Computers and Electronics in Agriculture 163 (2019) 104844

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Review

A review of visualisations in agricultural decision support systems: An HCI perspective

Francisco Gutiérrez[a,*,1], Nyi Nyi Htun[a,*,1], Florian Schlenz[b], Aikaterini Kasimati[c], Katrien Verbert[a]

[a] Department of Computer Science, KU Leuven, Leuven, Belgium
[b] Geocledian GmbH, Am Wirtsanger 20, 84036 Landshut, Germany
[c] Agricultural University of Athens, Athens, Greece

ARTICLE INFO

Keywords:
Decision support systems
Human-computer interaction
Information visualisation
Precision agriculture

ABSTRACT

Decision Support Systems (DSSs) are used in precision agriculture to provide feedback to a variety of stakeholders, including farmers, advisers, researchers and policymakers. However, increments in the amount of data might lead to data quality issues, and as these applications scale into big, real-time monitoring systems the problem gets even more challenging. Visualisation is a powerful technique used in these systems that provides an indispensable step in assisting end-users to understand and interpret the data. In this paper, we present a systematic review to synthesise literature related to the use of visualisation techniques in the domain of agriculture. The search identified 61 eligible articles, from which we established end-users, visualisation techniques and data collection methods across different application domains. We found visualisation techniques used in various areas of agriculture, including viticulture, dairy farming, wheat production and irrigation management. Our results show that the majority of DSSs utilise maps, together with satellite imagery, as the central visualisation. Also, we observed that there is an excellent opportunity for dashboards to enable end-users with better interaction support to understand the uncertainty of data. Based on this analysis, we provide design guidelines towards the implementation of more interactive and visual DSSs.

1. Introduction

Decision Support Systems (DSSs) are designed to assist humans in making more effective decisions. In the field of agriculture, different stakeholders such as farmers, advisers and policymakers use software tools that facilitate farm management by gathering data from multiple sources, analysing these data and utilising a series of suggestions that are presented by different visual outputs. Many DSSs are designed to support the concept of precision agriculture (PA) which seeks to provide a holistic approach to assist farmers with optimising resources (Paustian and Theuvsen, 2017). McBratney et al. (2005a) defined PA as the "*kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits*". Thus, PA research concentrates on enabling users to make the right decisions considering both space and time.

In the history of agricultural systems, user-driven data and model development has played an essential role in meeting users' analysis need for decision-support (Jones et al., 2017). Still, models remain unfriendly, inside a black-box and behind DSS software. This black-box nature often leads to trust issues, notably when suggestions coming from a DSS fail (He et al., 2016). Moreover, an increase in the use of farm sensors, high-tech harvesters and drones, among others, has created a massive amount of data that might be difficult for decision-makers to grasp (Manos et al., 2004). Users, therefore, need additional tools for understanding and interpreting their data (Ruß et al., 2009a). Visualisation is a powerful technique to address these issues and has demonstrated its usefulness in PA (Wachowiak et al., 2017) to communicate uncertainty from both the data and the models (Frías et al., 2018). Visualisation techniques have been used to assist users to better interact and understand data by aggregating, filtering, searching or otherwise sifting through and scaling down relevant information. Moreover, visualisations are often explicitly designed to assist our visual system in handling detail that might otherwise require significant cognitive effort. For instance, visualisations provide information that

* Corresponding author.
E-mail addresses: francisco.gutierrez@cs.kuleuven.be (F. Gutiérrez), nyinyi.htun@kuleuven.be (N.N. Htun), florian.schlenz@geocledian.com (F. Schlenz), akasimati@aua.gr (A. Kasimati), katrien.verbert@cs.kuleuven.be (K. Verbert).
[1] Shared first authors.

https://doi.org/10.1016/j.compag.2019.05.053
Received 9 January 2019; Received in revised form 27 May 2019; Accepted 29 May 2019
Available online 21 June 2019
0168-1699/

can be easily perceived, recognised and processed into inferences. In this sense, visualisations also offer short-term or long-term memory aids to reduce memory and cognitive load. Such support can make data, including potentially complex information, more easily consumable. As Rind et al. (2013,) suggest, visualisation tools and techniques "*combine the processing power of modern computers with human cognition and visual abilities to better support analysis tasks*".

In line with participatory DSS development, visualisations can be especially practical and useful when following user-centred design approaches (Hertem et al., 2017). In fact, a number of qualitative PA studies highlighted the importance of using a participatory-design approach (Odom, 2010; Aragó Galindo et al., 2012a), where the farmer's perspective is used as the central focus of the design. A key goal of such an approach is to support complex data analysis by providing diverse visualisation techniques and adapting the tool according to the farmer needs (Stojanovic et al., 2017a).

A great number of visualisations and visual analytics tools have been proposed in the domain of agriculture with the aim to support the decision-making process. However, to the best of our knowledge, a comprehensive analysis of such tools, by considering their application areas, visualisation techniques and intended end-users, does not yet exist. Previous literature reviews in agriculture have focused on similar areas such as DSSs and PA, but not on visualisation techniques. For example, Kamilaris et al. (2017) presented a survey on the recent practices of big data analysis in agriculture that would help farmers and companies to extract value from data, improving their productivity. This survey highlighted the opportunities of big data analysis for smarter farming. A different systematic review (Le Gal et al., 2011) highlighted the methodologies that can be used to support farmers in designing innovative agricultural production systems. In the context of precision agriculture, Imam et al. (2015) reviewed design issues for wireless sensor networks and showed a comparison of different characteristics of humidity sensors, such as sensor type, their sensitivity and power consumption, which play a key role for wireless sensor networks for precision agriculture applications. As such, a number of reviews have addressed the issues surrounding DSSs and PA, but the use of visualisations in DSSs has yet to be understood.

To address this gap, in this paper, we review the use of information visualisation techniques in 61 articles that report their support for end-user decision-making. From an HCI (Human-Computer Interaction) perspective, we explore the design methodology behind the implementation of such systems and investigate the rationale behind the use of visual components in different application domains. HCI is a discipline in which users as well as technology and environment are emphasised in the design process (Saizmaa and Kim, 2008). For example, paying little attention to the environment could result in the DSS being unfit for the intended environment. A recent study (Rose et al., 2018) explored the reasons behind the lack of interest by farmers in the computer-based support systems and highlighted the importance of HCI perspectives when designing DSSs. The study also found clear benefits of designing a DSS that is easy to use, fits the existing workflow of users, performs well and incubate trust (Rose et al., 2018), which are some of the most commonly accessed metrics of HCI research. We had two specific goals in this review: our first goal was to examine user interaction with DSS for agriculture (i.e., input to the system, output from the system and other interface factors) in order to identify design features that go into the making of effective DSS. Our second goal was to gain insight into the evaluation of DSS, as well as to learn from these evaluations to identify opportunities for future research. To guide this work, we have defined our research questions as follows:

- RQ1: What visualisation techniques are being used across different domains in agriculture?
- RQ2: How are these visualisations being used by end-users to make decisions?
- RQ3: What is the role of uncertainty in the visualisation tools that support decision-making?
- RQ4: What is the role of HCI in the design and development of visualisation tools to support end-user decisions?

The contributions of this paper are the following: first, we present an extensive overview of visualisation and visual analytics techniques that have been elaborated in the agriculture field, highlighting the potential of DSSs and their use of visualisations for decision-making in agricultural contexts. Second, we present an analysis of a wide range of characteristics, including visualisation techniques that are commonly used, how data is captured and how these systems have been evaluated. Based on this analysis, we outline guidelines for the design of DSSs as well as directions for future research for this area.

2. Method

In this section, we first elaborate the method employed for the selection of articles/papers for our systematic review. We also define the different categories that were used for coding the existing tools.

2.1. Eligibility criteria

This review includes articles that investigated or reported the usage of DSSs involving visualisation techniques to support end-users in the field of agriculture. The eligibility criteria were specified according to the PICO framework (Table 1), stated in the preferred reporting items for systematic review and meta-analysis statement (Moher et al., 2009).

No restrictions were placed on the date. All the included papers were written in English. The population was targeted to all articles reporting end-users (i.e. farmers, policymakers or advisers) using any kind of decision tools, (i.e. demos, proof-of-concept tools, dashboards and simulations) in the agriculture domain and being supported by the use of any type of visualisation for decision-making. DSSs were included without restrictions on the platform of use (i.e. desktop, web-browser or mobile applications). Literature was included if they added a clear description of the DSS, stating the data input, collection and

Table 1
Overview of the search strategy, keywords identified and search-terms, based on the PICO framework.

PICO Ref.	*Inclusion criteria*	*Search Term*	*Keywords*
Population	Decision support tools with visualisation outputs to support farmers in decision-making scenarios	agriculture	agri∗, farm∗, urban agriculture, precision agriculture
		DSS	dss, decision support systems, whole-farm, simulation, tool, monitoring
		visualisation	visual∗, data, big data, algorithm, techniques, tools, data viz
		end-user	farm∗, advis∗, agro∗, policymaker, technician, analyst
Intervention	Not used		
Comparison	Not used		
Outcome	Guidelines for the design of visualisation in DSSs as well as directions of future research for this area.	design guidelines	design∗, ux, ui, user experience, user study, gui
Study	cross-sectional, prospective		

Table 2
Overview of the number of documents scouted from diverse database explorations.

database	*count*	*search query*
Google Scholar	(76)	agriculture farm user study tool UX UI design visualisation DSS "big data"
ScienceDirect		
Field Crops Research	(148)	{FilterBy: JournalName}, {Keywords: agri∗, farm∗, "urban agriculture", "precision agriculture", DSS, simulation, tool, monitoring, visual∗, data, "data viz", farm∗, advis∗, agro∗, design∗, ux, ui, "user experience", "user study"}
Agriculture, Ecosystems and Environment	(242)	
Agricultural and Forest Meteorology	(179)	
Advances in Agronomy	(123)	
Applied Soil Ecology	(274)	
Precision Agriculture	(43)	
Computers and Electronics in Agriculture	(476)	
IEEE Xplore		
	(484)	{SearchBy: FullTextAndMetadata} {Keywords: agri∗, farm∗, "precision agriculture", DSS, visual∗, data, tool, data viz, farm∗, advis∗, agro∗, design∗, ux, ui, "user experience", "user study"}
ACM Digital Library		
	(87)	{SearchBy: AnyField} {Keywords: agri∗, farm∗, "precision agriculture", DSS, visual∗, data, tool, data viz, farm∗, advis∗, agro∗, design∗, ux, ui, "user experience", "user study"}
Total:	(2132)	

outcome for any end-user involved in the agriculture domain (i.e. farmers, advisers, policymakers). Articles describing the use of visualisations in text or figures were included. Papers that reported the design process of the tool and user studies regarding visualisation techniques were included and analysed in detail separately.

2.2. Search strategy

A scoping exercise to nail down search keywords was conducted in the Google Scholar and ScienceDirect databases in May 2018. The keyword identification was complemented by using keyword services such as Google Keyword Planner and Keyword Tool. The produced keywords are presented in Table 1. Using the defined keywords, *hand searching* (i.e., a method of manually examining a paper to identify all eligible criteria (Higgins et al., 2005)) of relevant authors and articles was conducted in Google Scholar. As Google Scholar provides a broad result of papers, we used the advanced search functionality for initial searches and narrowed down the search using the specific keywords defined in the eligibility criteria section, and listed in Table 2. Journals in the agriculture domain were identified using ScimagoJR.[2] The search of papers within the identified journals was done in the ScienceDirect platform. Results from the search are presented in Table 2.

2.3. Literature selection

Results from each database were imported into Mendeley (n = 2132). Titles and abstracts were screened, excluding those who were not relevant to our research and/or did not meet the previously defined eligibility criteria. Afterwards, the remaining articles were retrieved and assessed for eligibility at full-text (n = 140). The process of paper selection is illustrated in Fig. 1. In summary, the search identified 2132 papers, from those, only 140 documents were retrieved and reviewed in full-text from this initial set based on our criteria. This narrowed the scope of this literature review to sixty-one articles.

2.4. Data extraction

Data from the included articles were coded and extracted in a spreadsheet designed for this review: https://goo.gl/SeJDdV. The 61 papers included in this review were coded based on the following main categories: end-user, tool type, development status, platform, the visualisation technique, data source, research domain and evaluation. At the beginning of this stage, an inter-coder reliability assessment was conducted between the researchers using Cohen's kappa (McHugh, 2012). A random selection with 20% of the papers was listed in a spreadsheet and coded following the defined coding categories and subcategories. The decisions made by the second researcher were compared against the first, generating Cohen's Kappa statistics. The statistics revealed a substantial agreement between the researchers, $k = 0.76$ (95% CI, 0.62 to 0.89), $p < 0.001$. Disagreements were discussed and resolved. Consistency in coding was kept throughout the remaining reviewed papers.

Categories and subcategories were identified based on our research questions and objectives, most of them emerged as common themes derived from the articles in this review, for all the categories we used both open and closed coding approaches (see Table 3 for an overview of the categories). In the following subsections, we briefly describe these categories.

