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REVIEW

A comparative review of the state and advancement of Site-Specific Crop Management in the UK and China

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Abstract Precision agriculture, and more specifically Site-Specific Crop Management (SSCM), has been implemented in some form across nearly all agricultural production systems over the past 25 years. Adoption has been greatest in developed agricultural countries. In this review article, the current situation of SSCM adoption and application is investigated from the perspective of a developed (UK) and developing (China) agricultural economy. The current state-of-the art is reviewed with an emphasis on developments in position system technology and satellite-based remote sensing. This is augmented with observations on the differences between the use of SSCM technologies and methodologies in the UK and China and discussion of the opportunities for (and limitations to) increasing SSCM adoption in developing agricultural economies. A particular emphasis is given to the role of socio-demographic factors and the application of responsible research and innovation (RRI) in translating agri-technologies into China and other developing agricultural economies. Several key research and development areas are identified that need to be addressed to facilitate the delivery of SSCM as a holistic service into areas with low precision agriculture (PA) adoption. This has implications for developed as well as developing agricultural economies.

Keywords remote sensing, decision support, responsible research and innovation, digital soil mapping

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1 Introduction

Emerging in the mid-1980s, precision agriculture (PA) is a farming management concept based on observing, measuring and responding to variability in agricultural production through the employment of the right technologies in the right place at the right time in the right way to improve production while minimizing environment impacts[1]. The technologies and methodologies for PA are always evolving with advances in technology and improvements in our understanding of the actual needs in agriculture. Site-Specific Crop Management (SSCM) is one facet of PA for cropping systems. SSCM is defined as an information technology-based agricultural management system to identify, analyze and manage spatial and temporal variability within field crops for optimum profitability, sustainability, and the protection of the environment[2]. SSCM has become a popular approach in developed agricultural systems with field comparisons between uniform and variable fertilizer applications clearly demonstrating that there are advantages to management at scales finer than the field scale[3]. The need for differential in-field management is due in part to the interactions of variable natural soil formation factors and processes associated with anthropogenic soil management activities, generating considerable spatial variability in soil properties, such as texture, structure, depth, pH, stoniness and chemical fertility, at both the farm and field levels[4,5]. In conventional farming, seeds, fertilisers, herbicides and pesticides are typically applied uniformly at a field average, leading to over-application in some places and under-application in others. In contrast, SSCM allows growers to improve efficiencies in input use by adjusting to the observed variations within fields.

A SSCM strategy has several key attributes for measuring and managing the within-field spatial variability of soil and the environment and its impact on crop growth/productivity. Geo-referenced spatial measurements are now possible due to the rapid development, miniaturisation and improved accuracy of global navigation satellite system (GNSS) technology, of which the USA's global positioning system (GPS) is the most commonly used. GNSS has been widely employed in machinery guidance, auto-steering and controlled traffic farming systems. A range of commercial soil and crop sensors, which are GNSS-linked, are available to measure the within-field variability of different soil and crop parameters and monitor their evolution in space and time. Another key element that makes SSCM possible is variable rate technology (VRT) that allows precise differential seeding, fertilising and spraying and is able to respond to the observed spatial soil and plant information. A geographic information system (GIS) based farm management information system (FMIS) is required to transform all types of data and information into maps (or something similar) that farmers can understand and utilize to drive spatial agronomic decision-making.

SSCM has increased substantially in the UK over the past two decades, predominantly for nutrient management. VRT was named one of the Top 5 PA technologies in both 2013 and 2014 by the Precision Ag magazine and is a driving force to improve productivity using variable fertiliser application technology[6,7]. To support the recent increase in VRT decision-making, multi-spectral satellite images for fertiliser application and for soil mapping have been increasingly used by famers in the UK. Data solutions (i.e., data integration) are also emerging as a key tool for PA and was also one of the Top 5 PA technologies listed in both 2013 and 2014 by the Precision Ag magazine[6,7]. The 2012 Farm Practices Survey reported that 22% of English farms used GNSS, 20% used soil mapping and 11% used yield mapping. These numbers represented an increase of 8%, 6% and 4% respectively compared with the 2009 results[8]. The reasons cited for the increase in the UK are to reduce fertiliser and agrichemical input costs (indicated by 63% of farms), to improve accuracy of application (indicated by 76% of farms) and to manage crops to soil conditions (indicated by 48% of farms).

It is recognized that the degree of PA development varies from one place in the world to another due to the differences in technology (availability and support), agronomy, economy and culture[1]. PA adoption is relatively high in developed countries, such as the UK, USA and Australia, especially compared to countries in the Global South, such as China. Recent research in China has highlighted limited awareness and adoption of PA technologies on family farms in China[9] and suggests that PA technologies currently mainly hold relevance for larger farms[10]. This is thought to be due to the lack of technology relevance to smaller farm scales, and issues with the land fragmentation of growing family farms, which makes it difficult to apply these technologies[11] and can hinder financial investment in agricultural technology more broadly[12]. However, this is not to say that research on PA in China (or other large developing countries) is not advanced or widespread. In China, The National Engineering Research Centre for Information Technology in Agriculture (NERCITA) was established in 2001 to promote PA research and application. There were also several PA research centers set up in institutions such as the China Agriculture University[13]. PA was in the national 863 Programme (State High-Tech Development Plan) and tens of demonstration farms have been established in China to showcase PA systems[13,14]. Laser guided land levelling systems for smoothing and reshaping field surfaces, especially for irrigated land, and GPS guided auto-steering have been adopted in China in recent years[15]. The gap in PA adoption in China (and other developing countries) has been in the translation from a research to a commercial context. There are many reasons for this, but in part due to a lack of capacity in the industry and in the population to exploit technology and a lack of IT infrastructure to support PA[16].

The agricultural landscape in China is changing quickly in response to the rapid economic development that has occurred over the past three decades and the latest round of land reforms. As a result, non-commercial small plot holdings are diminishing and commercial farms and larger family-run farms are emerging. This shift in production size provides opportunities and a demand for PA development in China. Furthermore, issues arising from the degradation and deterioration of farm land and the national cap on total national usage of fertiliser and pesticides by 2020 is also forcing Chinese growers to improve productivity. PA, and more particularly SSCM, has a potentially critical role to play in achieving this improved productivity.

It is clear that agriculture globally faces many different challenges in a rapidly evolving technological world. To better understand these challenges, this paper aims to review: (1) the current status of the key SSCM technologies; (2) the opportunities and limitations of SSCM adoption in China and the UK; and (3) the future direction of SSCM and PA.

2 Key PA technologies

PA involves data collection, data analysis and information management, all of which are supported by technological advances in positioning systems, sensor design, remote sensing systems, computer processing, and communication technologies. The ‘state-of-the-art’ in each of these technologies will be briefly reviewed in the following sections.

2.1 Global navigation satellite systems (GNSS)

Different PA applications required different positioning accuracy[17]: (1) low accuracy (meter level) can be used for asset management, tracking and tracing; (2) medium accuracy (sub-meter level) can be used for tractor guidance, via manual control, for lower accuracy operations such as spraying, spreading, harvesting bulk crops and for area measurement and field mapping; (3) high accuracy real time kinematic (RTK) systems (centimeter level) can be used for auto-steering systems on tractors and self-propelled machines (harvesters and sprayers) and for precision operations such as planting. In PA, it is well recognized that GNSS are the major enabler of ‘precision’.

GNSS represents a constellation of satellites providing signals from space transmitting positioning and timing data with global coverage. A GNSS receiver employs trilateration to determine its position on or near the earth’s surface by timing signals from four or more GNSS satellites. There are two fully operational GNSS systems at present, the United States’ GPS and the Russian Federation’s Global Orbiting Navigation Satellite System (GLONASS). The Chinese Beidou Navigation Satellite System is still being deployed, but provides operational coverage in regions such as Asia, Australia and New Zealand. The European Union’s Galileo system is in initial deployment phase, scheduled to be fully operational by 2020.

Due to various error sources, including satellite orbit errors, receiver clock errors and atmospheric delays, standalone GNSS provides worldwide positioning services with an accuracy of 3–5 m at best. There are several commonly used techniques for improving GNSS performance:

(1) Differential GNSS. The base station with a high precision coordinate determines the pseudorange corrections to GNSS satellites in view and sends them to rovers using a data link, and the rovers incorporate the corrections into their position calculations. DGNSS services (e.g., UK General Lighthouse Authorities’ (GLAs) public marine Differential Global Positioning System, and China Beidou Radio Beacon-Differential Beidou Navigation Satellite System (RBN-DBDS)) can provide a meter positioning accuracy but degrade as the rovers move away from the base location[18].

(2) Space-based augmentation system (SBAS). SBAS broadcasts regional pseudorange correction signals from geostationary satellites instead of from the ground-based reference stations as for DGNSS. SBAS examples include European Geostationary Navigation Overlay Service (EGNOS) within Europe and South-east Asia, the wide area augmentation system (WAAS) within North America, the GPS and geo-augmented navigation (GAGAN) within India and the multi-functional satellite augmentation system (MSAS) within Japan. The typical accuracy of the EU EGNOS is < 3 m[19], which has been found useful for agricultural users.

