Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Image-Based Solutions for Precision Food Loss Evaluation

Adrián Csordás

Faculty of Economics and Business, University of Debrecen, Hungary

Abstract

The high amount of food loss and waste significantly challenges the sustainable development. The agriculture needs rapid and fundamental transformation to enhance its efficient and sustainabile operation. However, to measure precisely the effect of the new policies and practices is also difficult. The present study analyses the applied methods' data sources, as one of the key factors regarding the effective estimation of food loss and waste. By conducting a systematic literature review using the PRISMA approach, a lack of scientific focus was found related to the new data collection methods. Based on the selected articles reasonably slight amount joined the application of image processing to food loss estimation related purposes. The reviewed studies principally used the image-based solutions for the prevention and reduction of on-farm food loss. This recognition lighted up the application of image processing in agriculture, but only the thematic map analysis revealed the privileged status of "plant disease detection" within the studied area. The results suggest the possibility of applying image-based data sources to quantify food loss. Even though the limitations of agricultural image processing, the application of new data sources, and methods could considerably improve the accuracy of food loss and waste quantification in addition to the operation on farm level in short term.

Keywords

Computer vision, sustainable development, data collection, smart farming, innovation, digitalisation.

Csordás, A. (2024) "Image-Based Solutions for Precision Food Loss Evaluation", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 33-43. ISSN 1804-1930. DOI 10.7160/aol.2024.160403.

Introduction

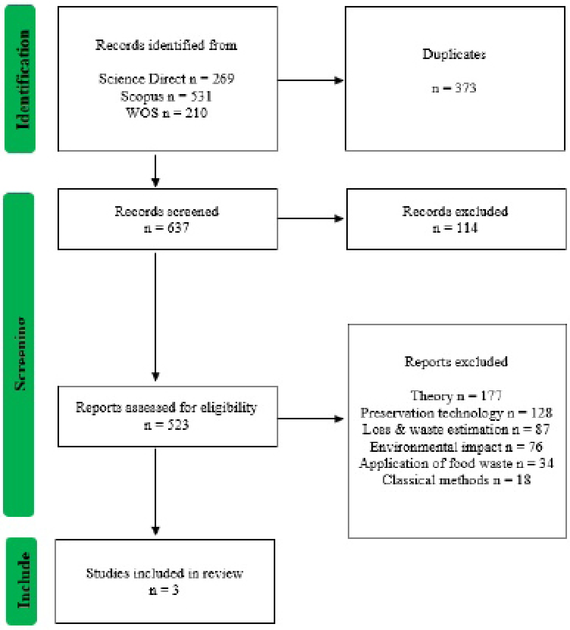
The issue of food loss and waste (FLW) is a critical global concern, that presents considerable obstacles to sustainability, food security, and economic development. Based on the estimation of the Food and Agriculture Organization of the United Nations (FAO) one-third of all food produced for human consumption is lost or wasted globally (FAO, 2011). FLW contributes among others to greenhouse gas emissions (Abbade, 2023; Guo et al., 2020; Khatri-Chhetri et al., 2022; Zhu et al., 2023) water pollution (Abbade, 2020; Marston et al., 2021; Sun et al., 2022) and land degradation (Capone et al., 2020; Pagani et al., 2020; Sun et al., 2022). Its economic costs are also significant, estimated to exceed USD 400 billion from harvest up to, but not including retail (FAO, 2019). The share of FLW along the value chain differ significantly related to the various crop (Corrado and Sala, 2018; Dal' Magro and Talamini, 2019; Hartikainen et al., 2018) and the geographical location (Anriquez et al., 2021; Ishangulyyev et al., 2019; KC et al., 2016). The usage of different concepts and approaches also makes the navigation in the field of FLW more complicated (Boiteau and Pingali, 2023; Chaboud and Daviron, 2017; Ellison et al., 2019), in addition, some studies often combine and analyze the different stages of the food supply chains together (Chauhan et al., 2021; Luo et al., 2022). The above briefly mentioned issues are some of the reasons why, accurate and comprehensive quantification of FLW remains a complicated task. Various methodologies are utilized to measure FLW (Shee et al., 2022), including field surveys (Johnson et al., 2018), household interviews (Redlingshöfer et al., 2017), data analysis (Garcia-Herrero et al., 2018), economic modeling (Soltani et al., 2020) or development of own methods (Delgado et al., 2021). Although these approaches are tailored to specific products and stages of the supply chain, the challenges related to quantification are still significant. The lack of standardized methodologies, the quality data, and the complexity of the topic demands the adoption of innovative approaches and research strategies. The development of new and more robust quantification methods, the integration of data from diverse sources, and the use of advanced statistical techniques are all avenues for enhancing the understanding of FLW. The current study is focused on the preharvest and harvesting loss. These stages cover the losses in crops caused among others by pests, weather, weeds, crops left in the field, or poor harvesting techniques before and during harvesting (Delgado et al., 2017). The present research aimed to discover and propose a new data collection method for the precision evaluation of food loss based on published scientific works, in addition to fostering the scientific discussion of the new data collection and quantification methods.

Materials and methods

To gain a deep insight into food loss, a comprehensive collection of relevant articles was gathered from three respected online databases; Science Direct, Scopus, and Web of Science. The possibilities related to the keywords were restricted, while in Science Direct the application of astrix is not allowed anymore, and the utilization of more than eight operators is also prohibited. Considering the constraints, the following search query could cover the widest range of relevant results ("food loss") AND ("estimate" OR "measure" OR "calculate" OR "evaluate" OR "declare" OR "method" OR "technique"). The title, abstract, or keywords must contain the previously mentioned expressions. The study focused exclusively on English-language research. References from the studied works were also examined, but no relevant studies were found. This could be due to the specialized nature of the topic. The selected articles had to significantly differ in the data collection method compared to the traditional (survey, interview, weighing) approach. Other sources (grey literature) could not be involved.

