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Review Article

A Review of Smart Agricultural Prime Movers and Its Potential Use for Paddy and Pineapple Production in Malaysia

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Abstract: This work reviews the current state of the art for smart agricultural prime movers in Malaysia. The definition and levels of autonomy are discussed to help readers understand the context of such vehicles. It examines the use of smart agricultural prime movers in the global market. It also discusses the issues and challenges facing its implementation in Malaysia. The role of smart agricultural prime movers in realizing Malaysia's fourth industrial revolution (IR4.0) aspirations in Malaysia is explored. Finally, areas of where this technology can be implemented are proposed.

Keywords: Pineapple; Industry 4.0; Cyber-Physical System, Autonomous prime movers, Smart agriculture

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1. Introduction

The world is currently undergoing an industrial revolution. Known as Industry 4.0 or the fourth industrial revolution, it allows the personalization and customization of products (EDB, 2018). It is powered by three technological pillars; automation, connectivity and intelligence. These three pillars allow society to be interconnected with businesses and machines (Frank *et al*., 2019; Lasi *et al*., 2014).

Production of goods by machines without human intervention is possible through automation. Connectivity enables production processes to be connected to one another. Machine-to-machine and machine-to-human communication is only made possible through the internet. Machine intelligence leads to smart systems and autonomous execution of processes (EDB, 2018).

A culmination of technologies characterizes Industry 4.0. Artificial intelligence, big data analytics, augmented reality and internet of things and autonomous machines are some of the enablers of Industry 4.0 (Koppen-Seliger *et al.*, 1995). An example of such technologies is an internet search engine powered by machine learning algorithms that harnesses user data to return search results that best fits the user's profile (Killoran, 2013). Another example is a home appliance such as a light that can be switched on or off using a mobile device connected to the internet (Aldossari & Sidorova, 2018; Wang *et al.*, 2018). Smart vehicles are particularly exciting. The idea that a vehicle can have the intelligence to execute a task such as driving on a road without human intervention opens up many potential applications.

Smart vehicles have garnered a lot of attention from researchers in recent years (Abu Bakar & Veres, 2010; Kumar *et al*., 2013). In agriculture, the ability to have farm machinery or agricultural prime movers work autonomously and intelligently is very interesting as it can cut cost and increase productivity (Balafoutis *et al*., 2017; Lioutasi *et al*., 2022). Although very promising, the implementation of this technology on a commercial scale is not without its challenges. Issues regarding technology readiness, safety, affordability and reliability are still seeing lively debate (Fan *et al*., 2021; Lioutas *et al*., 2022; Zhou *et al*., 2013). In the context of the Malaysian agricultural scenario, the concept of smart agricultural prime movers is still new.

The Malaysian government realizes that it cannot afford to fall behind in its effort to modernize the agriculture sector. In the twelfth edition of the Malaysian Plan (12MP) running from the year 2021 to 2025, which is a development roadmap set out by the government every five years, it has emphasized the need to utilize IR4.0 technologies such as smart prime movers to modernize Malaysia's agriculture sector (EPU, 2021a; EPU, 2021b). Therefore, it is essential that factors regarding development of such systems, cost and viability be discussed and understood in order for relevant stakeholders to move forward with its implementation.

This work reviews the current state of the art for smart agricultural prime movers (SAPM) in Malaysia. The current scenario of Malaysia's agriculture sector is first detailed. The definition and levels of autonomy will then be discussed to help readers understand the context of such vehicles. It will examine the use of smart agricultural prime movers in western nations. It will then discuss the issues and challenges facing its implementation in Malaysia. In the final section, areas of where this technology can be implemented will be proposed.

2. Smart Agricultural Prime Movers

The agriculture sector contributed 7% or RM 107 billion to Malaysia's GDP in 2020 (MoA, 2020). The oil palm industry made up about 3.6% of that contribution, whereas the other 3.4% was due to the agrofood industry. The agriculture sector employed 1.6 million workers in 2020.

The world is forecasted to face a sharp increase in population by 2050. To add to this problem, the size of land used for agriculture is shrinking due to urbanization. Making sure that enough food is produced to cater to this population sustainably requires the agriculture sector to transform the way it does business.

Challenges faced in Malaysia echoes the situation globally. Other than shortage of land and increase in population, Malaysia is also faced with the challenges of low productivity, aging farmers and shortage of labour. Since foreign workers are the primary source of labour in Malaysia, shortage of labour was more evident during the COVID pandemic when all entry to the country was halted.