2.4.1. End-users

Stakeholders are the main targets of DSSs in agriculture. In this review, we identified four types of stakeholders: farmers, domain experts (farm advisers or agronomists), academic researchers and policymakers (see Table 3). In this review, we used the end-user category to identify the types of visualisations that are targeted at specific types of stakeholders.

2.4.2. Tool type

Some DSSs are designed to provide a simulation approach where farmers can walk-through simulated farming scenarios to explore and better understand their practices (e.g. Dolinska, 2017). This approach can also help leverage learning of farmers. Unlike the simulation approach, there are DSSs that have been designed for practical applications in real farms. Such systems provide decision support solutions for a particular decision-making scenario (e.g. irrigation scheduling, fertiliser application, etc.). In addition, there are systems that provide farmers with necessary tools for the planning required for the whole farm. As such, we categorised the papers into three tool types based on their approach: simulation, real practice and whole-farm management.

2.4.3. Development status

DSSs are often evaluated at different stages of the development life circle. Thus, although certain papers present the systems that are currently being applied in real farms, there are others that are under development or at a concept stage. We used this category to identify the status of the application and understand the usage of visualisation at

[2] https://www.scimagojr.com/.

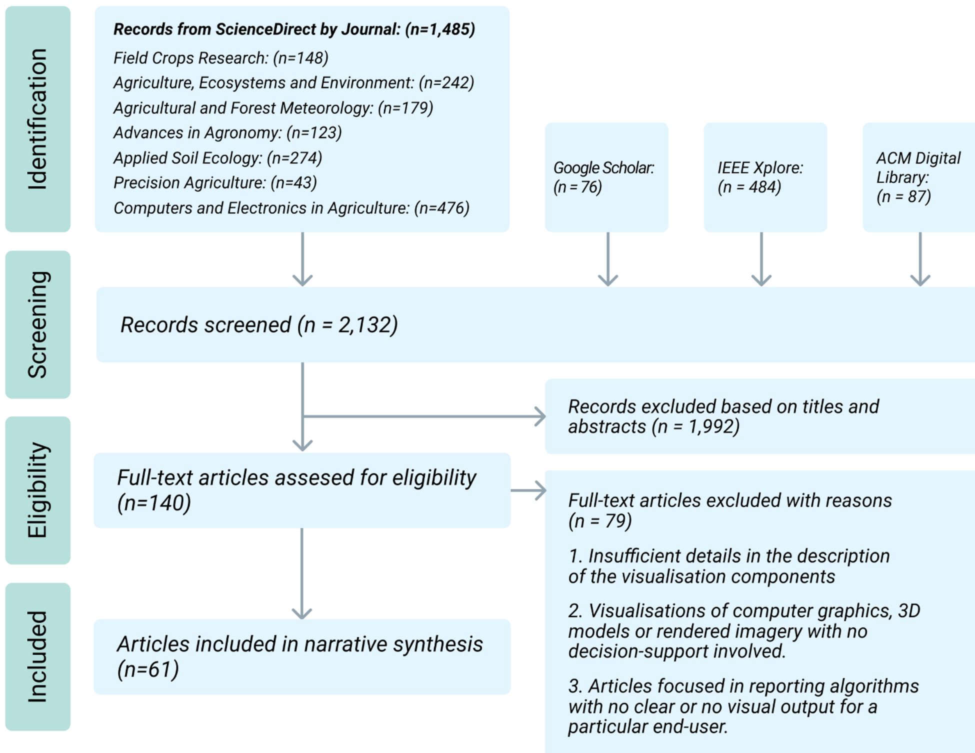

Fig. 1. Flow diagram illustrating the literature selection process.

Table 3
Definitions of categories and subcategories for data extraction.

category	*subcategory*	*short definition*
End-user	farmer	A farmer primarily engages in farming, can be a land owner or land manager
	domain expert	A farm adviser or agronomist concerned with guiding farmers and with the health and well-being of crops
	academic	An individual related to education and with research interests
	policymaker	Involved in the formulation of policies often working for the government (e.g. rural extension technicians)
Tool type	simulation	A system that simulates farming scenarios allowing users for self-reflection, exploration and discovery of new perspectives and scenarios
	real practice	Software that can be used in real farming practices for a particular decision-making scenario (e.g. irrigation scheduling, fertiliser application, etc.)
	whole-farm	A system that provides a holistic approach for farm management based on short and long-term vision of a farmer
Dev. status	concept	The tool is a proof-of-concept
	prototype	The tool is a working prototype
	production	The tool is available to use and accessed by many users
Platform	mobile	Intended to work in mobile devices
	desktop	Intended to work in desktop systems
Visualisation		The visual technique used to represent and communicate data
Data Source		Type of data collected and used by the tool
App. Domain		The application domain where the tool was used
Design approach	participatory	An approach that involves all stakeholders in the design process to satisfy requirements and usability
	focus group	A small group of people whose opinions are studied to discover their attitudes towards a product or service
	iterative	A design methodology based on a cyclic method of prototyping, developing and evaluating a product
Evaluation	observation	A study to understand user behaviour by observing user interactions with a system
	questionnaire	A method to gather feedback from users by administering a set of written questions
	interview	A method to gather feedback from users by verbally asking questions
	workshops	A method to gather feedback from a group of users

different levels. Subcategories include concept, prototype and production.

2.4.4. Platform

Since the scale of agricultural operations has increased over the years, DSSs are required to support on-the-fly access and in-field decision-making (Tan et al., 2012). Thus, many researchers have started looking into the use of different devices (i.e. desktop or mobile). The systems themselves and visualisation requirements can differ according to the platform. In this review, we identified the papers that are intended for mobile and/or desktop uses.

2.4.5. Visualisation techniques

One main goal of this review was to identify visualisation techniques that are proposed for agricultural decision support systems. Visualisation techniques may vary according to the needs of the users, application domain, visual literacy, etc. With this category, we identified an exhaustive list of visualisation techniques that are used to display agricultural data and predictions.

2.4.6. Data source

Outputs of DSSs are driven by data (Pham and Stack, 2018). The type of data collected and how they are utilised play an important role in providing optimal decisions and can vary depending on the decision-making requirements. Thus, we identified data sources of the selected DSSs.

2.4.7. Application domain

There are diverse sub-domains in agriculture, some of which include: wheat production, irrigation management, crop management, etc. Depending of the domain, decision requirements can also vary vastly. Since our initial analysis showed that DSSs have been proposed for many sub-domains of agriculture, we identified the application domain of each DSS.

2.4.8. Design approach

The design stage has been identified as one of the critical steps in the development of visualisation tools and agricultural DSSs (Parker and Sinclair, 2001). It also plays an important role in the adoption of the system (Lindblom et al., 2017). Thus, significant efforts have been put into applying user-centred approaches for developing DSSs (Parker, 1999). We categorised the selected DSSs based on the following user-centred design approaches: participatory, focus group and iterative. A brief definition for each of these categories has been provided in Table 3. It is important to note that the design approach generally defines a framework for evaluating a system. Various evaluation methods maybe used under a selected framework. These evaluation methods are described in Section 2.4.9.

2.4.9. Evaluation methods

Evaluation is an important part of the software development life circle as it ensures that all the requirements of the software are met. As mentioned in Section 2.4.8, different evaluation methods can be used under a selected design framework. Our initial analysis showed that a number of evaluation methods have been used by previous work in agriculture. Thus, we identified DSSs based on the following evaluation methods: observation, questionnaire, interview and workshop. A brief definitions for these categories can be found in Table 3. In general, user observations are conducted "in the wild" where users are typically allowed to explore a given tool freely. Interactions with the tool are observed and recorded. In certain cases, questionnaires may be administered to users who then provide written answers to a set of questions which can include both open- and close-ended questions. Unlike asking the questions verbally as in interviews, questionnaires demand less effort from the questioner and provide structured sets of answers. On the other hand, interviews involve delivering both questions and answers verbally. Interviews allow the questioner to capture in-depth feedback and to pose further questions which is not possible with the questionnaire approach. Workshops, unlike interviews, involve a group of users answering to a set of questions which are typically introduced by the questioner. Workshops create a great environment to capture rich opinions from users by allowing them to discuss the questions and come up with solutions.

3. Analysis

We analysed the selected papers based on the nine categories presented in Table 3 as explained above. An overview of the number of papers identified within each category is shown in Fig. 2. In the following subsections, results of our analysis are presented.

3.1. Application domain

In this section, we provide an overview of DSSs that have been elaborated in various application domains and demonstrate how they have been applied to assist with decision support tasks. Although many of the systems are grouped by their application domain, some fall under various domains, as illustrated in Fig. 3. Although this figure is by no means exhaustive, it provides insights into the typical cross-domain supports of current DSSs in agriculture. A complete list of DSSs under each application domain is presented in Table 4.

3.1.1. Viticulture

Visualisations in viticulture enable a better vineyard monitoring, reducing costs and at the same time, generating a more transparent representation of the existent variability in the vineyard, which is valuable for the optimisation of the harvest and producing high-quality grapes (Best et al., 2005). Rossi et al. (100 (2014)) is a DSS for crop management of vineyards (Fig. 4a). Using sensors, the system shows visual information about soil water content to help farmers monitor adequate water levels. Decision support modules provide information about vine growth, pest control and diseases in grape berries. The visualisation of real-time information supports farmers to make informed decisions and maintain a record behind each management action. Blauth and Ducati (2010) introduced a map visualisation of the land usage in vineyards (Fig. 4b). The system monitors grape variety, production and inventory information, using a map to indicate vineyards, vegetation, bare soil or nearby urban areas. Terribile et al. (2017) provides support to farmers at a landscape level (Fig. 4c) with an interactive dashboard that allows the selection and comparison of areas of interest together with multiple data layers on top of a map.

3.1.2. Dairy farming

According to an annual report published by United States Department of Agriculture,[3] feeding animals for dairy farming is one of the highest expenses for dairy producers across the states. In order to optimise productivity, dairy producers focus on formulating diets based on the growth rate, milk production and reproduction. Thus, DSSs have also become widely popular in dairy farming. Oliver et al. (2017) is a DSS that provides a visualisation of the agricultural land to manage microbial pollution risks (Fig. 5a). A participatory design approach was used to engage with stakeholders in order to create a user-friendly system for guiding on-farm risk assessment. The resulting tool visualises patterns of E. coli in space and time. Cabrera et al. (2005) is a DSS intended for producers and regulatory agencies. The main purpose of this tool is to integrate nutrient budgeting, crop and optimisation models to assess nitrogen leaching from dairy farm systems. The user interface of DyNoFlo Dairy provides a graphical representation of all system modules and their connections, allowing users to interact with different models in order to optimise nitrogen leaching and profit (Fig. 5b).

3.1.3. Wheat production

Wheat is grown on more land area than any other commercial crop and continues to be the most important food grain source for humans. Its production leads all crops, including rice, maize and potatoes. We found four tools (Armstrong and Nallan, 2016; Lorite et al., 2013; Thierry et al., 2017; Lundström and Lindblom, 2018) that visually support end-users in the wheat production domain. Armstrong and Nallan (2016) provides valuable information for Western Australian wheat growers, using diverse visualisation techniques to illustrate seasonal rainfall and yield production (Fig. 6a). AquaCrop (Lorite et al., 2013) provides simulation analysis towards the impact of climate change on wheat yield in Southern Spain by visualising yield and rainfall (Fig. 6b). ATLAS (Thierry et al., 2017) simulates crop availability at the landscape scale by visualising in 2D and 3D maps different crop scenarios in relation to pests, diseases and biological control (Fig. 6c). cropSAT (Lundström and Lindblom, 2018) is a DSS to visually analyse nitrogen fertilisation of winter wheat using satellite images: farmers can recognise and explain visualised variation in the crop biomass (Fig. 6d).

[3] https://www.ers.usda.gov/data-products/milk-cost-of-production-estimates/.

