



IoT-based monitoring workflow for continuous analysis of apple ripening delay and maturation patterns under agrivoltaics

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Abstract Agrivoltaic systems, combining solar energy generation with agricultural activities, offer a sustainable approach to maximising land efficiency. However, these systems can present challenges, such as potential shading effects that may impact fruit quality or crop yields. This study evaluated the impact of overhead agrivoltaic systems on apple (*Malus domestica* L. cv. Gala) ripening and maturation patterns in a temperate orchard near Lake Constance, Germany. Experiments compared apples grown under conventional conditions (control) with those under agrivoltaic setups equipped with semi-transparent photovoltaic panels utilizing spatially distributed cells for 40% light transparency installed with a 70% ground-coverage ratio. Key metrics, including fruit diameter, length, volume, and BBCH phenology stages, were monitored throughout the 2024 growing season. An IoT-based monitoring workflow was

developed, combining fixed RGB image acquisition, automatic apple detection, colour-based ripening quantification, and time-series analysis to monitor visible maturation dynamics under field conditions. Results indicated that apples under agrivoltaic conditions showed delayed visible red-colour development, reaching comparable image-derived colour-maturity thresholds approximately 10–12 days later than the control group. On September 13 (harvest), no significant differences were found in mean length, while the diameter of agrivoltaic apples was significantly smaller (65.59 mm versus 70.98 mm), indicating slightly smaller dimensions under shaded conditions. Fruit volume and weight were approximately 16% lower under agrivoltaic conditions, averaging 161.16 cm³ (138.6 g) versus 191.58 cm³ (164.8 g) in the control. The delayed visible maturation was consistent with reduced light availability under the solar panels, although fruit-level light availability and physiological maturity indicators were not directly measured. These findings suggest that overhead agrivoltaic systems can significantly delay apple phenology and fruit maturation. Depending on the agricultural goals, the desired harvest timing and the cultivar, this may be challenging or beneficial, e.g., if it adapts the crop against climate change impacts or other factors such as local climate conditions, latitude and geographic region, and market demand. Integrating IoT-based monitoring with machine learning enhances the precision of agricultural assessments, providing valuable

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data for managing the effects of agrivoltaic systems on crop development.

Keywords Agrivoltaics · Precision agriculture · Internet of things (IoT) · Apple phenology · Fruit development · *Malus domestica* L. cv. Gala

Introduction

Apples (*Malus domestica* L.) are among the most widely grown fruit crops around the world, playing a key role both economically and nutritionally (Bramel & Volk 2019; Średnicka-Tober et al. 2020). Apples are harvested for fresh consumption, cider production, and processing uses, and the domesticated apple is believed to have originated primarily from its wild progenitor *Malus sieversii* L., a species native to Central Asia and parts of Western China (Volk et al. 2021). Regarding global apple production, China leads by a considerable margin, producing over 47 million tons in 2022, representing a substantial share of the total output of the world. Other important apple-producing nations include Turkey, the United States, and Poland, with yearly outputs of about 4.8 million, 4.4 million, and 4.2 million tons, respectively (FAO 2022).

Recent research into apple phenology has pointed out how climate change impacts the timing of ripening, as seen in shifting flowering and fruit-setting dates caused by rising temperatures (Ru et al. 2023). This situation calls for new strategies to adapt, and one possible solution could be using agrivoltaic systems. By altering the orchard microclimate and providing partial shading, agrivoltaic systems may help buffer excessive solar radiation and heat stress, potentially moderating climate-driven shifts in phenology, fruit development, and harvest timing (Graham et al. 2021; Lopez et al. 2023).

Agrivoltaics, which involves integrating photovoltaic panels into agricultural production, was first proposed in 1981 by researchers at the Fraunhofer Institute for Solar Energy Systems ISE (Goetzberger & Zastrow 1982). In recent years, these systems have gained traction as a sustainable way to optimise both land use and energy production (Amaducci et al. 2018; Dupraz et al. 2011). Although agrivoltaic setups can present challenges for traditional precision agriculture techniques (Vélez et al. 2024b), recent

advances in technology and the pressing need for a transition towards low-carbon energy systems have helped to drive their adoption (Hu 2024). Agrivoltaic designs vary widely depending on crop type, management requirements, and system objectives. In fruit-crop and other horticultural systems, one common configuration consists of elevated photovoltaic modules installed above the crop canopy (Trommsdorff et al. 2022). This overhead configuration provides partial shade, limiting light availability (Marrou et al. 2013) and potentially affecting plant growth and fruit ripening (Hudelson & Lieth 2021).

This shading effect is particularly important in apple farming since it is well-known that light directly influences fruit development and quality (Jackson 1970). Given the role that light plays in the ripening process, accurately determining when apples are ripe is crucial for deciding the right time to harvest, which affects not just quality but also how long the apples will store and their value in the market (Knee 2002). Apple ripeness is influenced by various factors, such as starch breakdown, firmness, and ethylene production, which can all be measured to pinpoint the optimal harvest period (Skic et al. 2016). Harvesting apples at the right time ensures better texture, flavour, and longer storage potential, with maturity significantly impacting the post-storage quality and overall taste of the fruit (Hasan et al. 2024).

Traditionally, assessing the ripeness of fruits has relied on the experience of agronomists, who typically evaluate visual characteristics such as skin colour, firmness, and the overall appearance of the fruit (Blanpied & Silsby 1992). Although these methods are subjective and can vary between specialists, they have long been the most commonly used approach and remain in practice today for determining fruit maturity and different stages of phenological development (Ramos & Yuste 2023). Many experts base their assessments on standardised scales like the BBCH scale (Meier 2001), which offers a uniform system for categorising plant development stages. While these traditional methods are not always precise, they still play an important role, having formed the basis of ripeness evaluation for many years.

However, advancements in precision agriculture have introduced newer technologies to make these assessments more accurate and efficient (Ariza-Sentís et al. 2023; Gu et al. 2024). One notable development is the use of fixed cameras integrated into Internet

of Things (IoT)-based monitoring systems, which acquire field images and transmit them remotely for the continuous assessment of fruit growth and ripeness (Lee et al. 2022; Rajak et al. 2023). These systems rely on computer vision and machine learning algorithms to analyse images, allowing them to detect small changes in fruit colour and size that indicate the stages of ripening (Olorunfemi et al. 2024).

The use of IoT technology has further enhanced the capabilities of these monitoring systems. Sensors for temperature, humidity, soil moisture, and light intensity now provide real-time data that can guide decisions about crop management (Shahab et al. 2024). These IoT-based systems gather data from the field, send it to a cloud platform, and enable detailed analysis (Song et al. 2024). Studies have shown that these systems can significantly improve agricultural productivity and resource management (Khuwaja et al. 2023), allowing for real-time monitoring of critical factors like temperature, humidity, and soil conditions. This capability helps farmers track field conditions remotely, receive timely alerts for critical situations, and optimise their practices, saving time and labour while boosting efficiency and sustainability (Oguz et al. 2024).

IoT camera networks, in particular, are key to collecting continuous data and remotely monitoring crops (Jayaraman et al. 2016). These cameras are also effective for pest detection, using high-resolution sensors to track crop conditions, which enables farmers to respond more quickly to potential infestations (Rajak et al. 2023). Combined with machine learning, such systems are highly accurate in predicting plant diseases and optimising farming techniques (Nayagam et al. 2023), which leads to better decision-making and improved yields.