(3) Real time kinematic (RTK) GNSS. Using carrier phase measurements (instead of pseudorange measurements only for Differential GNSS and SBAS), RTK GNSS establishes the most reliable and accurate solution for GNSS applications in real time, producing typical errors of less than 2 cm. This level of precision is not needed for general site-specific farming, but it does permit treatment of small specific locations, such as a plant-specific operation, and is essential for precision guidance, controlled traffic farming, mechanical inter-row weed control, inter-row sowing or crop thinning. In its basic form, a single reference RTK is located at a known point close to where the vehicle operates and communicates with rovers through a radio-transmitter. Rovers determine their position using algorithms that incorporate ambiguity resolution (i.e., determining the number of carrier cycles between the satellite and the rover receiver) and differential correction. Note that ambiguity resolution is not required for Differential GNSS or SBAS since they utilize pseudorange measurements rather than carrier phase measurements. The main issue with single reference RTK is that the accuracies obtained are distance dependant. Therefore, the greater the distance between the reference and the roving receivers, the less accurate the results will be. This is because the atmosphere present at each receiver cannot be assumed to be identical and as such, cannot be eliminated from the observations. Baselines greater than approximately 30–70 km (depending on conditions and hardware) are said to be the maximum without jeopardising data quality. A new reference station would then have to be established beyond this point. Accuracies for short baselines can be in the range of 2–3 cm[20]. With a network RTK system, such as Leica’s SmartNET in the UK, there is no need for surveyors to set up their own reference stations, as a network of reference stations are available which provide corrections and eliminate the distance dependant errors. Figure 1 shows the overlap of the reference network ranges so that areas which are covered by more than one reference station can have more than one set of corrections sent to the rover. The accuracies of the computed rover positions can be maintained over larger distances between the reference stations and the rover. The main disadvantages of network RTK include: (1) the price of subscribing to an already established system, and (2) the effects of the distance and height difference between the rover and the nearest station. The typical positioning accuracy of RTK GNSS is 10–20 mm horizontally and 15–30 mm vertically[21]. As of April 2015, network RTK GNSS surveying is available in Great Britain through three commercial service providers, Leica’s ‘SmartNet’, Trimble’s ‘VRS Now’ and Topcon’s ‘TOPNet +’. All of these services rely largely on the Ordnance Survey’s high density ‘OS Net’ network of

around 160 continuously recording GNSS stations (Fig. 1). In China, there is no RTK GNSS service available across the whole country, although local RTK networks have been rapidly developed in the past few years[22]. It is clear in Fig. 1(b) that there is only a limited number of GNSS stations available in western, southern and north-eastern China.

(4) Precise point positioning (PPP) GNSS. PPP differs from RTK in the sense that it does not require access to observations from reference stations but provides an absolute positioning instead of the location relative to the reference station as RTK does. A dual-frequency GNSS receiver is required to remove the first order effect of the ionosphere. PPP can achieve the same level of accurate positioning as RTK GNSS with potentially lower capital and running costs[23,24]. Precise satellite information (e.g., precise satellite clock and orbit) is required to be generated at processing centers, and broadcast to rovers. Recent studies demonstrated a multi-layer processing scheme for PPP regional augmentation to avoid processing large reference networks and suggested the positioning accuracy of 12, 10, and 25 mm in east, north, and vertical directions can be obtained in real time[24,25].

2.2 Soil mapping

Variability in soil is the major driver of variation in crop production, assuming no undesirable management effects. Detailed spatial soil information is critical for effective SSCM. With increased precision in soil data, farmers can make better decisions by targeting crops, inputs and technologies more efficiently. The national soil map (NSM) of England and Wales consists of 747 soil series that are distributed in 300 soil associations (Soil Survey Staff, 1984). NSM is very informative on general soil conditions and there are semi-detailed surveys at the scale of 1:5000 to 1:50000, but the majority of the UK is still only mapped at the scale of 1:250000. Maps at this scale lack detail of the within-field variability of soil properties, such as texture, depth, organic matter, stone content and pH, and are insufficiently precise for SSCM. Soil survey maps in China are at an even coarser resolution and often at a scale of 1:12000000[26]. Providing better, relevant, soil information at the farm and field scale will be needed for SSCM to be effective in China.

High-resolution soil mapping methodologies fall into two categories: traditional and digital approaches. The former relies on soil survey with pits and cores and an expert soil scientist's interpretation. The latter utilizes sensor technologies and quantitative data-fusion techniques to model and predict soil properties and in some cases it may incorporate traditional knowledge via soft-computing approaches. Digital soil mapping techniques are becoming more common and effective for intra-field applications[27].

(1) Traditional soil survey. Figure 2 shows a typical example of data derived from a traditional pit survey, with such approaches common for characterizing soil variability in high-value horticulture and viticulture systems pre-planting. In this approach, a soil surveyor's expertise is used to partition the landscape into different soil types based on subjective multi-attribute field judgments of intrinsic soils characteristics. It does not usually require revision, but it is a slow, expensive process, hence its use in high-value cropping systems.

(2) Soil nutrient mapping. Most commercial nutrient surveys globally are performed as manual surveys, but are much quicker than a traditional soil survey as it only focuses on soil nutrients relevant for crop growth. Georeferenced soil samples are collected in the field, usually only from the topsoil (e.g., for arable fields, UK 0–15 cm; China 0–20 cm), on a grid at a density of typically 1 sample per ha in the UK (i.e., multiple samples per field (Fig. 3)) and are sent directly to a laboratory for

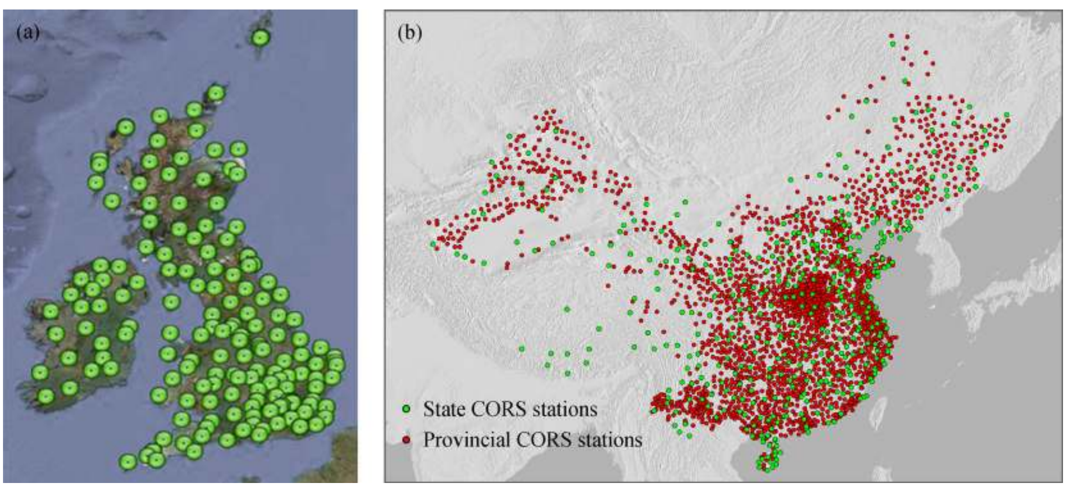

Fig. 1 Distribution of continuous GNSS stations. (a) OS Survey Net stations in the UK in 2015 (BIGF, 2015); (b) CORS stations in China in 2017.

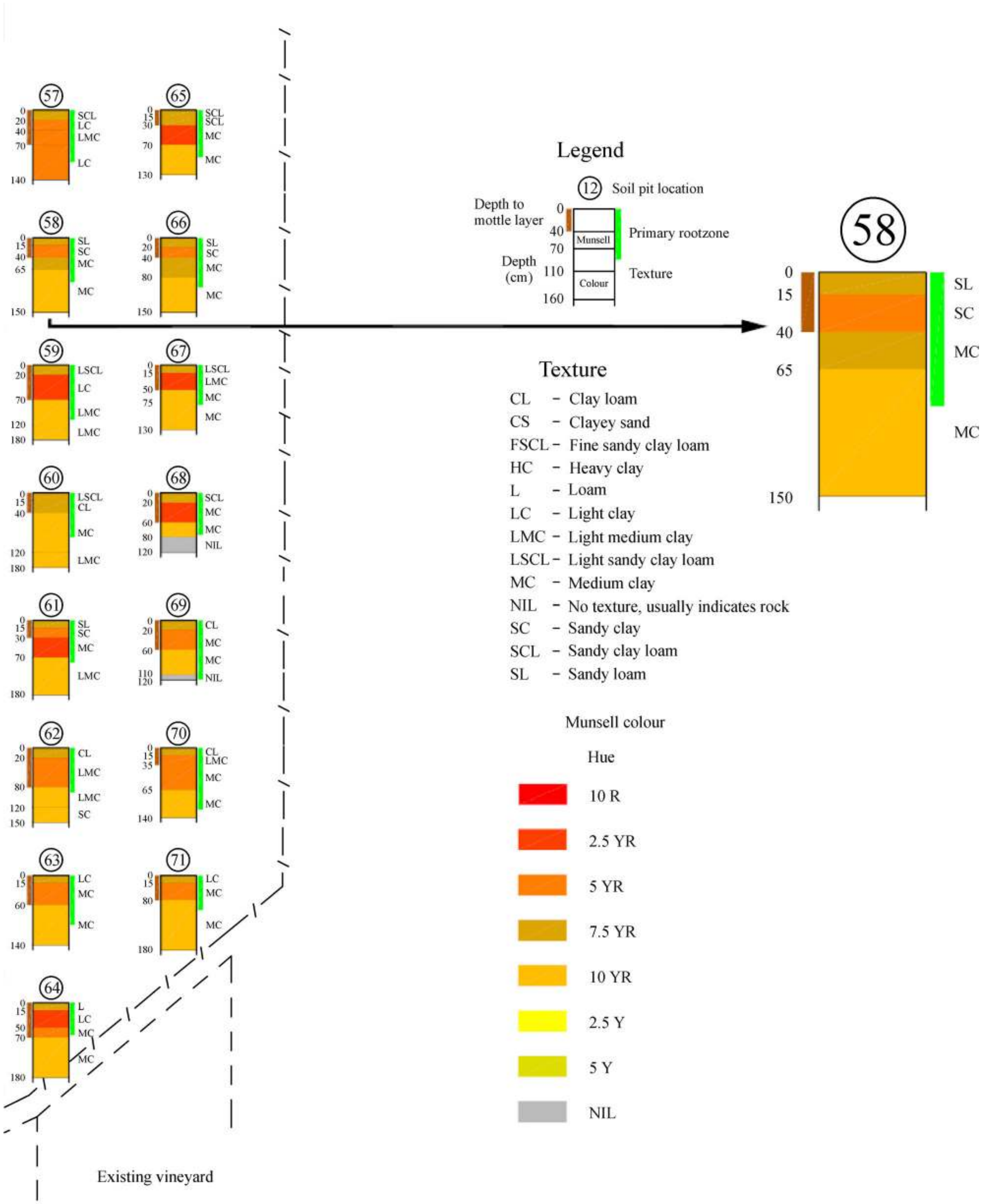

Fig. 2 Example of a descriptive soil map generated from a soil pit survey by a chartered surveyor on a vineyard site (reproduced with permission from Taylor & Minasny[28]).

