Augmenting Strawberry Agronomy: From Systematic Literature Review to Value Flow Map*

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Abstract. As the world faces the challenges of climate change and growing population, the role of agriculture in ensuring food safety is becoming more important. This paper explores how augmentation and autonomous systems can improve the efficiency of crop cultivation and support agronomists in managing the process of strawberry production. The paper first synthesises current approaches for automation and augmentation with a systematic literature review. It then identifies production and management processes and their key performance indicators. Finally, following the grounded theory approach, the paper analyses the production processes into functional key performance indicators and syntheses an agronomic value flow map of strawberry production. The comprehensive review supports researchers and agronomists to identify critical bottlenecks and offers insights into the potential for automation and augmentation in strawberry agronomy.

Keywords: Strawberry Cultivation · Agronomy · Automation · Augmentation.

1 Introduction

Commercial Strawberry agronomy involves series of actions for producing and activities for managing yielding strawberries.In contrast to industrial manufacturing processes, where the products are created from parts by applying forming, joining, removing, deforming, and material property modification processes [1, p.77], agriculture crop cultivation focuses managing conditions to promote development of marketable crops that can be sold with economic gain [2, 3]. Modern strawberry agronomy engineers the crop environment specific to the requirements of the strawberry's development stages to promote the respective development critical germination, leaf development, flowering, and ripening to maximise agronomic gain.

This research project is motivated by the potential of augmenting agronomist's decision . The ambition to maximise the agronomic gain requires investing resources into continuously improving and innovating the efficiency of the most critical processes. This is currently complex due to two reasons. Firstly, lacking guidance for agronomist to synthesise which automations and augmentations are beneficial in their circumstances. Secondly, lacking resources that allow researchers to identify the limiting factors of agronomists and how these can be overcome. The conducted literature review approaches progress in both areas. making.

Current state of the art augmentation technologies do not yet fully exploit the potential of visualising critical performance indicators when autonomous systems are used [4]. To understand which

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information is critical for agronomists, the agronomic value flow is synthesised based on a literature survey of the current state of the art of automation and augmentation technologies. The resulting value stream mapping can be used to identify the critical performance indicators for agronomists and enables value-driven development for augmenting agronomic strawberry production.

2 Methodology

2.1 Research strategy

The current research gap of synthesising critical improvements of value-driven strawberry agronomic technology is approached in two steps. First, research contributions that implement augmentations or autonomous systems for agricultural application are identified and synthesised into pragmatically relevant conceptual frameworks. Secondly, the agronomic gain of the academic contributions is analysed. These include: (1) classes of approaches for automating specific crop production processes, (2) described conditions under which these automations are applicable (external validity), and (3) qualifying their contribution to producing process outputs from an inputs based with reported performance indicators. The identified qualities are used in the subsequent section to create a of the agronomic value stream grounded on synthesised process elements and associated key performance indicators.

2.2 Sytematic Literature Review

The literature review's objective is to identify autonomous systems in strawberry agronomy. Relevant literature is identified using the query "Strawberr* AND (FARM OR Agriculture OR Agronomy OR Horticulture) AND (Autonomous Systems OR Robot* OR AI OR ML OR Artificial Intelligence OR Machine LEARNING OR AR OR VR OR Augmented Reality OR VR)". The papers are selected based on category, title, abstract and content. First, papers are filtered based on their category and included if study: 'Horticulture', 'Food Science & Technology', 'Agronomy', 'Agriculture, Multidisciplinary', 'Computer Science, Interdisciplinary Applications', 'Automation & Control Systems', 'Multidisciplinary Sciences', 'Robotics', 'Agricultural Economics & Policy', 'Education & Educational Research'. The remaining papers are analysed using their title, keywords and abstract for an in-depth review. After an in-depth review of the papers, 82 papers are identified that cover autonomous systems in strawberry agronomy. These are coded regarding augmentations and autonomous systems and their Key Performance Indicators (KPIs) or how they are integrated into production and management processes, retaining 43 papers.

2.3 Conceptual Framework

The conceptual framework is synthesised from the literature review. It focuses on developing a grounded theory-inspired framework that is used to model the value flow in strawberry production and management. For the grounded theory approach, inter-activity key performance metrics are integrated using axial coding into intra-process activity-class relationships using a functional model (IDEF0) [5, 6, 7]. Subsequently, inter-process relationships between these KPIs are extracted using focused and selective coding and synthesised a value flow map [8, 6].