In image analysis for agriculture, the YOLO model has gained popularity. For instance, Parico & Ahamed (Parico & Ahamed 2021) developed a pear-counting system using YOLOv4, which performed accurately and quickly. Koirala et al. (Koirala et al. 2019) applied the YOLO algorithm to RGB images to detect fruit and assess its ripeness, showcasing the potential for real-time applications, and Mutha et al. (Mutha et al. 2021) used YOLOv3 and convolutional neural networks to identify the maturity and position of tomatoes, supporting automated harvesting with robotic arms.

In apple production, real-time detection is critical for monitoring growth stages and estimating yield. Tian et al. (Tian et al. 2019) introduced the YOLO-V3 Dense model, which improves detection accuracy, especially in challenging conditions like overlapping fruits, by incorporating DenseNet and image augmentation techniques. This model surpassed Faster R-CNN with VGG16 in both speed and precision. Similarly, Gao et al. (Gao et al. 2022) created a method using YOLOv4-tiny and CSR-DCF algorithms to track apple tree trunks instead of individual fruits, further enhancing speed and accuracy in orchard settings, highlighting its potential for broader yield estimation. One of the latest versions of the algorithm, YOLOv8 (Jocher et al. 2023), has demonstrated superior performance in fruit detection tasks. It has outperformed Faster R-CNN in apple detection tasks (Sawant et al. 2024) and Mask R-CNN, achieving higher precision and recall across both datasets. This makes YOLOv8 ideal for real-time applications like robotic harvesting (Sapkota et al. 2024).

With this context in mind, this study evaluates the effects of agrivoltaic systems on apple ripening, hypothesising that shading and microclimate changes from agrivoltaics impact the ripening process. To test this, experiments were conducted in two settings: apples growing under conventional conditions (control) and apples growing under an agrivoltaic setup. Throughout 2024, fruit-level metrics, such as fruit diameter, length, shape, volume, weight, and BBCH phenology stages, were monitored. Ripeness, based on colour changes, was assessed using an IoT fixed-camera system and a curated time series of valid telephoto RGB images. While RGB-based computer vision and object-detection methods have previously been applied to fruit detection, sizing, and maturity assessment, this study develops and applies an IoT-based monitoring workflow for time-series analysis of visible apple ripening dynamics under field conditions. The workflow integrates fixed RGB imaging, automatic fruit detection, colour-based ripening quantification, and temporal analysis to compare maturation patterns between agrivoltaic and control orchard conditions.

Materials and methods

Study site

The experiments were conducted during the 2024 growing season in a 0.4 ha agrivoltaic orchard situated at 425 m above sea level in Kressbronn am Bodensee (9.60425°E, 47.6017°N, WGS 84), south-western Germany, near Lake Constance. The proximity to the lake and the surrounding alpine region contribute to a temperate climate that supports intensive apple production, making this area one of the main apple-growing regions in Germany (Von Königslöw et al. 2022). These conditions make the site suitable for evaluating agrivoltaic systems in a commercial fruit-production context.

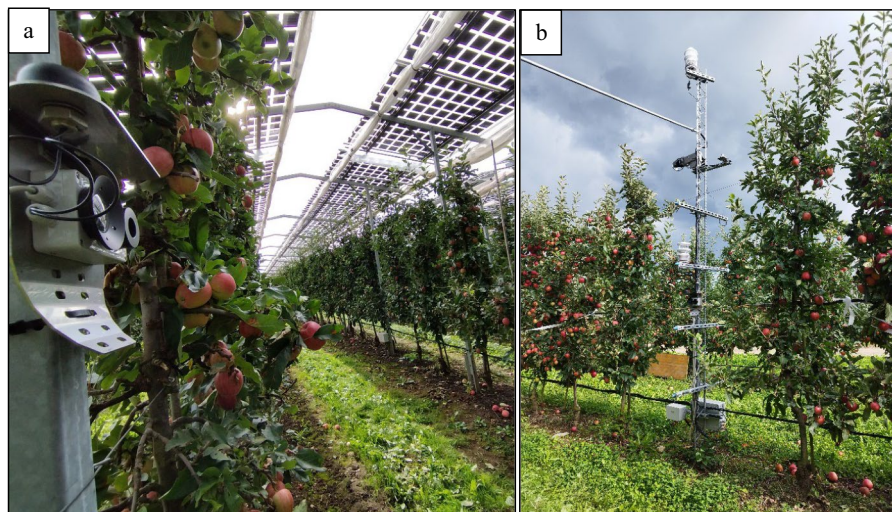
The orchard consisted of apple trees (*Malus domestica* L.) cv Gala grafted onto M.9 rootstock. The agrivoltaic structure was installed in 2022 in an existing commercial apple orchard. The orchard had two distinct zones: agrivoltaic and control (Fig. 1). In the agrivoltaic zone, the focus was on the southern part, where plants grow beneath an elevated structure equipped with semi-transparent photovoltaic solar panels made of certified double glass modules (EN12600) suitable for overhead installation. These solar panels, each with a power capacity of 260 Wp, were constructed using monocrystalline cells, featuring 50 cells per module and providing 40% light transparency due to the spatial distribution of the cells. The agrivoltaic system offered an approximate total power output of 147 kWp and had a 70%

ground-coverage ratio, meaning the solar panel structure covered 70% of the available land. The projected area of the modules more than completely covered the trees; in contrast, the control zone had no such structures.

The main difference between the two zones was the presence of the solar panels and the structure. The whole orchard was managed uniformly throughout the year. This included the same pruning, thinning, irrigation, and ground-cover management in the agrivoltaic and control zones. The apple rows had an NE-SW orientation in both zones, optimising sunlight exposure. The orchard floor was maintained with natural vegetation cover in both zones. Both the agrivoltaic and control zones were managed under the same drip-irrigation programme throughout the growing season to ensure a consistent water supply. Using specialized stations, temperature (°C) and relative humidity (%) trends were recorded between June 1 and September 13 (Fig. 2), using shielded air-temperature and relative-humidity sensors installed within the tree canopy in both the agrivoltaic and control zones.

