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TOPICAL REVIEW

Soft robotics for farm to fork: applications in agriculture & farming

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Abstract

Agricultural tasks and environments range from harsh field conditions with semi-structured produce or animals, through to post-processing tasks in food-processing environments. From farm to fork, the development and application of soft robotics offers a plethora of potential uses. Robust yet compliant interactions between farm produce and machines will enable new capabilities and optimize existing processes. There is also an opportunity to explore how modeling tools used in soft robotics can be applied to improve our representation and understanding of the soft and compliant structures common in agriculture. In this review, we seek to highlight the potential for soft robotics technologies within the food system, and also the unique challenges that must be addressed when developing soft robotics systems for this problem domain. We conclude with an outlook on potential directions for meaningful and sustainable impact, and also how our outlook on both soft robotics and agriculture must evolve in order to achieve the required paradigm shift.

1. Introduction

Agriculture and farming are complex and multi-faceted industries, which have many different activities focused on generating nutritious food in an efficient manner. The agri-food industry has a significant impact on the global economy [1], public health [2, 3] and the environment [4, 5]. However, it also contributes significantly to global greenhouse gas production, reduces biodiversity, and more. There is a critical need for agriculture to become more efficient and sustainable from economic, environmental and social perspectives [6, 7], whilst also providing enough nutritious food for the growing population.

Historically, agriculture has been an industry that can respond to change through technological innovation. This includes mechanization post World War I, the green revolution which led to the adoption of chemical pesticides, fertilizers and high-yielding varieties, and, most recently, digitalization [8]. Digitization encompasses the adoption of robotics and automation technologies, large-scale data capture, intelligent planning and modeling. Here, robotics is already showing significant impact through data-capture, harvesting and more, yet technologies deployed to the field most often reflect traditional, rigid robotic systems [9]. Soft robotics, an increasingly mature research field [10, 11], has the potential to provide new methodologies and technologies for agricultural robotics whilst also providing means of modeling and understanding components in agriculture that show many similarities to soft robotic systems.

The use of soft robotics has the potential to contribute to agriculture in two ways, as illustrated in figure 1. The first contribution is through the application of soft robotic technologies. Here, soft robotic technologies include sensors, actuators, and compliant structures which enable the development of robots that exploit the inherent softness in their bodies for increasingly complex interactions with the environment [12]. These technologies, combined with advancements in soft robotics modeling and

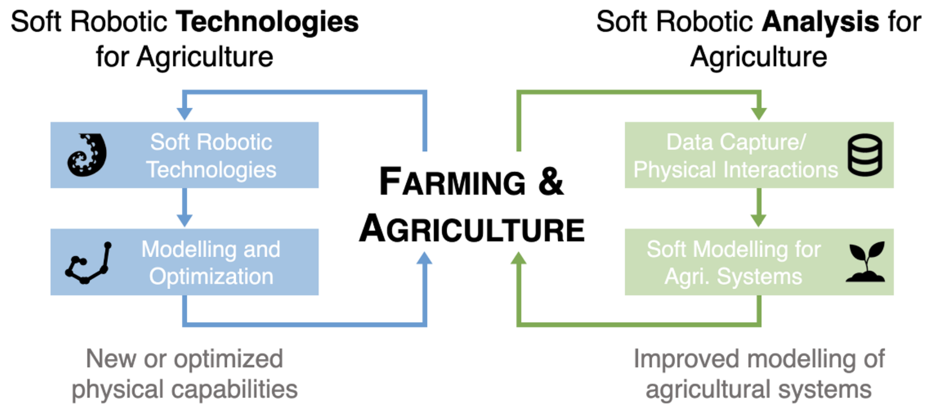

Figure 1. The role of soft robotics in agriculture. To both provide physical capabilities but also improve modeling and representation of agricultural systems.

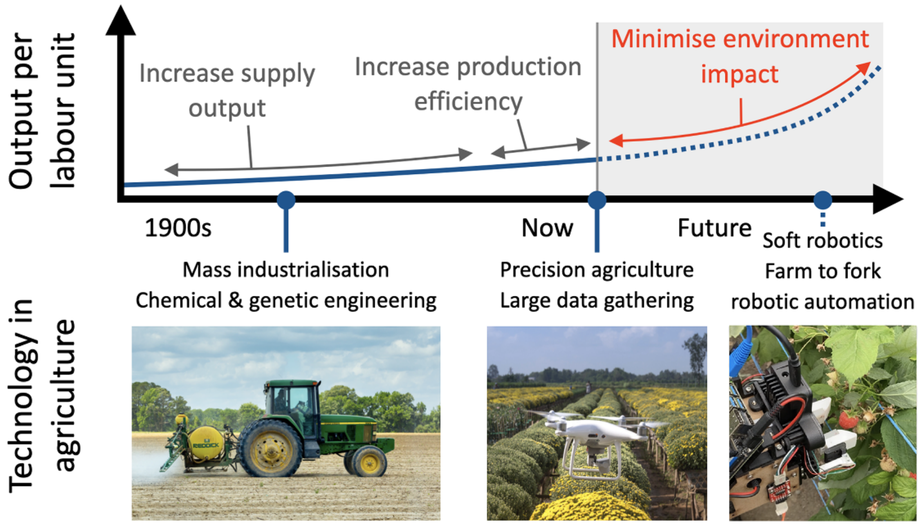

Figure 2. A time line of agricultural robotics and the potential role of soft robotics (rightmost picture from [13]) Mark Stebnicki / Pexels.com. Quang Nguyen Vinh / Pexels.com. Reproduced from [13]. CC BY 4.0.

optimization methods, can lead to more capable robots that can aid productivity, remove the need for humans to perform labor-intensive tasks, and contribute to making agriculture more sustainable. The second contribution is through the use of soft modeling techniques to analyze existing data of agricultural systems. Due to the inherent similarities between soft robots and agricultural systems, many modeling techniques developed for soft robots can be directly applied to analyze agriculture. For example, the shape of a continuum robot arm and the stem of a plant can have a close resemblance, allowing for modeling techniques to bridge the gap efficiently.

This dual relationship means we can think of soft robots and agricultural systems as coupled research areas, with many of the challenges we see in modeling and representation of soft robotics systems also applying to agriculture. Furthermore, as soft robotic technologies and their role in agriculture mature, this dual contribution can improve one another: soft robotic technologies can assist in better data capture and the captured data to further improve soft robotics technologies. Considering the timeline of agricultural mechanization and technological advances (figure 2), and the impact these have had on agriculture, we propose that soft robotics can have a significant role in increasing productivity and minimizing the environmental impact of agriculture in the coming years.

In this review, we detail the current and future role of soft robotics technologies and modeling in agriculture. We first present state-of-the-art soft robotic technologies and modeling methods and the role they play in arable agriculture and horticulture from sowing through to post-harvest (specifically in the context of arable farming, section 2). To structure this review we consider each stage of the farm-to-fork pipeline and detail the requirements and needs for each specific step. We then follow with technologies or modeling methods that could contribute to achieving such requirements and finally, we report soft robotics solutions that are currently in use or that are directed toward the specific stage. Although there is a scarcity of ongoing work in the area of soft robotics for livestock management and fisheries, it is briefly reported in section 4 as a future application area. The review concludes with a discussion on the future of soft robotics in agriculture, considering new technology advances required and the impact they could make. We widen the discussion to the wider landscape of soft robotics in agriculture, presenting key steps for developing methodologies for field research and the wider ethical, social, and political context.