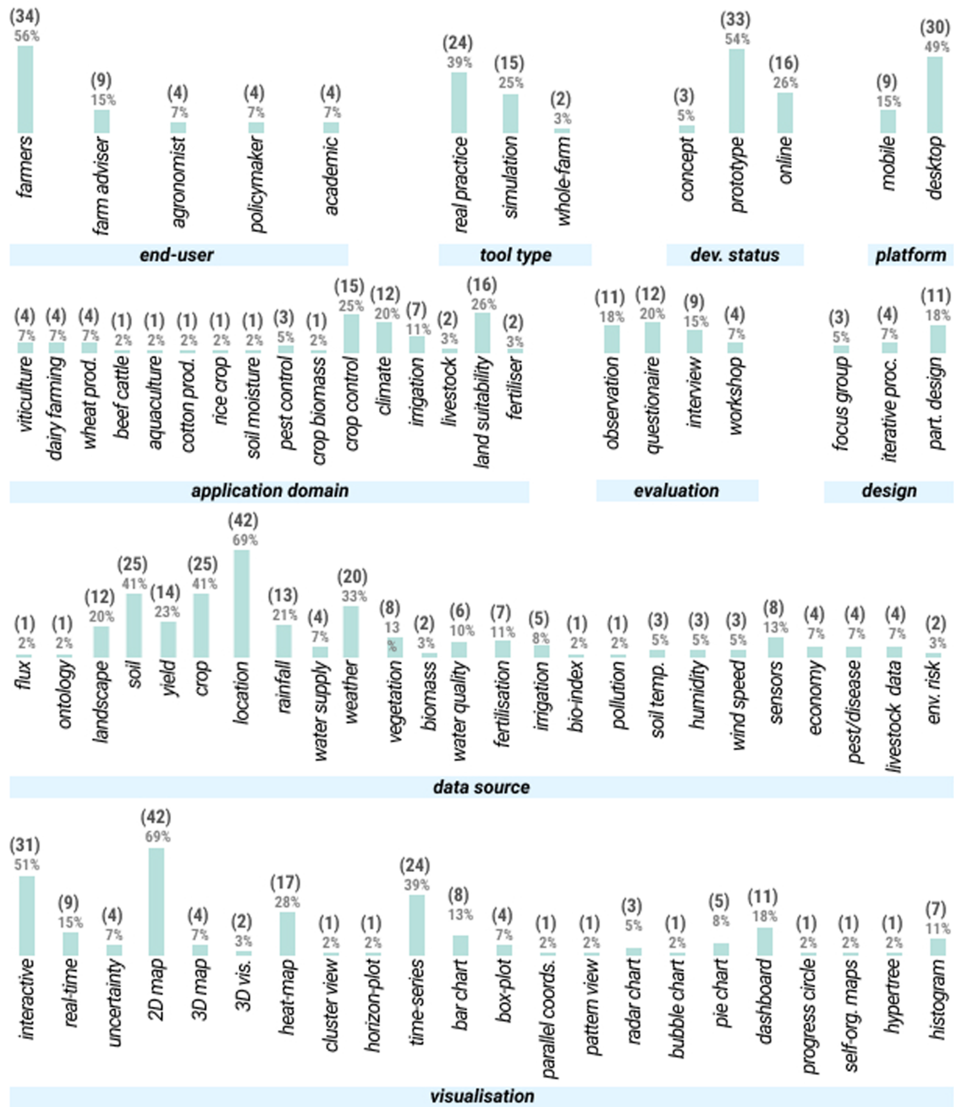

Fig. 2. Overview of the data extraction results by categories. The number of papers identified for each category is indicated between parenthesis.

3.1.4. *Pest and disease control*

Pest control is a vital process in the agricultural business, as pests and diseases can lead to important economic and ecological losses (del Águila et al., 2015). A number of DSSs have focused on providing support for farmers to identifying and treating (Rossi et al., 100 (2014); Rupnik et al., 2019) a particular pest (see Fig. 7). CognitiveInputs (Devitt et al., 2017) (Fig. 7a) is an interactive tool aimed for cotton growers that allows them to explore weed management decisions while considering uncertainties under climate conditions. Designed as an extension for existing farm management systems, AgroDSS (Fig. 7b) (Rupnik et al., 2019) uses data mining and statistical methods to make predictions for simulated scenarios and to better understand the dependencies within a domain. This includes identifying pest populations and species. AgroDSS uses time-series graphs to visualise such data. Vite.net (Fig. 7c) (Rossi et al., 100 (2014)) is a comprehensive farm management system that can also visually represent pest occurrences over the season. Time-series graphs are used to show in-depth information regarding a disease, an infection chain and/or infection severity. Further decision support is provided for treatment plans using a decision tree. In addition, a dashboard shows alert levels of a disease and protection of the last fungicide spray against diseases.

3.1.5. *Irrigation management*

Irrigation advisory services provide the farmers with assistance in

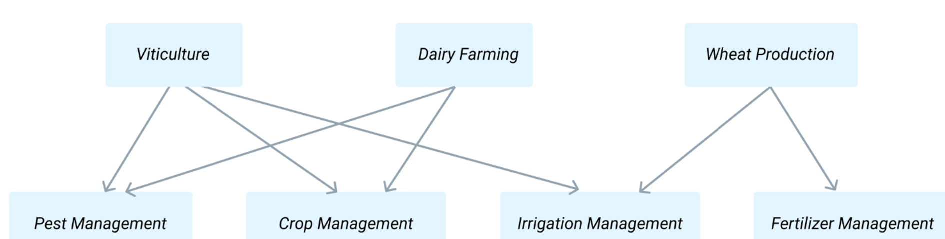

Fig. 3. Example application domains and cross-domain supports of DSSs.

Table 4
DSSs categorised by different application domains.

	viticulture	*dairy farming*	*wheat prod.*	*beef cattle*	*aquaculture*	*cotton prod.*	*rice crop*	*soil-moisture*	*pest control*	*crop biomass*	*crop control*	*climate*	*irrigation*	*livestock*	*land suitability*	*fertiliser*
AgMine Armstrong and Nallan (2016)			•								•	•				
AgriAG Stojanovic et al. (2017b)											•				•	
AgriSuit Yalew et al. (2016)															•	
AgroDSS Rupnik et al. (2019)									•							
AquaGIS Lorite et al. (2013)			•										•			
ATLAS Thierry et al. (2017)											•				•	
Blauth et al. Blauth and Ducati (2010)	•															
Byishimo et al. Byishimo and Garba (2016)													•			
CAMDT Han et al. (2017)												•				
CropGIS Machwitz et al. (2019)										•	•					
CropSAT Lundström and Lindblom (2018)			•													•
DIDAS Friedman et al. (2016)													•			
DyNoFlo Cabrera et al. (2005)		•										•				
Galindo et al. Aragó Galindo et al. (2012b)											•					
GeoVisage Jarvis et al. (2017)												•				
Geovit Terribile et al. (2017)	•															
GramyaVikas Adinarayana et al. (2008)															•	
HydroQual Accorsi et al. (2014)													•			
Li et al. Li et al. (2017)												•				
LMTool Falloon et al. (2018)												•			•	
Luvisi et al. Luvisi et al. (2011)	•															
mDSS Mysiak et al. (2005)													•			
SmartScape Tayyebi et al. (2016)											•				•	
VBoxReporting Bimonte et al. (2016)																
Vite.net Rossi et al. (100 (2014))	•								•							•
visualizeR Frías et al. (2018)												•				
ViPER Oliver et al. (2017)		•														
Ochola et al. Ochola and Kerkides (2004)															•	
Falcao et al. Falcao et al. (2006)															•	
LandCaRe DSS Wenkel et al. (2013)															•	
ValorE Acutis et al. (2014)														•		
Agroland Laudien et al. (2010)															•	
Gandhi et al. Gandhi et al. (2016)							•				•					
CaNaSTA O'Brien (2008)												•				
eFarmer Pettit et al. (2007)															•	
FARMERS Río et al. (2011)														•		
PlanteInfo Thysen and Detlefsen (2006)									•							
CropScape Han et al. (2012)															•	
SIMAGRI Han et al. (2019)												•				
FDSSFIS Yang et al. (2017)													•			
MOTIFS Meul et al. (2008)		•														
CarrotAge Le Ber et al. (2006)											•					
AgriSensor Kubicek et al. (2013)			•								•	•				
CognitiveInputs Devitt et al. (2017)						•			•							
Ruß et al. Ruß et al. (2009b)																
Tan et al. Tan et al. (2012)											•					
INT-VIS Gibbs et al. (2015)		•														

(*continued on next page*)

Table 4 (*continued*)

	viticulture	*dairy farming*	*wheat prod.*	*beef cattle*	*aquaculture*	*cotton prod.*	*rice crop*	*soil-moisture*	*pest control*	*crop biomass*	*crop control*	*climate*	*irrigation*	*livestock*	*land suitability*	*fertiliser*
Piplani et al. Piplani et al. (2015)					•											
HyperTree de Souza et al. (2003)				•												
iGreen Ebert et al. (2011)											•					
Munro et al. Munro et al. (1996)											•					
DEVA Reed et al. (2001)											•				•	
Zhong-Xiao Leng and Yimit (2009)													•			
Fegraus et al. Fegraus et al. (2012)															•	
LandEx Stepinski et al. (2014)															•	
RF-CLASS Zhang et al. (2013)											•					
FluxDataONE Yan et al. (2014)															•	
Mudisshu et al. Mudisshu et al. (2016)												•				
CLIMSAVE Savin (2015)												•				
Zheng et al. Zheng and Altamimi (2017)											•					
SMAP Hu et al. (2017)								•								
Num. Papers:	4	4	4	1	1	1	1	1	3	1	15	12	7	2	16	2
Percent (%):	7	7	7	2	2	2	2	2	5	2	25	20	11	3	26	3

irrigation scheduling knowledge, considering crop water conditions in different crops, optimising production and cost-effectiveness. Visualisations support farmers with a better overview of water distribution to their crops by showing moisture content, water uptake, etc. Such views allow farmers to adjust their irrigation process depending on the soil, farm area and season in order to optimise crop production. As an example, the tool designed by Byishimo and Garba (2016) uses real-time data collected from in-field sensors to produce live visualisations allowing farmers to monitor and process information about the soil, temperature and irrigation. Interaction is limited as users can only hover over the time-series visualisation to see annotations indicating details about the data over time (Fig. 8a). Another example is DIDAS (Friedman et al., 2016), a tool that allows to evaluate a farm based on a number of inputs such as soil, evaporation, plant resistance and land structure and assists with the design and scheduling of drip irrigation systems (Fig. 8b). By visualising water flow, DIDAS can assist farmers in taking decisions about irrigation schedules under conditions where water is a crucial limiting factor in crop productions. HydroQual (Accorsi et al., 2014) uses a dataset consisting of sequences of biological indices and physico-chemical values for geo-localised river stations and allows experts to visually analyse river water quality of different geographical areas (Fig. 8c).

3.1.6. *Crop management*

Crop production is deeply dependent on climate conditions, diseases and pests, making it essential to provide farmers with risk management technology. AquaGIS (Fig. 9a) (Lorite et al., 2013) is a visualisation tool that uses AquaCrop, a crop growth model, to simulate results of crop management in multiple fields and seasons. AquaGIS features visualisation modules that facilitate the presentation of spatial data. It allows an efficient visualisation in a map using different colours that facilitate spatial visualisation. An interactive component allows interaction between different maps that describe the evolution over time of the results provided by AquaCrop. AgMine (Fig. 9b) (Armstrong and Nallan, 2016) is a DSS that comprises multiple components of statistical analysis powered by visualisation modules. Visualisation is used in this tool as a powerful technique for geo-spatial analysis, climate and crop-yield mapping. With the proposed framework, farmers can use the visualisations to detect seasonal patterns of rainfall and see the effects on various scenarios comparing dry and wet years in crop production.

3.1.7. *Fertiliser management*

The aim of precision agriculture is to optimise farm outputs while preserving resources (McBratney et al., 2005b). Thus, fertiliser management plays an important role in precision agriculture. CropSAT (Fig. 10) (Lundström and Lindblom, 2018) is a tool developed for calculation of variable rate application files for nitrogen fertilisation from satellite images. The images generated in CropSAT show visual representations of crop biomass variation, which is difficult to achieve by just walking or driving in the field.