The sensors were connected to a field data-acquisition cabinet equipped with an ExpertDAQ EX-9132C RS232-to-RS485 converter (ExpertDAQ, Germany) and Phoenix Contact STEP POWER supply units (Phoenix Contact GmbH & Co. KG, Blomberg, Germany). The sensor data were collected through the field acquisition system using wired serial communication and subsequently transferred to the project database through the site's internet-connected data infrastructure for storage, export, and analysis. An

Fig. 1 **a** Apple trees under solar panels in the overhead agrivoltaic facility located in Kressbronn am Bodensee, Germany (9.60425°E, 47.6017°N, WGS 84), monitored by a fixed camera. **b** camera monitoring the control orchard zone outside the shaded region



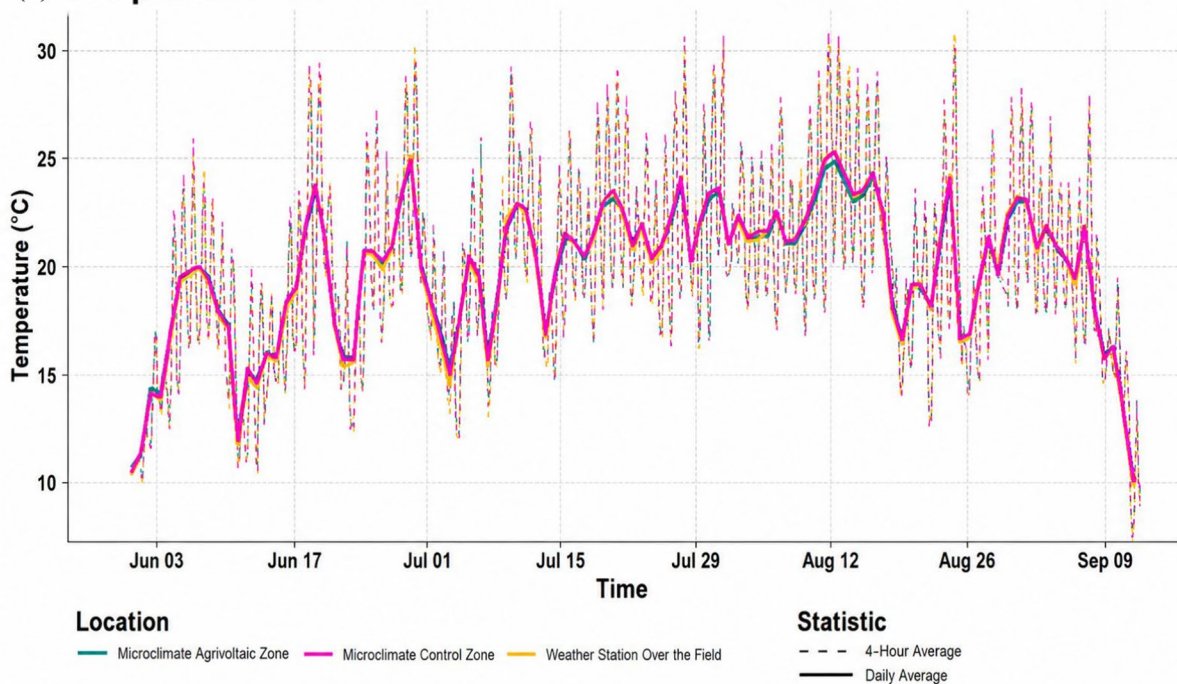
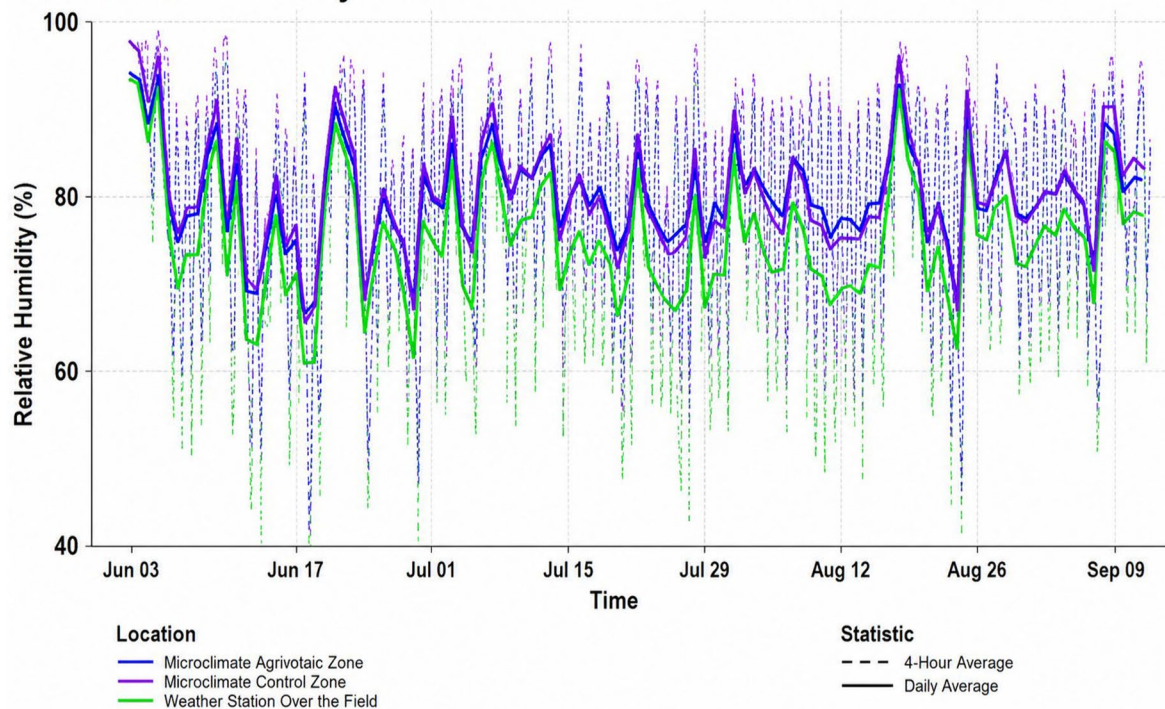
(a) Temperature**(b) Relative Humidity**

Fig. 2 Seasonal evolution of microclimatic conditions in the orchard between June 1 and September 13, 2024: **a** air temperature (°C) and **b** relative humidity (%). Measurements cor-

respond to the agrivoltaic zone, the control zone, and the elevated weather station above the field. Dashed lines indicate 4-h averages, while solid lines indicate daily averages

elevated weather station located above the solar-panel installation recorded the general weather conditions of the field.

Phenology and agronomic data collection

Apple tree phenology and fruit maturity were manually monitored on June 19, July 18, and September 13. Expert agronomists collected field data to track fruit maturation and assess phenological stages, comparing growth patterns in both agrivoltaic and control zones (Fig. 3). This approach provided insights into the developmental stages and potential effects of the agrivoltaic environment and microclimate on the progression of the fruit. Thus, the apple phenology was assessed through visual inspection and tactile assessment using the BBCH scale (Meier 2001). For skin colour, the apples were inspected, noting the progression of redness, which serves as a natural ripeness indicator. For firmness, the fruit was pressed, observing texture variations that signify ripening. Additionally, general appearance was assessed to observe overall tree growth, leave and fruit size, and uniformity.

On each sampling date, five trees per treatment were selected for manual fruit measurements. Five apples were measured on each side of each selected tree, resulting in 50 apples per treatment and date and 300 fruit measurements across the two treatments and three sampling dates. Fruit length and diameter were measured with Vernier callipers (Christodoulou & Culham 2021). These measurements were used to calculate fruit volume and the fruit shape index, expressed as the length-to-diameter (L/D) ratio, a commonly used descriptor of apple fruit shape and varietal consistency (Currie et al. 2000; Tabatabaefar & Rajabipour 2005; Tromp 1990; Zhou et al. 2021). The sampled fruit were treated as subsamples within the monitored agrivoltaic and control zones. Individual fruits were not tracked repeatedly across dates, and the available dataset did not retain a hierarchical tree-level identifier suitable for mixed-model analysis. Therefore, the statistical comparisons should be interpreted as fruit-level comparisons between the monitored zones and dates, rather than as fully replicated treatment-level inference.