2. Soft robotics technologies for arable agriculture

Soft robotics technologies show compliance, sensing and actuation capabilities that can enable many of the complex interactions required for agriculture applications. Agriculture has many different tasks that range in size, form, and objective. However, there are some commonalities: the unstructured and variable nature of the environment, the potential for compliant or delicate objects, and the complex coupling between the task and the environment [14, 15]. These task characteristics make the capabilities of soft robotic technologies particularly relevant. In the following section, we break down agricultural processes from seed to fork (figure 3), and review key requirements, existing capabilities of soft robotic technologies, and future potential. We primarily focus on the role of soft robotics through to the post-harvesting stage. Whilst existing work has identified the opportunities for soft robotics beyond this in food manufacturing and storage [16, 17], the environment is often more static and the coupling between soft robotics and the task is lower.

2.1. Soil preparation, seeding & cultivation

Requirements: key to successful crop growth is soil preparation. Typically this involves plowing to loosen the soil and to enable improved aeration and penetration for plant root systems. Leveling and the application of manure are possible additional steps to create soil that has the best possible nutrients, conditions, and soil mechanics. Following this, seeds, or, plant plugs must be added to the soil. The soil preparation can have a significant impact on the success of crop efficiency [18]. Many of these tasks (e.g. plowing, seeding, planting) are currently performed by large tractors or equipment, this can have negative side effects such as soil compression [19].

Potential applications: soft robotic actuator technologies can be used in various morphologies to create soft robots that can locomote [20] (figure 4). These robots have advantageous properties for agriculture including being lightweight, efficient, and also miniature [21]. Some untethered soft robots have shown the capabilities to exploit their morphology to overcome obstacles [22] which could allow them to explore uncertain agricultural terrains. In addition, there are a number of bio-inspired or biomimetic robots inspired by earthworms, which could be deployed in field environments to assist with soil preparation, breaking down, and aerating the soil. This includes soft robots that exploit anisotropic forces for digging in soil [23] and soft robots with a 3D-printed artificial hydrostatic skeleton that can locomote within soil [24]. The development of biodegradable materials or soft robot structures [25], could be used to assist with soil improvements. By creating swarms of soft robots that can explore and sense soil conditions, they could release nutrients at targeted locations in the environment through degradation.

Current solutions: in many of these cases the soft robotic technologies remain in the lab testing phase although their development may be motivated by potential agricultural applications. Further work is required to adapt and optimize the technologies for sustained agricultural deployment.

2.2. Weeding, crop care & monitoring

Requirements: throughout the life span of crops, there are many physical interactions that are required for healthy growth and progression, and also for monitoring and assessment. Such tasks include weeding, side shoot removal, pest removal, leaf removal, pollination, and in-field monitoring. These are highly manual and often unpleasant for human workers. Although a number of these tasks can be simplified through the use of pesticides or herbicides, these are a 'blunt instrument', are costly, and can lead to significant ecological damage. By developing robots that could contribute to these tasks, they could assist in improving the yield of plants and could also reduce the reliance on pesticides.

Potential applications: soft robotic systems can show a similar impedance and compliance to plants, which can allow soft structures to interact with plants without damage. Whilst there are many soft robotic systems which are *inspired by* plants to enable the growth of robotic systems [26, 27], there is also a number that also utilizes bio-inspiration to create structures that can support plant structures. This includes structures that show vine-like curving and wrapping around plants to provide physical support. In addition, continuum robots can offer the ability to perform plant care, for example in agroforestry scenarios [28].

Current solutions: looking forward, the ability to generate soft robots that have symbiotic interactions with plants could aid and improve plant growth [29]. Flying robots mounted with soft structures have been proposed to assist with the pollination of flowers [30]. Non-destructive quality

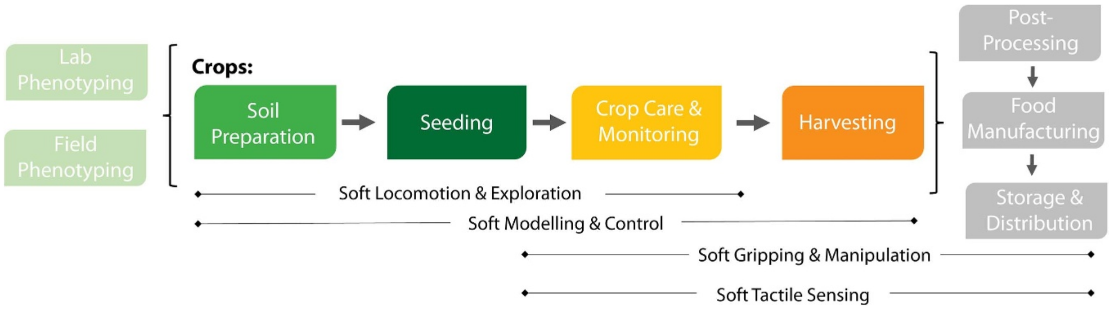

Figure 3. Summary of the key processes in arable farming, and the role of soft robotic technologies to be deployed along this process timeline for the various processes.