Related to the determination of food loss various methods are defined, although given stages like preharvest are often out of their range (Boiteau and Pingali, 2023). Proposed and widely implemented estimations focus on the post-harvest stages (Koester and Galaktionova, 2021), but even associated with these activities modern image-based solutions are not broadly studied. The well-known organizations (FAO, World Business Council for Sustainable Development, World Resources Institute, United Nations Environment Programme, World Health Organization, International Food Policy Research Institute) either do not address this or seek to provide more accurate estimation methods by refining traditional data collection practices, methods. Connected to the current concepts (FAO, 2011) numerous criticisms have stressed their inaccuracy. Spang et al., (2019) identified inconsistencies and gaps in the definitions of FLW, noting substantial data deficiencies, particularly regarding food types and stages of the food supply chain. Redlingshöfer et al., (2017) expressed skepticism regarding FLW quantification databases and methodologies. A part of their concerns lies in the application of FAO and USDA definitions, which exclusively pertain to edible, safe, and nutritious food. Xue et al., (2017) also stressed the significant discrepancies in nationally-focused estimates of food loss and waste. Among the estimates they examined, numerous did not conduct new measurements; rather they applied outdated or surrogate data from other countries. The authors emphasize that the deficiency of data is not solely a global concern; the majority of countries lack comprehensive food loss and waste data. However new data collection approach has not been suggested.

To reveal innovative alternatives a systematic literature review was conducted. Among the scientific databases, 1010 articles fulfilled the above-described criteria. The systematic literature review was managed by Rayyan (Rayyan, 2023) – an online platform for this purpose –, applying the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The aim of it is to recognize the motivation, method, and result of the examined article. Initially, it was introduced in 2009, and later in 2020, it was extended (Page et al., 2021). The first stage is pinpointing the research query, succeeded by the formulation of a search strategy to locate relevant databases. In the next phase the publications' title, abstract, or in given cases full text is checked. Based on the defined conditions, the studies are categorized (Moher, 2009). In the final analysis, a detailed evaluation of the selected articles is undertaken, and the most pertinent publications to the research aim are carefully separated (Swartz, 2011). Based on the above briefly demonstrated approach, multi-round screening (Figure 1) was applied.



Source: own elaboration, 2023

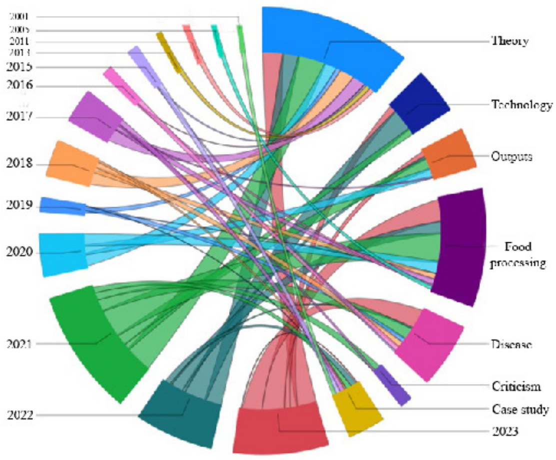
Figure 1: Pathway of the research.

In the first round, the duplicates were selected. This resulted in the elimination of 373 works, so 637 studies created the base of the analysis. After these were filtered out by Rayyan (Rayyan, 2023) started the initial screening which resulted in 114 excluded articles. This stage was followed by the in-depth analysis of the remaining 523 studies, to identify the diverse areas within the estimation of food loss. Considering the growing number of articles related to the Sustainable Development Goals (SDGs) in addition the recent rise in food prices could stimulate high interest related to this topic. These phenomena could explain why a large number of weakly connected works were excluded from the further study. Within the analyzed works the following main research directions were identified: theory (177), preservation technology (128), food loss and waste estimation (87), environmental impact (76), application of food waste (34), and classical methods (18). The present study covers all the related publications until 14 November 2023. Although PRISMA is a widely used research method, it, and therefore this article, has its limitations. The work relies on three major academic databases and using a restricted set of keywords. As a result, some significant studies on food loss estimation might have been overlooked, particularly those that use alternative phrasing or published in journals that are not indexed by these sources. Grey literature often provides valuable insights and data that are not available in peer-reviewed academic publications. However, finding these is challenging. Moreover, the exclusive focus on English-language studies, potentially excluding relevant research conducted in other languages. Finally, the study's time constraint, which only covers publications up until 14 November 2023, limits its ability to capture the most recent developments in this rapidly evolving field.

Results and discussion

Related reviews

To justify the relevance and growing interest related to food loss, the published reviews were analyzed in depth. The search method was similar to the one explained above, but this time reviews were included only. The high number of publications provides the opportunity for proper classification to reveal the main directions within the studied area. However, a review of innovative data-collecting methods has not been published as seen in Figure 2.