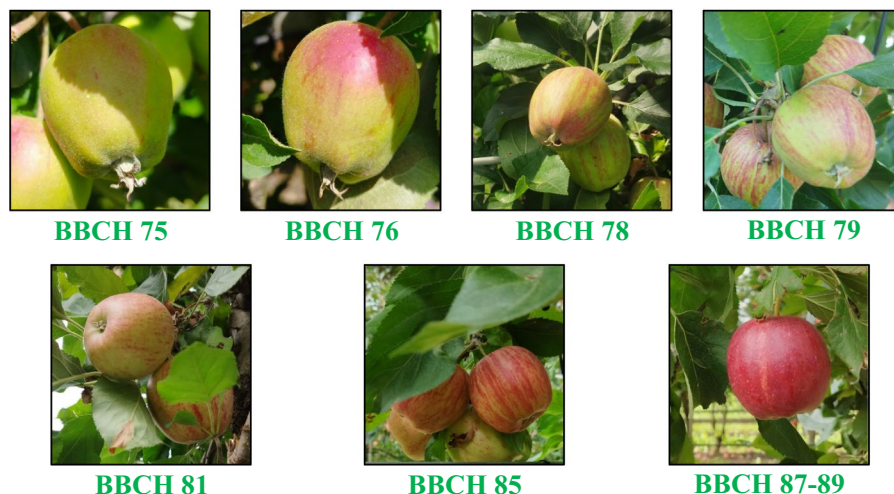


Fig. 3 Apple developmental stages recorded during the experiment located in Kressbronn am Bodensee, Germany (9.60425°E, 47.6017°N, WGS 84), monitored in 2024 under the overhead agrivoltaic facility through various BBCH growth stages (Meier 2001): Fruit development (BBCH 75—Fruit about half final size, BBCH 76—Fruit about 60% final size, BBCH 78—Fruit about 80% final size, and BBCH 79—Fruit

about 90% final size), and Maturity of fruit and seed (BBCH 81—Beginning of ripening with the first appearance of cultivar-specific colour, BBCH 85—Advanced ripening with increased colour intensity, and BBCH 87–89—Full ripeness, ready for picking and consumption with typical taste and firmness)

IoT data collection and transmission

RGB image acquisition was scheduled during the 2024 monitoring period using IoT-capable RGB cameras to monitor apples and evaluate their visible phenology and maturation dynamics. Manual field assessments were conducted on June 19, July 18, and September 13, 2024. The image-derived colour analysis was based on the curated subset of valid morning CAM_2 telephoto images retained after quality screening and normal orchard-management operations.

Although the BBCH scale for pome fruit (Meier 2001) was used for tracking growth, it presented limitations in accurately establishing maturity levels with the studied cultivar, which exhibited cultivar-specific colour before the BBCH 81 stage (Fig. 3). The BBCH codes in growth stage 7 are oriented towards assessing final fruit size rather than the colour change, which starts to be considered in stage 8 (BBCH 81: Beginning of ripening, or first appearance of cultivar-specific colour). Due to this limitation, the IoT camera was essential in supplementing the BBCH scale by providing continuous, objective data on fruit colour and size progression, offering an additional assessment of maturation.

Therefore, data were collected using the METOS CropVIEW Dual system (Pessl Instruments GmbH, Weiz, Austria), an IoT-based agricultural monitoring solution designed for remote monitoring of crop and

fruit growth by capturing real-time, high-resolution images of the crops at regular intervals. The system featured a dual-camera setup housed in an IP65-rated weatherproof casing, ensuring its durability in various environmental conditions.

The camera system (Fig. 4) was equipped with 10-megapixel CMOS MT9J003 RGB sensors with a sensor size of 2/3 inches. It included a wide-angle lens (DSL377A-650-F2.8) with a focal length of 2.5 mm and a telephoto lens (DSL901J-650F3.0) with a focal length of 12 mm. The wide-angle lens was used only to provide a panoramic contextual view of the orchard and was not used for colour-based maturity analysis. All image-derived ripening metrics were calculated from the telephoto images, which provided a narrower and more detailed view of the monitored fruit area.

To ensure the system was completely autonomous and suitable for installations in remote field locations, it was powered by a rechargeable 6 V, 12Ah battery capable of operating within a temperature range from -35°C to 80°C . The battery was recharged with a solar panel measuring 17.5×17.5 cm, capable of providing continuous power via an output of 7.2 V and 333 mA.

Each IoT RGB camera system was installed at a height of 1.7 m in the field. Image acquisition was scheduled for one daily capture at 09:00 local time. The exported CropVIEW filenames retained the recorded acquisition timestamps from the system,

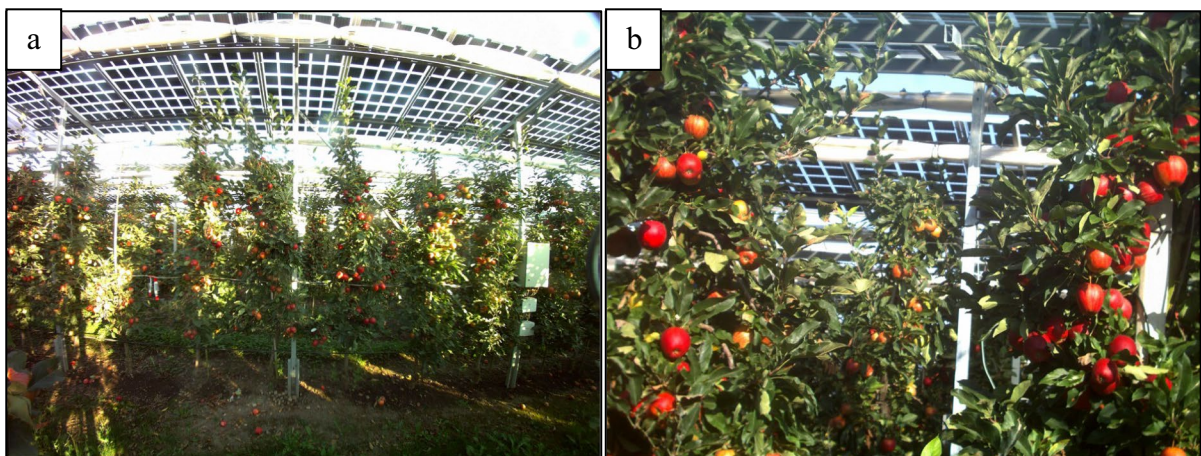


Fig. 4 Example images collected by the IoT-capable RGB camera system during the 2024 monitoring period. The system included two high-resolution sensors: **a** a wide-angle lens used

for panoramic orchard context and **b** a telephoto lens used for image-based fruit-colour analysis. Images were transmitted to the cloud platform for remote analysis

and these timestamps did not always exactly match the nominal scheduled time. Therefore, to avoid excluding valid scheduled acquisitions because of timestamp deviations and to ensure broadly comparable illumination conditions for colour-based analysis, only valid morning CAM_2 telephoto images with recorded timestamps between 07:00 and 11:59 were retained; images captured at noon or later were excluded. Image availability differed slightly between dates and zones because the curated image subset reflects the available field-image records after quality screening and normal orchard-management operations. The cameras were placed in the row adjacent to the monitored tree row and pointed towards the northwest (NW) to reduce direct sunlight during image acquisition and minimise overexposure. The approximate camera-to-canopy distance was 3 m, corresponding to the row spacing between the camera row and the monitored tree row.