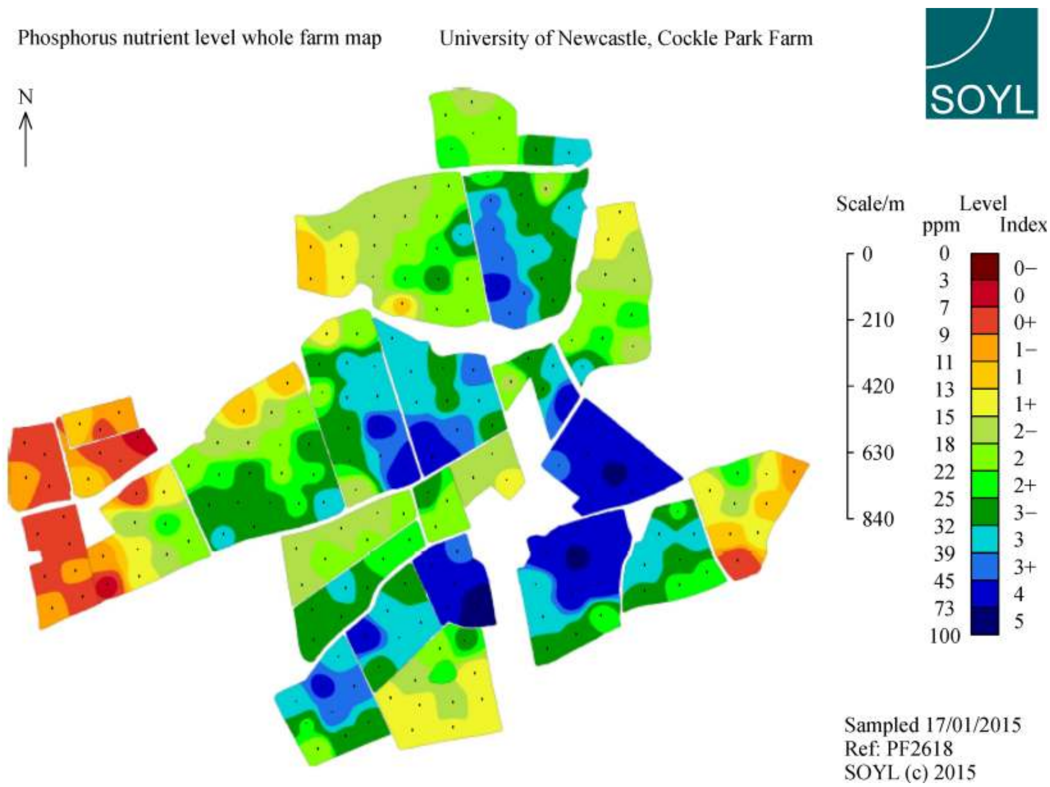

Fig. 3 Example of a commercially supplied soil nutrient (phosphorus) map generated for University of Newcastle's Cockle Park Farm, Northumberland. Black points indicate the sampling locations.

analysis of a few key soil nutrients. According to the soil nutrient analysis, a nutrient map is generated to show within-field nutrient distributions. This is used for phosphorus (P), potassium (K) and magnesium (Mg) in the UK, nutrients that are relatively stable in the soil system. Soil nitrogen, particularly mineralisable nitrogen (N) is rarely mapped in this way as it is more transient in the soil. This method gives relatively dense data and is possible as the collection and laboratory systems in the UK (and other developed agricultural economies) are well developed. This means that soil can be quickly gathered and analyzed, with turn-around times of typically less than one week. The method does incur labor and laboratory costs and is typically done on approximately a 5-year cycle by UK growers. In China, soil nutrient sampling is often performed at a density of 1 sample per 10 ha or coarser (i.e., normally multiple fields per sample).

(3) Apparent electrical conductivity (EC_a) and on-the-go soil sensing. Several on-the-go soil sensors exist that are capable of assessing a soil response, with the most common sensors being EC_a sensors. Two types of EC_a sensors exist: (i) electromagnetic induction (EMI) sensors that are non-contact sensors, and (ii) electrical resistivity (ER) sensors that are invasive sensors requiring contact with the soil. Both EMI and ER systems can be mounted, linked to a GNSS and towed behind a vehicle to provide high spatial density EC_a information. The EC_a response is affected by multiple soil properties that influence electrical conductivity, including texture (clay %), clay mineralogy, soil moisture content, salinity, cation exchange capacity, pH, temperature and organic matter level[29]. On-the-go EC_a surveys are relatively quick but do require careful interpretation and ground-truthing as the EC_a response is a relative not an absolute value. To obtain actual maps of soil properties, such as a clay percentage map, a local calibration function is needed. This in turn requires soil sampling, but usually at a much lower sample density than that used for nutrient mapping.

(4) Bare soil imagery and remote sensing. It is well-known that there are several factors affecting the diffuse reflectance spectra of soil in the visible and near infrared range. These include mineral composition, organic matter, soil moisture, and soil texture[30] along with surface roughness. Bare soil images have often been used, when available, to identify soil variability within fields. A recent advance on this is the development of commercially available high-resolution soil brightness products (e.g., AgSpace Ltd., Swindon, UK). Using the red, blue, green and near infrared reflectance, an algorithm classifies the reflectance and generates a 'soil brightness' (SOB) map (Fig. 4(b)). It is clear that there is a spatial correlation between the traditional soil survey, SOB map, crop vigour map and the final yield map (Fig. 4). In the UK and other regions, where cultivation is a common practice, SOB maps can be generated from historical, archived satellite imagery and allow farmers to see where variation occurs in

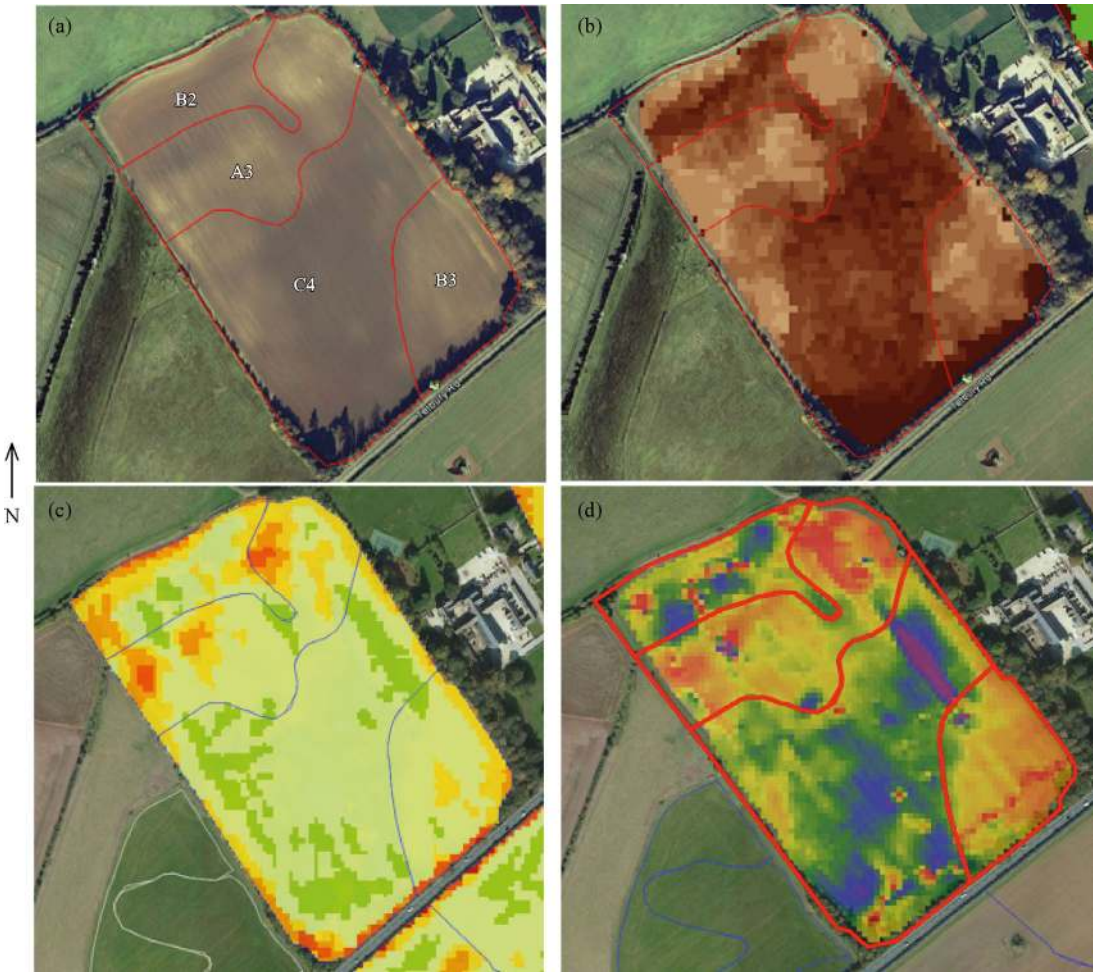

Fig. 4 Cirencester Park Farms, Cirencester, Gloucestershire: (a) bare soil image; (b) soil brightness map (SOB); (c) normalized differences vegetation index (NDVI) map showing crop vigour mid-season (red = low to green = high); (d) yield map (red = low to blue = high). All maps are overlaid with polygons indicating changes in soil types within the field. Images courtesy of Courtyard Partnership Ltd., UK.

their fields and, alongside their agronomist, create management zones based on the spatial differences. SOB is unable to explain what factors the variation relates to but coupled with a farmer's knowledge of their land it can be used as an inexpensive alternative to soil surveying. Similar to the EC_a mapping, this method requires careful interpretation and some ground-truthing, but it is very rapid and can be applied quickly over much larger areas than is possible with ground-based soil sensors or manual sampling approaches.