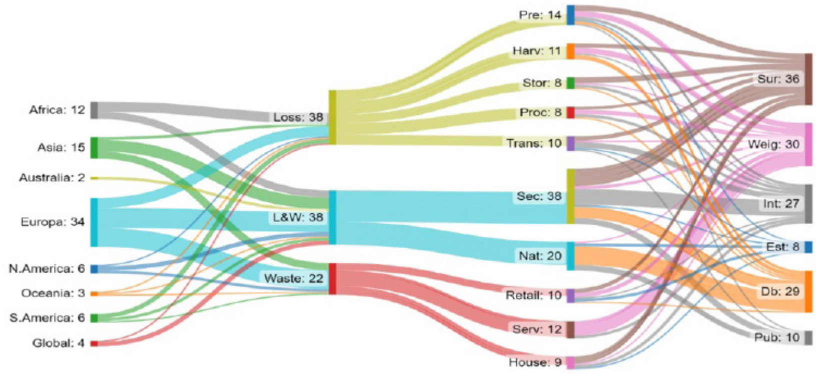
Source: own elaboration, 2023

Figure 2: The distribution of review articles by year and topic.

The emerging interest could be traced back to 2017, a year after the SDGs came into force. The sorted works rather focus on areas like food processing or theory, where often the challenges and obstacles in addition to the good and bad practices are presented. The need for a proper dataset has not been critically reviewed.

Academic papers

The articles excluded from the in-depth review and grouped into the cluster of "food loss and waste estimation" were screened to expose the most widely applied methods. The mapping of these articles in Figure 3. showed the leading position of the European studies.



Note: abbreviations: N. America: North America, S. America: South America, L&W: loss and waste, Pre: preharvest, Harv: harvesting, Stor: storage, Trans: transportation, Sec: sector/supply chain, Nat: countrywide, Serv: services, Sur: survey, Weig: weighing, Int: interview, Est: estimation, Db: database, Pub: publication
Source: own elaboration, 2023

Figure 3: The share of applied methods in the FLW studies.

The high number of sector/supply chain and countrywide (in addition to international) studies in L&W can suggest the endeavor of generalizability, although these rough estimations are mostly based on mathematically improved estimations (database), publications, or surveys. The high number of these works distorts the diagram since the L&W studies involved all the stages of the chain and were based on more than one source of information. From the food loss-related studies the high share of the preharvest, and harvest phase is distinct. The application of questionnaires is quite common, albeit many of the studies are frequently founded on weighing. The resource intensity of the latter technique is unquestionable, but to date, no other method of comparable effectiveness has been used in the reviewed studies.

While traditional methods such as weighing and questionnaires are prevalent in food loss studies, there is growing opportunties in more advanced, data-driven approaches. Although precision agriculture has been widely studied, the use of computer vision specifically for food loss estimation has not been comprehensively explored. One of the few relevant studies in this field is written by is Hassanzadeh et al., (2022), where unmanned aerial systems (UASs) made images were analyzed to evaluate pod size crop maturity. This work aimed to facilitate identifying the optimal harvesting date, to reduce food loss at farm level. The study was conducted in Geneva, NY, USA for the summer 2019, and in Seneca, NY for the summer 2020. There were 18 plots in the latter-mentioned area, while in the other location, 24 were created. The size of each plot was 1.5 m long and 0.75 m wide, where six different cultivar of snap bean was cultivated. They were sowed around 4 cm deep and 20-26 plants were placed per meter. The images were made by the hyperspectral imager (“Nano Hyperspec”, Headwall Photonics, USA) was equipped on a DJI Matrice-600 quadcopter that flew five times each year during the crop pod formation. In the study, five key stages were defined and utilized to preprocess and analyze the gathered data. The preprocessing phase involved activities such as calibrating to reflectance, extracting plots and identifying vegetation, reducing noise, and preparing the data. In the analysis phase, the preprocessed data underwent the application of a feature selection library. The authors contrasted their method’s outcomes to the top-performing test (RF-Kaiser-B3) on simulated annealing, comparing it with eight frequently utilized vegetation indices. Where their findings demonstrated superior performance compared to the others. So, this research demonstrated that accurately evaluating the maturity of snap beans in the growth stage for large-sieve cultivars (based on unmanned aerial systems made images), such as Huntington and Venture, is feasible when distinguishing between those ready for harvest.

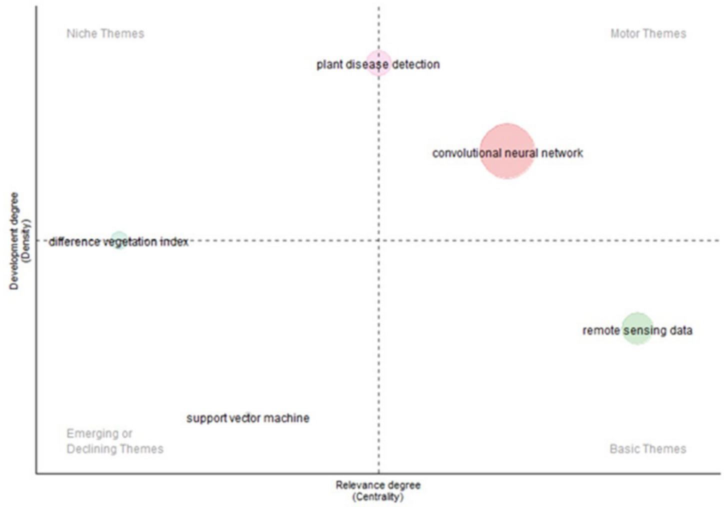
Similarly to the previous work, the study of Wang et al., (2023) focused on (drone)image-based harvest data prediction of broccoli. The research was conducted on the farm of the Institute for Sustainable Agro-ecosystem Services (ISAS), Tokyo, Japan in 2020 and 2021. Throughout the two-year trial, the identical broccoli variety (Jet dome) was cultivated, with the same field management practices. However, the plot size was reduced in the second year from 0.2 ha to 0.1 ha.