Smart agricultural prime movers (SAPM) could help in addressing the problems above. It could help in reducing labour as well as increase productivity. A sensing system onboard the vehicle could help save on inputs such as fertilizers and chemicals. However, the cost of such systems would be too expensive and unviable in the current scenario where most farmers in Malaysia own less than 1 hectare of land. Nevertheless, this technology could potentially revolutionize farming. It is therefore useful to look deeper into SAPM.

Agricultural prime movers are vehicles or machinery used in the farm that uses a motor or engine to convert one or more forms of energy (chemical, electrical, fluid pressure/flow) into mechanical force (Stone & Ball, 2004; Sanaye *et al*., 2008). Tractors are a good example of a prime mover because it is self-propelled. On the other hand, agricultural machines that are not self-propelled are called implements. An example of this is a harrow which is attached to a tractor and is driven by the power takeoff (PTO) of the tractor.

An SAPPM refers to the ability of the prime mover to carry out a task without human intervention (Bonadies *et al*., 2016). The task in question could be for a tractor to drive in a straight line or even avoid collision. A tractor is said to possess a level of intelligence if it is able to make decisions based on the situation it perceives through sensors.

Any SAPM typically consists of at least a sensor, a control unit and actuator (Gonzalez-De-Santos *et al*., 2020; Ruckelhausen *et al*., 2009). This is shown in Figure 1. A sensor is used to perceive a parameter such as geolocation, temperature or nutrient status of a crop. A control unit uses its logic to make a decision based on what the sensor perceives. A signal is then sent from the control unit to an actuator to carry out a mechanical task such as spraying of chemicals or steering a tractor.

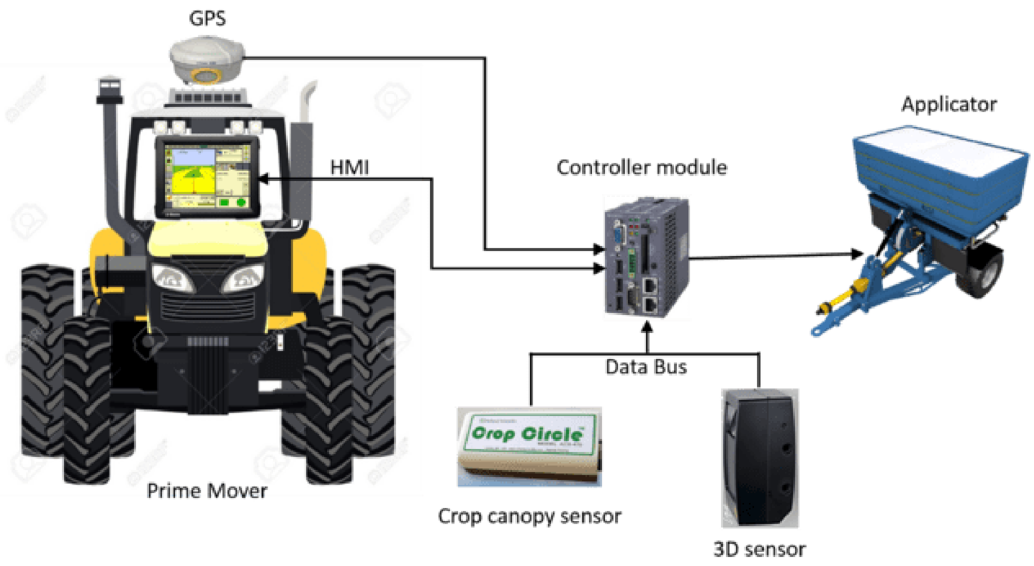

Figure 1. Components of a smart agricultural prime mover.

The term 'smart' is often used as a catch all phrase to describe the ability of a vehicle to do any automated task. In fact, smart vehicles can be categorized according to their level of intelligence. SAE International, formerly known as the Society of Automotive Engineers classifies autonomous vehicles according to six levels (Geenen, 2020; SAE International, 2021). They are shown in Table 1.

Table 1. Levels of vehicle intelligence (Source: SAE J3016)

Level	Name	Definition
0	No Automation	Human operator handles all driving and implement control
1	Driver Assistance	Human operator handles all driving and implement control. Assistance such as obstacle detection and warning,
2	Partial Automation	System takes over some of the tasks such as speed, steering, braking, and control of implements. Ability to react to surrounding is limited. Human operator needs to control some tasks and may need to take over with manual operation
3	Conditional Automation	Driving and implement control done by system, but human operator is required as fallback if something goes wrong.