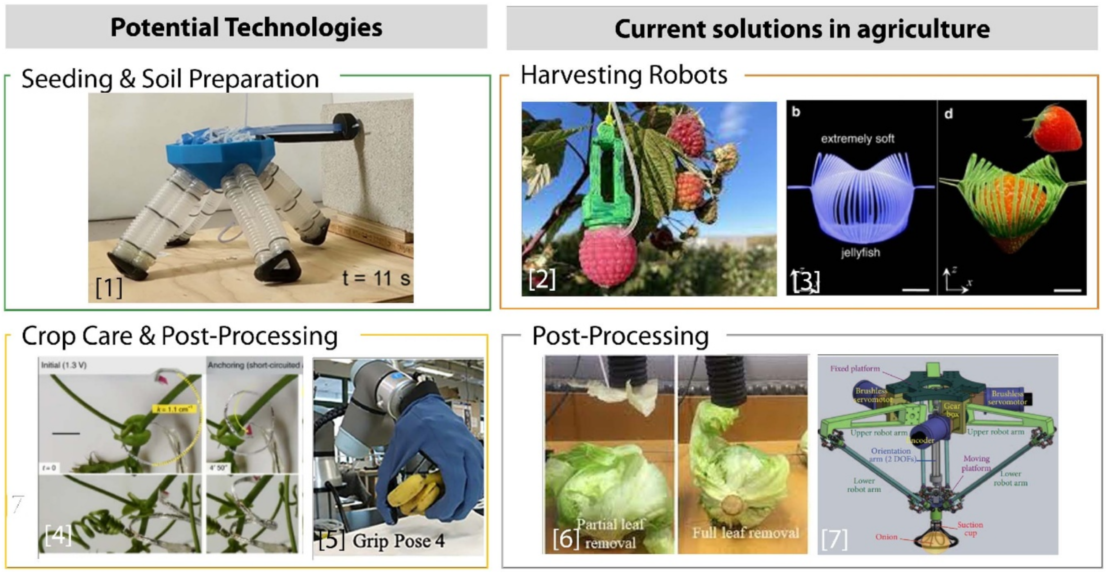

Figure 4. Examples of soft robotic technologies which have applications for Agricultural Research. (1) Un-tethered robots for locomotion. From [22]. Reprinted with permission from AAAS. (2) Physical simulators for raspberry harvesting. Reproduced from [13]. CC BY 4.0. (3) Soft gripper for handling fruit of animals. Reproduced from [54]. CC BY 4.0. (4) Plant-inspired robots. Reproduced from [55]. CC BY 4.0. (5) Pneumatic hand for food manipulation. Reproduced from [56]. CC BY 4.0. (6) Removal of ice-berg lettuce leaves. © [2018] IEEE. Reprinted, with permission, from [50]. (7) Soft suction tip for onion handling. Reproduced from [52]. CC BY 4.0.

monitoring through gripping and tactile sensors for ripeness assessment has also been reported in the literature [31, 32]. Another method equips robotic grippers with electrodes to measure intrinsic qualities of fruits such as acidity, sugar content, and even weight through electric impedance tomography (EIT) technologies [33]. Notable examples of crop care and post-processing robots are given in figure 4.

2.3. Harvesting

Requirements: although a significant number of crops are harvested using automated machinery, crops that are delicate, have complex structures, or grow in hard-to-reach structures currently escape automation. This includes crops such as delicate salads, ground-based structures such as broccoli, and delicate fruit and vegetables including soft fruits, stone fruits, and some tree fruits. Currently, many of these crops require workers to manually harvest them. Although humans are extremely adept at these tasks and offer high cycle times as well as the ability to detect and determine when crops are ripe, there are challenges in the sustainability of this approach [34].

Potential applications: harvesting is a well-reviewed area of soft robotics in agriculture [35–37], and although it is the most common arable farming task to feature in soft robotics research, prominent reviews, such as [35], have determined that there is a lack of soft actuators designed for picking fruit and vegetables within soft robotics literature. Advances in soft robotic actuators that show robustness have particular interest. Tactile sensors that show similar robustness through approaches such as self-healing [38] or damage detection [39] could also assist in improving the deployability of soft robotic systems.

Current solutions: grippers designed for the food handling/packaging industry, such as [40] and [41], show potential in the delicate grasping of fruits and vegetables. However, the precise motion and forces required for harvest in unstructured environments require a greater level of complexity. Recently some progress has been made beyond publications that only highlight agriculture as a potential use-case for soft end-effector designs, towards highly specialized soft grippers made for harvesting a specific fruit or vegetables, such as plums [42], tomatoes [43] and apples [44].

In addition to end-effectors developed for specific crops, some consideration has also been given to multi-purpose soft grippers such as [45] and [46], the latter being re-sizable depending on the targeted fruit or vegetable. In the context of raspberry harvesting, there has also been work on developing soft robotic simulators to train robots for harvesting [47], to enable rapid deployment to the field for such delicate crops [13]. Three diverse examples of harvesting solutions spanning from raspberries to peppers are summarized in figure 4.

2.4. Post-harvest tasks

Requirements: after harvest, there are typically a number of tasks that must be performed to prepare the produce for storage or the next stage of the food chain. Tasks include trimming or leaf removal, classification of produce into different classes or groups, and also separating or combining produce for packaging. Typically, these tasks require highly dexterous manipulation (e.g. for leaf removal or trimming), and reliance on both visual and tactile information.

Potential applications: post-harvest tasks are typically manual and rely on human workers. Robotic manipulation technologies could assist in this area, however, the dexterity required is very high. Developments of bio-inspired hands which can show robust in-hand manipulation [48], and manipulators that combine different modalities of actuation could assist [49]. However, the environment, variability in the task and the complexity of the tasks means that many such tasks remain out of reach of current technologies.

Current solutions: post-processing presents a challenge for soft actuation as compliance is needed for soft and delicate interactions but sufficient force is also required to achieve other actions. Examples of soft robots that have been used in this area include soft suction robots for the post-harvest removal of lettuce leaves [50], for handling delicate produce [40, 41] as well as re-configurable soft grippers [51] and robots with integrated soft suction cups for the handling of onions and artichokes [52] (figure 4).

2.5. Food handling

Requirements: many tasks require dexterous manipulation to allow for handling of soft or variable form food items. There is also a food security challenge, where the robot systems must be cleanable or anti-bacterial to allow for safe handling of food items.

Potential applications: handling of delicate produce is a well-developed application of soft robotics in the food industry with commercial solutions, such as the pneumatic mGrip^{TM} [53] used in food processing lines. For food handling, somewhat driven by the COVID-19 period, there has been considerable work in soft robotic manipulators that can be used for food handling, for plating, or packaging in factory environments, however, on-farm handling tasks remain with less structured environments.

Current solutions: many of these tasks could leverage wider developments in soft manipulation and sensing, however, there are some additional requirements in terms of speed, repeatability and robustness to variability in environment that are required for these post-harvest tasks. Many of these interactions are driven by consumer requirements (e.g. trimming, or leaf removal), opposed to being truly required. As consumers become more aware of sustainability issues, some of the demand for these tasks may also be reduced.

2.6. Remaining challenges

From this section of the review, a number of observations can be made about the state of soft robotics technologies in agriculture. Firstly, for most processes soft robotic technologies provide future-looking applications opposed to immediately deployable solutions. Harvesting is the one area where there are a number of current solutions. However, despite these advances, in many cases, these remain as case studies or research applications as opposed to showing long-term deployment and large-scale field tests. To enable the successful deployment of Soft Robots in agricultural environments we can identify a number of remaining challenges that must be addressed:

- **Scaleable fabrication for soft robots.** To enable wide spread adoption far more scaleable fabrication is required which moves away from molding and casting yet still has the required material properties.
- **Robust and 'life-long' soft sensors.** For interactions with agricultural environments soft sensors are required, however, these must last the life-span of the soft robot.
- **Sustainable materials and biodegradability.** The materials from which soft robots are made must be reuse-able or recyclable, or offer biodegradability such that the environmental load is reduced.
- **Variable stiffness mechanisms.** Many tasks require online changeable stiffness mechanisms such that compliance and high force can be achieved.
- **On board-energy storage.** For the long term, robust operations having robots that can source or

find energy from the environment would be a key enabling technology.

- **Co-design with users.** Many solutions can reveal hidden possibilities or drawbacks by including users' experience, while new solutions can be conceived.
- **On board-energy storage.** For robust and reliable conclusions, soft robots have to be tested extensively in the field, after initial laboratory validation.