It is no coincidence that the most successful SSCM service providers in the UK have all had a firm business model for delivering high-quality spatial soil data to growers. Different companies target different technologies to generate and ground-truth soil information, but all deliver sub-field scale soil maps and prescription variable-rate fertiliser and lime requirement maps. Growers can quickly see a benefit for variable fertiliser, seed rate and lime application, particularly in situations where non-application is recommended and the input is directly saved. The success of correctly targeting variable fertiliser, seed rate and lime is reflected in uptake of these approaches by over a fifth of British farms.

For SSCM to be adopted successfully in China (and other developing agricultural economies), comparable soil information must also be delivered, particularly to the larger farms. At the moment this data are not available to all growers. Although a soil database has been established and is available to the public via a website[26], the data are still in a low spatial resolution and difficult to utilize for PA practice or practical farming. Without accurate high-resolution soil information it is difficult, if not impossible, to correctly identify agronomic drivers of spatial crop production.

2.3 Remote sensing of crop attributes

In PA, remote sensing is based on the interaction of electromagnetic radiation with soil or plant material and involves non-contact measurements of radiation reflected or emitted from agricultural fields[31]. An early example of remote sensing for PA was the use of Landsat imagery, one of the first earth observation satellites for civilian use, to estimate the spatial patterns in soil organic matter, soil phosphorus and crop yield potential[32] and understanding the growing environment and production potential still dominates applications of earth observation to PA[33].

Earth observation can be performed from three different types of platforms: satellite, aerial and ground-based platforms. These are differentiated by altitude and distance to the target (crop), which influences the potential resolutions achievable and the potential for external interference in the data, such as cloud presence and atmospheric effects on data from satellite and to a lesser extent, aerial platforms. It is clear from Fig. 5 that the frequency of cloud-free conditions varies from place to place and from season to season[34]. The overall frequency of cloud-free conditions is about 20% in the UK, with the highest frequency in the summer[35], a period when there is little agronomic intervention in production. However, northern and western regions are cloudier than southern and eastern areas of the UK[36] where arable agricultural land use is concentrated. The overall frequencies of cloud-free conditions in western China are about 60%, much higher than those in Southeast and Northeast China (typically 20%–30%)[34]. The highest cloud-free frequency in China was in boreal autumn, while the lowest was in boreal winter, a period when information on initial crop establishment and growth in winter cereals is desirable.

The wavelengths used in most agricultural remote sensing applications cover only a small region of the electromagnetic spectrum. The visible region of the electromagnetic spectrum ranges from approximately 390 to 700 nm, the infrared region extends from 700 nm to 1 mm, and the microwave from 1 mm to 1 m. Both the visible and near-infrared (NIR, 700–1050 nm) regions are commonly used in agricultural remote sensing and applications of these data are well developed and commercially exploited. Where specific wavelengths within this region exhibit sensitivities to vegetation parameters, such as color or chlorophyll content, these act as a proxy for measures of crop type, development and health. Images, however, captured in these wavelengths are affected by cloud cover. Data in the microwave region is less affected by cloud cover and potentially more suited to areas where cloud cover during key agronomic stages is common, such as is the case in the UK and parts of China. Microwave surface interaction is dependent on the geometric and dielectric properties of the vegetation and is further influenced by parameters of the radar system such as wavelength, polarization, and incidence angle. Historically it has been difficult to unstitch these elements to establish fully unique signatures for different crops. More recently, research and development are being focused on radar observations in the microwave region for estimating crop varieties and biomass variation with great success[37,38].

There are several key factors to consider when employing remote sensing for a particular PA application, including the spatial, spectral, radiometric and temporal resolution of the data.

(1) Spatial resolution of a sensor is the size of the smallest object that can be detected as separate to its surroundings and is determined by the instantaneous field of view of the sensor and platform height. Frequently, the quoted spatial resolution of an image corresponds to the size of an individual image pixel. The smaller an area represented by one pixel, the higher the resolution of the image. Increasing numbers of high spatial resolution satellite images have been or are becoming available, e.g., 0.31 m WorldView-3 and 0.25 m TerraSAR-X (Table S1). The spatial resolution required depends on the decision and end management operation to be performed. For example, crop scouting and weed identi-

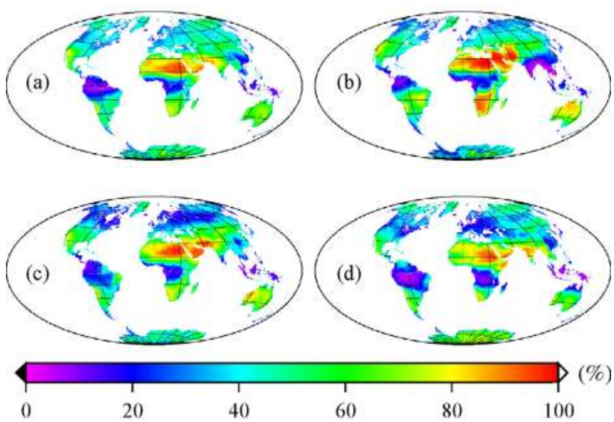

Fig. 5 Seasonal frequencies of cloud-free conditions across the globe derived from six years of Terra MODIS Atmosphere Monthly Global Product (from March 2000 to February 2006)[34]. (a) Boreal spring (March–May); (b) boreal summer (June–August); (c) boreal autumn (September–November); (d) boreal winter (December–February).

fication may require very high-resolution imagery (< 0.5 m) to identify small infestations and potentially individual plants (for example from terrestrial or low-altitude aerial platforms[39]). In contrast, if differential fertiliser application is limited by the width of the spreader (typically 24 m in the UK) then lower resolution imagery (5–10 m pixels) is sufficient to make a sensible management decision. In Chinese production systems, agronomic equipment tends to be smaller in scale (typically 3–5 m) permitting finer scale management and therefore requiring higher spatial resolution (smaller pixel) imagery. Both the UK and China are characterized by small field sizes (< 20 ha) in cereal production systems. This creates limitations on the use of imagery with larger pixel sizes (> 10 m) as there are relatively few pixels per field and many are mixed pixels incorporating edge effects. The number of 'pure' pixels per field on which to base an agronomic decision is therefore small. In larger fields, typical of cereal production in Eastern Europe, Australia and North America (often > 50 ha) this effect is diminished.

(2) Spectral resolution refers to the number of bands and the wavelength width of each band. A band is a narrow portion of the electromagnetic spectrum. Narrower wavelength widths can be measured by higher spectral resolution sensors. Multispectral imagery measures several wavelength bands (typically 3–10 bands), such as visible green or NIR. Hyperspectral imagery measures energy in narrower and more numerous bands (typically > 20 and usually > 100) than multispectral imagery. The narrow bands of hyperspectral imagery are more sensitive to subtle variations in reflectance with wavelength and, therefore, have a greater potential to detect crop stress than multispectral imagery. For example, recent research has demonstrated the potential of hyperspectral data to detect nitrogen stress in potato[40] and water stress in cereals[41], among numerous other applications. However, for spaceborne instruments, physical limitations result in trade-offs in instrument design, so that hyperspectral data are not generally available at high spatial resolution[42]. Such data acquisition therefore requires ground sensors, costly airborne acquisition or, as an emerging technology, the use of unmanned aerial vehicles. However, it is clear from Table S1 that the number of spectral bands available for analysis from satellite platforms has improved, from four bands for Landsat 1 to eight bands for WorldView-2 and 13 bands for Sentinel-2, while bandwidths decreased from 60 to 40 nm or less. This trend is continuing, with the 2014 launch of WorldView-3 (16 bands and 1.24 m spatial resolution for visible—NIR bands) and future planned missions such as EnMap (OHB System AG and DLR) and HyspIRI (NASA).

(3) Radiometric resolution refers to the sensitivity of a sensor to variations in the radiance levels detected. The higher the radiometric resolution of a sensor, the more sensitive it is to detecting small differences in reflectance values, allowing subtle variations in earth surface characteristics to be detected.

(4) Temporal resolution refers to how often a remote sensing platform can provide coverage of an area. Satellite temporal resolution has improved from 18 days for Landsat 1–3 to 1 day for WorldView-3 (Table S1). High earth orbit geostationary satellites can provide continuous sensing while low earth orbiting satellites can only provide data each time they pass over an area. Revisit times vary from a few days to a few weeks. Remote sensing acquired from cameras or scanners mounted on airplanes and unmanned aerial vehicles (UAVs) can acquire data at user-defined intervals and can potentially be used to provide data for applications that require more frequent sensing at higher spatial resolutions than satellites can provide. Effective revisit times for both airborne and satellite systems can be extended by cloud cover that can interfere with the data from a scheduled overpass. Alternatively, proximal sensors using the same sensor technology can be located in fields or attached to agricultural equipment (terrestrial systems) to provide timely and frequent temporal resolutions. These systems can collect information during any management operation and usually provide the most flexibility for growers, although the recent rapid rise in the availability of UAV platforms has also allowed greater flexibility and end-user control in airborne data acquisition[43]. Other flexible approaches have also been developed to utilize low-cost ground-based sensors, such as smart phones, for example the development of the 'CanopyCheck' smart phone tool for monitoring potato canopy development (NIAB CUF, Cambridge, UK), designed to be used directly by growers.