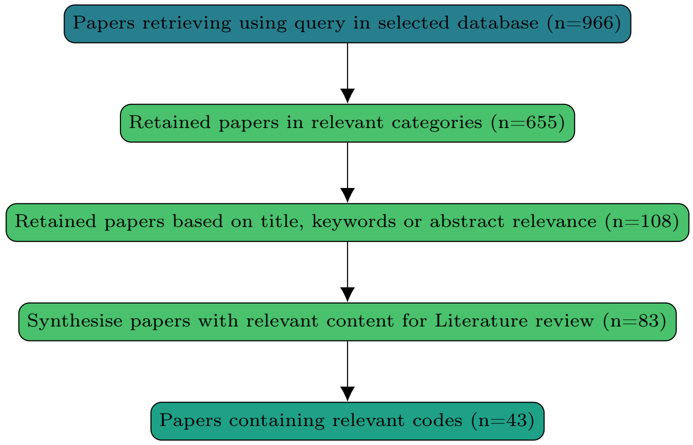

Fig. 1 Systematically synthesising relevant papers.

3 Systematic Literature review

Prior work. Existing reviews, deal with the technological status quo or customer preferences but fail to contextualise contributions in their agronomic value. General robotics are reviewed by [9]. Additionally, robotic systems with a focus on strawberry robotics are reviewed by [4]. Aspects of robotic systems specific to strawberries are highlighted for actuators [10], Sensing [11], Human synergies [12], operations after harvesting [13], innovation drivers [14]. Recent reviews identify the essential role of economic benefits for developing effective technologies and guidelines [4]. However, no contribution's are not linked to the expected agronomic gain. If economic potential is reviewed, then it is analysed based on consumer preferences [15] without direct linkage to the involved technologies, Thus, this review focuses on the agronomic value produced by strawberry production processes based on state of the art key performance measures [4].

Review structure Conceptualising augmentations and automations by activities, resulted in transplantation, harvesting, environment engineering, and pest and disease management activities by creating a hierarchy of identified in-vivo codes. This reflects that the transplantation and harvesting activity are the only processes in which autonomous (which are potentially automated systems) directly perform the critical product transformation from intra-stage inputs to outputs. In other life-stages, ensuring the appropriate environment requires managing pest and diseases, and active considerations regarding the varieties genetic not converting and input to an output but rather to cultivate the plant with inter-life-cycle-stage-processes to promote its ability to develop the ultimate produce. The automation in productions and augmentations for management are aggregated in separate sections due to the role (human or automated) labour can have in the development stage. In agronomic gain in the production processes is also depending on the work efficiency and effectiveness of the constituent process steps. The only processes where labour produces all inputs from outputs are transplantation and harvesting. In the other cases, conditions can only be cultivated by labour to promote a plants synthesis of strawberries.

3.1 Production processes

Transplantation: Transplantation is the first step of most commercial strawberry farms [14]. Transplantation constitutes:

1. grabbing;
2. translocation;
3. and placing

of a seedling [16]. This is repeated for each seedling with key performance indicators for working efficiency: $\frac{time\ per\ plug}{\#seedlings/plugs}$, plants/h: $\frac{plants}{h}$, and work effectiveness (value creation) regarding success rates of subsumed process steps of grapping, transformation (rotation + translation), and placing a seedling ($\frac{succeeded_{\square}}{attempted_{\square}}$)[16]. Subsequent process performance, might be affected if variations in the planting process (inter-row, intra-row, and perpendicular variation) exceed tolerances subsequent processes [16]. Comparing two automation systems requires equivalent working conditions such as space between plants and manipulated container dimensions as the effectiveness KPI are sensitive to these metrics.

Harvesting

The harvesting process constitutes:

1. transport to potential crop;
2. locate next crop, decide if ripe enough to hit quality targets;
3. if yes, access the crop, harvest the product;
4. after harvesting the product, store product in buffer;
5. if buffer full, transport to collection storage area;
6. if not done with all plants, restart with 1 [17].

Accessing the plant and harvesting the crop requires obstacle-separation and path-planning algorithms to allow the successful harvest due to the necessity to transport to strawberries and extract those that are surrounded by other strawberries [18].

