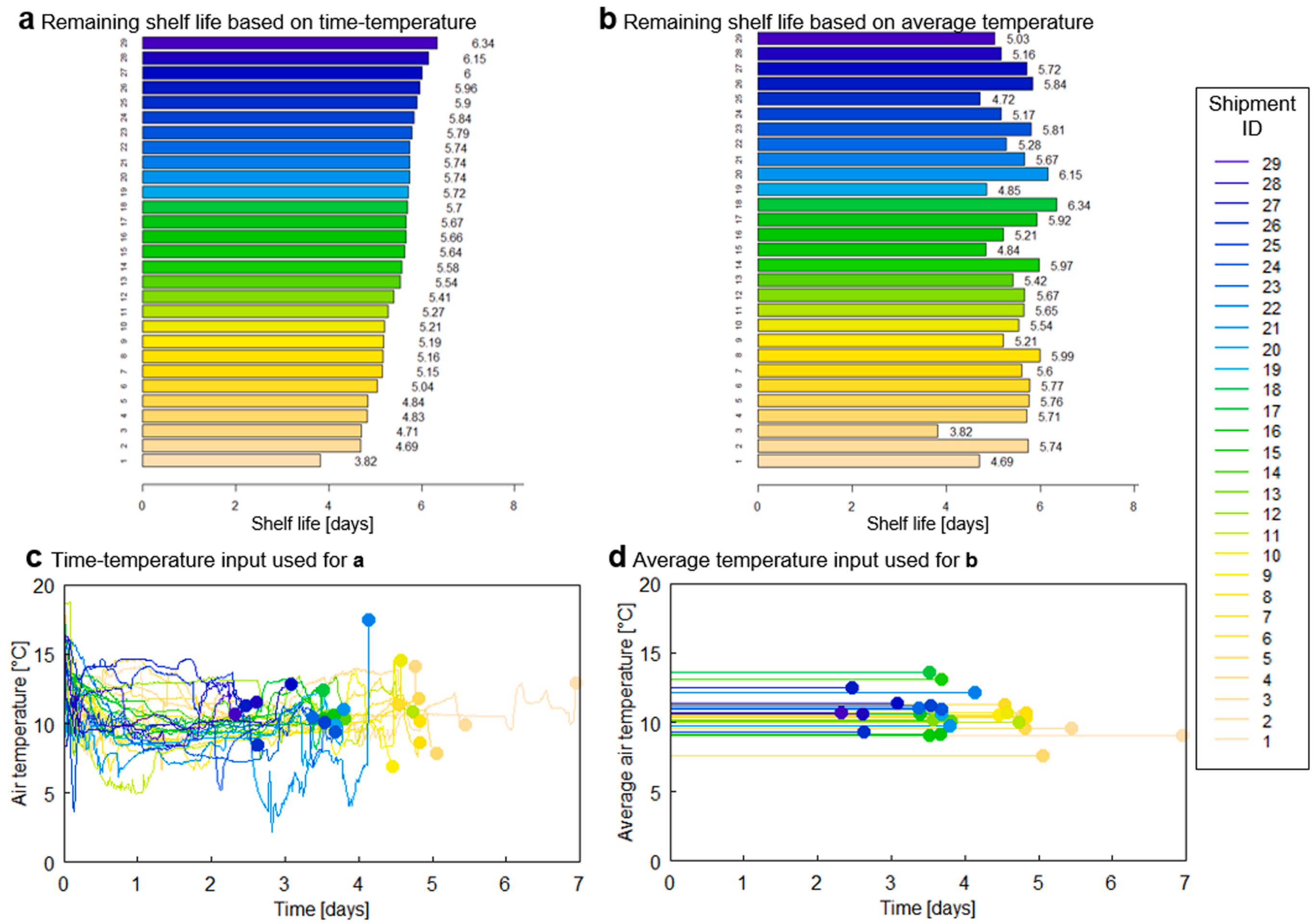

Fig. 12. Remaining shelf life upon arrival at retail store calculated by the digital twins based on dataset B cucumber shipments using (a) time-temperature input and (b) average temperature input for corresponding shipment time length. The inputs used for (a) and (b) are shown below as (c) and (d), respectively, and the dots show the arrival at a retail store. Shipments ID and their corresponding color gradients in all graphs are ordered by time-temperature based shelf life (a).

between different shipments, which was substantial. Such an actionable metric was missing decisive information for the retailers to convince stakeholders to implement new measures to prolong shelf life and thereby reduce food loss. Lastly, monitoring the entire postharvest life with more environmental parameters, such as relative humidity, coupled with the digital twins in real-time, enhances the benefits of the digital twins and opens more opportunities for their applications. In future studies, the predictive power of the digital twins should be explored as it enables conducting virtual experiments prior to commercial pilots to quantify the impact of possible solutions.

Author contributions

T.D. conceptualized this study and performed project administration; T.D. also wrote the proposal and secured project funding; T.D., D.O., S. S., and K.S. developed the methodology for this study; K.S. and S.S. performed calculations, data analysis, and interpretation; K.S. performed visualization of the results and wrote the original draft of the manuscript with key inputs from S.S., and C.S.; All critically reviewed and S.S., C.S. and T.D., edited the manuscript; K.S. revised the manuscript based on their suggestions.

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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2021.105914.

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