One common application of remote sensing in SSCM is to use imagery to quantify ground cover and greenness. This information can be fed into crop models as an indication of the N status of the crop and therefore the nitrogen requirement of the crop. Typically, satellite images are obtained a few weeks to a few days before fertiliser application and a prescription map generated for differential N application in a field. For terrestrial systems with on-board proximal sensors, the sensing and decision-making can be done in real-time as the tractor and spreader traverse the field. Managing N fertiliser on the crop canopy is quick and cost effective in comparison to soil mineral N testing but it does not actually quantify the available soil N.

Satellite-based sensing systems are rapidly expanding and evolving. Table S1 lists the satellite platforms and sensing systems that have previously been available, are currently available or will soon be available to UK and Chinese users. It is clear that prior to 1990 there were very few options, with a very long revisit time for applications to agriculture. Even in the 1990s, sensor options were limited and pixel size was restricted to 20 m or greater for multispectral sensors. In agricultural systems with smaller field sizes, as is the case in both the UK and China, large pixel sizes create problems with mixed pixels at field boundaries and limit the amount of usable information over a field. In contrast, users now have access to many more systems with both higher spatial and temporal resolution. Multispectral sensors with < 6 m pixel size are available from Chinese, North American and European-based platforms (Table S1), with more planned. The result is that satellite systems are much more amenable for agricultural applications, provided that costs permit service providers to access data from multiple systems. This has been mirrored by an increase in the use of satellite-based imagery by third-party agronomic service suppliers in the UK over the past 5 years. Service suppliers can now confidently deliver satellite-based products to growers. Another advantage is that satellite information, especially information that relates to crop vigour and biomass, are routinely collected and archived providing a historical record of crop growth that can be accessed by new entrants to PA globally in both developed and developing countries.

Another emerging area for optical sensing in both the UK and China is crop scouting. The deployment of unmanned aerial vehicles with cameras now permits growers to achieve very high-resolution images (< 0.1 m pixels) of production systems. Satellite imagery is typically too coarse (> 5 m pixels) to distinguish anomalies in a field, such as a weed infestation, until they are having an impact on production. Correctly processed high-resolution imagery has the ability to identify very small effects and permit targeted early intervention to avoid crop losses. In the UK, this approach is being used to target management of black grass (*Alopecurus myosuroides*) control. In both the UK and China, commercial UAV applications are governed by aviation rules which place some restrictions on service provision.

2.3.1 Hyperspectral imaging system (HIS)

The development and application of imaging systems on unmanned aerial vehicles/systems (UAVs or UASs) and unmanned ground vehicles (UGVs) has increased dramatically over the past 5 years[44]. This has enabled deployment of more advanced imaging systems, in particular hyperspectral imaging systems (HIS). UAV-HSI or UGV-HIS (> 15 bands) provide more information, higher spatial and spectral resolution, than commercial multi-spectral imaging (MSI), as well as providing flexibility with data collection. The system includes a UAV or UGV body, flight or ground control system, HSI sensors and oil/electric energy.

(1) UAV and UGV involve platforms for plant information collection near, or up to 4 km from the ground. The UAV body could be a multi-rotor, helicopter, fixed-wing, blimp, or flying wing[44]. The gross weight (6–318 kg) and payload capacity (7–67.5 kg) increases with the growing cost of each UAV. The UGV platforms, phenomobiles or stationary platforms, are relatively more flexible than the UAV[45]. Payload capacity, including multi-sensors, is larger than the UAV platform, while data collection speed is limited.

(2) The flight control system of a UAV, one key technology of a UAV system, is the core of the whole flight process, including take-off, flying in the air, executing tasks and recovery. Generally, UAV flight details, including flight height, flight speed, flight location, and missions, can be pre-set by a rout planning tool, and transmitted to the flight control system through a data transceiver. For field UGV platforms, the diverse UGV control systems are based on the designed objectives. The Field Scanalyzer at Rothamsted Research, Harpenden (UK), for example, is one stationary field solution platform for field phenotyping, moving along designed fixed rails[46]. Some tractor-based systems, e.g., low crop UGV by NERCITA[47], can be remotely controlled based on GNSS (Section 2.1).

(3) Hyperspectral imaging sensors are configured to obtain information from a large number of narrow and continuous bands. In contrast, HSI with high spectral resolution collects more information on spectral characteristics of the crop in field and spectral differences between crops than MSI. Given the commercial application, small, light, and low-cost HSI sensors should be considered for deployment on UAV platforms. XiSpec, which is 26 mm $\times$ 26 mm $\times$ 31 mm and 31 g, is the world's smallest HSI camera, and is suitable for UAV and UGV platforms[48]. NERCITA also developed one HSI, mircro-Agrihawk 2014, to deploy in a UAV platform weighing 900 g. A UAV or UGV platform equipped with hyperspectral sensors, is becoming a promising approach for high throughput monitoring of plant variables, e.g., measurements of biomass and nitrogen in wheat and barley[49], hydrological soil surface characteristics[50], chlorophyll content and green biomass of pasture and barley[51], water status[52], and pest and disease monitoring[53,54]. Hyperspectral imagery deployed on UAV or UGV overcomes the shortcomings and complements the advantages of satellite imagery and hyperspectral field data regarding spectral resolution, spatial resolution and data acquisition flexibility[55].

2.3.2 Light detection and ranging (LiDAR)

LiDAR technology can be mounted on UGV, UAV or aircraft platforms and provides detailed three dimensional information on the ground surface in the form of an x, y, z coordinate 'point cloud' and intensity measurements. This point cloud can provide the basis for generating digital elevation models and models of vegetation canopies. In a research context, on-ground or airborne unmanned LiDAR sensor platforms have shown promise for generating data on, for example, crop biomass[56], grain yield[57], leaf area[58], and nitrogen status[59] and for crop phenotyping[60]. Airborne LiDAR has been shown to successfully estimate maize height and biomass at the tasseling stage in Gansu Province, China[61], while in the UK, it has been used to monitor the agri-environment[62,63]. Detailed digital elevation models derived from airborne LiDAR can also allow the modeling of water flow, accumulation and runoff from fields[64].

Uptake of LiDAR methods in agriculture in the UK and China remains low, with barriers including data availability, sensor cost and required level of processing expertise, as well as challenges in accurately estimating crop parameters in dense, low canopies, for example, early in the growing season[61]. However, data availability is improving (airborne LiDAR for much of the UK is now freely available from the UK Environment Agency) and further miniaturisation and development of LiDAR technologies, including multispectral and hyperspectral LiDAR sensors, will offer new possibilities for PA, including monitoring of crop biochemistry[65].

2.3.3 Portable hand-held sensors

Portable hand-held sensors have been developed for crop growth parameter measurement, based on several channels with high throughput spectrum signal. They provide measurements of some specific crop parameters, such as normalized difference vegetation index (NDVI) or canopy cover (CC), with sensors that are small, low-cost and suitable for field use. More importantly, these portable hand-held sensors could also be fixed in the field for high frequency temporal monitoring of crop growth status. Some commercialized products that have been developed included the SpectroSense2 Meter for NDVI (Skye Instruments Ltd., Llandrindod Wells, UK)[66], the Force-A Dualex Scientific (Force-A, Orsay Cedex, France)[67], Decagon SRS-NDVI (Decagon devices, Washington, USA)[68], and CropSense (NERCITA, Beijing, China)[47]. Taking the CropSense as an example (Fig. 6), the diagnosis models of crop growth status of CropSense are the core of the CropSense app; it is based on a long time-series of crop monitoring data collected over the past 15 years in China's major grain producing areas. The crop modeling is sensitive to the change of crop condition at the key growth stages of wheat, corn, and rice. The common monitoring and diagnosis parameters include the NDVI, leaf-area index (LAI), vegetation fraction (FVC), chlorophyll content (C_{ab}), yield and nitrogen fertilizer amount (Nc). The CropSense app is also customized to provide simple and clear information such as seedling condition, disease and pest condition, drought and health condition for primary agriculture managers and family farmers.