This can extend to allow selectively harvesting according to maturity level. The effectiveness of such systems is reported with up to 54.9% (where 42.8% failed due to unsuccessful detection and 2% failed due to error in peduncle detection). The work efficiency can be measured in form of the harvesting cycle time (steps 1-6) and are reported to be as low as 8.6s. [19] Advanced robot systems are able to push strawberries aside to access ripe strawberries. This requires obstacle detection and extraction of relevant strawberry [18]. Additionally, special adaptive perceptual systems can be implemented to mediate the challenging light variations and uncertainties on the field. While the success rate of such systems and the time required for picking are better - increasing the potential agronomic gain of adapting the robot - challenging cases in which strawberries are surrounded by unripe strawberries can still lead to a failure of the robot [18].

Additionally, harvesting systems can allow to place the picked product directly into the final container - thus automating the isolated harvesting process [19] The storage of the produce into the final container is called packaging. Success rate of complete automatic packing was 97.3%. Differentiated in Supply unit success of 98% and Packing unit of 99.3%. Overall process time per fruit was 7.3 (parallel operation of two units). Sorting and packing by hand approximately 5 to 8s per fruit [19].

For transportation of the full harvesting buffer [20] In human-robot collaboration scenarios, utilisation of available critical productive capabilities is integral to the overall agronomic gain [21]. Under the assumptions that, humans provide higher agronomic gain then robotic systems for picking strawberries but robotic systems are more cost efficient for transporting the strawberries to collection stations, the agronomic gain can be maximised by utilising as much productive time of the specialised (e.g. human) labour. In such heterogeneous workforces, critical capabilities should be utilised and other systems can support them to maximise overall agronomic gain. The optimal transport in this situation requires minimising the unproductive time of humans when waiting for a robot to collect the full tray. The resulting optimal labour efficiency is then the ratio between productive time over the unproductive time. [21] Besides the physical assistance of the humans through robots, the robots cognition capabilities can also improve the overall performance. Basic implementations are reactive autonomous systems that collect the trays when they are full [22]. In contrast, predictive autonomous systems are based on stochastic optimisation to forecast and adapt behaviour for collecting the buffers with minimal delay (e.g, based on pickers position and harvester produce as a function of time) [20] thus maximising the production efficiency.

Using machine learning, existing vision systems can be used to estimate strawberry qualities and potentially escalating actions [23]. For example, shape quantification and classification of strawberry ripeness using Principle progression of k Clusters.

Additionally, labour that is hired for harvesting is usually also responsible for reporting crop waste (expected quality vs actual quality), reporting pest and diseases, instruct new labour, and personal maintenance [17].

3.2 Management processes

Environment management The environmental conditions determine the plant's ability to synthesise strawberries from nutrients in the soil and air.

Climate management: Control over the climate allows to influence crop growth [24]. Crop growth is most influenced by CO_2, synthetically active radiation, and temperature (all directly influence photosynthesis); however, temperature is the major concern when controlling the plant development, and qualities (i.e. yield quantity) [24, 25].

Natural ventilation is the most important method for maintaining greenhouse temperature by mixing external and internal air. However it's control is complex. Most control models are physics or empirical based modeling. However, physical simulation approaches are generally not applied for green houses, since multi-paned window control effects on airflow is not well understood [24]. The state of the art controllers use PID logic that requires tuning and suffers from long response times due to the complex relationship of factors, most studies are simulated and not generally suited for application in diverse settings [24]. Alternatively, machine learning models can be used to autonomously manage environmental conditions and accurately model the control logic. Additionally, machine learning approaches such as neural networks can be extended to predict interventions with allow optimising costs by appropriate modelling of the optimal environment conditions $C_m(k) = \frac{1}{2}e_m(k)^2$ [24, 25].

Machine learning based control models outperform conventional models by over 1°C and are able to also chose appropriate actions based on prediction of external factors (i.e. outside temperatures) [24, 25].

Soil management: The soil composition significantly influences the reproductive and quality characteristics. Reproductive characteristics such as number of flowers, flowering time, number of flowers, number of fruits, the fruit weight, acidity content, and sugar content [26].