In conformity with the commercial regimes through the machine planting the seedlings were 35 cm apart from each and rows of seedlings were separated by a distance of 70 cm. The images were made by DJI Phantom 4 v2 and, DJI Mavic 2 Pro in 2020 while in 2021 DJI Phantom 4 RTK was used. The resolution of all the pictures was 5472x3648 pixels. After the data collection and data preprocessing, broccoli position detection, broccoli head segmentation, and broccoli head size calculation were conducted. Compared to the previous work the researchers even developed a model to predict the optimal harvest time, so maximize the income, and minimize the food loss. In the studied case one day shift in harvest date (compared to the forecasted one) could have led to a significant income loss of up to 20%. Even though this study concentrated on broccoli, according to the authors the framework lightly could be adopted to similar vegetables like cabbage, cauliflower, or artichoke. Although this outstanding work shows up several technical improvements it has some limitations too. Plant phenotyping is a big challenge in image processing, and this issue can be seen here too. To solve temporarily this problem only those broccoli heads were studied in the research that were clearly visible. Some manual inspection is also needed for seedling position detection, detection of omissions, duplications, and drifts. Although many farmers own some general IT knowledge, this model is neither fully automated nor app-based which requires some more background in the field of computer science. As the source code is open-access, the further development of this work is supported and encouraged by the authors.

Not only vegetable cultivations were studied by image processing. The research of Assunção et al., (2022) applied a deep learning approach to detect peaches supporting the yield estimation. The analyzed pictures were made by an Eken H9R camera (5472x3648 pixels). All the photos were taken in the same orchard - whose fruits were yellowish - located in Beira Interior, Portugal. To train the model 200 photos with 1934 annotated fruits were used. To test it 40 pictures with 410 annotated peaches from the same farm and some images from another orchard with reddish peaches were taken to see the generalisability of the R-CNN based model. The study revealed the great potential of using the R-CNN model for peach detection. The difficulties belonging to an uncontrolled environment like light changes, occluded or bunches of fruits were well managed. In addition, the change of fruit and leave colors was handled by this robust deep learning technique too.

The examination revealed a scarce existence of relevant literature applying new data collection methods for food loss evaluation purposes. According to the studied works and their references, the recent image-based approach is being studied in agriculture. However, the focus of these articles differs from the current research's direction. The studies focus on preventing and reducing on-farm food loss, rather than quantifying it. The very small number of connected studies suggests that the application of image processing in this area is still in its early stages.

To examine the landscape of the image-based research directions related the farming issues a thematic map was made. The purpose of this figure is to understand the current state and reveal the future of the studied field. By analyzing the connections between groups of abstracts, thematic analysis revealed underlying themes, that have specific attributes, namely, density and centrality (Aria and Cuccurullo, 2017). The latter measures how closely related different topics are to each other, while density measures how interconnected the nodes within the topic are. These two properties together determine a topic's development and importance. The more connections a topic has, the more important it is. Similarly, the more interconnected the nodes, the more cohesive the research field is (Agbo et al., 2021). On the map, each circle symbolizes a group of related terms, and the circle's size reflects the number of terms it encapsulates. The map could be divided into sections (Q1-Q4). The driving themes are located in the upper right quadrant (Q1). The highly specialized matters are found in the upper left corner (Q2). The emerging or disappearing issues are presented in the lower left area (Q3), and the lower right section (Q4) shows the underlying themes (Yu and Muñoz-Justicia, 2020). To collect relevant studies the "image-based" AND "agriculture" search query was used in the same scientific databases. After the data cleaning, 433 work created the base of the thematic map (Figure 4).



Source: own elaboration, 2023

Figure 4: The thematic map of image-based studies in the agriculture.

The analysis of more than four hundred articles outlined the most relevant factors. The map made visible in the Q4 section the essential need for ”remote sensing data”, which is the basis and very important for the further development of the studied field. It is not surprising, since this is the information source of the studies. In section Q3 the emerging or declining themes are presented. In the current case the extremely small circle of ”support vector machine” is located here. The support vector machines (SVMs) are supervised machine learning algorithms dedicated to classification and pattern recognition tasks (Otchere et al., 2021). These functions make them ideal for analyzing agricultural images. The widespread of drones, satellites, and other imaging technologies (Hall and Wahab, 2021), the development of machine learning algorithms (Alzubi et al., 2018), the growing demand for precision agriculture (Sishodia et al., 2020), and even the decreased computational costs (Xie et al., 2021) rather support the rise, than the fall of the cluster. At the junction of highly specialized matters (Q2) and emerging or disappearing issues (Q3) located a bit bigger circle, the so-called ”difference vegetation index”. The DVIs (difference vegetation indices) are a type of vegetation index that measures the disparity in reflectance between two different wavelengths of light (Huang et al., 2021). In agriculture this ability is utilized among others for monitoring crop growth and development (Mandal et al., 2020), detecting and mapping vegetation (Rokni and Musa, 2019), estimating crop yield (Ji et al., 2021), or identifying areas of nutrient deficiency (Sharifi, 2020). This group has less centrality but is compensated with a relatively higher level of interconnection.