3. Soft robotic modeling for agriculture

Soft robotic tools for modeling, design, optimization, and control of robotics systems can be readily applied to robotic technologies within agronomy. In particular, a great number of approaches have been presented for the modeling of soft grippers [57], and their generality allows for use in applications agriculture and food production applications [35]. However, from a research point of view, the modeling of the agricultural system components themselves, rather than the robots, appears as a more promising and interesting perspective. Soft robotics literature is brimming with bio-inspired and bio-mimicking solutions, including the replication of plants. Accordingly, the tools that have been originally presented to describe such robots' behaviors appear naturally suitable for the modeling of the biological systems that inspired them. These tools should be extended to efficiently consider some aspects that are often neglected or not critical when modeling soft robots but that are fundamental to understanding biological systems.

Following the 'farm to the fork' path, we can identify different scales of useful modeling techniques, which are discussed in the following sections. Soft robotics modeling approaches can be applied for the description of the kinematics, statics, and dynamics of deformable structures encountered in agriculture, especially in botanical systems (roots, trunks, branches), to predict their growth, interaction, and their reaction to general external stimuli. At the same time, the approaches can provide insight into the systems' phenotype, or they can be employed for control, to support the decision-making process, and, finally, for the optimization of the employed robots. To conclude, we can identify two main motivations for the application of soft robotics approaches in agriculture: modeling for scientific purposes (how and why the process happens and what are the functional relations between the variables) and for decision or policy support.

3.1. Modeling soft structures for agriculture

Representing the state and configuration of animals and plants is a complex task. This requires not only modeling of the kinematics or morphology but also modeling at the biological or chemical level. Soft robotics and the expertise of the soft robotics community is best suited to modeling or capturing the morphological and structural properties of agricultural systems, thus we have tools for capturing and representing this aspect of biological systems. In the field of soft robotics modeling, much inspiration comes from continuum mechanics and computer graphics. Reviewing the literature from these disciplines, we can identify the most critical properties to measure or capture and that should be considered for the modeling of soft agricultural forms. Figure 5 summarizes some of the modeling tools that are mentioned in the following. These are capable of capturing the compliance of the plant, and environmental and robot interactions in the study of plant statics and dynamics.

3.1.1. Plant's growth, roots, and soil interaction

The robotics community has seen a number of soft robots inspired by plant growth [26], soil penetration [58] and the behavior of plants. Plant growth modeling is a key and growing topic within agriculture and environmental sciences disciplines, and can be approached in an interdisciplinary way, leveraging domains from mathematics to biology and computer graphics. In general, the study of plant growth allows the prediction of yield and quality of the products but also helps the design of plant systems [59]. Currently, the vast majority of the modeling tools for plant growth are data-driven, i.e. they rely on fitting some functions on large sets of empirical data. Clearly, these approaches are extremely specific, as they are calibrated on a particular species, and they also require an extensive and time-consuming data collection process. While the modeling of the response, or tropism, of plants of environmental factors (light, temperature, humidity) appears challenging, soft robotics tools can offer insight into the description of the geometrical development over time at the whole-plant level. Plant growth can be seen as the combination of two main components: a growth direction and a growth rate. This has similarities to some soft robotics modeling approaches, where the deformed backbone of the soft body is represented as a curve growing along a direction field from the base to its tip, with a specific magnitude rate [60]. Another class of soft robotic systems that are characterized by a variable domain is made by concentric tube robots (CTRs). Recently, the growing and shrinking of the variable domain were included in the equations of motion of CTR in [61] and, more in general, for soft sliding rods in [62].

One other important aspect is the modeling of root systems geometry, which reflects the capacity of the plant to take up water and nutrients and, hence, its growth. Once again, while the effect of environmental aspects such as humidity and temperature are not considered in standard soft robotics models, such tools can offer an insight into the geometry of

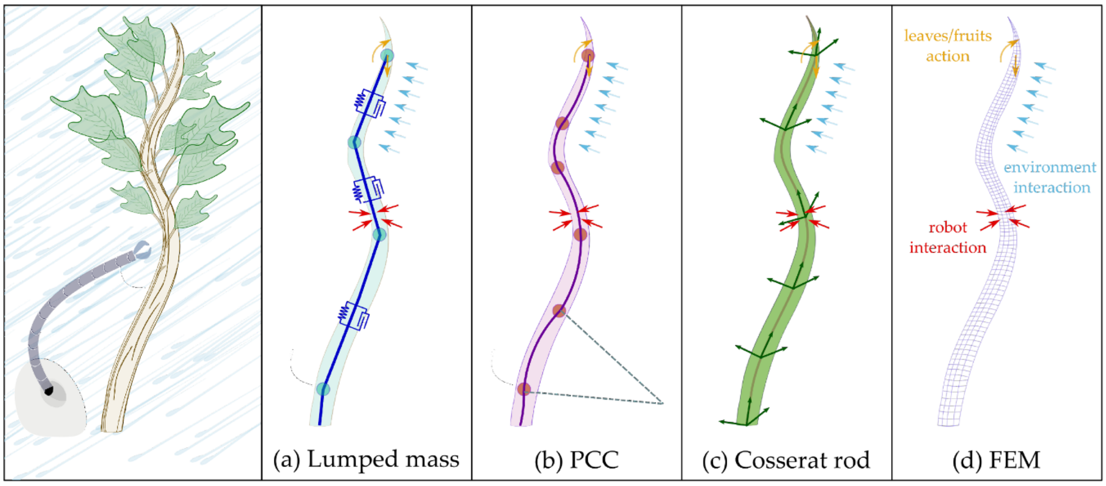

Figure 5. Examples of the application of traditional soft robotics modeling techniques for the study of plant statics and dynamics: (a) Lumped mass models; (b) piecewise constant curvature models; (c) Cosserat rod approaches (d) finite element methods.

the system, considering, in particular, their growth within cluttered environments [63].

3.1.2. Kinematics, statics, and dynamics

The modeling of the kinematics [64, 65], statics, and dynamic [66, 67] of botanical systems is crucial to understanding their evolution and behavior under specific loads such as wind or fruit weight. Trunks, branches, and roots are all deformable and slender bodies characterized by one direction (the length) prevalent with respect to the other two (the cross-section), and, from a mechanical perspective, they can be described as beams. This is also the assumption that lays at the base of the vast majority of soft robotics modeling tools [68], such as those based on Cosserat rod theory, where the soft body is represented by a curve (the backbone) and a continuous stack of local reference frames (directors) [62, 69–71]. The main benefit of these approaches is that, while being based on a 1D representation of the deformable body, they can efficiently model torsion, stretching, and shears, which appear as fundamental components for modeling botanical systems. Within this scenario, other popular approaches, such as the piecewise constant curvature (PCC) [72–75], where the soft body is represented as a finite set of arcs, or discrete methods, such as lumped-mass models [76], do not appear as the best solution for this application field's requirements. It should also be noted that, while on one side, the model should be accurate, the computational costs should be reduced, especially for online processes, and the proper compromise between *realism* and *efficiency* should be pursued. For this reason, finite element methods (FEM) [77, 78], while being extremely accurate and capable of efficiently modeling a vast number of problems (including contact, friction, adhesion, and impact), might be redundant for such applications as there are simpler, less computationally intensive, ad-hoc tools available.