3.1.8. *Weather prediction and climate*

Weather forecast is a big challenge in the practical application of seasonal predictions in different economic sectors (Frías et al., 2018). Fortunately, interactive visualisation is well known for facilitating the analysis of probabilistic predictions under uncertainty (Spiegelhalter et al., 2011; Diehl et al., 2017), particularly towards non-expert users (Kay et al., 2016). An example tool, Geovisage (Jarvis et al., 2017), is a web-based decision support system designed for farmers that displays graphs of current sensor data from several weather stations. The tool visualises real-time data in a time-series plot offering a quick view of recent weather conditions where time periods and different weather stations are compared; a table provides extra details with statistical information (Fig. 11a). CAMDT (Fig. 11b) (Han et al., 2017) is another example that aims to facilitate probabilistic seasonal weather forecasts. The tool provides a user interface to help decision-makers adjust their

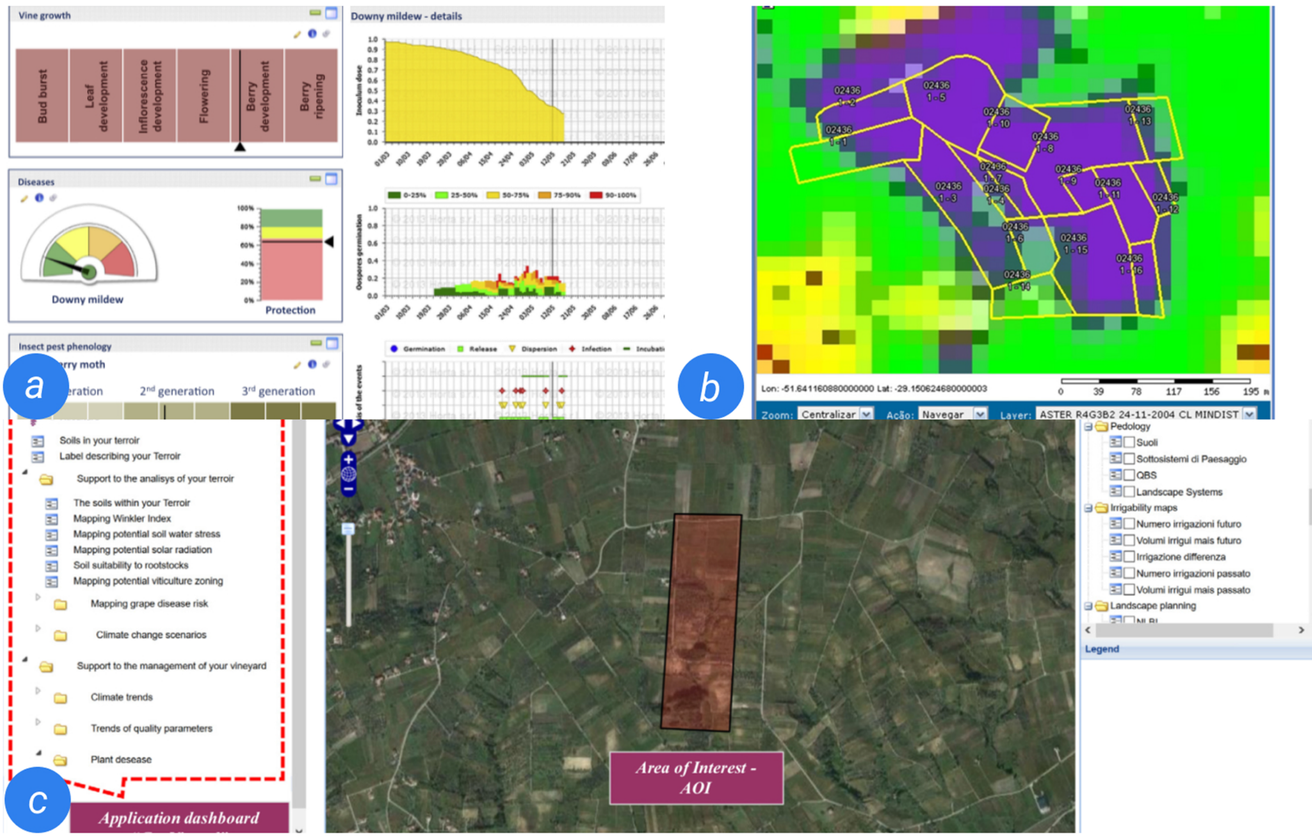

Fig. 4. The use of visualisation in the viticulture domain: (a) Vite.net (Rossi et al., 100 (2014)), (b) Blauth and Ducati (Blauth and Ducati, 2010), (c) Geovit (Terribile et al., 2017).

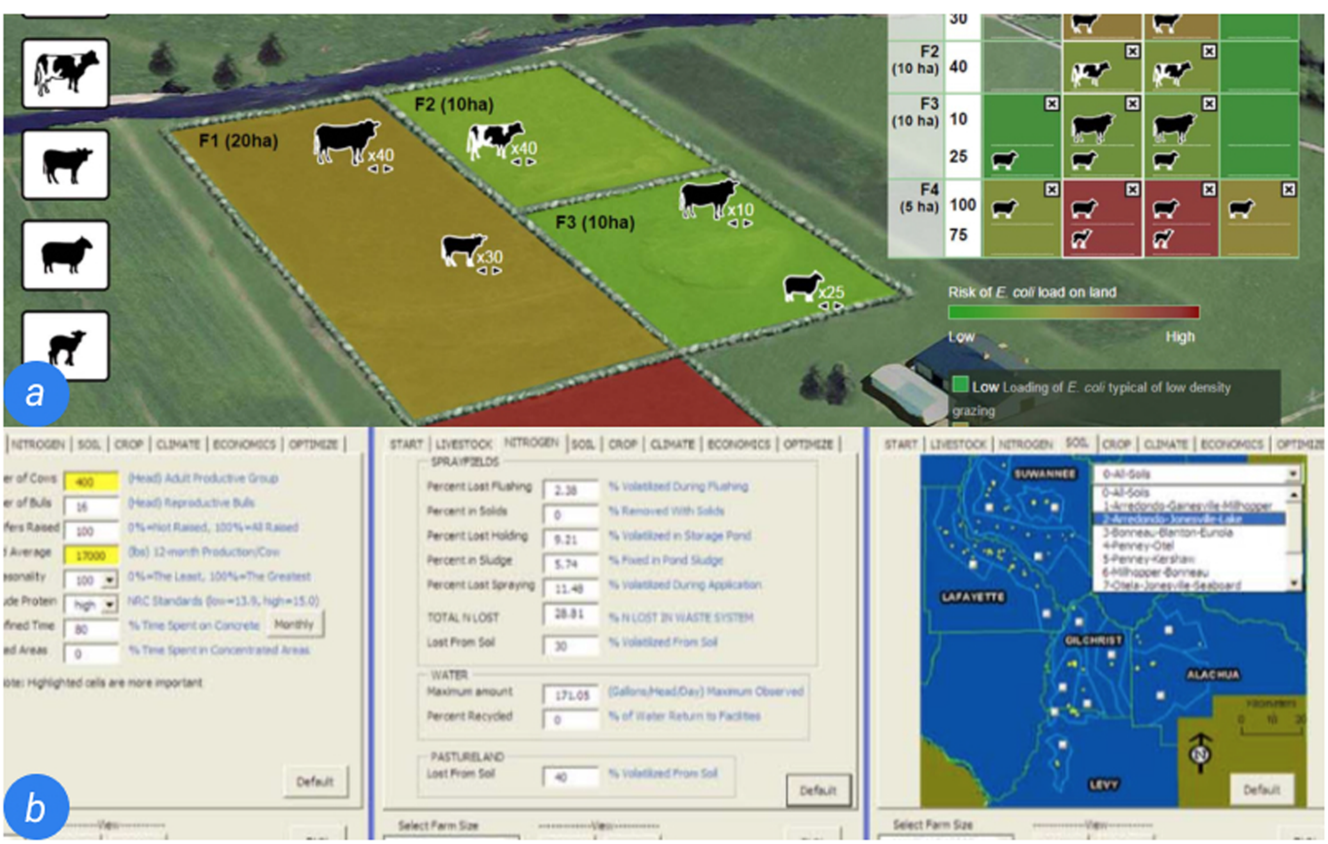

Fig. 5. The use of visualisation in dairy farming. (a) ViPER (Oliver et al., 2017), (b) DyNoFlo (Cabrera et al., 2005).

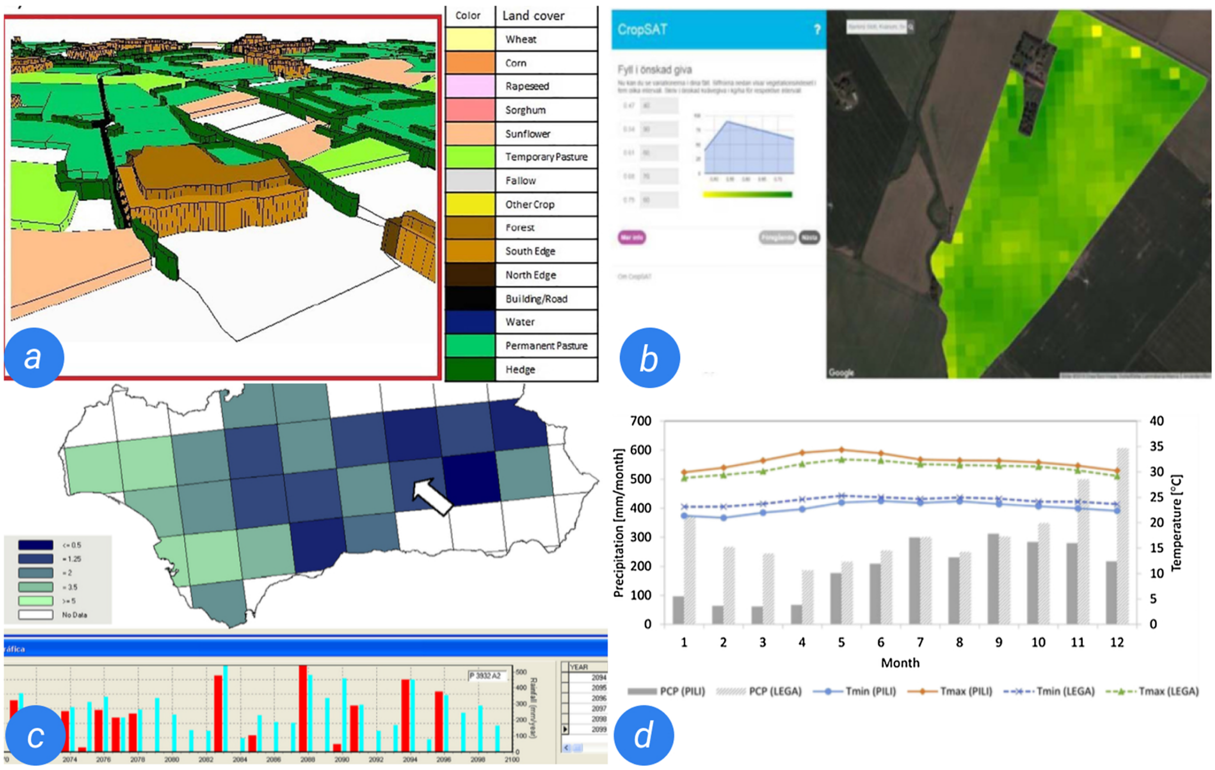

Fig. 6. The use of visualisation in wheat production (a) AgMine(Armstrong and Nallan, 2016), (b) AquaGIS/AquaCrop (Lorite et al., 2013), (c) ATLAS (Thierry et al., 2017), (d) cropSAT (Lundström and Lindblom, 2018).

Fig. 7. The use of visualisation in pest and disease control. (a) CognitiveInputs (Devitt et al., 2017), (b) AgroDSS (Rupnik et al., 2019), (c) Vite.net (Rossi et al., 100 (2014)).

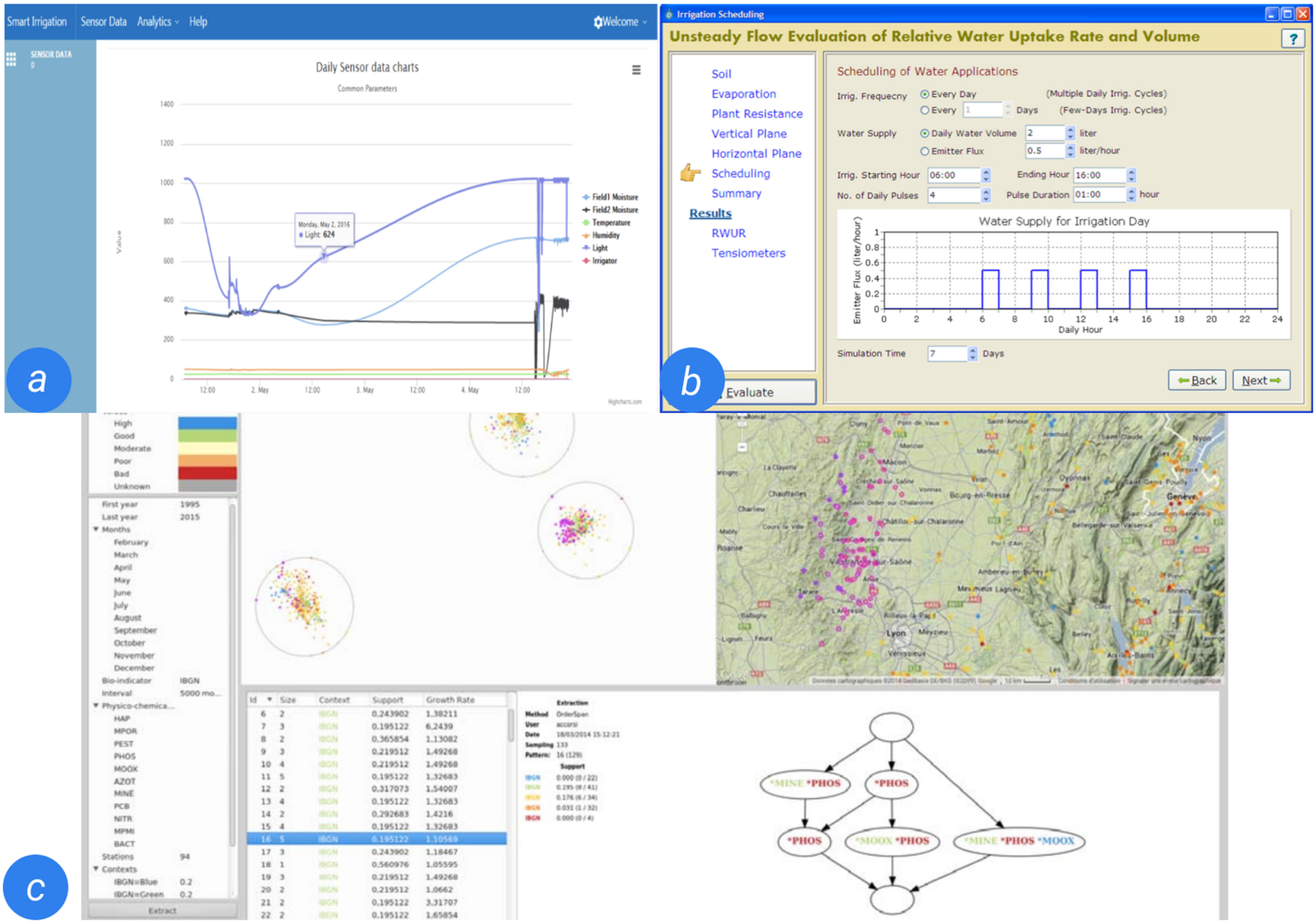

Fig. 8. The use of visualisation in irrigation management. (a) Byishimo and Garba (Byishimo and Garba, 2016), (b) DIDAS (Friedman et al., 2016), (c) HydroQual (Accorsi et al., 2014).

crop and water management practices that may improve outcomes given the expected weather condition of the growing season. It provides "what-if" scenarios where the forecast is presented for visual comparison.