Soil key quality metrics indicate the soil's capacity to perform crop production. [27] Soil KPI are sensitive to management performance, easy to interpret and measure, associated with key ecological and biological processes, and representative of the field quality given the management approach [27]. However, individual soil biological, chemical or physical indicators are not suitable soil quality performance indicators due to their high variability over time and space [28], calling for a holistic view [29, 30, 27]. Soil quality are not very well understood from the perspective of KPIs due the the complexity of involved biochemical and physical processes [27]

Irrigation and and application of fertiliser has a significant influence and yield quality but requires appropriate management to reduce waste [31]. While irrigation and fertilisation have interactive effects, they also have isolated effects [31]. Too high irrigation causes hydric stress [18, 32] which reduces the photosynthetic rate leading to smaller leaf areas and produce quality [31]. If the natural water availability is insufficient to cover the evaporative demand, irrigation prevents crop dehydration and associated yield reduction [31]. Therefore, the optimal irrigation provides the plant with sufficient water to prevent dehydration, but does not stress the plant to maximise agronomic gain. Furthermore, too high fertilisation leads to a higher presence of salts which causes salt stress that reduces the absorption of essential nutrients and water which reduces yield [31]. However, too low fertiliser dosages prevent the plant's effective metabolic cycle which reduces key produce qualities such as sugar content, and yield [32]. Therefore, optimal fertilisation provides the plant with sufficient nutrients but does not stress the plant to maximise agronomic gain and accurate control of bio-fertilisers and irrigation can significantly increase shoot, plant and strawberry quality. [33] Organic matter such as manure can be an excellent treatment to improve physio-chemical properties. Additionally, the appropriate medium (e.g., coir), can contribute to moisture holding and aeration properties, slower provision of nutrients [26]. Microorganisms in the soil of the plant can have a significant positive effect on yield and produce quality. The characteristic sweetness of a high quality strawberry is due to low acidity levels with comparably high sugar content. The ratio of sugar and acid concentration is modulated by the interaction between soil's bacteria and fungi colonies. While fungi (i.e. Ri5) can lower the acidity (pH) of strawberries, the interaction between fungi and bacteria (Pf4 and Fm) significantly modulates the sugar concentration. The productivity of a plant is especially significantly higher when symbiotic fungus are present in the soil.[33]

Irrigation systems can change the composition of the soil by injecting substances in the irrigation solution [26]. Additionally, irrigation allows influencing the root zone soil temperature. While fluctuations of the root zone temperature between 7°C and 35°C do not negatively affect photosynthesis, fluctuations that fall outside of these temperatures negatively affect photosynthesis with impedes plant growth, fruit yield, and qualities [34].

Hygene

Pest and disease management: Humans are able to detect many pest and diseases using senses. However, some fungal diseases such as anthracnose crown rot and powdery mildew are only detectable for humans when the fungal infection produces spore producing fruiting bodies which lead to infections in other crops. To maximise agronomic gain, it is critical to contain infections as early as possible to minimise spread of the disease and its negative economic impact.

Hyper-spectral camera images can be used to recognised disease threats before they are visible to the human eye. These approaches are able to detect asymptomatic but infected plants with an accuracy of up to 84% which allows reducing the negative impact of diseases thought early detection systems significantly. [35]

Allows inexperienced growers to diagnose plant diseases. It is based on multi-access key identification that allows remote diagnosis based on images. The system is complementary to expert systems and differentiates itself by being approachable and information can be tailored to the user. The average time to completion was 2.8 and allowed all participants (n=5) to classify the disease correctly. [36]

Powdery mildew is commonly managed using fungicides applications independent of immediate risks. However, machine learning approaches, such as classification trees, allow to predict infection risks with a mean accuracy of 89.5%, sensitivity of 80.0%, and specificity of 92.5%. These can be implemented into decision support systems to allow efficient use of fungicides and promote production effectiveness. [37]

Disease management needs to adapt to new legislation's and policies restricting the use of pesticides and herbicides that promote emergence of new or reemergence of old pests and diseases and challenges agronomists to find effective, sustainable and economic solutions. For example, crown and root rot are spreads are challenging to contain without the recently banned methyl bromide. [38, 39]

Weed management: If weed infestation or pests decreases agronomic gain, herbicides and pesticides allow to control outbreaks and optimise agronomic gain. However, excessive use of pesticides and herbicides can also impede short term and long-term agronomic gain by spending more than necessary or harming the environment. Accurate detection of unwanted organisms allows sensitive detection and precise spraying of unwanted infestations. For example, weeds can be detected with an accuracy of 95.3% and on average can detect crops and weeds with with an accuracy 94.73%; resulting in a kappa coefficient of 89%. This allows to decrease the investment in agrochemicals and increases labour efficiency. Nevertheless, systems are only economic if sensitive enough to weeds to reduce weed infestations sufficiently and precise enough to not harm crops and spray unnecessary. [40]