Finally, the collected data were automatically transmitted via the communication module (Cortex M4 processor module) equipped with UMTS (3G) and LTE (4G) standards to a cloud-based platform (FieldClimate, Pessl Instruments GmbH, Weiz, Austria).

Image processing and analysis

An IoT-based image-analysis workflow was implemented to derive a time-series visible-colour maturity index from fixed RGB images. Images acquired with the telephoto lens of the IoT RGB camera system in both the agrivoltaic and control orchard zones were processed and analysed to assess apple ripeness and phenological progression based on visible colour changes. The complete workflow is summarised in Fig. 5, from field image acquisition and remote data transfer to image preprocessing, apple detection, colour quantification, and temporal maturity analysis.

Figure 6 provides a representative example of the main image-preprocessing and apple-detection steps applied to the RGB images. The image-processing stage started with image coregistration, normalisation, and masking. Coregistration ensured consistent spatial alignment across images acquired on different dates, correcting minor positional shifts caused by environmental factors such as wind or natural changes in fruit position. The Scale-Invariant Feature Transform (SIFT) algorithm was used for this purpose (Lowe 1999), allowing the same tree area to be analysed throughout fruit development. Following alignment, histogram matching was applied independently to the RGB channels using scikit-image to reduce image-to-image

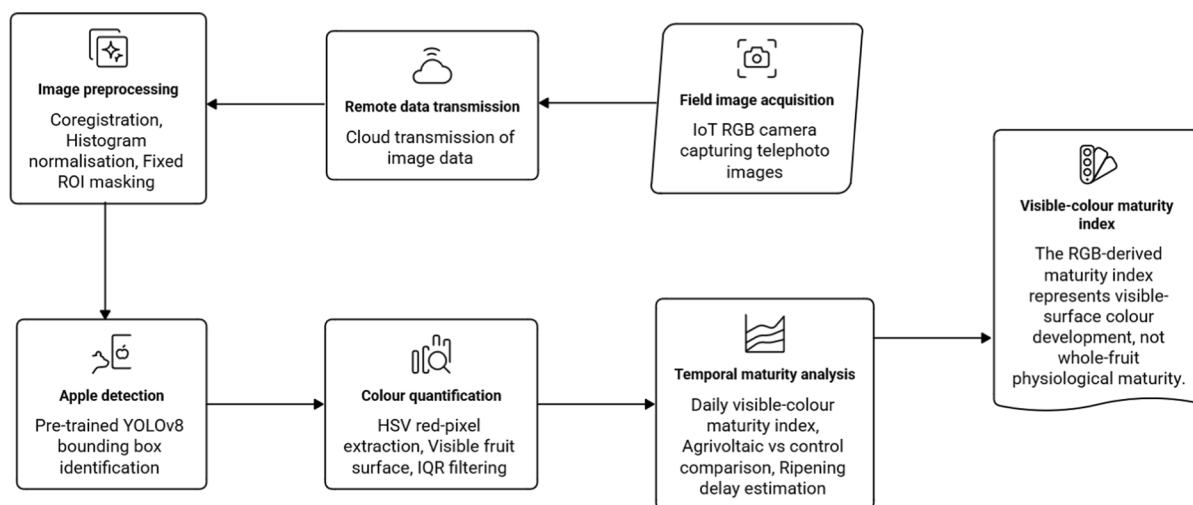


Fig. 5 IoT-based workflow used to derive the time-series visible-colour maturity index from fixed RGB images. The workflow included field image acquisition, remote data trans-

fer, image preprocessing, apple detection, HSV-based colour quantification, and temporal comparison of maturation dynamics between the agrivoltaic and control treatments

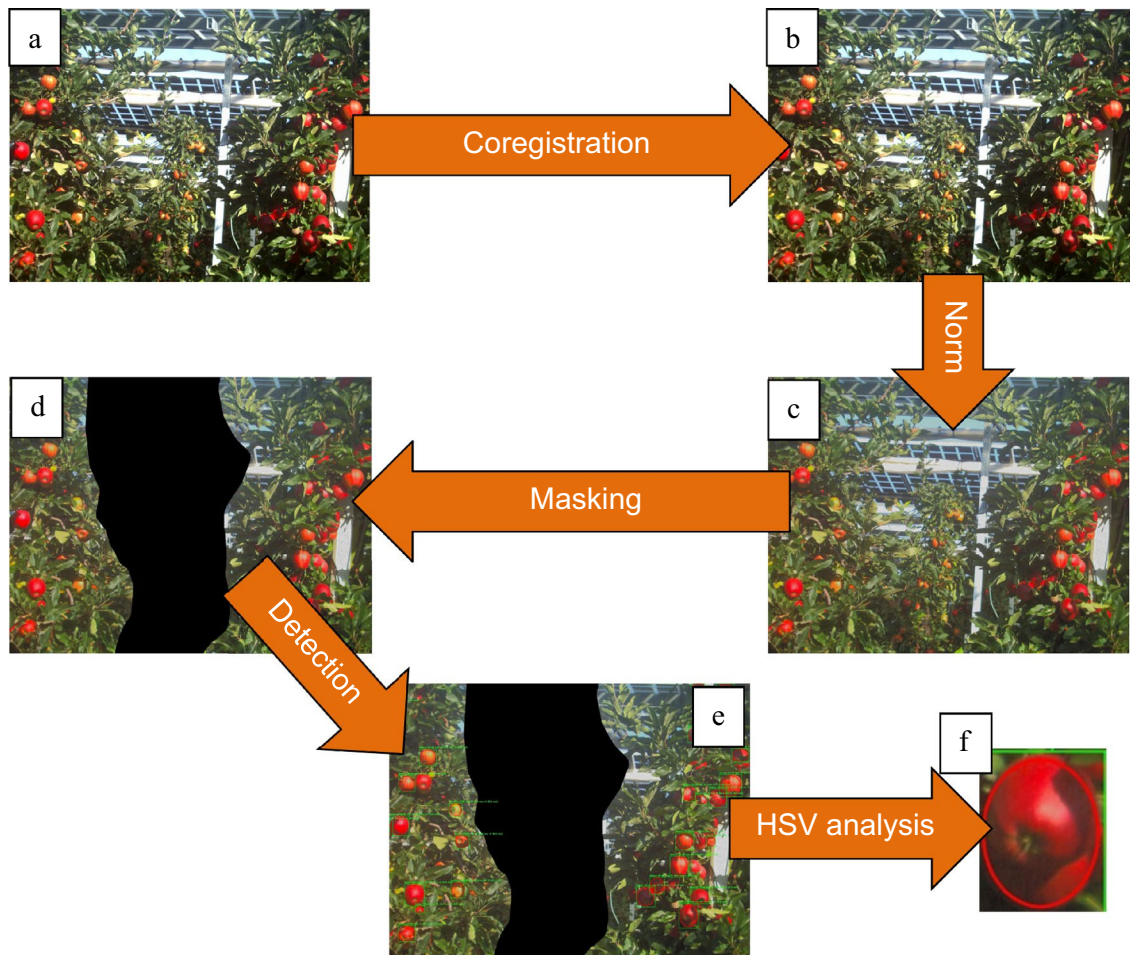


Fig. 6 Representative example of image preprocessing, apple detection, and HSV-based colour analysis. Telephoto RGB images were coregistered to align the monitored tree area across dates, normalised to reduce illumination differences, and masked to retain the fixed region of interest while exclud-