3.2. End-users

While the majority of tools we reviewed are designed to support farmers, there are some that also support other end-users including domain experts (farm advisers and agronomists), policymakers and academic researchers. In this section, we present our findings of tools that have been designed to help different stakeholders in agriculture. A comprehensive list of these tools is presented in Table 5.

3.2.1. Farmers

We discovered that a large number of tools in agriculture (34 out of 61) are designed for farmers. These tools focus on assisting farmers with various aspects of farming. The majority of the tools used one or more visualisation techniques to help the farmers better understand the status of their farm and crops and to be able to make accurate decisions regarding irrigation schedules (Fig. 8), fertiliser applications (Fig. 10), pest control (Fig. 7), etc. Details of individual visualisation techniques found in each of these tools are presented in Section 3.3.

3.2.2. Policymakers

We found a total of four tools (Tayyebi et al., 2016; Gandhi et al., 2016; Río et al., 2011; de Souza et al., 2003) that are designed to be used by policymakers. Policymakers, such as rural extension technicians, use DSSs to facilitate the evaluation of consequences of changes in agriculture, such as crop affectations in landscapes. For instance, SmartScape (Tayyebi et al., 2016) provides diverse visual components, such as maps and radar charts, to provide assistance to policymakers in evaluating the consequences of ecosystem services in agriculture landscapes (see Fig. 12). In addition, some tools (e.g. de Souza et al., 2003) are designed to help with information dissemination, allowing policymakers to exchange knowledge back and forth with farmers.

3.2.3. Domain experts

Farm advisers, including agronomists, are considered domain experts who are often consulted by farmers, as well as by researchers for designing DSSs (Adinarayana et al., 2008; Accorsi et al., 2014; de Souza et al., 2003). They also assist policymakers to implement farming policies and in changing farmer behaviour (Ingram, 2008).

Farm advisers typically assess the farms by using varieties of statistical models and analysis methods, evaluating the risks of different management scenarios and finally propose strategies/guidelines for farmers. Thus, the tools designed for both farm adviser and farmers are typically capable of conducting analyses and simulations, as well as visualising the resulting guidelines for farmers (Fig. 8c). There are nine tools (Han et al., 2017; Lorite et al., 2013; Yalew et al., 2016; Aragó Galindo et al., 2012b; Rossi et al., 100 (2014); Oliver et al., 2017; Acutis et al., 2014; Thysen and Detlefsen, 2006; Han et al., 2019) that have been designed to support farm advisers.

Agronomists, amongst all domain experts, are known for establishing good communication with farmers due to regular on-site meetings, local knowledge and long-term relationships with farmers (Ingram, 2008). Agronomists tend to provide practical farming decisions that are more likely to coincide with those of farmers, instead of

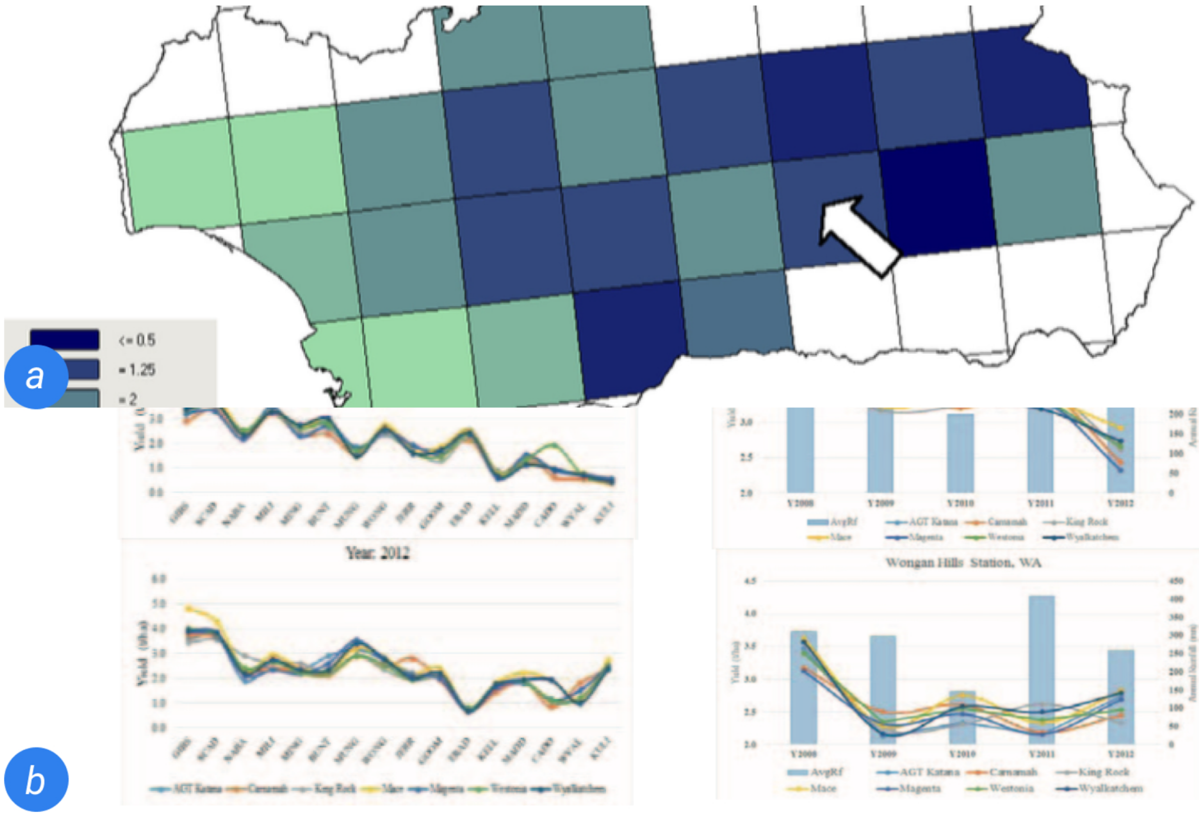

Fig. 9. The use of visualisation to support crop management. (a) AquaGIS (Lorite et al., 2013) (b) AgMine (Armstrong and Nallan, 2016).

urging new initiatives or regulations as some advisers do (Ingram, 2008). In this review, we found a total of four tools (Stojanovic et al., 2017b; Han et al., 2017; Le Ber et al., 2006; Devitt et al., 2017) that have been designed to support agronomists.

3.2.4. Academics

We found four tools (Stojanovic et al., 2017b; Ochola and Kerkides, 2004; Gandhi et al., 2016; Tan et al., 2012) that have been designed for academics. AgriAG (Stojanovic et al., 2017b) was developed with the aid of academics that provided feedback to the elaboration of the tool. Mostly, these applications (Tan et al., 2012; Gandhi et al., 2016) are used by academic researchers to explore new technologies to support agricultural decision-making.

3.3. Visualisation techniques

Through this review, we found a number of visualisation techniques currently being used in DSSs for agriculture. Table 6 shows an exhaustive list of different visualisation techniques that are found in the papers we reviewed. In the following subsections, we present the ten most common visualisation techniques.

3.3.1. Map

Maps are overwhelmingly used in agriculture to visually communicate geo-spatial data, providing an overview of the farms. In total, our review identified 46 papers (i.e. 75%) that used a type of map visualisation (see Table 6 for details). As seen in Fig. 13, both 2D and 3D map

Fig. 10. CropSAT (Lundström and Lindblom, 2018), an example of visualisation in fertiliser management.

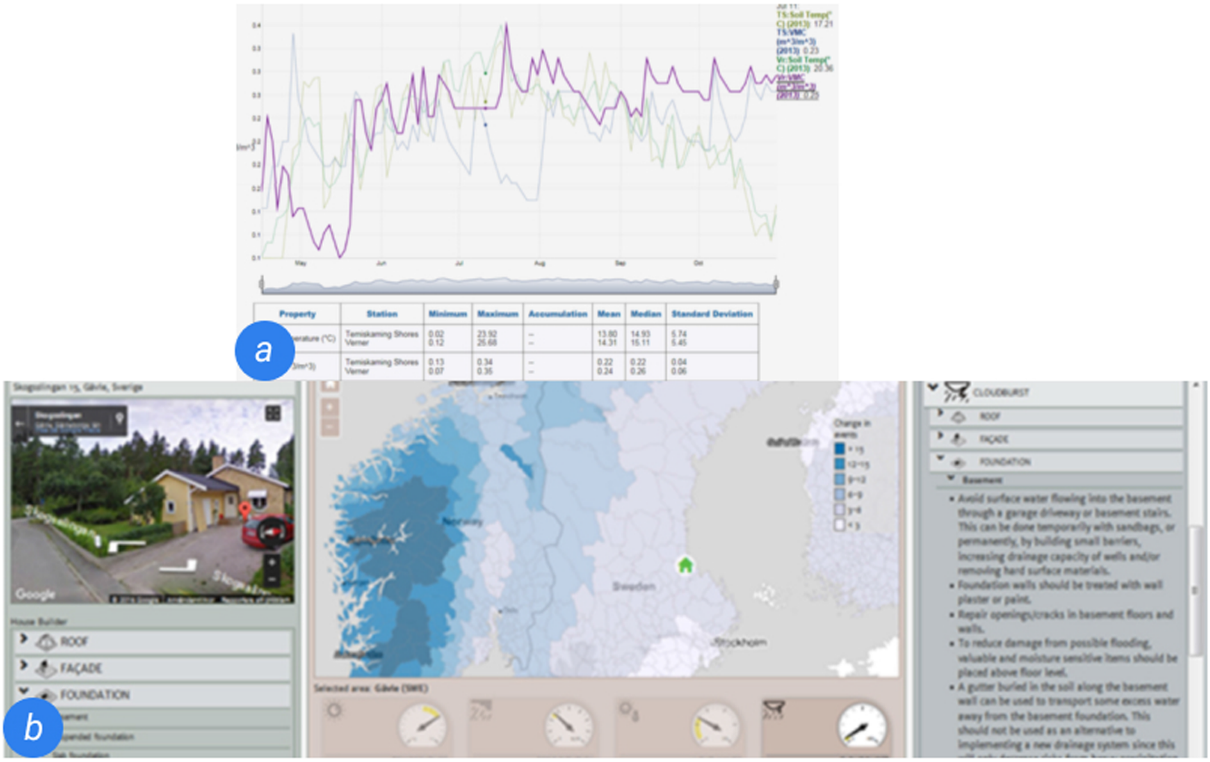

Fig. 11. The use of visualisation in weather forecast. (a) Geovisage (Jarvis et al., 2017), (b) CAMDT (Han et al., 2017).

visualisations have been proposed to represent physical landscapes. Out of the 46 papers, a large proportion (i.e. 42 papers) have implemented 2D maps. Examples include ViPER (Oliver et al., 2017) (Fig. 13a) and AQUAGIS (Lorite et al., 2013) (Fig. 13b), where plots of physical landscapes are virtually displayed on a 2D map. Example usage of 3D maps includes AgriAG (Stojanovic et al., 2017b) (Fig. 13c) and ATLAS (Thierry et al., 2017) (Fig. 13d). Both 2D and 3D maps are often layered with various colour representations, such as a heatmap to further visualise areas of interest in the farm.

3.3.2. Heatmap

Heatmaps represent data values contained in an area of interest using a colour range. Since heatmap visualisations generally highlight areas of interest, they are often used as an overlay on top of geographical maps. Heatmaps are for instance used to represent the Normalised Difference Vegetation Index (NDVI) to indicate the density of green on a patch of land. Other types of data visualised with heatmaps include biomass, weather, water density, risk of flooding, etc. We found a total of 17 tools that used heatmaps to visualise regions of interest across landscapes (see Table 6). CropSAT (Lundström and Lindblom, 2018), for example, uses heatmaps to indicate biomass in a patch of farm using satellite-based images (see Fig. 10). Another example is the vineyard management tool designed by Blauth and Ducati (2010) (see Fig. 4b) that uses a heatmap to differentiate vineyards from other vegetation, bare soil and urban areas. CAMDT (Han et al., 2017), as shown in Fig. 11b, uses heatmaps to indicate areas of land that are at the risk of flooding.