In the top right corner (Q1) positioned the biggest cluster. According to the thematic map "convolutional neural network" is the driving theme in the studied field. The centrality and the density of CNN (convolutional neural network) are fairly high, which could be explained by the excellent suitability for for image-based analysis of this deep learning algorithm (Indolia et al., 2018). The sandwiched lay of the "plant disease detection" cluster on the borders of the niche (Q2) and driving (Q1) sections shows up the one indeed agricultural related matter of the analyzed studies. Even though "plant disease detection" is prioritized, the results further support the assumption that image-based data sources could also be applied to quantify food loss. However, the new data collection method has not only great potential but also significant hurdles. One of the primary barriers lies in the complex nature of plant phenotyping. Not only adapting the method to different types of plants can be challenging, but also analysing the plants belonging to a particular species. Given that the visual characteristics of a species can vary significantly due to factors such as genetic diversity, environmental conditions, diseases or pests. These variations can make it difficult for image processing algorithms to accurately identify and classify different plant stages or anomalies. Another challenge is the potential for errors in data collection and processing. Despite advancements in UAS technology, factors such as atmospheric conditions, camera calibration, and image quality can introduce noise and distortions into the collected data. These errors can impact the accuracy of subsequent analyses and predictions. Moreover, the development of robust image processing algorithms requires extensive training data, which can be time-consuming and resource-intensive to acquire. Furthermore, the practical implementation of image-based food loss estimation systems in real-world agricultural settings can be hindered by factors such as cost, technical expertise, and infrastructure requirements. While the initial investment in UASs and image processing software may be substantial, the ongoing operational costs associated with data collection and analysis must also be considered. The successful deployment of these systems often requires specialized technical knowledge and skills, which may not be readily available to all farmers. A key concern in the use of image processing particularly related to data ownership, privacy, and security. As drones and advanced imaging systems capture vast amounts of detailed data from farms, questions arise about who controls this information. Farmers may face challenges in ensuring their data remains secure, especially when third-party platforms or cloud services are involved in data processing. Some of the arguments pro and con the new data collection method are presented in Table 1.

	Pro	Con
Labor	It reduces the labor need, through provides a remote and fast tool for food loss assessment.	It requires some IT skills, and may some on-site checks.
Accuracy	It can achieve high accuracy in quantifying food loss.	Accuracy can be affected by various factors (e.g. crop, weather).
Scalability	It can be easily scaled to cover large areas and multiple crops.	It depends on the quality and quantity of training data.
Implementation	It can provide insights into the causes of food loss, which can inform targeted interventions.	It requires specialized equipment and raises data privacy concerns.

Source: own elaboration, 2023

Table 1: Some advantages and disadvantages of the image-based food loss quantification.

However, it is crucial to consider the farms' characterisitcs before the implementation of the proposed image-based solution. Since, applying image processing to different agricultural systems, such as mixed cropping or agroforestry, presents unique challenges. In such systems, multiple crops or trees are grown in close proximity, making it harder to isolate and analyze individual plants. In mountainous regions or hilly landscapes, capturing consistent, high-quality aerial images can be more difficult due to elevation changes and shadows cast by the terrain. Moreover, a different approach could be needed for certain species (e.g. wheat, rice, and maize), as their development based on internal characteristics, rather than purely visual ones. Over time the hardware and software-related challenges could be mitigated, further improving the adequacy of the image-based approach. But to do so consideration and consistent research of the addressed area would be needed.

Conclusion

Agriculture has a critical role in achieving the Sustainable Development Goals. Through its effective operation, multiple SDGs could be neared and addressed simultaneously. However, to measure proper the effect of the new practices and policies adequate methodologies are needed. Lately, the widely adapted approaches are rethought, developed, and discussed, but the information sources of the food loss and waste estimations are sporadically studied. The traditional methods such as weighing and surveys, are often inaccurate or labor-intensive. Directly the studied articles did not reveal new data collection methods related to food loss and waste quantification. However, through the smart farming concept, the application of image processing in the preharvest, and harvesting phases gets identified for food loss reduction purposes. The comprehensive exploration of the newly specified area highlighted its infancy. The driving theme in this field seems to be the "convolutional neural networks", which is a deep learning algorithm dedicated to image analysis. However, the rise of "support vector machines" is also visible. Related to the farming issues, only "plant disease detection" appeared, thus designating the main research direction in the studied area. Even though the proposed method is in its early stage, it can be highly beneficial for farmers to monitor crop health, estimate food loss, and optimize harvesting processes. The latest technology enables more accurate and real-time data collection, which can lead to better decision-making on the farm. So the overall yield and profit of the farmers could be improved. By integrating image-based data collection, agriculture becomes more data-driven, reducing the labour involved in farming and enhancing sustainability. The ability to prevent food loss at the preharvest stage is critical for improving efficiency and reducing the environmental impact of agriculture. These advancements can help the agricultural sector meet the growing global demand for food while minimizing resource consumption and environmental damage. However, several areas warrant further research to fully realize the benefits of this technology. It is essential to explore the potential of image-based food loss estimation for a wider range of crops and agricultural systems. While the studies focused on specific crops, the future's principles and techniques have to be suitable to apply on other agricultural commodities too. The development of more robust and accurate plant phenotyping algorithms is critical for the success. Even the studies made significant strides, there is still room for improvement in distinguishing between different plant stages, detecting anomalies, and accounting for variations in plant appearance. Another important research direction is to focus on addressing the practical challenges associated with implementing image-based food loss estimation systems in real-world agricultural settings. This includes developing user-friendly interfaces, reducing the cost of hardware and software -what would be particularly relevant for developing regions-, and ensuring the reliability and scalability of these systems. Additionally, efforts should be made to address data privacy concerns and develop secure and ethical data management practices. Policymakers play a crucial role in creating an enabling environment for this method. By providing funding for research and development, and implementing supportive regulations, they could facilitate the widespread use of this method.