ing background rows. The default COCO-pretrained YOLOv8 weights provided by Ultralytics were then used to detect visible apples from the COCO “apple” class and generate bounding boxes. Colour maturity was quantified separately from the detected fruit regions using HSV-based red-pixel analysis

differences in brightness and contrast. A common reference histogram was constructed from the full telephoto image set, including both agrivoltaic and control images, and the same reference was applied to both treatments. This avoided using treatment-specific references that could artificially increase or reduce colour differences between the monitored zones. This step reduced the influence of variable illumination, glare, and exposure differences, helping to ensure that the observed colour changes were mainly related to fruit development rather than to lighting inconsistencies (Gonzalez & Woods 2018). No physical colour calibration target was installed

in the field; therefore, the RGB-derived maturity index was interpreted as a relative visible-colour indicator rather than as an absolute colourimetric measurement.

Finally, a fixed region of interest was used to standardise the analysed area and exclude background rows from the analysis. Unlike dynamic masking approaches that automatically detect the first row of vegetation (Vélez et al. 2024a), a dynamic row-detection step was unnecessary here because the images consistently captured the same fixed scene using a stationary camera. After preprocessing, visible apples were detected using the default COCO-pretrained

YOLOv8 weights provided by the Ultralytics library (Jocher et al. 2023). The model was used with the COCO “apple” class to identify apple bounding boxes in the RGB images. No additional training or fine-tuning was performed using orchard-specific images. Inference was performed using the default Ultralytics settings for image size, confidence threshold, and intersection-over-union threshold.

Ripeness was then quantified using a rule-based colour analysis within each detected bounding box, rather than as a direct YOLOv8 classification output. Each image was timestamped for chronological tracking. Within each bounding box, an elliptical mask was applied to reduce the influence of corners and surrounding background pixels, and red hues were isolated in the HSV colour space. The percentage of red pixels was then calculated for each detected fruit and used as an image-based indicator of colour development. Occlusions caused by leaves, branches, or neighbouring fruits were handled by restricting the analysis to the visible fruit area detected in each image. Detections with extreme red-pixel percentages were removed using an interquartile range (IQR) filter. However, the method did not reconstruct non-visible fruit surfaces; therefore, the resulting maturity metric should be interpreted as a visible-surface colour index rather than a whole-fruit physiological maturity measurement.

Data processing and analysis were performed on a computer equipped with an Intel i5-11600 K CPU, 32 GB RAM, and an NVIDIA GTX 970 GPU. Custom scripts were written in Python 3.11.9 and R 4.4.1. Image processing was performed using OpenCV 4.10.0 for image coregistration, masking, and HSV colour-space operations; scikit-image 0.24.0 for histogram matching and image normalisation; and ultralytics 8.2.87 for YOLOv8-based apple detection. Statistical analyses were conducted in R using the Shapiro–Wilk test for normality. Because normality was not met consistently across variables, dates, and treatments, fruit-level comparisons of continuous variables between the monitored agrivoltaic and control zones were performed using the Mann–Whitney U test. BBCH phenology stages were compared using Fisher’s Exact Test. These tests were used as descriptive comparisons of sampled fruit distributions and observed phenological stages and did not account for a hierarchical tree-level structure or replicated

treatment plots. Data processing and visualisation used ggplot2, dplyr, readxl, and tidyr.

Results

Field observations showed clear differences in phenological development between the control and agrivoltaic treatments across the 2024 growing season. On June 19, apples in both treatments were still at an early developmental stage, although control apples showed slightly more advanced colour development than those in the agrivoltaic zone. By July 18, fruit size had increased in both treatments, but red colouration remained more advanced in the control group. By September 13, the control apples had reached full ripeness, whereas apples in the agrivoltaic zone remained at a less advanced ripening stage, with lower red colouration and slightly smaller fruit size.

The field-based measurements confirmed these visual observations (Table 1). Fruit diameter, volume, and weight were generally lower in the agrivoltaic treatment than in the control treatment. On June 19, mean fruit diameter was 36.22 mm in the agrivoltaic group and 39.78 mm in the control group. By September 13, mean diameter reached 65.59 mm in the agrivoltaic group and 70.98 mm in the control group. Fruit length showed smaller differences between treatments; although agrivoltaic apples were shorter than control apples in June, length differences were no longer statistically significant later in the season. At harvest, mean fruit volume was 161.16 cm³ in the agrivoltaic group and 191.58 cm³ in the control group, while mean fruit weight was 138.6 g and 164.8 g, respectively.

Phenological assessment using the BBCH scale also indicated delayed development under agrivoltaic conditions (Table 1). On September 13, the control group had reached BBCH89, corresponding to full ripeness, whereas the agrivoltaic group remained at BBCH85, indicating advanced but incomplete ripening. This difference was consistent with the lower red colouration observed in the agrivoltaic apples at the end of the monitoring period.

The image-derived maturity index based on RGB colour analysis showed a similar pattern (Fig. 7). The control group showed earlier and faster red-colour development than the agrivoltaic group. From June to August, the image-derived maturity index indicated

Table 1 Summary of mean values ($\pm$ standard deviation) for fruit-level metrics measured in the control and agrivoltaic zones in 2024

	Variable	Date	Control	Agrivoltaic	<i>p</i> -value
Phenology values are the most frequent BBCH stage (mode). Continuous fruit variables were compared using the Mann–Whitney U test, while BBCH phenology stages were compared using Fisher's Exact Test. Bold value indicate <i>P</i> -values below 0.05 indicate statistically significant fruit-level differences between sampled apples from the monitored zones and dates	Diameter (mm)	19/06/2024	39.78 $\pm$ 5.84	36.22 $\pm$ 6.67	0.01
		18/07/2024	51.40 $\pm$ 7.34	47.51 $\pm$ 8.46	0.02
		13/09/2024	70.98 $\pm$ 8.12	65.59 $\pm$ 9.59	0.01
	Length (mm)	19/06/2024	41.30 $\pm$ 5.47	37.80 $\pm$ 6.79	0.01
		18/07/2024	51.92 $\pm$ 7.04	49.18 $\pm$ 8.19	0.11
		13/09/2024	70.05 $\pm$ 8.19	67.54 $\pm$ 9.26	0.16
	Fruit shape index	19/06/2024	1.04 $\pm$ 0.04	1.05 $\pm$ 0.04	0.22
		18/07/2024	1.01 $\pm$ 0.05	1.04 $\pm$ 0.05	<0.01
		13/09/2024	0.99 $\pm$ 0.04	1.03 $\pm$ 0.03	<0.01
	Volume (cm ³)	19/06/2024	36.22 $\pm$ 15.32	28.52 $\pm$ 15.53	0.01
		18/07/2024	75.85 $\pm$ 31.34	63.28 $\pm$ 33.14	0.04
		13/09/2024	191.58 $\pm$ 61.10	161.16 $\pm$ 67.15	0.04
	Weight (g)	19/06/2024	31.15 $\pm$ 13.17	24.53 $\pm$ 13.36	0.01
		18/07/2024	65.23 $\pm$ 26.95	54.42 $\pm$ 28.50	0.04
		13/09/2024	164.76 $\pm$ 52.55	138.60 $\pm$ 57.75	0.04
	Phenology	19/06/2024	BBCH76	BBCH75	0.05
		18/07/2024	BBCH77	BBCH76	0.10
		13/09/2024	BBCH89	BBCH85	<0.01

earlier red-colour development in the control group, whereas the agrivoltaic group showed a delayed increase in red colouration. This result is presented as a descriptive trend based on the image-derived maturity index, not as a separate statistical test. By early September, the control group reached approximately 70% maturity according to the image-derived colour index, while the agrivoltaic group reached approximately 40% over the same period.