Level	Name	Definition
4	High Automation	Driving and implement control done by system, respond to unforeseen conditions by putting the vehicle in a stable, stopped condition.
5	Full automation	Same as level 4, but has self-repairing capabilities to respond to unforeseen conditions.

The automation level in table 1 was originally created for on-road/passenger vehicles. In addition to automating the driving task, a smart agricultural prime mover has to potentially have another layer of intelligence in that it has to carry out field tasks with the implements attached to it such as preparing the land, doing crop maintenance or harvesting. Therefore, the definition of the automation levels in Table 1 was improved to take into account the added field tasks associated with agriculture.

3. State of the Art for Smart Agricultural Prime Movers

A lot of research has been done to develop smart agricultural prime movers. Some have worked directly on automating the vehicle (Blackmore, 2009; Gonzalez-De-Santos *et al*., 2020; Steward *et al*., 2019). Others have worked on automating the agricultural task such as fertilizer and chemical application (Abu Bakar *et al*., 2021; Holland & Schepers, 2010; Jimenez *et al*., 2020; Schepers & Holland 2011). Figure 2 shows a picture of a SAPM developed by researchers at Harper Adams university.

Figure 2. Autonomous arable crop prime mover.

3.1 Sensing System of SAPM

A crucial aspect of SAPM is its sensing system. Arguably the most important parameter to detect is the location of the SAPM. Geolocation refers to the identification of geographic location of a SAPM via a variety of data collection mechanism (Wang & Noguchi, 2019). The geolocation of vehicles using satellite navigation have been heavily researched (Jing *et al*., 2021; Li *et al*., 2021; Zhang *et al*., 2022). A global navigation satellite system GNSS can be very accurate, down to sub centimeter. However, agricultural vehicles work in muddy an undulating condition that causes it to slip significantly. The effective navigation of these vehicles has challenged researchers to come up with ways to solve this.

Another concept commonly used is the localized location of the SAPM where the location of the vehicle is in reference to its surrounding. The use of light detection and ranging (LiDAR) technology allows the vehicle to have a map of its surrounding. A SAPM can then use this map as a reference for its location and develop a navigation plan (Blatrix *et al*., 2022; Kurashiki *et al*., 2021).

Another important parameter in a smart system is vision. Machine vision enables a SAPM to detect and recognize its surrounding objects. It could also be used to navigate a path. Research such as the ones found in (Ai *et al*., 2021; Fue *et al*., 2020; Kneip *et al*., 2020) focused on the method of vision sensing. The complexity of the task dictates which vision system is suitable. For example, following a straight line on a relatively even terrain does not require a sophisticated system. A monocular camera would be sufficient. In contrast, following a curved path on an undulating terrain requires more information from the environment, such as the steepness of the terrain and angle of curvature. Here, a vision system with depth sensor such as LiDAR would be more suitable (Shi *et al*., 2015; Sari, 2022). Another factor determining an effective vision system is the algorithm processing the data.

In the last 10 years a variant of the neural network, deep learning has been the algorithm of choice for many researchers (Couliably *et al*., 2022; Ismail & Malik 2022; Zapotezny-Anderson & Lehnert, 2019;). The advantage of deep learning compared to other machine learning algorithms lies in its performance. The performance of a traditional machine learning algorithm such as support vector machines saturates after a threshold amount of data is reach. With a deep learning algorithm, the performance increase is proportionate with the increase of data (Kamilaris & Prenafeta-Boldú 2018).

All SAPM rely on at least one of these two sensors to carry out automated tasks. All Agricultural tasks such as land preparation, crop maintenance and harvesting require coordination between sensors and actuators.

3.2 SAPM for Automated Agricultural Tasks

A seeding SAPM was developed using a mobile agriculture robot swarms (MARS) architecture (Blender *et al*., 2016). The authors focused on the functionality of the central unit governing the swarm of agricultural robots for a seeding task. The so called “OptiVisor” supervised the swarm by determining the action and navigation path of each robot. The authors demonstrated the architecture on the field to show the effectiveness of the approach.

A group of researchers in Germany developed a SAPM for individual plant phenotyping in the field (Ruckelhausen *et al*., 2009). The system called “BoniRob” was based on 4-wheel hub motors and hydraulic components that made it flexible in terms of shape and navigation. The flexibility aspect is important since different crops require different planting configurations. Row spacing, plant density and plant size are some of the parameters that need to be considered when automating a task. BoniRob was able to change its height, wheel base distance and wheel base shape to adapt to different crops. Other researchers have also developed a SAMP for crop phenotyping (Alenya *et al*., 2013; Busemeyer *et al*., 2013).