2.4 Harvest and production sensors

Remote sensing provides an indication of how a crop develops in size and vigour during the season. On-harvester sensors allow the actual production to be measured and audited at harvest. Sensors for cereal

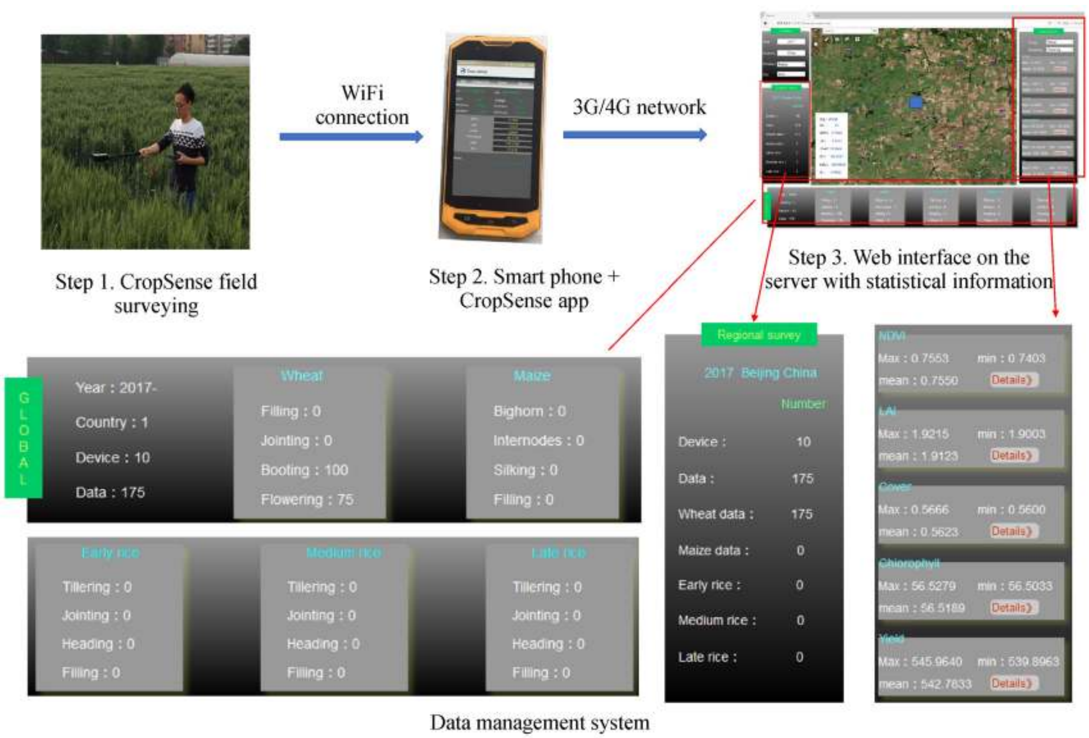

Fig. 6 Workflow of the CropSense system developed by NERCITA, China

production systems are the most advanced, although yield monitors are available for most crops. Production sensors that are available for mounting on-combine for cereal systems include:

(1) Yield monitors. Yield mapping refers to the process of collecting geo-referenced measurements of crop yield while harvesting (an example in Fig. 4(d)). Yield monitors for cereal production were introduced in the early 1990s and are sold standard on new combines in developed countries. However, despite the accessibility of this technology, UK growers do not routinely collect and use these data, nor do they ensure that yield sensors are properly calibrated at harvest. Only a small percentage (8%) of UK growers are using the information[69].

(2) Moisture sensors. The actual yield must be corrected against the moisture content in the crop. Moisture content of grain can vary considerably across a field. Grain moisture sensors are a standard part of all yield monitoring systems. They provide information on where grain moisture, which is ultimately related to soil moisture, is low or high in a field at harvest. Grain moisture sensors are typically capacitance-based sensors and very susceptible to error with any surface moisture, a common harvest problem in the UK.

(3) Protein sensors. As well as measuring quantity in combinable crops, harvester-mounted quality sensors are also commercially available[70]. Currently these systems are not commercially supported in the UK and are only used in research situations; however, quality sensing is a key parameter in assessing the productivity and profitability of a crop.

Crop production is weather dependent and seasonal. To assess the effects of weather or other unpredictable factors, the temporal variation of yield distribution within fields over multiple years (ideally 5 years or longer) should be collected and evaluated to define areas with potentially high and low yields[71]. The indifference to yield data collection in the UK is therefore a concern for effective future implementation of many systems. Without yield data, production is not properly spatially audited. If data are not collected at harvest it is lost, unlike biomass and vigour data that can be retrospectively mapped from archived satellite images. When combined with soil, landscape variables, other environmental factors and management (inputs), the processed yield maps can be used to investigate productivity and efficiency spatially within a field[71]. This informs differential management in subsequent seasons. While only anecdotal, the indifference to yield mapping can be traced to the inability of growers to effectively use the information and the time, albeit small, to set up the equipment during a hectic time of year (harvest). Both points, particularly the former, are valid arguments. SSCM service providers in the UK have often not provided effective pathways for yield map processing and decision support that includes yield maps. The success, and fiscally quantifiable success, of variable rate fertiliser management based on soil nutrient mapping and biomass sensing has lessened the importance of yield maps for in-season management in the UK. As a result, there appears to be less appreciation in the farming community of the latent value of yield maps, especially for interpreting seasonal (temporal) effects on production.

In China, the situation with yield mapping of cereals, including rice and maize, has not been fully surveyed but the technology is not widely utilized for a number of reasons: (i) a lack of farmers' interest, (ii) the high cost of GNSS coupled yield monitors, (iii) the incompatibility between yield monitors and tractors, and (iv) a lack of technology support. Regardless of the reasons for the lack of access and adoption of yield monitors, the lack of historical yield data in commercial Chinese production systems will also provide a stumbling block to PA implementation. As for the UK, if yield data are not collected at harvest, it is lost.

2.5 Variable rate technology (VRT)

VRT refers to any technology that enables users to vary the rate of management operations, including crop inputs. Typically, this combines a variable rate control system with a GNSS on agricultural machinery and equipment. In the UK, most agricultural machinery sold, including seed drills, fertiliser spreaders and sprayers, are now capable of variable-rate application. Variable fertiliser spreader and seed drills are not widely available in the Chinese market, however, although a limited number of farms and research institutions have started to apply VRT for fertiliser and seed.

There are three different approaches to implementing variable-rate applications (VRA):

(1) Manual approach. The machinery operator is responsible for varying the application rates on the controller during the operation;

(2) Map-based approach. A differential prescription map is generated from prior soil and/or crop mapping information and analysis. The prescription map is uploaded to the controller (computer system) that controls an actuator (or similar) capable of automatically changing the rate of input/management as the machinery moves across a field.

(3) Sensor-based approach. Appropriate sensors mounted on farm machinery are used to assess crop or field conditions in real-time as an operation is being performed. This real-time information is passed to a controller that instantaneously determines an optimum rate, based on a predetermined formula, to vary application rates 'on-the-go'.

For application purposes GNSS are not needed for (1) and (3), however without them the operation cannot be recorded and analyzed later. Option (2) is conditional on access to a GNSS. In the UK, VRT is well developed but the agronomic success of VRA is dependent on the quality of the decision process used. This is the same the world over, including in China. A poor decision will yield the wrong result even if the VRA is correctly done. The three approaches above each have different limitations. A manual approach relies on the operator to correctly (subjectively) identify and respond to variation, while also ensuring that the equipment is operating correctly. This is a difficult task for even skilled operators. The prescription map approach permits a quantitative analysis that can be followed by validation and discussion with the grower before implementation. This should allow prescription maps to be manually adjusted based on local expert knowledge to generate the best decision based on available information and knowledge. However, this is a time-consuming approach and is reliant on good communication and knowledge exchange between growers, agronomists and SSCM service providers. Real-time approaches are also quantitative but assume that this local knowledge is captured within the software (decision support system). This is rarely true in current systems, so the variable applications are rarely done optimally, although better than a uniform application. Also, 'on-the-go' systems are often unable to respond to anomalous situations in fields without direct, manual operator intervention.

Correct VRT provides benefits through[72]:

(1) Economically improved crop yields via the optimal use of inputs;

(2) Improved in-field equipment efficiency and;

(3) A smaller environmental footprint by minimizing the over-application of inputs and thereby reducing the risk of pesticide and fertilizer runoff or leaching into the environment.

It should be noted that the effort involved in managing variable rate inputs does raise costs, and that VRT requires good knowledge of machinery and good compatibility between hardware (different pieces of equipment) and software (controlling) systems. On most farms, tractor implements and controllers are often purchased from different manufacturers and cross-compatibility and communication issues can reduce reliability and increase user frustration, creating a barrier to adoption[14]. This is true in both developed and developing countries, primarily because the driving factor of maintaining market share is the same in both situations. The issue of cross-compliance is being addressed in developed countries and developing countries should gain from this, either through better co-operation between large manufacturers or via intervening third-party controllers, such as Frontier's iSOYL iPad application (Frontier Agriculture Ltd., Witham St. Hughs, Lincolnshire, UK) that are able to link different systems. Hopefully, the limitations in communication protocols that have been a part of SSCM in the UK for the past 20 years will not be replicated in China as VRT becomes more common.

2.6 GIS-based farm management information system (FMIS)

GIS is a computer system allowing the visualizing, questioning, analyzing and interpreting of spatial and temporal data to understand their relationships, patterns and trends. An effective GIS should consist of two fundamental components: precise map data and powerful computer software to perform calculations and analysis. The basic functions of a GIS are:

(1) To store different layers of information, which for SSCM should include soil maps, soil nutrient levels, remotely sensed data, and crop yields;

(2) To display geo-referenced data adding a visual perspective for interpretation;

(3) To combine and manipulate data layers to produce a desired spatial/temporal analysis.

More specifically, FMIS is a GIS-based system for collecting, processing, storing and disseminating data and information needed to carry out operations on-farm. A recent study[73] suggested that FMIS should meet the following requirements:

(1) Have a design aimed at the specific needs of farmers;

(2) A simple user-interface;

(3) Automated and simple-to-use methods for data processing;

(4) A user-controlled interface allowing access to processing and analysis functions;

(5) Integration of expert knowledge and user preferences;

(6) Improved integration of standardized computer systems;

(7) Enhanced integration and interoperability;

(8) Acalability;

(9) Interchange-ability between applications;

(10) Low cost.