While the action of fluids is extensively considered in soft robotics (for example in underwater applications), other forms of external forces are often neglected. Self-contact, adhesion, and friction are all fundamental aspects to accurately model the interactions between the biological components and the environment. Currently, the theoretical models that account for these aspects are quite rare, and they are mostly part of the FEM family; thus, some efforts should be taken in this direction.

Moving to internal constraints and forces, it is possible to notice an interesting analogy between natural botanical structures and internally actuated soft robots. Plants are composed of fibers, which, in a strictly botanical definition, are elongated, thick-walled cells providing mechanical support and form to the plant. The mechanical properties of the fibers (density, Young's and shear moduli, tensile strength) and their positioning dictate some of the most important plant characteristics, such as their stiffness. In soft robots, this role is often taken by the internal actuation mechanism, such as tendons. Similarly to fibers, the tendon properties and routing inside the soft body result in different deformed shapes. While the modeling of other actuation forms is still tackled on a case-by-case basis, a great number of general solutions have been presented for thread-like design, since these are currently the most established ones. Within the Cosserat rods framework, the tendons are usually represented as friction-less force transmitters, which are added among external force densities ([79, 80]) or as internal stresses, which are added to the elastic restorative ones ([62, 81]). While FEM software allow the design of new and complex actuation principles, some ad-hoc FEM approaches for tendon-driven soft robots present a constrained-based approach [82]. When the tendon path is parallel to the mid-line, a cylindrical manipulator deforms into an arc, and the piecewise constant curvature approach becomes particularly suitable (in the absence of external forces). In particular, it is possible to define a transformation between the lengths of three parallel actuating tendons and the standard arc parameters employed to represent each CC segment [75]. Finally, it should be noted that the fiber structure of plants inspired the design of the so-called fiber-reinforced soft actuators, which are a popular trend in the field of soft robotics [83]. These actuators have a soft body wrapped or embedded inside an inextensible reinforcement, which, depending on the arrangement, provides nontrivial deformation shapes. This results in soft composite multi-materials, whose modeling has been mostly explored through FEM simulations [84].

3.1.3. Instability

Instability is traditionally associated with failure and, in general, as a phenomenon that should be avoided. As previously mentioned, plants are slender structures and, as such, the critical load associated with the onset of instability phenomena can be low. When the applied loads, such as the weight of the carried fruit, exceed this critical point, buckling and snap instabilities can occur, with sudden energy release and, eventually, failure of the structure [66].

In recent years, a shifting point of view has been presented through different disciplines, including robotics, from a *buckliphobia* to a *buckliphilia* [85]. The fast energy release and the sudden change in the configuration that follow buckling and snap-through/back instabilities can be exploited to obtain peculiar behaviors that would otherwise require a form of muscular actuation [86]. This shift falls within the embodied intelligence trend, i.e. the exploitation of intrinsic properties of the material or the structure to replace other forms of actuation or sensing [15]. While embodied intelligence is a recent trend in soft robotics, there are frequent examples of plants whose movement happens without requiring any muscles [87] and which inspired a wide spectrum of engineered materials and structures, from programmable flexible metamaterials [88], to bioinspired robots for biomedical applications and soft robotics. Mechanical metamaterials are engineered structures consisting of periodically arranged building blocks, with mechanical properties governed by their geometry rather than composition [89]. In particular, a great number of mechanical metamaterials are inspired by the origami and kirigami principles, which are often encountered in nature and which inspired a great number of reconfigurable and folding soft robots [90–92].

3.1.4. Modeling for phenotyping

Phenotyping represents a crucial step in the initial selection process of breeds [93], providing a quantitative measure of external agronomic traits. Image-based phenotyping is one of the most employed techniques, allowing the 2D and 3D shape reconstruction across different spatial scales, from the whole plant to the specific considered trait. The most recent and advanced techniques for automated image-based phenotyping employ data-driven techniques trained on large sets of data. The classification, detection, and segmentation of the image components can be obtained using convolutional neural networks trained on the images. As previously discussed, the collection of this data is challenging, as it requires an intense manual observation. Mechanical modeling, on the other hand, can help in predicting the shape, static, and dynamic behaviors of the agricultural systems in response to natural forces and constraints (cluttered environment, wind, water).

3.2. Modeling for control & decision making

In this section, we now discuss how similar soft robotic modeling techniques can be used for control and optimization of soft robots employed in agriculture. In section 2, we highlighted the potential of soft robotics technologies for manipulation tasks, locomotion, arable and animal farming. All these applications require ad-hoc control strategies, whose foundation can be offered by modeling tools currently available in soft robotics. In general, the model-based controller limitations and advantages are strictly related to the one of the employed modeling framework, such as, on one side, its reliability in representing the problem and, on the other, its computational time and cost. The balance between these two worlds becomes particularly relevant when requiring online decision-making, which might be an important task within agricultural systems, for example to define the readiness of fruit for harvesting.

Model-based control of soft robots is often seen as a challenging task due to the nonlinearities of soft systems, and, for this reason, most early soft robotics control strategies relied upon machine learning algorithms. More recently, the proliferation of reduced order and finite-dimensional modeling tools paved the way for new control strategies whose ground lies in these approaches and in their mathematical structure [94]. Some PCC model-based controller are presented in [95–98]. The PCC methods indeed offer explicit analytic maps from the actuation to the task space, which are tailored to kinematic control. On the other hand, these are valid only when the CC assumption is preserved. This limitation is valid for all the control strategies that rely on the assumption that the deformed soft body resembles a specific shape [99, 100], or which are restricted to planar cases [101]. More generic approaches are then relying on FE methods, such as [102] and [78], while some data-driven controllers were presented in [103] and [104]. Finally, control strategies based on the Cosserat rod model were presented in [105] and in [106]. It should be noted that when employing an internal (strain) parametrization, the state of the system can be observed more directly with strain sensors embedded within the robot, which is particularly important for real applications. However, obtaining this information can be challenging and requires external cameras and localization systems.

3.3. Optimization of systems

Model-based optimization in soft robotics is still a rather unexplored field, but it is gathering interest. This increasing popularity is fueled by the possibility of employing efficient gradient-based optimization solvers, thanks to the differentiability of some modeling approaches. Any optimization process consists of searching a global (or local) minimum of a cost (objective) function and, accordingly, the gradient of this function should be calculated or at least approximated. Among the different available solvers, the most employed ones are the Jacobian-based methods, the direct research methods, and the nature-inspired ones, such as genetic algorithms [107]. Gradient-based methods represent a canonical choice when dealing with differentiable (cost and constraints) functions and this led to the development of ad-hoc (differentiable) approaches for optimization purposes [108, 109]. On the other hand, direct research methods do not employ the derivative of the functions, but only their values, and they appear as a promising solution for nonlinear problems, such as those encountered in soft robotics [110]. A genetic algorithm solver, coupled with a Cosserat rod model, is employed in [111] to provide a general optimization tool for multisection, trunklike soft arms. One other example of an evolutionary optimization algorithm is the one employed in [112], where FEM are used for the shape optimization of a soft leg, given a specific usage.