3.3.3. Time-series

Time-series visualisations are used to show a distributions of data points that are ordered by time. They are similar to line graphs in that they present two dimensional data where a sequence of time (e.g. months) is usually plotted on the x-axis. Due to their simplicity and effectiveness in presenting data points through time, time-series are commonly seen in agricultural tools. We found a total of 24 tools (see Table 6) that used time-series to visualise various farm data. An example is CropGIS (Machwitz et al., 2019) which displays the biomass growth of a farm over time (see Fig. 10). In a similar way, DIDAS (Friedman et al., 2016) shows relative water uptake using time-series (see Fig. 8b). Other example applications include AgMine (Armstrong and Nallan, 2016), visualising wheat yield and rainfall patterns, and LMTooln (Falloon et al., 2018), visualising temperature, precipitation and wind speed.

3.3.4. Bar chart

Bar charts present bars clustered in groups, showing the values of more than one measured variable. One axis of bar charts shows the specific categories being compared and the other axis represents a measured value. We found a total of eight tools (see Table 6) that used bar charts to present data. We also discovered that, in agriculture, bar charts are commonly used in combinations with other types of visualisations. For instance, AgMine (Armstrong and Nallan, 2016) (Fig. 9b) uses bar charts with time-series to show average wheat yield between years. Similarly, DIDAS (Friedman et al., 2016) (Fig. 8b) shows water supply scheduling for irrigation over a 24-h period. AgriSuit (Yalew et al., 2016) (Fig. 14c) uses a heatmap and bar chart together to present the distribution of suitable agricultural lands in an area of interest.

3.3.5. Histogram

Histograms are used to represent an estimate of the probability distribution of a continuous variable (Pearson, 1895). It differs from a bar chart in the sense that a bar graph represents categorical variables, whereas in a histogram each column/bar represents a continuous quantitative variable. We found seven tools that used histograms to present farm-related data. SmartScape (Tayyebi et al., 2016) (Fig. 12) uses a histogram to illustrate simulation results of various crop change scenarios. The results illustrated include changes in vital soil chemical contents, bird habitat, biofuel, pollinators, net income and net energy. In AquaGIS (Lorite et al., 2013) (Fig. 6c), histogram is used to illustrate a comparison between crop yield and rainfall over time.

Table 5
Types of end-users reported in the different DSSs.

	farmer	*farm adviser*	*agronomist*	*policymaker*	*academic*
AgMine Armstrong and Nallan (2016)	•				
AgriAG Stojanovic et al. (2017b)	•		•		•
AgriSuit Yalew et al. (2016)		•			
AgroDSS Rupnik et al. (2019)	•				
AquaGIS Lorite et al. (2013)	•				
Blauth et al. Blauth and Ducati (2010)	•				
Byishimo et al. Byishimo and Garba (2016)	•				
CAMDT Han et al. (2017)	•	•	•		
CropGIS Machwitz et al. (2019)	•				
CropSAT Lundström and Lindblom (2018)	•				
DIDAS Friedman et al. (2016)	•				
DyNoFlo Dairy Cabrera et al. (2005)	•				
Galindo et al. Aragó Galindo et al. (2012b)	•	•			
GeoVisage Jarvis et al. (2017)	•				
Geovit Terribile et al. (2017)	•				
GramyaVikas Adinarayana et al. (2008)					
HydroQual Accorsi et al. (2014)					
Li et al. Li et al. (2017)	•				
LMTool Falloon et al. (2018)	•				
SmartScape Tayyebi et al. (2016)				•	
VBoxReporting Bimonte et al. (2016)	•				
Vite.net Rossi et al. (100 (2014))		•			
ViPER Oliver et al. (2017)		•			
Ochola et al. Ochola and Kerkides (2004)	•				•
LandCaRe Wenkel et al. (2013)	•				
ValorE Acutis et al. (2014)	•	•			
Gandhi et al. Gandhi et al. (2016)	•			•	•
eFarmer Pettit et al. (2007)	•				
FARMERS Río et al. (2011)	•			•	
Pl@nteInfo® Thysen and Detlefsen (2006)	•	•			
SIMAGRI Han et al. (2019)	•	•			
MOTIFS Meul et al. (2008)	•				
CarrotAge Le Ber et al. (2006)			•		
AgriSensor Kubicek et al. (2013)	•				
CognitiveInputs Devitt et al. (2017)	•		•		
Ruß et al. Ruß et al. (2009b)	•				
Tan et al. Tan et al. (2012)	•				•
INT-VIS Gibbs et al. (2015)	•				
Piplani et al. Piplani et al. (2015)	•				
HyperTree de Souza et al. (2003)	•			•	
Munro et al. Munro et al. (1996)					
Mudisshu et al. Mudisshu et al. (2016)	•				
Zheng et al. Zheng and Altamimi (2017)	•				
Num. Papers:	34	9	4	4	4
Percent (%):	56	15	7	7	7

3.3.6. Pie chart

A pie chart is a circular visualisation which is divided into slices with different colours to illustrate a numerical proportion. Much like bar charts, pie charts are used to visualise a distribution between categories of data. However, compared to bar charts, pie charts are less popular in agriculture. We found a total of five tools that used pie charts to visualise farm data. The VBoxReporting system (Bimonte et al., 2016) is an example of usage of the pie chart in agriculture. This tool uses pie charts to illustrate a comparison of work time and fuel consumption in a day between different plots.

3.3.7. Radar chart

Radar charts are frequently used to visualise multivariate data in the form of a two-dimensional chart. Thus, they can be used when three or more variables are present. In agriculture, however, radar charts are less common. In this review, we discovered three tools that uses radar charts. SmartScape (Tayyebi et al., 2016) (Fig. 12) is an example tool that uses a radar chart to illustrate environmental outcomes between current and hypothetical crop change scenarios. The outcomes include vital soil chemical contents, bird habitat, biofuel, pollinators, net income and net energy. As presented in Section 3.3.5, SmartScape (Tayyebi et al., 2016) also uses a histogram to illustrate such outcomes in two different ways.

3.3.8. Clustering

A clustering view shows clusters of similar information organised by colours and shapes. While clustering is a commonly used prediction technique, the visualisation of these clusters for interpretation by end-users is quite uncommon: we found only one tool, HydroQual (Accorsi et al., 2014), that offers such a view. In HydroQual, water stations across a map are illustrated in groups by their behavioural similarity (see Fig. 8c).

3.3.9. Temporal pattern view

Also in HydroQual (Accorsi et al., 2014) (Fig. 8c), a “temporal pattern view” is described, which is essentially a variation of a node-link diagram. It is used to illustrate patterns of changes in biological indices and physico-chemical parameters over time. In this review, we found the use of such a temporal pattern view, or node-link diagram, only in HydroQual.

3.3.10. Dashboards

Dashboards are a collection of visualisations that provide relevant information to be monitored on a single screen at a glance (Few, 2006).

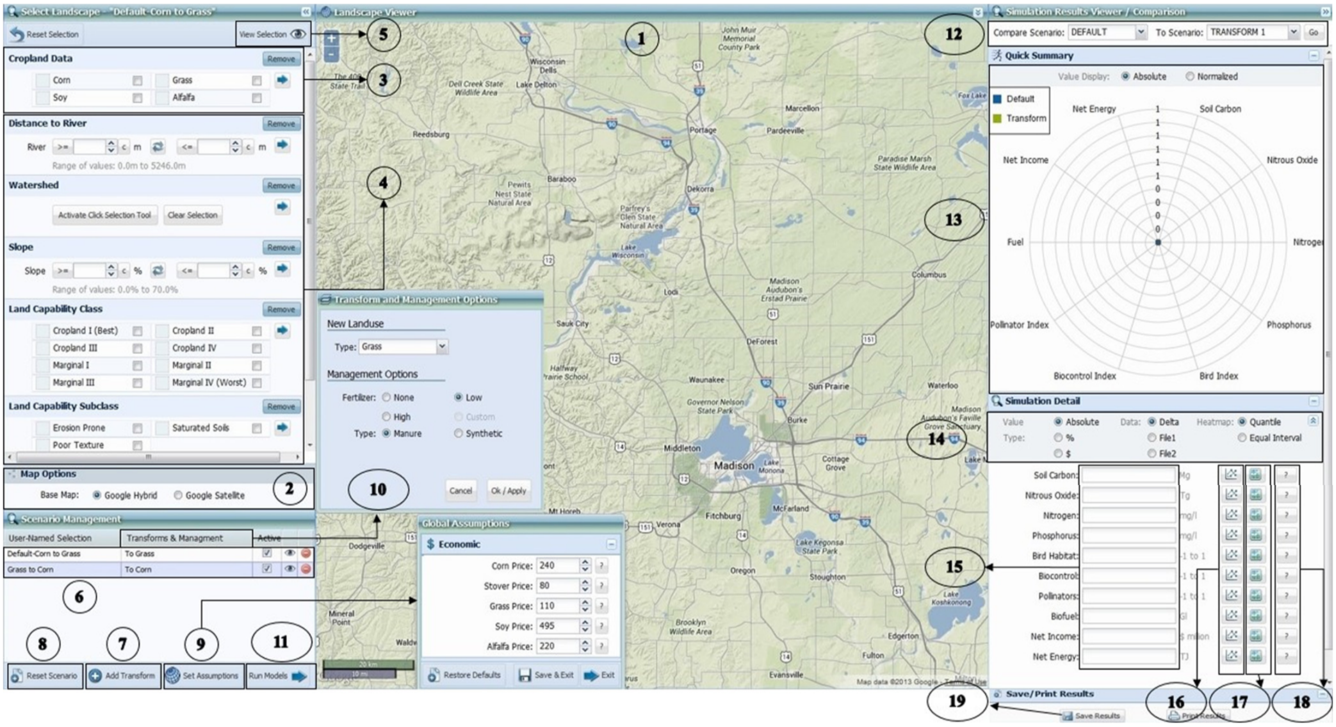

Fig. 12. User interface of SmartScape (Tayyebi et al., 2016), a tool to support policymakers.

They provide an easy access to diverse visual components to display detailed data, providing a unified display to the decision-maker for interaction and exploration (Saket et al., 2019). In this review, we identified 11 tools that use a dashboard. Fig. 14 illustrates example applications of dashboards in DSSs for agriculture. Notice how all five examples in this figure have a main interface from which various other visualisations can be accessed. For instance, Geovit (Terribile et al., 2017) (Fig. 14a), a dashboard designed for viticulture, provides diverse interactive components surrounding a heatmap, allowing instant access to various different features. Similarly, SmartScape (Tayyebi et al., 2016) (Fig. 14b), a spatial decision support system, uses a map together with a radar chart, histograms and various diverse interactive components. AgriSuit (Yalew et al., 2016) (Fig. 14c), tool for agricultural land suitability assessment, also uses a map which is augmented by heatmap and bar chart visualisations, surrounded by various interaction elements. HydroQual (Accorsi et al., 2014) (Fig. 14e), tool for visual analysis of river water quality, uses a clustering view together with a map and a pattern view. A vineyards management system, Vite.net (Rossi et al., 100 (2014)) (Fig. 14d), unlike the previous dashboards, does not use a map but rather a unique combination of progress bars, time-series, barometer, colour shades and decision tree.

We discovered that dashboards in agriculture are substantially used in farm management and landscape assessment tasks, with some tools (e.g. HydroQual Accorsi et al., 2014) designed for the analysis of river water quality. It appears that the primary goal of dashboards is to show an overview map to users, which is logical given that landscape is an important part of farm management. As shown in Table 6, the majority of the tools that have a dashboard (9 out of 11) use 2D maps to provide an overview of the landscape. A few other familiar visualisations used in the dashboards include heatmaps (6 tools), time-series (5 tools), a bar chart (2 tools), a histogram (1 tool), a radar chart (1 tool) and a pie chart (1 tool). We discovered that a few unique visualisations such as a cluster view, horizontal plots and a pattern view have also been used as part of a dashboard. Since dashboards are designed to provide a unified display to the decision-maker (Saket et al., 2019), we believe that the use of familiar visualisations is an important aspect of dashboards, especially because most end-users in agriculture are non-experts in visualisation and data analytics.

Overall, the 11 tools that have a dashboard covered the following application domains: land suitability assessment, crop biomass analysis, crop control, wheat production, fertiliser management, pest control, dairy farming and vineyard management. For the other domains such as livestock management, aquaculture analysis, cotton production, rice production and soil-moisture analysis (see Table 4), various visualisation tools exist but a dashboard has yet to be introduced. We believe that many of such domains can also greatly benefit from a dashboard. Based on an analysis of various aspects of these dashboards, we highlight opportunities for future research in Section 4.