Unsurprising there are few software platforms available that meet all these requirements. In the 1990s and 2000s, FMIS software was sold and marketed as a stand-alone package. With the rise of cloud-computing capabilities and fast broadband internet services, even to rural areas, the trend in the UK nowadays is strongly toward web- or cloud-based FMIS. This approach takes the processing onus off the grower and also provides more ready access for SSCM service providers to data. Web-based delivery and processing was recognized as one of the Top 5 PA technologies in both 2013 and 2014 by the Precision Ag magazine[6,7]. The web-based or cloud-based FMIS enables farmers and their agronomists and fertiliser adviser to access information simultaneously and anywhere with an internet connection. It provides the ability for growers to download prescription map files (e.g., a nutrient management plan or seed rate plan) direct to a computer/tablet/controller in a tractor with 3G/4G signals. Stand-alone software packages on fertiliser recommendations have been developed in many provinces in China but the majority of systems have only been installed in computers within agricultural extension offices. Farmers have little access to the software. Web-based or cloud-based packages will enable farmers to access or use FMIS more easily.

2.7 The evolution of smart and digital agriculture

Agriculture, like the rest of society, is an area for the development and deployment of smart, networked technologies. In the first instance, smart agriculture is likely to revolve around the networking and connectivity of existing systems. For example, data transfer from tractor/machinery to databases has historically relied on farmer intervention. Improved connectivity will remove the need for this intervention and ensure that all production data are properly aggregated, archived and made available for farm management[74]. Smart agriculture will be dependent on communications connectivity, which is still limited even in 'developed' countries such as the UK, USA and Australia[75,76]. Availability in developing agricultural economies, especially higher speed broadband connectivity, is unreported but likely to be limiting to smart agriculture in 'developing' countries as well. Smart and digital agriculture is in its infancy, but the ability to automate much of the data transfer and analysis will transfer the decision process in agriculture and should be applicable to all types of production systems, both large-scale and small-scale farming systems, regardless of the level of mechanisation in production. The CropSense sensor described above, is a good example of an existing technology that would be enhanced by being 'connected' and applicable to nearly any cropping systems.

3 PA adoption and responsible research and innovation (RRI)

PA adoption in China in general lags behind the UK; as an example, only 25% of farmland in one of the most advances growing regions, Heilongjiang Province, uses PA technologies[9]. The national average will be much lower. In contrast, the UK had 22% national adoption of GNSS-controlled steering in 2012 with a rising trend. This did not include adoption of other PA technologies[8].

The key drivers that affect the intention to adopt PA technologies fall into three categories[77]: (1) competitive and contingent factors, such as soil quality, farm size, and location; (2) financial resources, such as costs reduction, total income, and land tenure; (3) socio-demographic factors, such as Farmers' education, familiarity with computers, access to information via service provider and technology sellers.

The recent review available[77] reported that farm size was the most important driver affecting PA adoption, followed by farmers' confidence with computers. In England, the number 1 barrier to adoption identified by producers was that the technology was not cost effective (Fig. 7)[8]. This is linked to farm size and turnover but also to the ability of systems to demonstrate a return on investment. This is often complicated by the fact that many PA technologies provide a social and environment benefit that is difficult to translate into a fiscal value[78].

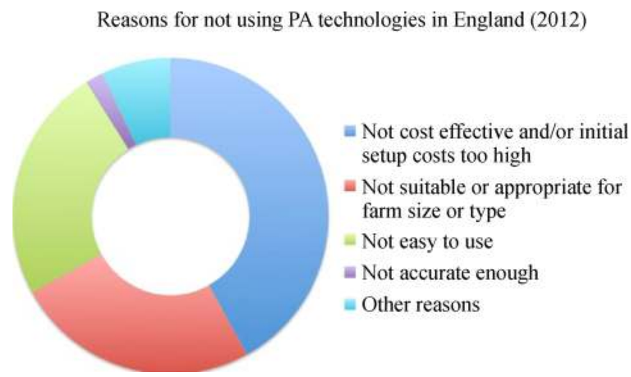

Fig. 7 Pie chart visualizing the reasons for farmers in the UK not adopting PA technologies collected from a Farm Practices Survey in 2012 from the Department for Environment Food and Rural Affairs[8].

In the view of US dealers and service providers, the two most potent limitations to adopting PA techniques are farm income and cost of precision services, but both financial barriers have significantly reduced from 2004 to 2013[79]. In China, the most important limitation factors are farm income, farmers' education level, farm size and land ownership[13]. In addition, lack of detailed soil information also constrains PA adoption. With increased precision of soil maps, farmers will be able to make better decisions or use of land by targeting crops, inputs and technologies more efficiently.

Another barrier noted in the VRT section, but applicable across the entire SSCM and PA system, is the lack of a globalized standardization for electronic communication in agriculture. In particular, co-operation among large agricultural equipment manufacturers about effectively implementing information transmission between farm machinery has been slow. Commercial entities have a conflict between being 'open-access' and protection of their proprietary products that can cause compatibility issues with equipment and computer systems from other manufacturers.

Basic and applied research in China was recognized at the 18th National Congress of the Communist Party of China (2012) as a priority if the quality of life of Chinese, and indeed global, citizens is to be improved. Policy translation of PA requires understanding of how the innovation process affects all stakeholders, including agricultural workers, local residents, and rural communities. A summary of these key stakeholders can be seen below (Fig. 8). Knowledge exchange between key actors and stakeholders will also ensure the inclusive adoption of novel agricultural technologies, which will ensure their implementation aligns with the preferences and priorities of end-users and local communities. In addition, ethical issues (for example in relation to environmental, health or socio-economic impacts of agricultural practices) must also be addressed. It is noteworthy that there are ethical concerns associated with not adopting a technology as well as with the unintended effects of technology implementation[80,81]. Therefore, the concept of RRI is clearly an important part of evolving policy agendas, but it has yet to be defined and made operational across different contexts and areas of application.

The importance of RRI as a part of institutional innovation activities is well recognized[82,83] and requires both systematic inclusion of stakeholder views and the social, economic, ecological and ethical parameters[84]. It has also been proposed that RRI can also support the introduction of technologies that touch primarily upon socially sensitive issues[85]. These might relate to ethical concerns, but also to the way in which local communities are (re)structured as a consequence of technology implementation. This may be particularly relevant in the case of agricultural technologies, as local communities may be highly dependent both economically and socially on the agricultural systems in which they are embedded. RRI is intended to help designers and manufacturers of new technologies identify and accommodate public, stakeholder and end user concerns when developing a new technology by engaging with a wide range of relevant actors in an interactive, transparent process. This is true for both developed and developing agricultural economies. To date, social-economic considerations have not been well incorporated into SSCM adoption in developed countries, and in some cases the failures of SSCM technologies can be linked to a failure to address these issues[86]. The concept of ‘knowledge exchange’ is also central to the development of effective RRI. However, the impacts of such RRI processes on policy and innovation trajectories have been frequently difficult to assess[87,88].

Capacity and knowledge of emerging agri-food technologies (e.g., in the case of precision farming) has been acknowledged as a limitation to adoption. In China, agronomic services to growers are mainly provided by local public extension agronomists. RRI must involve engagement and knowledge exchange not only with the growers but also the people that provide agronomic support. Affected communities (primarily rural) also need to be consulted, not least because community structures (for example, the skills profile and community arrangements) may be affected by new agronomic specializms being introduced into the social mix and shifts in employment patterns may result in social displacement of hitherto employed groups. Likewise, technical services are provided mainly via government agents. Engagement at the government level, as well as the grower level, is critical to success. Participatory approaches must be used to engage all levels of the production and service supply chain[89], and its impacts on agricultural technology policies evaluated[90]. Public participation regarding preferences for technology implementation and consumer

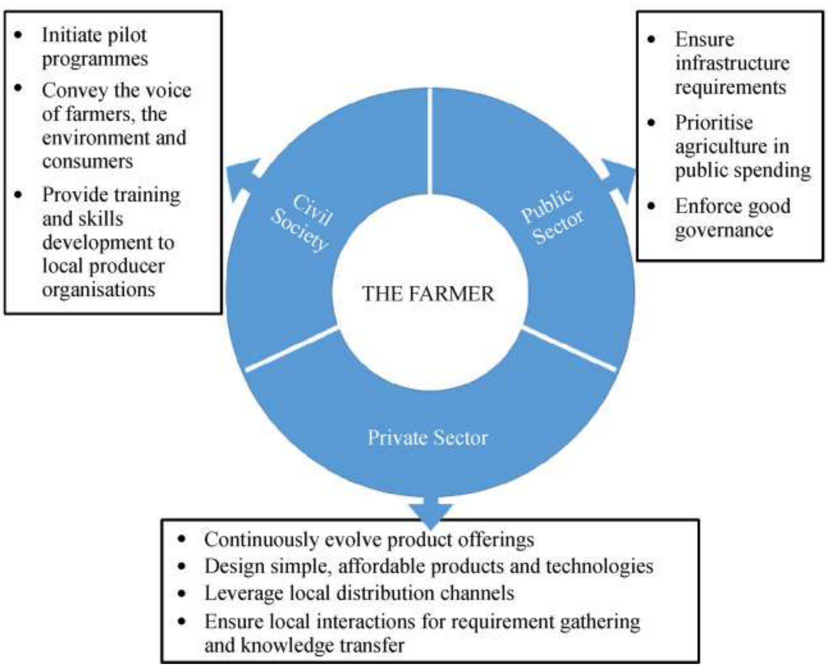

Fig. 8 Schematic view of the key stakeholders and their perceived roles in the innovation process in Chinese agriculture

research regarding the 'refining' of final products may optimise the innovation trajectories for agri-food technologies[91]. It is important to recognize that RRI does not assume a unidirectional communication process between stakeholders, and the principal of 'knowledge exchange' is a useful mechanism to ensure that a dialog between all actors and stakeholders, including the general public, is optimised.