Yield management Forecasting strawberry yield allows growers to optimally allocate resources and assist strategic business decisions. If environmental from different measurement systems, weather and climate forecasts and genetic information are available, machine learning techniques can be used to translate these parameters into yield forecasts. Together with production plans as priors, these forecasts allow to forecast harvests. Especially, neural networks show better performance than conventional approaches. Additionally, developed models can be used to simulate the outcomes of interventions to evaluate the impact of interventions. [41]

Critical growing conditions are predictable significantly better by transforming information from weather stations to local conditions using machine learning. For example, triangulated air temperature ($R^2 = 0.63, P < 0.001$) , relative humidity ($R^2 = 0.71, P < 0.001$) are significantly better predicted using least square regression based on trigonometric functions than directly using weather station values. [42] The cumulative fruit mass by time distribution follows a logistic growth curve and the coefficients of the growth curves depend on the growing conditions. [42] Predicting growing curves allow to predict plant phenology (sugar content ($R^2 = 0.61$), ratio between yield's classes, and yields (cumulative total yield, $R^2 = 0.97$) using, for example, fitted logistic growth equations that can be extended to include control variables to management conditions depending on the cultivar. [42]

4 Synthesising the agronomic gain in strawberry production

In the following, we conceptualise the review's results into conceptual frameworks. First, we synthesise functional specifications of the process activities. For biology-centric value crop processes (vegetation, flowering, and fruiting), no explicit biological specifications could be identified. Therefore, functional specifications can only be synthesised for the stages of transplanting and harvesting. Secondly, we synthesise the inter-process relationships in a value flow map.

Grounded theory The IDEF-0 model is developed for the transplantation (compare to Figure 2) and harvesting process (compare to Figure 3).

The transplantation process has the seedling (in the pot) as an input and the seedling (in the farm) as an output. The effectiveness of the process is determined by the ratio of seedlings (in the pot) that are produced into seedlings (in the farm) (r_{transp}). This can be analysed in terms of the individual plants that are successfully grabbed, transformed, and placed ($r_{transp} = r_{grab} \times r_{transf} \times r_{place}$). Functionally, transplantation consists of grabbing the seedling in the pot, transforming the seedling by moving it to the correct location, and placing the seedling.

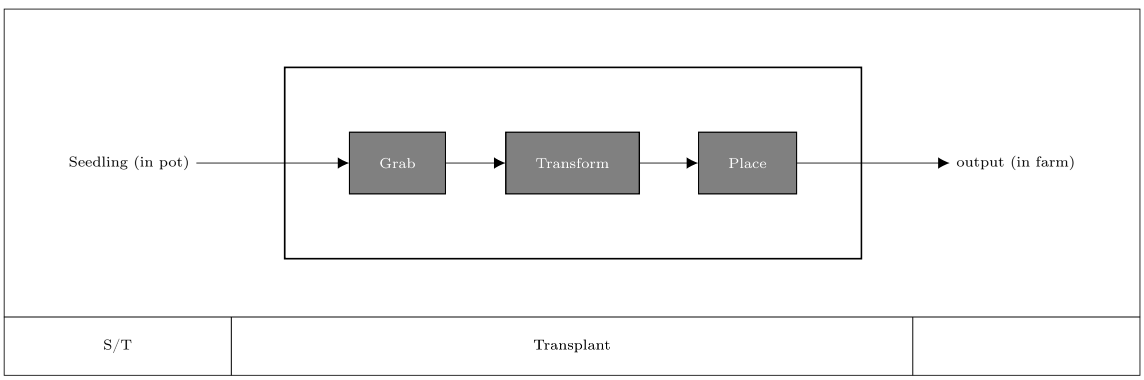

Fig. 2 IDEF0 specification for the transplantation process.

The harvesting process has the plant with ripe strawberries as an input and the plant with unripe strawberries (because all ripe strawberries are harvested), and the ripe strawberries (potentially in containers) as an output. The effectiveness of the process is determined by the ratio of Plants with ripe strawberries that are produced into plants with unripe strawberries and ripe strawberries (potentially in containers) ($r_{harvest}$). This can be analysed in terms of the rate of successful potential strawberries transported to, crop located, quality target determined as sufficient, crop accessed and harvested, stored in buffer, and transported to the collection area ($r_{harvest} = r_{transport} \times r_{locate} \times r_{quality} \times r_{harvest} \times r_{stored} \times r_{collected}$).