3.4. Remaining challenges

Despite the advances in soft robotics modeling and control methodologies, there remains a number of outstanding challenges which currently limit field deployment. These include:

- **Multi-modality simulators and models.** This is necessary to connect the modeling of mechanical properties to chemical and biological models such that plant based interactions can be more meaningfully assessed.
- **Modeling of hybrid soft-rigid robots.** Many robots used in agricultural systems leverage rigid-soft structures. modeling techniques which can predict behaviors or such structures would enable design optimization and novel controllers for such these robots.
- **Differentiable FEM simulation for contact based interactions.** Rapid, high accuracy simulations with gradient information will enable large scale optimization for tasks where there is rich contact.
- **Merging with current datasets/data collection tools.** How to exploit the vast amount of available datasets on crops with soft robotics modeling is a challenge that could improve adoption.

4. Soft robotics technologies for livestock and fisheries

Livestock and fisheries pose different challenges and requirements on soft robotics due to the different processes, environments, and needs. Although there are many similarities in the requirements of the technologies (i.e. the need to compliantly, and intelligently interact with the complex environments), there are additional challenges with regards to animal interactions. The summary of livestock and fisheries and the potential application of soft robotic technologies throughout the tasks is given in figure 6.

4.1. Safer interactions with animals

Animal farming saw very early integration of robotic technologies with milking robots for cows enabling improved yields, farm work-flow and the potential for improved animal welfare [113]. Involving soft and compliant structures in farming could enable increasingly involved interactions with animals. However, in comparison to arable farming, the development of soft robotics technologies for farming is still limited. This is due to the higher requirements for perception, and modeling when interacting with animals as they are typically not static. Secondly, the use of robots around animals is an ethically complex issue. Despite this, going forward there is potential to increase animal welfare through the use of soft robotic systems. Manipulation-based interactions are one future direction of robot-animal interactions, for example, for sheep shearing, health checks, or more. To achieve this, manipulators require the necessary compliance and force. The sensory-motor control must also be able to show safe interactions, whilst also reacting to the movement of the animals, and providing inherently safe interactions. Underwater robots have shown the ability to interact with sea life, for sampling and collection of animals. Technologies including jamming [114] and hydraulic actuation have been shown [115]. Here, there is potential for robots to assist with fisheries. Soft wearable and assistive devices have been shown to be beneficial for animal welfare and recovery [116]. Soft robotics has also been applied for processing tasks such

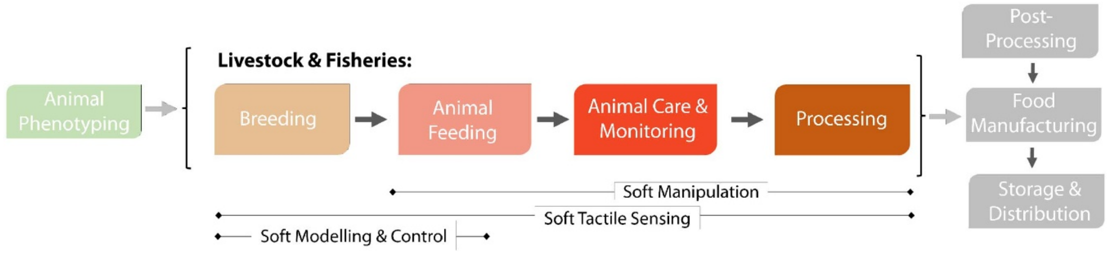

Figure 6. Summary of the key processes in livestock and fisheries, and the potential role of different soft robotic technologies along this process.

as meat handling and manipulation, for example for chicken [117].

4.2. Modeling animals

A great number of soft robots have been inspired by animals, from fishes to mammals and insects [10, 118, 119] and more, similarly, many soft robotics modeling tools have been specifically conceived to design, optimized and control these robots [120, 121]. The extension of these tools for modeling of the animals, rather than the robots, appears a natural and promising shift that should be considered. As discussed in this previous section, currently soft robot modeling tools largely focus on the kinematics and statics of an external natural environment. FEM and data-driven approaches appear as the most suitable for such complicated 3D problems, but there are also examples of approaches that also consider muscular actives [122, 123].

5. A methodology for soft robotics in agriculture

Agriculture is an intrinsically challenging domain for robots; harvesting robots have shown limited performance improvement despite thirty years of research [124], and a previous survey has reported a demoralizing commercialization success rate of *zero* for fifty robots analyzed [125]. This is a wake-up call for applied robotics in general, which falls within the huge gap between scientific efforts and the transfer of technologies into products. Although there are some natural delays and socio-economical factors into play, there are lessons to learn from existing robotic domains that show increased impact and have shown a far stronger transition from lab to field for soft robotics technologies.

To summarize the current development, we have framed many of the referenced works in our paper in a Cartesian space which seeks to capture reliability and also the impact of value added (see figure 7). Specifically, we consider two critical metrics for field robots:

- *How* often *can the robot perform a specific task, with respect to required repetitions?* This speaks to the reliability and robustness.
- *How* well *the robot perform the specific task, with respect to alternative solutions?* This corresponds to the value added by the solution.

The ideal agri-soft robot should contribute to the top-right corner of the picture (figure 7), while the bottom-left (where most of the current work sits) represents a contribution of Tier 0 level as per the scientific framework of [126].

This attempt to evaluate research as to its *task-solving* contributions does not evaluate the quality of the research or its potential to contribute to task-solving (any technology on the graph could evolve towards the top right corner with time and further developments). It does however depict the current state of soft-robotics in the agri-domain, highlighting the low readiness level, with only a few solutions belonging to the top-right corner of the graph. Given the clear potential of soft robotics for agricultural purposes, it seems timely to identify the key methodological elements that could drive the impact of soft robotics in this area. These methodological elements are now summarized.

Uptake method 1: design and development robots for field tests, and move from lab demonstrations to field tests. Lessons can be learned from underwater and space robotics communities which have pioneered methods of running and evaluating field trials, including competitions, shared facilities, and 'mock-up test-beds'. There is a need here to create facilities for testing and to coordinate improved relationships between academia and farmers to facilitate trials. To keep the entry bar for field tests as low as possible and to maximize efficiency, we require the necessary infrastructure for such trials.