Corresponding author
Dr. Adrián Csordás
Faculty of Economics and Business University of Debrecen
Debrecen, Böszörményi út 138 4032, Hungary
Email: csordas.adrian@econ.unideb.hu

References

[1] Abbade, E. B. (2020) "Land and water footprints associated with rice and maize losses in Brazil", *Land Use Policy,* Vol. 99, p. 105106. ISSN 0264-8377. DOI 10.1016/j.landusepol.2020.105106.

[2] Abbade, E. B. (2023) "Land footprint and GHG emissions from global food loss", *Journal of the Science of Food and Agriculture*, Vol. 103, No. 9, pp. 4430–4440. ISSN 1097-0010. DOI 10.1002/jsfa.12524.

[3] Agbo, F. J., Oyelere, S. S., Suhonen, J. and Tukiainen, M. (2021) "Scientific production and thematic breakthroughs in smart learning environments: a bibliometric analysis", *Smart Learning Environments*, Vol. 8, No. 1, p. 1. ISSN 2196-7091. DOI 10.1186/s40561-020-00145-4.

[4] Alzubi, J., Nayyar, A. and Kumar, A. (2018) "Machine Learning from Theory to Algorithms: An Overview", *Journal of Physics: Conference Series"*, Vol. 1142, p. 012012. ISSN 1742-6596. DOI 10.1088/1742-6596/1142/1/012012.

[5] Anriquez, G., Foster, W., Ortega, J. and Santos Rocha, J. (2021) "In search of economically significant food losses: Evidence from Tunisia and Egypt", *Food Policy*, Vol. 98, p. 101912. ISSN 0306-9192. DOI 10.1016/j.foodpol.2020.101912.

[6] Aria, M. and Cuccurullo, C. (2017) "bibliometrix: An R-tool for comprehensive science mapping analysis", *Journal of Informetrics*, Vol. 11, No. 4, pp. 959-975. ISSN 1751-1577. DOI 10.1016/j.joi.2017.08.007.

[7] Assunção, E. T., Gaspar, P. D., Mesquita, R. J. M., Simões, M. P., Ramos, A., Proença, H. and Inacio, P. R. M. (2022) "Peaches Detection Using a Deep Learning Technique—A Contribution to Yield Estimation, Resources Management, and Circular Economy", *Climate*, Vol. 10, No. 2, p. 11. ISSN 2225-1154. DOI 10.3390/cli10020011.

[8] Boiteau, J. M. and Pingali, P. (2023) "Can we agree on a food loss and waste definition? An assessment of definitional elements for a globally applicable framework", *Global Food Security*, Vol. 37, p. 100677. ISSN 2211-9124. DOI 10.1016/j.gfs.2023.100677.

[9] Capone, R., Berjan, S., El Bilali, H., Debs, P. and Allahyari, M. S. (2020) "Environmental implications of global food loss and waste with a glimpse on the Mediterranean region", *International Food Research Journal*, Vol. 27, No. 6. ISSN 1985-4668.

[10] Chaboud, G. and Daviron, B. (2017) "Food losses and waste: Navigating the inconsistencies", *Global Food Security*, Vol. 12, pp. 1-7. ISSN 2211-9124. DOI 10.1016/j.gfs.2016.11.004.

[11] Chauhan, C., Dhir, A., Akram, M. U. and Salo, J. (2021) "Food loss and waste in food supply chains. A systematic literature review and framework development approach", *Journal of Cleaner Production"*, Vol. 295, p. 126438. ISSN 0959-6526. DOI 10.1016/j.jclepro.2021.126438.

[12] Corrado, S. and Sala, S. (2018) "Food waste accounting along global and European food supply chains: State of the art and outlook", *Waste Management*, Vol. 79, pp. 120-131. ISSN 0956-053X. DOI 10.1016/j.wasman.2018.07.032.

[13] Dal' Magro, G. P. and Talamini, E. (2019) "Estimating the magnitude of the food loss and waste generated in Brazil", *Waste Management & Research*, Vol. 37, No. 7, pp. 706-716. ISSN 0734-242X. DOI 10.1177/0734242X19836710.

[14] Delgado, L., Schuster, M. and Torero, M. (2017) "Reality of food losses: A new measurement methodology", [Online]. Available: https://www.oneplanetnetwork.org/sites/default/files/the_reality_of_food_losses_a_new_measurement_methodology.pdf [Accessed: Dec. 2, 2023].

[15] Delgado, L., Schuster, M. and Torero, M. (2021) "Quantity and quality food losses across the value Chain: A Comparative analysis", *Food Policy*, Vol. 98, p. 101958. ISSN 0306-9192. DOI 10.1016/j.foodpol.2020.101958.

[16] Ellison, B., Muth, M.K. and Golan, E. (2019) "Opportunities and Challenges in Conducting Economic Research on Food Loss and Waste", *Applied Economic Perspectives and Policy*, Vol. 41, No. 1, pp. 1-19. ISSN 2040-5804. DOI 10.1093/aepp/ppy035.

[17] FAO (2011) "*Global food losses and food waste – Extent, causes and prevention*", Food and Agricultural Organisation of the United Nations. ISBN 978-92-5-107205-9.

[18] FAO (2019) "*The state of food and agriculture 2019. Moving forward on food loss and waste reduction*", FAO, Rome, pp. 2-13. ISBN 978-92-5-131789-1.