An autonomous robotic system was developed to harvest pumpkins (Roshanianfard *et al.*, 2022). An end effector was attached at the front of a commercial tractor similar to the one in Figure 2. The commercial tractor was converted to have autonomous functionality by installing a navigation system and a control actuator to maneuver it. The authors concluded that although the system was able to perform its attended task, it needed improvements to increase its accuracy. Similar systems were developed for different crops such as sweet pepper and strawberry (Arad *et al*., 2020; Sa *et al*., 2016).

3.3 Commercial Systems

Although these systems were tested in an experimental setting, implementing them in a real farm environment have been more of a challenge. Only a handful of solutions have been successfully commercialized.

Companies such as Trimble Ag and Ag Leader offer a solution that allows farm tractors to achieve level 2 intelligence (AgLeader, 2022; Trimble, 2022). These solutions are shown in Figure 3. Their systems are able to control speed and navigation of a tractor. An autopilot module that consists of a global navigation satellite system (GNSS), motorized steering wheel and a controller has to be fitted on the tractor so that the system can steer the tractor and change its speed. The operator has to initially set way points by driving the tractor through its intended course. The autopilot module can then be activated to control the tractor as well its implement for subsequent pass through the course. However, an operator has to be present in the cockpit as a safety measure in case of a system failure.

a. Trimble Ag FMX1000 b. Ag Leader Compass

Figure 3. Auto pilot solution from Trimble AG and Ag Leader. The system consists of an operator interface, main controller, and GNSS antenna.

These systems lack an obstacle avoidance sensor. Object detection and avoidance is achieved by marking an area on the user interface as an obstacle. This is done manually by the operator during the first pass. The tractor then avoids the area in subsequent pass by navigating the tractor around the obstacle.

A Chinese company FJ Dynamics has introduced a fleet of level 2 smart agricultural prime movers for seed sowing and fertilizer application (FJDynamics, 2022). This is shown in Figure 4. An operator has to first create a boundary by driving the prime mover around its intended work area. The system then automatically calculates the number of straight-line paths the tractor will follow within the boundary. Like Trimble Ag and Ag Leader, the system by FJ Dynamics requires an operator to be in the vehicle cockpit to assume control when needed. Unlike its competitors however, FJ Dynamics does not have the capability to allow the operator to set any arbitrary curved paths.

The smart agricultural prime mover systems introduced by the companies mentioned above are part of a larger smart agriculture solution provided by them. Each organization provides a software agriculture platform that gathers data from sensors mounted on the prime mover and connected to the internet. The data is used to analyze things such as vehicle performance, and fleet distribution.

Figure 4. FJ Dynamics F3000 series autonomous tractor.

A Japanese company YANMAR have been actively researching smart agricultural vehicles (Yokoyama, 2019). They have developed a robot tractor which can be categorized as having level 4 (high automation) intelligence. These robot tractors can be utilized in a variety of scenarios. One example given by the company is in a cooperative task setting. An operator sitting in one tractor has simultaneous control of an unmanned robot tractor. The operator is able to command the robot tractor to follow the manned tractor using an offset path. By doing this, work efficiency is doubled because the agricultural task can be done by two cooperating tractors. However, to the best of the author's knowledge, the level 4 robot tractor is not yet available commercially. Figure 5 shows the tractor discussed.

All manufacturers mentioned previously have only been able to commercialize level 2 smart agricultural prime movers. This could be due to a number of factors. One of the most important factors is the inability to adhere to safety standards and regulations (Bartolini *et al*., 2017). Any smart system must be able to guarantee with a certain level of certainty a predetermined behaviour in case of system failure. Since agricultural vehicles are generally big in their size, any unpredictable movements could potentially be lethal for humans. Ensuring predictable behaviour consistently is still a challenge.

Figure 5. Yanmar YT5113A robot tractor.

Another factor hindering the progress of smart systems has to do with cost. Smart systems usually come with expensive hardware and software components. At the moment, this technology would only be viable for large scale farms as the capital expenditure would be very high. For small scale farmers, a suitable business model has to be found in order for them to take advantage of the technology.