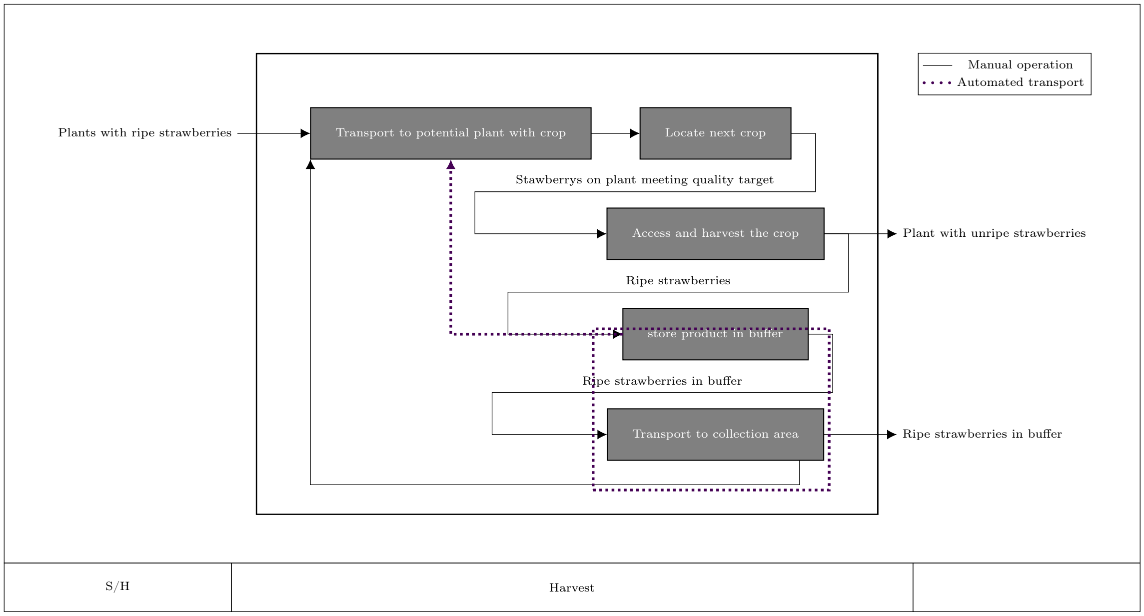

Fig. 3 IDEF0 specification for the harvesting process.

Value flow mapping Explicitly quantified, the amount seeds limit the potential number of germinating seeds These lim The successful transplantation rate determines how may of the bought plants make it into the farm. The germination rate limits how many of these seeds develop into seedlings. The budding rate limits the number of plants that can develop buds. The fertilisation rate limits the amount of buds that can develop into fertilised flowers. The adequate ripening rate limits the amount of flowers that turn into fruit. The adequately ripening of strawberries limits the amount of harvestable fruit. And the harvesting rate limits how many strawberries can be sold. This can also be expressed as a deterministic equation (compare to Equation 1).

$$yield_{strawberries} = num_{seed} \times r_{germ} \times r_{transp} \times r_{fertil} \times r_{ripe} \times r_{harvest} \tag{1}$$

The agronomic gain is directly influenced by the marketable value of fresh strawberries which, in addition to product quantity (*/#), market-dependent critical qualities such as color, integrity, size, contamination (e.g., soil, diseases, pests, moisture) (*/Q), and uniformity of color and form. The product, is partly determined by the processes in quantity (P/#) and other critical qualities (P/Q). Moreover, most farm have to commit to trading agreements (commonly two weeks in advance) with a volume they can sell [14, 17, 21]. Over and under estimation of the yield lowers the potential agronomic gain [43]. Therefore, the marketable yield is then a product of (1) the quantity of strawberries that meet quality objectives and (2) the accuracy of estimations due to trade agreements (compare to Figure 4).

Agronomic actors are directly producing the outputs from the inputs in the transplantation and harvesting process. In contrast, actions in the plant's vegetating, flowering, and ripening stage involve cultivating the plant to produce sufficient buds, flowers, and ripe strawberries respectively.