Based on the image-derived maturity thresholds, apples in the agrivoltaic treatment reached 30%, 40%, and 50% colour maturity approximately 12, 10, and 12 days later, respectively, than apples in the control treatment. These results indicate a consistent delay in visible red-colour development under the agrivoltaic structure.

Discussion

This study showed that overhead agrivoltaic shading was associated with delayed visible apple maturation, slightly smaller fruit size, and slower phenological progression compared with the control orchard. This pattern was consistent across field-based BBCH assessments, manual fruit measurements, and the image-derived maturity index. The RGB image time

series provided additional temporal resolution, showing that, similar to previous research where dynamic agrivoltaic systems with fluctuating shading affect apple ripening (Juillion et al. 2024), apples under agrivoltaic conditions reached colour-maturity thresholds approximately 10–12 days later than control apples, with the temporal evolution of maturity levels showing that by early September, the control group had reached a mean maturity percentage of approximately 70%, whereas the agrivoltaic group was about 40% (Fig. 7).

The delayed maturation trend observed in the agrivoltaic treatment, reflected by lower image-derived maturity percentages, delayed BBCH development, and a later onset of rapid red-colour progression, is consistent with reduced light availability under the photovoltaic structure. Light is a major driver of anthocyanin synthesis in apple skin, which is responsible for red pigmentation and therefore directly influences the colour-based maturity index used in this study (Mei et al. 2023). Reduced light exposure may also affect physiological ripening processes through changes in carbon assimilation and ethylene-related pathways, as reported for shaded apples (Klein et al. 2001).

Temperature can also affect anthocyanin biosynthesis, and cool nighttime conditions are often

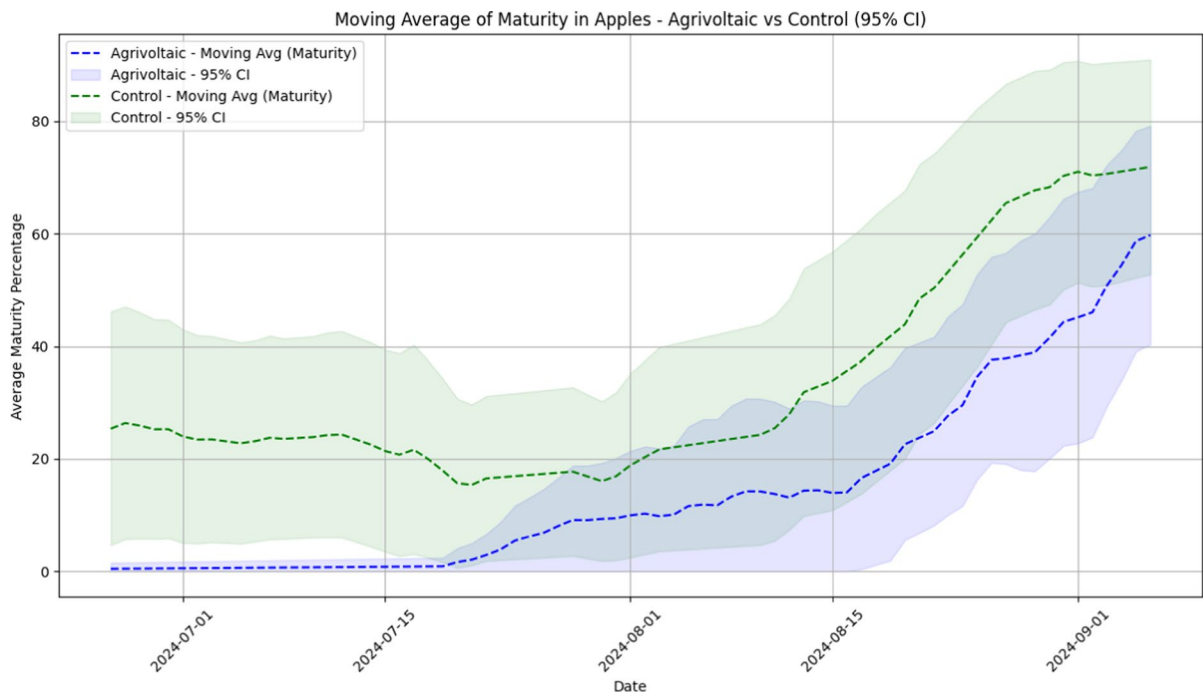


Fig. 7 Temporal evolution of the moving average of maturity (Red percentage) in apples for agrivoltaic and control groups. The dashed lines represent the weekly moving average, with shaded areas indicating the 95% confidence intervals (CI) for each group

reported as favourable for red colour development in apples (Ryu et al. 2017; Xue et al. 2021). However, the temperature and relative-humidity data recorded in this study did not show a clear or consistent increase in nighttime temperature under the agrivoltaic structure. Therefore, elevated nighttime temperature cannot be identified as the main driver of the delayed red-colour development observed here. Reduced light availability under the photovoltaic structure provides a plausible explanation that is consistent with the agrivoltaic treatment and with previous studies on apple colour development, but light availability at the fruit surface was not directly quantified in this study. Temperature and humidity may also have acted as secondary microclimatic modifiers, although their individual causal contributions could not be isolated in this experimental design.

This interpretation is consistent with previous agrivoltaic studies showing that shading can extend crop development cycles, although the direction and magnitude of the effect depend on crop type, cultivar, local climate, system design, and target harvest window (Elamri et al. 2018). (Juillion et al. 2022) reported no significant delay in apple ripening under

agrivoltaic shading when maturity was defined based on starch degradation and firmness. However, those studies were conducted on ‘Golden Delicious’, a yellow-green cultivar with limited red pigmentation, whereas the present study used the red-coloured cultivar ‘Gala’. This cultivar difference is important because colour-based responses to shading are likely to be more evident in red apple cultivars, where anthocyanin-related skin colouration is a major external maturity trait. A subsequent study by the same authors (Juillion et al. 2023) nevertheless reported differences in apple colour, highlighting the influence of shading on external fruit quality.