[19] Garcia-Herrero, I., Hoehn, D., Margallo, M., Laso, J., Bala, A., Batlle-Bayer, L., Fullana, P., Vazquez-Rowe, I., Gonzalez, M. J., Durá, M. J., Sarabia, C., Abajas, R., Amo-Setien, F. J., Quiñones, A., Irabien, A. and Aldaco, R. (2018) "On the estimation of potential food waste reduction to support sustainable production and consumption policies", *Food Policy*, Vol. 80, pp. 24-38. ISSN 0306-9192. DOI 10.1016/j.foodpol.2018.08.007.

[20] Guo, X., Broeze, J., Groot, J. J., Axmann, H. and Vollebregt, M. (2020) "A Worldwide Hotspot Analysis on Food Loss and Waste, Associated Greenhouse Gas Emissions, and Protein Losses", *Sustainability*, Vol. 12, No. 18, p. 7488. ISSN 2071-1050. DOI 10.3390/su12187488.

[21] Hall, O. and Wahab, I. (2021) "The Use of Drones in the Spatial Social Sciences", *Drones*, Vol. 5, No. 4, p. 112. ISSN 2504-446X. DOI 10.3390/drones5040112.

[22] Hartikainen, H., Mogensen, L., Svanes, E. and Franke, U. (2018) "Food waste quantification in primary production – The Nordic countries as a case study", *Waste Management*, Vol. 71, pp. 502-511. ISSN 0956-053X. DOI 10.1016/j.wasman.2017.10.026.

[23] Hassanzadeh, A., Zhang, F., Murphy, S.P., Pethybridge, S. J. and van Aardt, J. (2022) "Toward Crop Maturity Assessment via UAS-Based Imaging Spectroscopy—A Snap Bean Pod Size Classification Field Study", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 60, pp. 1-17. ISSN 0196-2892. DOI 10.1109/TGRS.2021.3134564.

[24] Huang, S., Tang, L., Hupy, J. P., Wang, Y. and Shao, G. (2021) "A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing", *Journal of Forestry Research*, Vol. 32, No. 1, pp. 1-6. ISSN 1007-662X. DOI 10.1007/s11676-020-01155-1.

[25] Indolia, S., Goswami, A. K., Mishra, S. P. and Asopa, P. (2018) "Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach", *Procedia Computer Science*, Vol. 132, pp. 679-688. ISSN 1877-0509. DOI 10.1016/j.procs.2018.05.069.

[26] Ishangulyyev, R., Kim, S. and Lee, S. (2019) "Understanding Food Loss and Waste—Why Are We Losing and Wasting Food?", *Foods*, Vol. 8, No. 8, p. 297. ISSN 2304-8158. DOI 10.3390/foods8080297.

[27] Ji, Z., Pan, Y., Zhu, X., Wang, J. and Li, Q. (2021) "Prediction of Crop Yield Using Phenological Information Extracted from Remote Sensing Vegetation Index", *Sensors*, Vol. 21, No. 4, p. 1406. ISSN 1424-8220. DOI 10.3390/s21041406.

[28] Johnson, L. K., Dunning, R. D., Gunter, C. C., Bloom, J. D. Boyette, M. D. and Creamer, N. G. (2018) "Field measurement in vegetable crops indicates need for reevaluation of on-farm food loss estimates in North America", *Agricultural Systems*, Vol. 167, pp. 136-142. ISSN 0308-521X. DOI 10.1016/j.agsy.2018.09.008.

[29] KC, K., Haque, I., Legwegoh, A. and Fraser, E. (2016) "Strategies to Reduce Food Loss in the Global South", *Sustainability*, Vol. 8, No. 7, p. 595. ISSN 2071-1050. DOI 10.3390/su8070595.

[30] Khatri-Chhetri, A., Costa Jr. C. and Wollenberg, E. (2022) "Greenhouse gas mitigation co-benefits across the global agricultural development programs", *Global Environmental Change*, Vol. 76, p. 102586. ISSN 0959-3780. DOI 10.1016/j.gloenvcha.2022.102586.

[31] Koester, U. and Galaktionova, E. (2021) "FAO Food Loss Index methodology and policy implications", *Studies in Agricultural Economics*, Vol. 123.1, pp. 1-7. ISSN 2063-0476. DOI 10.7896/j.2093.

[32] Luo, N., Olsen, T., Liu, Y. and Zhang, A. (2022) "Reducing food loss and waste in supply chain operations", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 162, p. 102730. ISSN 1366-5545. DOI 10.1016/j.tre.2022.102730.

[33] Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J. M., McNairn, H. and Rao, Y. S. (2020) "Dual polarimetric radar vegetation index for crop growth monitoring using sentinel-1 SAR data", *Remote Sensing of Environment,* Vol. 247, p. 111954. ISSN 0034-4257. DOI 10.1016/j.rse.2020.111954.

[34] Marston, L. T., Read, Q. D., Brown, S. P. and Muth, M. K. (2021) "Reducing Water Scarcity by Reducing Food Loss and Waste", *Frontiers in Sustainable Food Systems*, Vol. 5. ISSN 2571-581X. DOI 10.3389/fsufs.2021.651476.

[35] Moher, D. (2009) "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement", *Annals of Internal Medicine*, Vol. 151, No. 4, p. 264. ISSN 1743-9191. DOI 10.1016/j.ijsu.2010.02.007.

[36] Otchere, D. A., Arbi Ganat, T. O., Gholami, R. and Ridha, S. (2021) "Application of supervised machine learning paradigms in the prediction of petroleum reservoir properties: Comparative analysis of ANN and SVM models", *Journal of Petroleum Science and Engineering*, Vol. 200, p. 108182. ISSN 0920-4105. DOI 10.1016/j.petrol.2020.108182.