4. Implementing SAPM for Selected Crops in Malaysia

The Malaysian government encourages all industries in Malaysia to participate in developing and implementing Industry 4.0 technologies. It has laid down policies and introduced many initiatives to spur the modernization of all main industries contributing the Malaysian economy. The National Agrofood Policy 2.0 (NAP2.0) identified key agricultural sectors that would benefit from the fourth industrial revolution (EPU, 2021a; MAFI, 2021).

An issue to consider when implementing SAPM is the terrain for which it was designed for. For SAPM that has a small wheel base, terrains that are relatively rough such as that those found in the rice and pineapple industry would be unsuitable. SAPM such as the ones introduced by Yanmar and FJ Dynamic would be more suitable as they were designed to move on a variety of agricultural terrains. Other than terrain, economic viability should also be considered.

Smart agricultural prime movers would be viable for food crops that have a sizeable industry because using SAPM on small areas would not be viable economically (Abdullah Al-Amin *et al*., 2022). Paddy and pineapple production are two such industries that are large enough in terms of monetary value and land size. The land area planted with rice was more than 600,000 hectares in 2020. For the pineapple, it was 14,000 hectares in 2020 (MoA, 2020). These two industries are faced with issues such as labour, high cost of production, and low productivity. Smart agricultural vehicles can help in tackling these issues.

The whole production value chain of these two industries is very labour intensive. From land preparation all the way to post harvest handling, smart agricultural prime movers can be implemented to raise productivity and lower the dependency on skilled labour.

4.1 SAPM for Paddy Production

In the following, the potential for smart agricultural prime movers in rice production will be discussed.

In the land preparation stage of rice production, the land has to be tilled at least twice and smoothed once before seeding. This is done every season to ensure proper conditions for rice plants to grow and take up nutrient from the soil (Abu Bakar *et al*., 2019). This repetitive task can be done by smart tractors with a harrow as implement. The path could be planned using a mapping software before the task. A smart tractor would then follow the path using a GNSS enabled system. The implement would be lowered or raised based on its location. This could also be done for land levelling purposes. A smart tractor can be equipped with a land forming system with a scraper as the implement. The path is able to be set as previously mentioned. Figure 6 shows a SAPM developed by the Malaysian Agricultural Research and Development Institute (MARDI). This was done by retrofitting a 70 horse power tractor to have driverless navigation and automated task capabilities.

Figure 6. A retrofitted SAPM for land preparation developed by MARDI.

In the seed and fertilizer application stage, a variable rate application technique was developed by a group of researchers at Malaysian Agricultural Research and Development Institute (MARDI). Using this technique, seed and fertilizer are applied specific to an area based on different parameters collected by multiple sensors; the land leveling index for seed application and nitrogen content of the rice plants for fertilizer application (Rahim *et al*., 2021). A treatment map is generated and uploaded on to an on-board computer of a high clearance tractor equipped with a GNSS and a variable rate applicator. This task could be taken over by a smart prime mover. Since a GNSS system is already used for geolocation, an autosteering module added to it would give autonomous navigation capability to the system. Figure 7 shows a SAPM that was developed by MARDI for this purpose. A high clearance tractor was fitted with a satellite navigation system as well as a movement control system. A camera system was used to detect and avoid obstacles in the pathway of the SAPM. The developed SAPM could be used for seeding as well as a fertilizer application with an additional crop canopy sensor.

In the crop care stage, scouting for pest and diseases is often a tedious task. It involves walking in the field to look for symptoms which are often overlooked by an under trained personnel. A smart autonomous vehicle such as a field robot equipped with a high resolution camera can be used to scout the field on a determined schedule set by the farm manager (Mishra *et al*., 2020). The system could be trained to look for a particular symptom and report it in a farm management platform (Che'Ya *et al*., 2013).