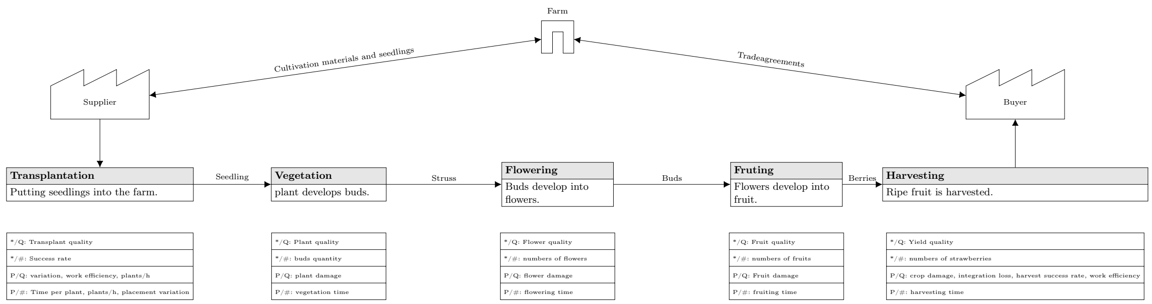

Fig. 4 Value stream mapping of strawberry agronomy

In these life stages, crop management with key responsibilities of environment management and pests and disease management.

Key quality indicators for marketing strawberries (i.e., size, texture, colour, and aroma) develop when ripening [33]. Ripening is a complex process in which the sugar, acids, vitamin, and volatile compounds contents significantly change [44, 45, 33]. Therefore, ripening is a key process that influences agronomic gain. The ripening of a strawberry is controlled genetically, based on the environment and developmental factors [33, 46, 47].

5 Discussion and Conclusion

Discussion. Regarding the literature review, determining the agronomic gain of adapting process designs is complex and involves uncertainty [48]. Previous reviews and derived economic analyses did not allow to relate between KPIs of a system and the implied agronomic value [49]. The lacking understanding of a contribution's value raised uncertainty for researchers to identify significant research potentials, and challenged industries to identify integrated production system potentials towards improving agronomic gain [49, 50, 43, 51]. The extracted material-focused KPIs and conceptualised processes are designed to enable fast analysis with metrics that are clearly grounded, conventionally measured, easy to obtain, and most critical to generate economic gain [52].

The developed conceptual framework and associated theory assumes minimal and soft requirements regulated by the specified process based on in- and outputs which is stark contrast to earlier analyses [50], Instead of enforcing hard constraints for specific optimisation processes, it is assumed that practical challenges can be regularised and must not be reflected in the abstraction to prevent unnecessary complexity through technicalities. Nevertheless, the system's compatibility, systems' absence of interdependence besides the regulated inputs and outputs, and the system's ability to work in the environment are required. These simple abstractions are motivated to enable augmenting managers' decision-making for process optimisation by lowering entry hurdles by abstracting technological processes to value critical KPIs [53]. Accordingly, the current framework allows pragmatic analyses of expected agronomic gain based on key performance indicators. This ability is especially useful for further analysing augmentation and automation potential in process structures agronomically. While the contribution focuses on analysing economic incentives (i.e., agronomic gain) as the key drivers of technology adaption [14, 21] on the micro-economic scale, the chosen perspective of closing the yield gap between the current yield and theoretically possible yield is the authoritative macro-economic strategy for ensuring food safety [43].

Future work Future work could extend the technological scope of the literature survey by including more sources and complimenting insights with agronomically relevant biological process' KPIs. The synthesis of biologically motivated key performance indicators are integral to effective management of strawberry crops. Additionally, empirical validation can confirm and refute parts of the synthesis to further guide technological development in current strawberry agronomy environments. Nevertheless, the provided value stream mapping is a important milestone for guiding economic research.

Especially, given the perspective of future resource shortages in the land, water, and fertilisation associated with climate change, the currently developed theory of agronomic gain should be extended to be valid under more critical resource constraints that are expected in the future [54]. While the current focus of evaluating the agronomic gain is, among other things, designed to enable assessing the agronomic gain when comparing human with autonomous production, human resources are only one of the critical resources that affect our ability to provide food safety [55]. Future research should extend the theory to allow evaluation of agronomic gain under the assumption of other critical resources shortages such as water, fertiliser, and land [43, 55, 54]. Furthermore, the developed grounded theory only scopes the farm's agronomic gain. Further research should investigate how agronomic gain propagates along the supply chain to ensure produced food reaches customers.

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