[37] Pagani, M., De Menna, F., Johnson, T. G. and Vittuari, M. (2020) "Impacts and costs of embodied and nutritional energy of food losses in the US food system: farming and processing (Part A)", *Journal of Cleaner Production,* Vol. 244, p. 118730. ISSN 0959-6526. DOI 10.1016/j.jclepro.2019.118730.

[38] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., Luke A McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P. and Moher, D. (2021) "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", *BMJ*, Vol. 371, No. 71. ISSN 1756-1833. DOI 10.1136/bmj.n71.

[39] Rayyan (2023) "Faster systematic reviews" [Online]. Available: https://www.rayyan.ai/[Accessed: Dec. 2, 2023].

[40] Redlingshöfer, B., Coudurier, B. and Georget, M. (2017) "Quantifying food loss during primary production and processing in France", *Journal of Cleaner Production*, Vol. 164, pp. 703/714. ISSN 0959-6526. DOI 10.1016/j.jclepro.2017.06.173.

[41] Rokni, K. and Musa, T. A. (2019) "Normalized difference vegetation change index: A technique for detecting vegetation changes using Landsat imagery", *CATENA*, Vol. 178, pp. 59-63. ISSN 0341-8162. DOI 10.1016/j.catena.2019.03.007.

[42] Sharifi, A. (2020) "Remotely sensed vegetation indices for crop nutrition mapping", *Journal of the Science of Food and Agriculture*, Vol. 100, No. 14, pp. 5191-5196. ISSN 1097-0010. DOI 10.1002/jsfa.10568.

[43] Shee, A., Parmar, A., Raut, S., Strum, B. and Bennett, B. (2022) "Assessing the measurement methods of post-harvest food loss and waste: opportunities and challenges", *Enterprise Development & Microfinance*, Vol. 33, No. 4. ISSN 1755-1986. DOI 10.3362/1755-1986.22-00062.

[44] Sishodia, R. P., Ray, R. L. and Singh, S. K. (2020) "Applications of Remote Sensing in Precision Agriculture: A Review", *Remote Sensing*, Vol. 12, No. 19, p. 3136. ISSN 2072-4292. DOI 10.3390/rs12193136.

[45] Soltani, A., Alimagham, S. M., Nehbandani, A., Torabi, B., Zeinali, E., Zand, E., Vadez, V., van Loon, M. P. and van Ittersum, M. K. (2020) "Future food self-sufficiency in Iran: A model-based analysis", *Global Food Security*, Vol. 24, p. 100351. ISSN 2211-9124. DOI 10.1016/j.gfs.2020.100351.

[46] Spang, E. S., Moreno, L. C., Pace, S. A., Achmon, Y., Donis-Gonzalez, I., Gosliner, W. A., Jablonski-Sheffield, M. P., Momin, M. A., Quested, T. E., Winans, K. S. and Tomich, T. P. (2019) "Food Loss and Waste: Measurement, Drivers, and Solutions", *Annual Review of Environment and Resources,* Vol. 44, No. 1, pp. 117-156. ISSN 1543-5938. DOI 10.1146/annurev-environ-101718-033228.

[47] Sun, H., Sun, Y., Jin, M., Ripp, S. A., Sayler, G. S. and Zhuang, J. (2022) "Domestic plant food loss and waste in the United States: Environmental footprints and mitigation strategies", *Waste Management*, Vol. 150, pp. 202-207. ISSN 0956-053X. DOI 10.1016/j.wasman.2022.07.006.

[48] Swartz, M. K. (2011) "The PRISMA Statement: A Guideline for Systematic Reviews and Meta-Analyses", *Journal of Pediatric Health Care*, Vol. 25, No. 1, pp. 1-2. ISSN 0891-5245. DOI 10.1016/j.pedhc.2010.09.006.

[49] Wang, H., Li, T., Nishida, E., Kato, Y., Fukano, Y. and Guo, W. (2023) "Drone-Based Harvest Data Prediction Can Reduce On-Farm Food Loss and Improve Farmer Income", *Plant Phenomics*, Vol. 5. ISSN 2643-6515. DOI 10.34133/plantphenomics.0086.

[50] Xie, G., Ma, W., Peng, H., Li, R. and Li, K. (2021) "Price Performance-Driven Hardware Cost Optimization Under Functional Safety Requirement in Large-Scale Heterogeneous Distributed Embedded Systems", *IEEE Transactions on Industrial Electronics*, Vol. 68, No. 5, pp. 4485-4497. ISSN 1557-9948. DOI 10.1109/TIE.2019.2905815.

[51] Xue, L., Liu, G., Parfitt, J., Liu, X., Van Herpen, E., Stenmarck, Å., O'Connor, C., Östergren, K. and Cheng, S. (2017) "Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data", *Environmental Science & Technology*, Vol. 51, No. 12, pp. 6618-6633. ISSN 0013-936X. DOI 10.1021/acs.est.7b00401.

[52] Yu, J. and Muñoz-Justicia, J. (2020) "A Bibliometric Overview of Twitter-Related Studies Indexed in Web of Science", *Future Internet*, Vol. 12, No. 5, p. 91. ISSN 1999-590. DOI 10.3390/fi12050091.

[53] Zhu, J., Luo, Z., Sun, T., Li, W., Zhou, W., Wang, X., Fei, X., Tong, H. and Yin, K. (2023) "Cradle-to-grave emissions from food loss and waste represent half of total greenhouse gas emissions from food systems", *Nature Food*, Vol. 4, No. 3, pp. 247-256. ISSN 2662-1355. DOI 10.1038/s43016-023-00710-3.