3.4. Interaction

Interaction is an important aspect of visualisation tools since perception and understanding of complex data can be strongly influenced by the interactivity of a visualisation component (Zudilova-Seinstra et al., 2009). The benefits of visualising complex data arise from being able to better interact and understand data by aggregating, filtering, searching or scaling down relevant information. Examples of interactive visualisation components can be found in various agricultural DSSs.

Thirty-one of the reviewed papers reported the use of interactive visualisations in their tools (see Table 6). Many of the reported interactive visualisations are included in dashboards, where visualisation components interact together to provide insights to user. ViPER (Oliver et al., 2017) is an example tool that provides an interactive drag-and-drop interface where users can explore livestock and examine "what-if?" scenarios. Moreover, AgriSuit (Yalew et al., 2016) provides an interface to allow a customised selection of weights based on user preferences to achieve better insights. Geovit (Terribile et al., 2017), provides an interactive dashboard that allows the selection of areas of interest: based on this selection, users can explore information about soil, climate and hydrology in real-time.

3.5. Tool type, platform and development status

All 61 papers of this review present one or more visualisations

Table 6
Visualisation techniques categorised among the tools reviewed.

	interactive	real-time	uncertainty	2D map	3D map	3D vis.	heatmap	cluster view	horizon-plots	time-series	bar chart
AgMine Armstrong and Nallan (2016)							•			•	
AgriAG Stojanovic et al. (2017b)	•	•		•	•		•				
AgriSuit Yalew et al. (2016)	•	•		•			•				•
AgroDSS Rupnik et al. (2019)	•									•	
AquaGIS Lorite et al. (2013)	•			•			•			•	•
ATLAS Thierry et al. (2017)					•						
Blauth et al. Blauth and Ducati (2010)	•			•			•				
Byishimo et al. Byishimo and Garba (2016)	•									•	
CAMDT Han et al. (2017)										•	
CropGIS Machwitz et al. (2019)	•		•	•			•			•	
CropSAT Lundström and Lindblom (2018)	•			•			•			•	
DIDAS Friedman et al. (2016)										•	
DyNoFlo Cabrera et al. (2005)				•							
Galindo et al. Aragó Galindo et al. (2012b)				•							
GeoVisage Jarvis et al. (2017)	•	•							•	•	
Geovit Terribile et al. (2017)	•	•		•			•				
GramyaVikas Adinarayana et al. (2008)	•			•							
HydroQual Accorsi et al. (2014)	•	•		•				•			
Li et al. Li et al. (2017)				•			•			•	
LMTool Falloon et al. (2018)	•			•						•	
Luvisi et al. Luvisi et al. (2011)	•			•							
mDSS Mysiak et al. (2005)	•			•			•				
SmartScape Tayyebi et al. (2016)	•			•							
VBoxReporting Bimonte et al. (2016)	•			•						•	
Vite.net Rossi et al. (100 (2014))	•	•								•	•
visualizeR Frías et al. (2018)			•	•							
ViPER Oliver et al. (2017)	•			•			•				
Ochola et al. Ochola and Kerkides (2004)	•			•			•				
Falcao et al. Falcao et al. (2006)	•	•			•						
LandCaRe Wenkel et al. (2013)	•			•							
ValorE Acutis et al. (2014)	•			•							
Agroland Laudien et al. (2010)	•			•			•				
Gandhi et al. Gandhi et al. (2016)				•						•	
CaNaSTA O'Brien (2008)			•	•							
eFarmer Pettit et al. (2007)	•			•	•						
FARMERS Río et al. (2011)	•			•							
PlanteInfo Thysen and Detlefsen (2006)		•		•						•	
CropScape Han et al. (2012)	•			•							•
SIMAGRI Han et al. (2019)										•	
FDSSFIS Yang et al. (2017)										•	•
MOTIFS Meul et al. (2008)											
CarrotAge Le Ber et al. (2006)											
AgriSensor Kubicek et al. (2013)	•	•		•						•	•
CognitiveInputs Devitt et al. (2017)	•		•								•
Ruß et al. Ruß et al. (2009b)											
Tan et al. Tan et al. (2012)	•			•		•					
INT-VIS Gibbs et al. (2015)	•									•	
Piplani et al. Piplani et al. (2015)				•						•	
HyperTree de Souza et al. (2003)											
iGreen Ebert et al. (2011)				•							
Munro et al. Munro et al. (1996)				•		•					
DEVA Reed et al. (2001)				•						•	
Zhong-Xiao Leng and Yimit (2009)				•							
Fegraus et al. Fegraus et al. (2012)				•			•				

(continued on next page)

Table 6 (*continued*)

	interactive	*real-time*	*uncertainty*	*2D map*	*3D map*	*3D vis.*	*heatmap*	*cluster view*	*horizon-plots*	*time-series*	*bar chart*
LandEx Stepinski et al. (2014)				•			•				
RF-CLASS Zhang et al. (2013)				•			•			•	
FluxDataONE Yan et al. (2014)				•						•	
Mudisshu et al. Mudisshu et al. (2016)										•	
CLIMSAVE Savin (2015)				•							
Zheng et al. Zheng and Altamimi (2017)											•
SMAP Hu et al. (2017)				•			•				
Num. Papers:	31	9	4	42	4	2	17	1	1	24	8
Percent (%):	51	15	7	69	7	3	28	2	2	39	13
	box-plot	*parallel coords.*	*pattern view*	*radar chart*	*bubble chart*	*pie chart*	*dashboard*	*progress circle*	*self-org. maps*	*hypertree*	*histogram*
AgMine Armstrong and Nallan (2016)											•
AgriAG Stojanovic et al. (2017b)											
AgriSuit Yalew et al. (2016)							•				
AgroDSS Rupnik et al. (2019)	•										
AquaGIS Lorite et al. (2013)											
ATLAS Thierry et al. (2017)											
Blauth et al. Blauth and Ducati (2010)											
Byishimo et al. Byishimo and Garba (2016)											
CAMDT Han et al. (2017)	•										
CropGIS Machwitz et al. (2019)							•				
CropSAT Lundström and Lindblom (2018)							•				
DIDAS Friedman et al. (2016)											
DyNoFlo Cabrera et al. (2005)											
Galindo et al. Aragó Galindo et al. (2012b)											
GeoVisage Jarvis et al. (2017)							•				
Geovit Terribile et al. (2017)							•				
GramyaVikas Adinarayana et al. (2008)											
HydroQual Accorsi et al. (2014)			•				•				
Li et al. Li et al. (2017)											
LMTool Falloon et al. (2018)	•										
Luvisi et al. Luvisi et al. (2011)											
mDSS Mysiak et al. (2005)											
SmartScape Tayyebi et al. (2016)				•			•				•
VBoxReporting Bimonte et al. (2016)						•	•				
Vite.net Rossi et al. (100 (2014))							•				
visualizeR Frías et al. (2018)					•	•					
ViPER Oliver et al. (2017)							•				
Ochola et al. Ochola and Kerkides (2004)				•							
Falcao et al. Falcao et al. (2006)											
LandCaRe Wenkel et al. (2013)											
ValorE Acutis et al. (2014)											
Agroland Laudien et al. (2010)							•				
Gandhi et al. Gandhi et al. (2016)											
CaNaSTA O'Brien (2008)											
eFarmer Pettit et al. (2007)											
FARMERS Río et al. (2011)											
PlanteInfo Thysen and Detlefsen (2006)											
CropScape Han et al. (2012)						•					
SIMAGRI Han et al. (2019)	•										
FDSSFIS Yang et al. (2017)						•					
MOTIFS Meul et al. (2008)				•							

(*continued on next page*)

Table 6 (*continued*)

	box-plot	parallel coords.	pattern view	radar chart	bubble chart	pie chart	dashboard	progress circle	self-org. maps	hypertree	histogram
CarrotAge Le Ber et al. (2006)		•									
AgriSensor Kubicek et al. (2013)											
CognitiveInputs Devitt et al. (2017)								•			
Ruß et al. Ruß et al. (2009b)									•		
Tan et al. Tan et al. (2012)											
INT-VIS Gibbs et al. (2015)											
Piplani et al. Piplani et al. (2015)											
HyperTree de Souza et al. (2003)										•	
iGreen Ebert et al. (2011)											
Munro et al. Munro et al. (1996)											•
DEVA Reed et al. (2001)											•
Zhong-Xiao Leng and Yimit (2009)											
Fegraus et al. Fegraus et al. (2012)						•					•
LandEx Stepinski et al. (2014)											•
RF-CLASS Zhang et al. (2013)											
FluxDataONE Yan et al. (2014)											
Mudisshu et al. Mudisshu et al. (2016)											
CLIMSAVE Savin (2015)											
Zheng et al. Zheng and Altamimi (2017)											•
SMAP Hu et al. (2017)											
Num. Papers:	4	1	1	3	1	5	11	1	1	1	7
Percent (%):	7	2	2	5	2	8	18	2	2	2	11

which are designed to support various farming applications (e.g. irrigation scheduling, fertiliser application, etc.) and platforms (e.g. mobile and desktop).

We found 15 tools (see Table 7) that are designed to assist with decision support requirements by using a simulation approach. These tools allow farmers to walk-through simulated farming scenarios helping them explore and better understand their practices. On the other hand, we found 24 tools that have been designed for applications in real farming practices (i.e. non-simulation). These tools are designed to assist with decision support requirements for a particular real-world decision-making scenario, for example, irrigation scheduling or fertiliser application.

Interestingly, while a number of tools have focused on individual farming practices such as irrigation scheduling or fertiliser application, only two out of the 61 tools used visualisations to support whole-farm planning. Whole-farm planning is a difficult task, and its practices are often delivered to farmers by technicians and experts.[4] Whole-farm planning systems provide users with necessary tools for all the planning required for the whole farm, something farmers have to engage in nearly every day. We believe that future tools should provide farmers with various plug-and-play components allowing them to perform plannings for the whole farm or individual requirements.

In addition, we found that many of the tools have been designed to support a particular device (i.e. desktop or mobile), with the exception of two tools (Tan et al., 2012; Mudisshu et al., 2016) that were designed for both mobile and desktop devices. Overall, 30 out of the 61 tools are desktop applications while only nine are mobile applications, out of which two are designed for both desktop and mobile devices. Clearly, the support for mobile devices has been considered less frequently. However, since the scale of agricultural operations has increased over the years, it is important that the tools are scalable and support multiple devices for on-the-fly access and in-field decision-making (Tan et al., 2012).

Finally, we also discovered that while some of the tools (16 out of 61) are being used in practice, the majority of them (33 out of 61) are under the prototype stage (see Table 7 for details). Out of the two DSSs we discovered for whole-farm planning, only one (Cabrera et al., 2005) is currently available for end-users whereas the other one (Acutis et al., 2014) is at the prototype stage. Similarly for the tools that are designed for mobile devices, we found only one (Luvisi et al., 2011) that is currently available for end-users, which again supports the argument that more tools should consider support for multiple devices for flexible decision-making (Tan et al., 2012).

3.6. Data source

Since PA is driven by data to support decision-making (Pham and Stack, 2018), the type of data collected and how they are utilised play an important role. We found various types of data that are being used amongst the DSSs reviewed in this paper. An overview of the different types of data together with the respective DSSs is presented in Table 8.

We found that *geographical data* such as coordinates is the most widely used data type in agricultural visualisation. In total, we discovered 42 tools (i.e. 69%) that used it geographical data. This result is unsurprising, as we also discovered that maps are the most common type of visualisation in agriculture (see Section 3.3.1). In order to plot map visualisations, coordinates are vital. The second most common data types are *soil* and *crop* data, both having been used in 25 of the tools. it Soil data usually contains vital elements for crops such as potassium, calcium, phosphorous, nitrogen, iron, magnesium, zinc, copper and pH. it Crop data often contains growth rate, species and any other data that is related to the particular crop's anatomy. Both it soil and crop data, separately or together, are often used to predict additional

[4] https://www.vabeginningfarmer.alce.vt.edu/planning.html.