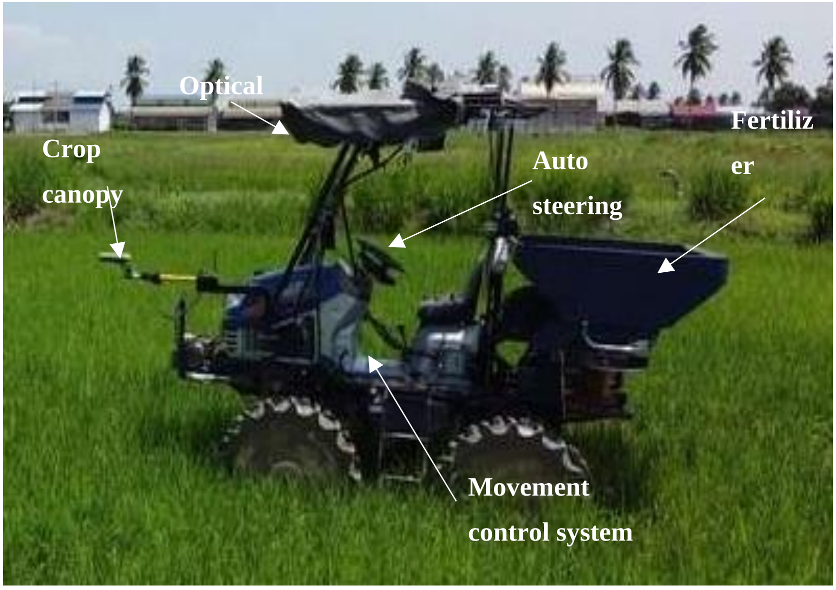

Figure 7. A retrofitted SAPM for fertilizer application developed by MARDI.

In the harvesting stage, a yield monitoring system mounted on a combine harvester is able to identify areas of low and high yield (Köksal & Tekinerdogan, 2018). This information can be useful not only to estimate yield, but also to predict problem areas in the coming seasons. A smart agricultural prime mover can be implemented to avoid these problem areas by analyzing the data that was acquired by the yield monitoring system (Zhai *et al*., 2020).

4.2 SAPM for Pineapple Production

The potential use of agricultural prime movers for pineapple production was detailed in (Abu Bakar *et al*., 2021). For the sake of completeness, it will be discussed in the following paragraphs.

In the land preparation stage, a smart decision support system can be developed to generate a soil fertility map. These maps would serve as the input to a SAPM for tasks such as liming to fix soil fertility issues. Preparation of the land can be done by autonomous machines. Smart tractors carrying implements can communicate and negotiate with other tractors on what tasks need to be done, such as bed preparation and tilling of the land.

In the crop cultivation stages, SAPM may be used to plant pineapple suckers eliminating the need for human workers. The precise location of each suckle can be specified making it easier for further maintenance. This gives the ability to phenotype each plant.

The decision support system could then prescribe intervention actions to SAPM This would presumptively be in the form of how much fertilizer and chemicals to spray for a specific pineapple plant. It could also decide when and where to apply hormones to stimulate fruit growth. The autonomous field robots would work in a multi-agent system carrying out these tasks.

In the harvesting stage, collaborative robots or cobots has the potential to be used to aid harvesting. As harvesting pineapples require a sequence of movements, these cobots could be taught this sequence (Wang *et al.*, 2012). Mounted on a harvesting conveyor of a SAPM, it is possible for them to check diligently for mature fruits to harvest.

The potential applications of Industry 4.0 in pineapple production mentioned above are just some of the areas that can be explored. Pineapple production is one of the rare relatively untouched industry that provides opportunity for researchers and academicians to delve into.

5. Conclusion

This work reviewed the state of smart agricultural prime movers or SAPM. It was argued that although a lot of research has gone into this field, only a handful of systems are available in the market. As these systems are often associated with safety concerns for human operators, smart agricultural prime movers are defined as having different levels of intelligence or autonomy to market them to potential buyers.

In Malaysia, the field of smart agricultural prime mover is still new. Potential applications for this technology in the Malaysian agricultural scenario were discussed. Although promising, this technology has to overcome issues such as cost, safety and reliability to be able to gain traction with the public.

Author Contributions: Badril Abu Bakar was responsible for the conceptualization, primary drafting of the manuscript, critical revision of technical sections, and overall project supervision. Siti Noor Alliah Baharom, Rohazrin Abd. Rani, Taufik Ahmad and Mohd Nizam Zubir were responsible for the literature review, organization of thematic sections, and development of background content on Industry 4.0 and SAPM technologies. Adli Fikri Ahmad Sayuti, Mohd. Nadzim Nordin, Mohammad Aufa Mhd Bookeri, Mohamad Fakhrul Zaman Omar were responsible for Assistance in describing commercial SAPM systems and evaluation of technical feasibility. Jusnaini Muslimin was responsible for compilation of application case studies, support in structuring arguments related to Malaysian implementation, and data organization. Ahmad Safuan Bujang was responsible for manuscript editing. Mohd. Zamri Khairi Abdullah, Ramlan Ismail and Muhammad Hariz Musa were responsible for advisory input on agricultural technology adoption, validation of applicability to Malaysian crops and visual improvements.

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