Uptake method 2: move to task-oriented metrics, rather than precise performance metrics and statistics. There are fundamental questions on the scope and means of testing (e.g. amount of autonomy, exposure to the environment) to allow for meaningful comparison between work and to truly understand

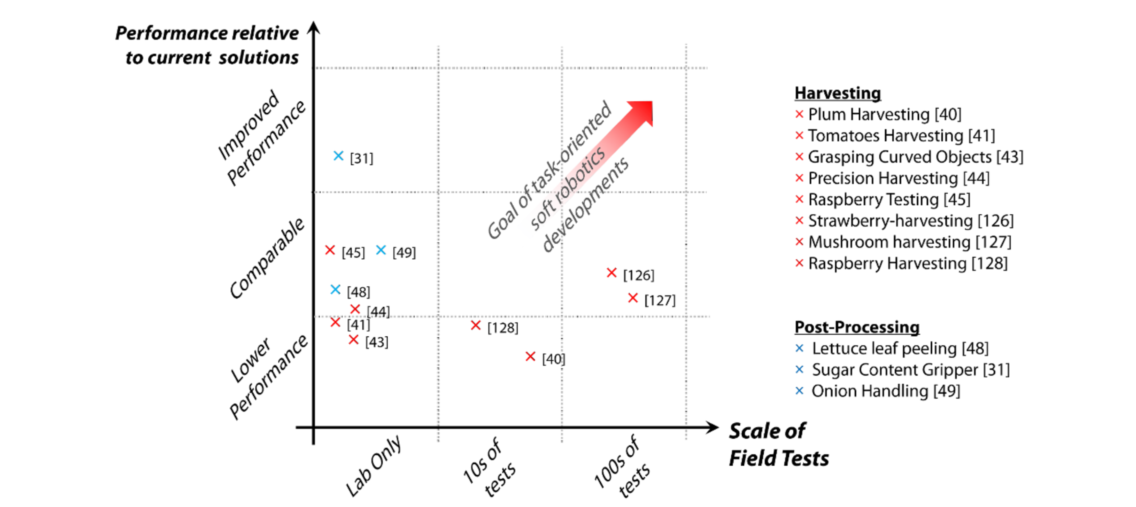

Figure 7. A Cartesian depiction reviewing the current state of performance of field soft robots by analyzing their performance relative to the current approach and also the scale of the field tests.

the contributions of task completion. Standards for describing different levels of field tests (e.g. proof-of-concept, reliability test, all-weather test) could assist.

Uptake method 3: gain end-user input and include key players in the research process to ensure that the task-focused metrics map to real work deployability. It is also important to ensure that the problems targeted by roboticists map and address real problems, and also fit with the other constraints in this environment.

Uptake method 4: enable recognition (and hence publishing) of research that pushes forward task-oriented metrics. Ensure that there are relevant publishing outlets for this work and that it receives the merit and recognition that reflects the challenges in field research. This could include developing new publishing models for field research, where the contributions of the field studies can be truly highlighted, shared and acknowledged.

5.1. Identifying impact areas for soft robotic deployment

As discussed previously, it is important to deploy soft robotics technologies in the correct application for meaningful impact. However, impact is multi-faceted, and can have both positive and negative attributes. To be able to assess the impact of soft robotic technologies and approaches have on agriculture, it is important to develop quantifiable metrics.

We divide impact into four areas: social, economic, environmental, and knowledge-based. Due to the multi-faceted nature of agriculture, many metrics could apply to a number of categories, but we present some key metrics in these categories.

5.1.1. Social metrics

Metrics which assess the social contribution or impact of new technologies on individuals and communities.

- Changing skill level of jobs. The creation of new jobs that require a new skill set or area of expertise. This could be measured as, for example, the change in the number of seasonal labor required per hectare, the change in the number of robotics engineers employed in agriculture-sector organizations, or the change in qualification requirements for jobs in agriculture.
- Worker health. The use of technologies that reduce the risk of injury or long-term conditions. This could be measured as the reduction in the number of sick or injury days from workers.
- Food security. Improved and sustained access to food, regardless of the economic or political situation. This could be measured in terms of the availability of certain produce, and the cost of key food items as a percentage of average income or cost of key items adjusted for inflation (e.g. has cost of domestic produced strawberries increased/decreased).
- Improved food quality. The nutrient quality or contributions of the food and also the wastage, i.e. does food harvested and packed by soft robotics have lower damage rates resulting in less waste at retailers and domestically?

5.1.2. Economic impact

Implementation of soft robotics approaches has a direct and indirect economic impact.

- Cost-savings. The potential for costs savings when using the new technology compared to current approaches, i.e. cost-benefit economic studies.
- Economic sustainability. The use of technology to improve the stability of the economic situation (e.g. reduce the risk of insufficient workers to harvesting crops and the resulting economic impact).

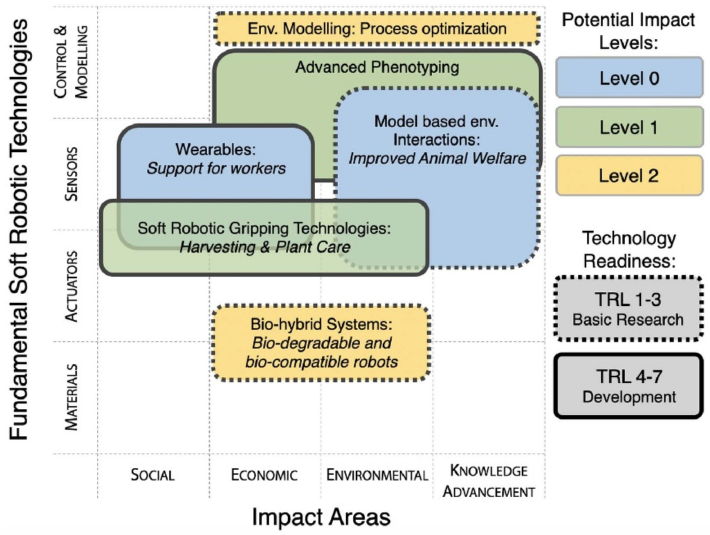

Figure 8. Opportunities created by new soft robotic technologies and their potential for impact on farms and technology readiness level (TRL).

5.1.3. Environment & sustainability impact

The implementation of soft robotics should minimize the environmental impact, maximizing sustainability goals, such as those identified by the UN [127].

- Bio-diversity. The change in the number of species present in a given environment.
- Resource usage. The reduction in resource usage including water, pesticides, and energy.
- Greenhouse gas creation. The reduction or change in the greenhouse gases that are created.

5.1.4. Knowledge advancement metrics

- Advances in robotic and engineering sciences. Driven by agricultural needs new robotic technologies could be developed which could be applied and exploited outside the domain of agriculture.
- Advances in plant sciences and agricultural sciences. The development and utilization of soft robotic technologies can further our knowledge and understanding of plant sciences and agricultural sciences.

In many cases metrics may be conflicting, for example economic (e.g. costs of the robotic system), vs. environmental impact. Thus, it is necessary to identify the trade-offs between these relative impact metrics that are suitable for the given application. The FAO has produced the sustainability assessment of food and agriculture systems (SAFA) framework [128], which provides some means of selecting the key sustainability criteria, balancing these, and choosing the appropriate metrics. No set of indicators can be definitive nor fit all contexts, but must be adjusted over time through implementation and shared learning. The SAFA tool seeks to facilitate the use of the SAFA indicators, as well as their further testing and development by food and agricultural enterprises. In striving to measure progress towards sustainable development, SAFA seeks to develop capacities.

There are a number of means of measuring impact. *Competitions* offer one means of comparing and contrasting different technologies and their impact [129]. Standardized *benchmarking* tasks also offer means of comparison. Widely used in computer vision, machine learning, and for robotic manipulation tasks, developing an agricultural-based benchmarking task that is both challenging and viewed to be impactful could enable progress to be monitored, and approaches compared.