Taking RRI activities through to impact is something which has infrequently been assessed, or indeed operationalised. For example, Owen & Goldberg[82] have observed that time lags exist between the development of novel innovations (e.g., nanotechnologies or genetically modified organisms), understanding of their wider impacts, and implementation of appropriate governance. This has led to repeated calls for more anticipatory and adaptive approaches to technology implementation. A key challenge is pragmatic implementation of RRI policies, and the agri-technology sector is an example of where effective RRI strategies are required[92]. Despite difficulties in making the RRI concept in agri-food production systems operational, effective agri-food technology innovation is contingent on understanding its impacts on both local communities and the supply chain.

RRI is facilitated by agri-food systems that are strongly vertically integrated from the farm to the consumer or, in the direct case of SSCM, from the field to the processor. This relates to vertical integration in product flow, information flow and service flow. In this context, Chinese agricultural production systems potentially hold a considerable advantage over many developed agricultural systems as service provision is still strongly integrated through government agencies. In the UK, agronomic services are provided via multiple commercial entities. The services supplied are fragmented, with different companies promoting different technologies and methodologies that suit their core business model, not the business model of the grower. This provides a barrier to growers being able to access a 'total' SSCM service for their own production system. In China, the dominance of government agronomy and agri-machinery agencies in providing support provides an opportunity to provide effective support to PA adoption. Unlocking this latent potential will be contingent on effective government policy and the development of capacity for PA service provision within these government agencies. The latter is a particularly difficult proposition and a known limitation to adoption[86,92] and will require a coherent national approach.

4 Opportunities for SSCM development in China and other developing agricultural economies

The previous two sections have reviewed, compared and contrasted the key technologies used in SCM and identified the socio-technological needs associated with technology translation. The generation of these two sections has helped to structure the way forward for SSCM and PA in China (and other developing agricultural economies) and to set some key questions for framing future research, development and knowledge exchange activities. These can be summarized as following.

4.1 Optimisation of approaches to collect spatial and temporal data

Developing agricultural systems lag behind developed systems in the amount of spatial information that could be or is collected in cropping systems. In some cases this data are lost; however for other data layers, archived remotely sensed data can be used retrospectively to generate information. Satellite-based sensors therefore have a key role to play in providing archived soil and crop information. Agriculture in developing countries is generally characterized by higher labor inputs and lower levels of mechanization. Consequently, there are options for the development of novel sensing systems and crop diagnostic tools to gather ancillary crop and soil data from the labor force. In these systems, the higher labor component may actually enable an easier route to measuring crop parameters, particularly crop quality attributes and crop protection issues (pest/disease pressure).

Key questions: What and where are the spatio-temporal information gaps in the agri-systems? What technologies are needed to fill these gaps—are new sensors/systems needed or are there transferable options? What are the limitations to collecting relevant information?

4.2 Better understanding of agronomic relationships

Merging data sets from various sources may provide new insights into the spatial variability of crop performance and thus lead to a better understanding of the impact and interactions of soil properties, topography, climate, management and other factors on crop productivity. The key to unlocking this is to ensure that good crop data, including quality as well as quantity data, is collected in every production system. If data and information cannot be ground-truthed and validated it cannot be used with confidence in any agronomic decision-support. Collecting large quantities of sensor data, particularly satellite data, is now fairly easy and routine. Collecting 'real', quality-controlled on-ground data remains a major limitation to PA research and extension.

Key questions: What are the relationships between measurements, management and crop growth/yield? What are the optimal approaches to merge different data sets? What extra information can be extracted when merging different data sets?

4.3 Spatial decision support systems

Technological failures and shortfalls in the adoption of PA can generally be linked to an inability to generate a good decision from the technology, rather than a failure of the technology itself. Agri-tech that provides good data but cannot be translated into a sensible, effective decision will not be adopted by growers. The most successful PA technologies all have effective decision support and can be linked to improved productivity and profitability. For example, GNSS guidance and auto-steering systems have a very simple decision process—Am I driving straight and parallel at an exact distance from my last pass? This can be linked to reduced overlap and inputs. Agronomic decisions that are responding to crop growth and potential growth are much more complex. Adding a spatial variance dimension makes them even more complex. In these situations, incorrect decision-making renders good data redundant and makes producers distrustful of new technologies. If PA is further adopted in the UK or is to become common practice in China, spatial decision support structures must be in place to support the growers' use of technology. In many cases, this will be reliant on good spatial crop modeling, an area which has not been well advanced in developed agricultural systems.

Key questions: What will be an appropriate spatial decision support systems (DSS)? All in One? Customized (with specific aspects only)? How should it be delivered? How should local knowledge be incorporated?

4.4 Assessment of economic and environmental benefits of PA

In nearly all current applications, SSCM is a spatialized systems approach to improved production efficiencies. While adoption of agri-technologies is usually driven by an economic benefit, there are many potential social and environmental benefits to the adoption of an SSCM strategy. If the social and environmental benefits can be metricized or translated into a fiscal value, then the true value of SSCM could be determined and used by growers to inform decisions on adoption. Currently, such metrics do not exist and growers make decisions mainly on an economic basis. Proper demonstration of potential benefits from a production, social and environmental perspective in different regions will increase farmers' awareness and in turn adoption of PA.

Key questions: What will be appropriate criteria/metrics for assessment of the value of technology? Is it required to be expressed in monetary form? Will policy or attitudes permit socio-environmental value to be 'paid' to a producer?

4.5 Big data and data sharing

PA and SSCM has always been information rich but is becoming increasingly so. More data can be beneficial if used properly, but equally can lead to 'information overload' and result in a confused decision process for end-users. Big data management is key to ensuring that only relevant and reliable information is fed forward into decision support structures. With particular consideration of remotely sensed data, which is becoming increasingly important for SSCM, the latest generation of earth observation (EO) missions will produce a nearly continual stream of high-dimensional data. This unprecedented increase in data will, however, come with its own challenges not least data access and processing. The development of computationally efficient techniques for converting massive amounts of remote sensing data into time critical operational services is imperative for the widespread reliance and uptake of EO technologies.

Metadata and uncertainty analysis has an important role to play in this domain and this area must not be neglected or lost as more data becomes available. This is not an issue unique to agriculture, regardless of whether it is in a developed or developing countries, and the agriculture community needs to work with other domains to optimize 'big data' analysis.

Cloud-computing and data-sharing developments are also integral to the success of a big data approach in agriculture. These will be critical in developing countries as it minimizes the computing infrastructure and capacity that is needed 'in country'.

Key questions: What will be the best way to process next-generation agricultural data? How can data sharing be done cost-effectively and maintaining data security? How will communication regulations in China impact on data-sharing and cloud-computing agronomy? How does agriculture link into the big data community for its own benefit?

4.6 Smart devices

Linked to cloud-computing is the functionality of everyday smart devices that can be adapted to agricultural uses. The advantage is that this technology is almost as ubiquitous in developing countries as in developed countries. Therefore, developments on this platform can be quickly transferred. Multiple apps already exist for single purpose applications, e.g., crop scouting and canopy area, and more integrated systems for tablet PCs are in development or have recently been released in the UK and USA. Smart devices are internet-enabled and are effective data-sharing tools as well as basic sensing systems. Typically, sensing is done via image analysis using a camera function but there exists a real opportunity to augment the sensing and diagnostic capabilities of smart devices through add-ons and to develop new apps for smart phone/tablet for field use.

Key questions: What will be the more effective ways for the users to collect, analyze, interpret and share information, in terms of both smart devices and apps? How 'good' is this data for validation? Is crowd (farmer)-sourcing of information valid for good decision support?

4.7 Knowledge exchange and transfer (KET) requirements

A range of technologies and knowledge are in place which makes PA viable. However, PA adoption rates vary from place to place, highlighting the importance of KET[86]. There is a need to ensure that technology adoption is facilitated and not hindered through socio-economic factors. The structure of the Chinese agricultural economy, with its strong vertical integration in its agronomy and machinery service supply, provides a method for the federal government to support and promote adoption. This will likely require some fusion of commercial and governmental services to fill technology and knowledge gaps, and this will provide challenges. Access and availability of information and communication technology (ICT) services will also determine the potential for KET for SSCM and PA adoption.

***Key questions*:** How is agri-tech implemented in a society that is not highly technologically advanced? What are the best methods for education of the populace in technology? How does China (federal governments) ensure capacity for service support in a potentially rapidly evolving and expanding technology field? What infrastructure is required to support ICT services in rural communities?

The topics and the key questions posed above address issues associated with technology development, integration and acceptance. While wide ranging, they are not intended to be exclusive items but to provide a pathway for PA going forward. Likewise, these topics and questions should never be considered in isolation. The linkages between the topics will be important—smart technologies must link to big data structures and address known or desired agronomic decision process. PA will not be effected by having one smart, connected system but rather an integrated, 'smart' system of systems.

5 Conclusions

Despite their potential, PA and SSCM have not been universally adopted in highly mechanised, developed agricultural systems. Adoption rates in the UK are rising, mainly in response to better developed agronomic services based on the maturity of existing technologies. Agricultural systems that have a very low rate of technology adoption will have the opportunity to benefit from these mature technologies and to learn from the mistakes made in economies that have had a higher level of SSCM adoption. Many SSCM services, especially satellite-based service, that are currently available in the UK, could be quickly deployed into China. Global developments in ICT have significantly reduced the gap in potential technology transfer from developed to developing economies. However, successful adoption will also be reliant on how the technology is presented and integrated into the agri-food system. Key limitations to technical adoption of SSCM will be costs (and benefits), a lack of service capacity and a lack of access to key data layers, including high-resolution soil maps and historical spatial crop production data. Socio-economic limitations are likely to be associated with issues of acceptance by growers, communities and administrative agencies and the changes that the technologies induce in production practices and the rural economy. Research into this area has been very limited to date and will be critical to further adoption in both developing and developed agricultural systems.

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