Similar delays in fruit ripening under shaded conditions have been reported in other studies. For instance, Jackson (Jackson 1970) observed that reduced light intensity in apple orchards led to delayed fruit maturation, with large and well-coloured fruits only developing under high light-intensity conditions. Serra et al. (Serra et al. 2020) found that photoselective netting reduces red colour development in apples by altering the light spectrum, particularly by decreasing UV and red-to-far-red wavelengths essential for anthocyanin production. These findings

align with the findings of this study, suggesting that shading from agrivoltaic panels reduces light availability, thereby slowing down the physiological processes involved in ripening. The discrepancy may be due to differences in shading intensity and stability, as dynamic agrivoltaic systems with fluctuating shading could have varied effects. This research studied overhead agrivoltaic systems that provided consistent shading, possibly applying a greater influence on ripening processes.

The smaller fruit diameter, volume, and weight observed under agrivoltaic conditions are consistent with previous studies showing that shading can reduce apple fruit size and weight by limiting photosynthesis and carbohydrate availability (Miller et al. 2015). However, agrivoltaic studies have reported mixed effects on fruit size, with initial reductions followed by more stable responses in later years, possibly related to improved water retention under shade (Juillion et al. 2022). These contrasting results indicate that fruit-size responses under agrivoltaics depend on cultivar, season, water availability, and system design. Although the observed reductions in diameter and length at harvest were below 10%, they remain relevant for commercial grading and harvest planning.

The fruit shape index showed small but significant differences at later stages, suggesting that agrivoltaic shading may have slightly altered fruit morphology. However, because seed formation, flower position, crop load, and tree-vigour variables were not quantified, the mechanisms behind this response cannot be isolated in the present study. Previous work indicates that fruit shape is often influenced indirectly by environmental and developmental factors rather than by a single direct driver (Reher et al. 2024; Tromp 1990).

Alongside the points mentioned above, it is essential to note that this study not only examines the agronomic aspects of the crop but also uses IoT-based monitoring for enhanced assessment. The IoT-based monitoring workflow enabled automated detection and quantification of visible apple colour development from fixed RGB image time series. This approach provided continuous, objective data on fruit ripening, complementing traditional agronomic observations. Although RGB imaging does not provide the spectral resolution of multispectral or hyperspectral sensors and was not specifically

designed to measure physiological ripeness, the curated image time series provided consistent visual information on fruit colour development. Therefore, RGB-based monitoring was useful for comparing relative maturation dynamics between the agrivoltaic and control treatments, while absolute maturity should still be interpreted together with conventional agronomic indicators. The use of a physical colour calibration target could improve absolute or cross-site colour comparability, although its routine use may be less practical in commercial orchard deployments because of maintenance, weathering, dirt accumulation, shading, and occlusion.

The findings highlight a potential disconnect between discrete, size-oriented phenological assessments and continuous indicators of visible maturity under shaded conditions. The BBCH scale remains useful for standardized field assessment, but stages BBCH 75–79 primarily describe fruit-size development, whereas cultivar-specific colour development is only explicitly incorporated from BBCH 81 onward (Meier 2001). The integration of IoT-based monitoring systems therefore raises a broader question: are standardised phenological scales such as BBCH still sufficient on their own for tracking fruit development, or should they be complemented with continuous, objective, and remotely collected indicators, not only in agrivoltaic orchards but also in other cropping systems?

Although the temperature and relative-humidity data provided useful microclimatic context, threshold-based analyses of heat stress, frost risk, sunburn risk, and water-use efficiency were outside the scope of this study. Other studies have reported potential protective functions of overhead agrivoltaic systems, including frost protection, hail protection, and reduced sunburn risk (Juillion et al. 2022; Trommsdorff et al. 2022; Wittich 2021). These functions should be evaluated in dedicated multi-season studies before being weighed against delayed fruit maturation.

Finally, this study has several limitations. It was limited to a single cultivar, one growing season, one monitored agrivoltaic zone, and one monitored control zone. Therefore, the results should be interpreted as differences between the monitored zones under the conditions of this study, rather than as fully replicated treatment-level effects. Responses may differ across cultivars, seasons, regions, and agrivoltaic system designs. Tree-vigour variables, such as trunk diameter, trunk cross-sectional area, shoot growth, and leaf area

index, were not measured; future multi-season studies should include these parameters to distinguish direct fruit-level responses from longer-term changes in vegetative growth. Future work should also evaluate agrivoltaic design options, economic viability, fruit storage performance, and crop-development trade-offs across multiple seasons and cropping systems, since previous studies have shown that crop responses to agrivoltaic shading can vary substantially depending on species, climate, and system configuration (Marrou et al. 2013; Sekiyama & Nagashima 2019). From a monitoring perspective, future implementations could extend the RGB workflow to continuous fruit-size estimation, although image-derived diameter measurements would require geometric calibration, scale referencing, or depth/stereo information. Edge-processing functions, such as filtering overexposed, incomplete, or atypical images and compressing repetitive data, could further reduce unnecessary data transmission (Bu & Wang 2019).

Conclusions

This study evaluated apple ripening and maturation patterns in one monitored conventional control zone and one monitored agrivoltaic zone in a commercial ‘Gala’ orchard near Lake Constance, Germany, during the 2024 growing season. A central contribution of the study was the development and application of an IoT-based monitoring workflow for continuous analysis of visible apple maturation dynamics under field conditions. The workflow combined fixed RGB image acquisition, COCO-pretrained YOLOv8 apple detection, HSV-based red-pixel quantification, and temporal maturity-threshold analysis to complement conventional agronomic and BBCH-based assessments.

The results showed delayed visible colour development, slower BBCH progression, and slightly smaller fruit size in the agrivoltaic zone compared with the control zone. At harvest, apples in the agrivoltaic zone had lower mean diameter, volume, and weight than those in the control zone, whereas fruit length did not differ clearly between zones. The image-derived maturity index showed that apples in the agrivoltaic zone reached comparable visible colour-maturity thresholds approximately 10–12 days later than apples in the control zone. On September 13, the control apples had reached BBCH89,

corresponding to full ripeness, whereas the agrivoltaic apples remained at BBCH85, indicating advanced but incomplete ripening.

Reduced light availability under the photovoltaic structure provides a plausible explanation for the delayed red-colour development observed in the agrivoltaic zone, particularly because red skin colouration in ‘Gala’ apples is closely related to light-dependent anthocyanin accumulation. However, fruit-level light availability and physiological maturity indicators were not directly measured. Therefore, the results should be interpreted as zone-level differences observed under the conditions of this case study rather than as fully replicated treatment-level effects.

The proposed IoT-based workflow provided objective, time-resolved information on visible fruit-colour development and helped reveal maturation differences that would be difficult to characterise using only discrete manual assessments. This demonstrates the value of combining fixed camera systems, object detection, and colour-based image analysis for monitoring crop development in agrivoltaic orchards. Future versions of the workflow could be extended to earlier phenological stages, including blossom detection and counting, to support thinning decisions, spray timing, and yield estimation.

Future studies should evaluate replicated agrivoltaic designs across multiple seasons and cultivars, include tree-vigour and physiological maturity measurements, and assess additional functions such as frost protection, sunburn reduction, water-use efficiency, storage performance, and economic viability. Optimising agrivoltaic system design will require balancing energy production with crop-development objectives, and IoT-based monitoring workflows such as the one developed here can provide practical support for these decisions.

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Data availability The dataset supporting this study is available at <https://doi.org/10.5281/zenodo.21895185>.

Declarations

Conflict of 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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