5.2. Future opportunities for soft robots in agriculture

Soft robotics can achieve different levels of impact [126]; it can be particularly challenging to achieve impact which is beyond the soft robotic technologies demonstrations. Using the impact metrics identified we can explore the potential for soft robotic technologies and modeling to assist in these different areas. In figure 8 we introduce a grid where we summarize some of these key areas for impact on farms, the form of impact, and also the potential for impact and technology readiness. These technology areas are analyzed in terms of the current technology readiness level (TRL) as previously defined [130] and with specific reference to agriculture/horticulture [131], where we group technologies as being at a level of research, development, or commercialization. The second metric is the potential impact level, where level 0 refers to local 0 making contributions to one area of the metrics identified in section 5.1, level 1 contributing to two or more areas, and level 2 having a wide and systemic impact across all (or most) metrics.

This includes current approaches and technologies that are of a high technology readiness and such are already (or soon) to be deployed. In addition, we also have early-stage technologies that could significantly change the landscape of soft robotics and agriculture. Starting from the applications where the technologies are of a higher technology readiness:

- **Wearable technologies** could be used to support workers in the fields, providing both physical assistance to reduce injury, and also to improve performance, for example by providing haptic feedback. This could have social and economic benefits.
- **Soft robotic gripping technologies for harvesting** enabled by advances in technologies, including tactile sensing and self-healing materials. Robust harvesting technologies could be developed which have the dexterity to perform complex harvesting crops of high value crops. This could improve efficiency and reduce waste.
- **Advanced phenotyping** could be achieved by combining tactile sensing with soft modeling tools so more can be instood about the plants. This could include fruit properties (e.g. stiffness, ripeness), but also plant properties, and it could assist with optimizing growing conditions and plant varieties).

In addition, there are some technologies from a lower technology-readiness level.

- **Bio-compatible robots** could allow for more precise application of pesticides, and also for data gathering on a large scale, as swarms of robots could be deployed, collect data and then degrade, such that collection would not be required.
- **Soft robots for animal welfare.** Autonomous soft robots could roam around animals without disturbing, to allow their conditions to be monitored and optimized. By combining with modeling, this could enable early prediction of disease and optimization of conditions.
- **Co-design of environment and robot.** Utilizing the abilities to use both soft robotic techniques to model the environment and robots can we co-optimize the design of agricultural systems (e.g. phenotype/genotype/growing structure) in addition to the soft robotic technologies.

From this analysis, in figure 8 it can be seen that there are very limited examples of soft robots that are of a TRL 8-10 and that have been shown to be actively deployed in agricultural scenarios, out of the context of research project. Although we are seeing some highly successful applications of robots to agriculture, e.g. drones, weeding robots, harvesting or data collection robots, these are not typically soft.

However, we see two things. Many have 'soft elements', even if many cannot be intrinsically described as soft. This could include soft material or surfaces, or more extensive 'softness'. Thus, we must consider the role of soft robot components and system in 'hybrid' rigid-soft systems. This is highly bio-inspired, with humans and animals also showing and exploiting their rigid-soft embodiment to achieve a wide range of tasks capabilities. Secondly, they are often interacting with an agricultural environment which is soft. If we consider both the environment and the robot to be part of the 'system', we see that we are still experiencing soft interactions, and the associated feedback from the environment. Thus, there is still softness in the system and many of the approaches, methodologies and technologies from soft robotics apply.

5.3. Ethical, safety & regulatory considerations

An additional hurdle facing the deployment of soft robotics is the need to meet or exceed the ethical, safety, and regulatory considerations. These are particularly challenging due to the potential for agricultural environments to be highly hazardous, and also due to the need for food safety.

5.3.1. Ethics & consumer perception.

The relationship between food and consumers makes agriculture a charged ethical. Genetically modified crops exemplify this, with many countries still prohibiting this approach. Food is central to community, culture, and economies. For soft robotics to be successfully integrated into agriculture, ethical considerations must be considered. In addition to the ethical dimension, there is also a challenge in consumer perception. Consumers have high demands in terms of produce appearance and requirements, changing or adjusting consumer behaviors or expectations may allow for easier application of soft robotic systems, e.g. non trimmed vegetable or blemished produce. In addition, there is a need to educate consumers about the realities of robotic technologies such that they can make informed decisions regarding the use of robotics in food systems.

5.3.2. Regulation & safety.

Agriculture is tightly regulated. Agricultural equipment must meet key standards both in safety and also for food security. These requirements must be taken into account when developing soft robotic systems. For farming, there is also a need to ensure that the health and wellbeing of animals is maintained. This means robotic systems must be inherently safe. Whilst this is a key advance of soft robots over more traditional robotic methods, this must be proven or demonstrated.

To ease the incorporation of soft robotics into agriculture, this may require changes or adaptations to policy to reflect the changing technological landscape. This may, for example, include developing regulation that extends to bio-hybrid robotic systems, and the deployment of biodegradable robotic systems. In addition, the policy surrounding autonomous systems may need to adapt or change to allow for the inherent compliance of soft robotic systems to be varied.

5.4. Re-envisioning agriculture

An opportunity opened up by soft robotic technologies is to re-envision the structure and processes of agriculture. Currently, the structure of fields and the width of crops are primarily dictated by the standard widths of farm vehicles used. Crops are also grown in mono-culture because that allows for mass-scale harvest. In light of the potential of soft robotic technologies, it becomes possible to 're-design' farming environments to discover approaches that may offer improvements, be it in sustainability or other areas.

Agroforestry, a land use management system in which trees or shrubs are grown around or among crops or pastureland, is often challenging for traditional automation solutions due to the reduced structure in the environment. Soft locomotion systems that could be deployed for weeding, planting or other purposes could aid in making this possible. The development of soft actuators and the corresponding sensing and control could harvest a variety of different crops, enabling poly-culture. This is the practice of planting several kinds of crop species on the same piece of land at the same time. Choosing to adopt polyculture tries to imitate the diversity found in the natural ecosystems, offering improved environmental sustainability.

Moving away from the field, vertical farming and urban farming offer alternative approaches to growing, providing very space-efficient methods of farming. Due to the easier environment in which data can be collected in these environments, modeling techniques could be used to assist in planning planting, prediction of readiness and early stage disease detection. This could aid the feasibility and efficiency of such approaches.

6. Conclusions

Agriculture and farming are facing significant pressures and demands, with a need to increase sustainability whilst also significantly increasing output, the challenge of which is multiplied by increasingly volatile and uncertain climate conditions. Robotics has already been adopted by agriculture for precision task completion, where there can be considerable gains in efficiency and waste reduction. The compliance of soft robotics matches both the compliance in structures seen in agriculture and also the need for physical robustness in the physically unstructured landscape of agriculture. Thus, adopting soft robotic technologies can extend the task and application domain of robotics in agriculture. However, soft robotics is not the only solution, but a means of complementing other technologies, including more traditional rigid robotic systems, drones, and machine learning, all of which must come together to enable a significant change in agriculture.

Long term there is an opportunity to rethink the models of agriculture both structurally and also process-wise. Soft robotics technologies could support a move away from mono-culture to a more unstructured growing environment. In addition, the potential for robust autonomy could allow for more urban farms, placing food and agriculture at the heart of communities, decentralizing farming, and connecting growers and consumers.

Data availability statement

No new data were created or analysed in this study.

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