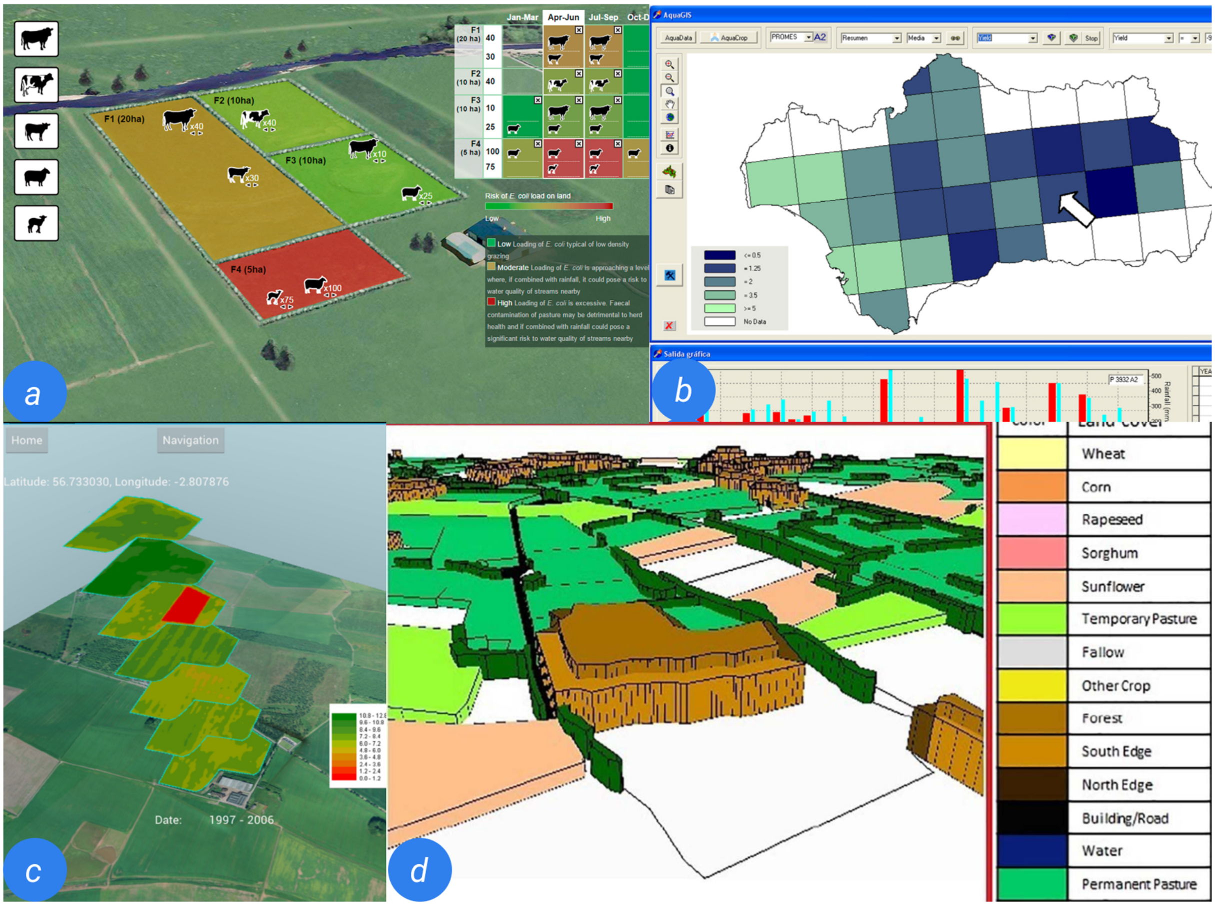

Fig. 13. Examples of use of map visualisation in agriculture: (a) ViPER (Oliver et al., 2017), (b) AQUAGIS (Lorite et al., 2013), (c) AgriAG (Stojanovic et al., 2017b) and (d) ATLAS (Thierry et al., 2017).

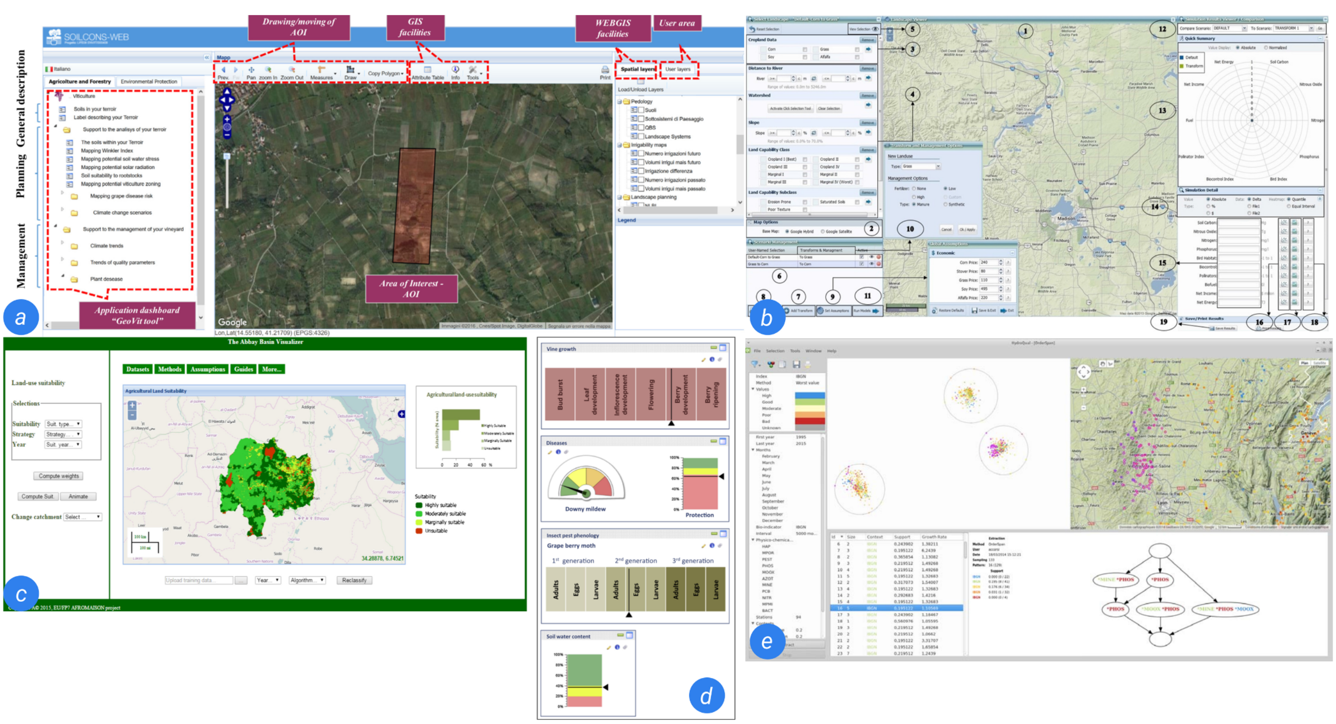

Fig. 14. The use of dashboards in agriculture: (a) Geovit (Terribile et al., 2017), (b) SmartScape (Tayyebi et al., 2016) (c) AgriSuit (Yalew et al., 2016) (d) Vite.net (Rossi et al., 100 (2014)) (e) HydroQual (Accorsi et al., 2014).

Table 7
DSSs using visualisation as categorised by tool type, development status and platform categories. Empty rows within a category mean “unclear” or “not mentioned” by the paper.

	real practice	*simulation*	*whole-farm*	*concept*	*prototype*	*production*	*mobile*	*desktop*
AgMine Armstrong and Nallan (2016)	•							
AgriAG Stojanovic et al. (2017b)					•		•	
AgriSuit Yalew et al. (2016)					•			
AgroDSS Rupnik et al. (2019)	•			•	•			•
AquaGIS Lorite et al. (2013)		•			•			•
ATLAS Thierry et al. (2017)		•			•			•
Blauth et al. Blauth and Ducati (2010)	•				•			
Byishimo et al. Byishimo and Garba (2016)					•			
CAMDT Han et al. (2017)	•	•			•			•
CropGIS Machwitz et al. (2019)		•			•			
CropSAT Lundström and Lindblom (2018)	•					•		
DIDAS Friedman et al. (2016)		•				•		•
DyNoFlo Cabrera et al. (2005)	•		•			•		•
Galindo et al. Aragó Galindo et al. (2012b)				•				
GeoVisage Jarvis et al. (2017)						•		
Geovit Terribile et al. (2017)	•	•						
GramyaVikas Adinarayana et al. (2008)					•			
HydroQual Accorsi et al. (2014)					•			•
Li et al. Li et al. (2017)						•		
LMTool Falloon et al. (2018)					•		•	
Luvisi et al. Luvisi et al. (2011)	•					•	•	
mDSS Mysiak et al. (2005)	•	•			•			•
SmartScape Tayyebi et al. (2016)	•					•		
VBoxReporting Bimonte et al. (2016)					•			
Vite.net Rossi et al. (100 (2014))	•	•				•		
visualizeR Frías et al. (2018)						•		•
ViPER Oliver et al. (2017)	•					•		
Ochola et al. Ochola and Kerkides (2004)	•				•			•
Falcao et al. Falcao et al. (2006)		•						•
LandCaRe Wenkel et al. (2013)	•	•			•			
ValorE Acutis et al. (2014)	•	•	•		•			
Agroland Laudien et al. (2010)	•							•
Gandhi et al. Gandhi et al. (2016)	•				•			•
CaNaSTA O’Brien (2008)	•							
eFarmer Pettit et al. (2007)					•			
FARMERS Río et al. (2011)								•
PlanteInfo Thysen and Detlefsen (2006)	•					•		
CropScape Han et al. (2012)						•		
SIMAGRI Han et al. (2019)	•	•				•		•
FDSSFIS Yang et al. (2017)	•	•			•			•
MOTIFS Meul et al. (2008)						•		•
CarrotAge Le Ber et al. (2006)						•		•
AgriSensor Kubicek et al. (2013)					•			
CognitiveInputs Devitt et al. (2017)		•		•			•	
Ruß et al. Ruß et al. (2009b)					•			
Tan et al. Tan et al. (2012)					•		•	•
INT-VIS Gibbs et al. (2015)					•			•
Piplani et al. Piplani et al. (2015)					•		•	
HyperTree de Souza et al. (2003)					•			•
iGreen Ebert et al. (2011)					•		•	
Munro et al. Munro et al. (1996)					•			•
DEVA Reed et al. (2001)								•
Zhong-Xiao Leng and Yimit (2009)	•							
Fegraus et al. Fegraus et al. (2012)	•				•			•
LandEx Stepinski et al. (2014)								•
RF-CLASS Zhang et al. (2013)								•
FluxDataONE Yan et al. (2014)					•			•
Mudisshu et al. Mudisshu et al. (2016)					•		•	•
CLIMSAVE IAP Savin (2015)		•				•		•
Zheng et al. Zheng and Altamimi (2017)					•		•	
SMAP Hu et al. (2017)	•				•			•
Num. Papers:	24	15	2	3	33	16	9	30
Percent (%):	39	25	3	5	54	26	15	49

requirements for any given farm, which includes irrigation planning, fertiliser management, environmental management, etc. SmartScape (Tayyebi et al., 2016) (Fig. 12), for example, uses both data to evaluate and compare different crop change scenarios, assisting policymakers with their decisions.

The third most commonly found data type is *weather data*. Our review has seen a total of 20 tools that use it weather data to provide decision support. Both soil and weather play an important role for crops development. They are also unpredictable as changes can occur rapidly and without warning. Soil chemicals, for example, can vary frequently depending on animal waste on the farm. Thus, many DSSs take into account these data. As we can see in Table 8, it weather and soil data

Table 8
DSS categorised by different types of data used to provide decision supports.

	flux	*domain ontology*	*landscape*	*soil*	*yield*	*crop*	*location*	*rainfall*	*water supply*	*weather*	*vegetation*	*biomass*
AgMine Armstrong and Nallan (2016)				•	•		•	•		•		
AgriAG Stojanovic et al. (2017b)			•		•		•					
AgriSuit Yalew et al. (2016)			•	•			•					
AgroDSS Rupnik et al. (2019)												
AquaGIS Lorite et al. (2013)				•		•		•		•		
ATLAS Thierry et al. (2017)			•			•	•					
Blauth et al. Blauth and Ducati (2010)							•				•	
Byishimo et al. Byishimo and Garba (2016)				•		•						
CAMDT Han et al. (2017)				•	•	•		•		•		
CropGIS Machwitz et al. (2019)				•	•	•	•					•
CropSAT Lundström and Lindblom (2018)				•		•	•				•	
DIDAS Friedman et al. (2016)				•								
DyNoFlo Dairy Cabrera et al. (2005)				•		•	•			•		•
Galindo et al. Aragó Galindo et al. (2012b)				•	•	•	•					
GeoVisage Jarvis et al. (2017)				•			•	•		•	•	
Geovit Terribile et al. (2017)				•			•			•		
GramyaVikas Adinarayana et al. (2008)			•				•				•	
HydroQual Accorsi et al. (2014)							•					
Li et al. Li et al. (2017)						•	•			•		
LMTool Falloon et al. (2018)							•	•		•		
Luvisi et al. Luvisi et al. (2011)							•					
mDSS Mysiak et al. (2005)							•					
SmartScape Tayyebi et al. (2016)			•	•	•	•	•	•				
VBoxReporting Bimonte et al. (2016)							•					
Vite.net Rossi et al. (100 (2014))				•		•		•				
visualizeR Frías et al. (2018)					•		•			•		
ViPER Oliver et al. (2017)							•					
Ochola et al. Ochola and Kerkides (2004)			•	•	•		•			•		
Falcao et al. Falcao et al. (2006)			•				•					
LandCaRe Wenkel et al. (2013)			•		•	•	•			•		
ValorE Acutis et al. (2014)				•		•	•					
Agroland Laudien et al. (2010)			•	•		•	•			•		
Gandhi et al. Gandhi et al. (2016)					•	•	•	•				
CaNaSTA O'Brien (2008)							•	•				
eFarmer Pettit et al. (2007)			•	•		•	•					
FARMERS Río et al. (2011)				•			•					
PlanteInfo Thysen and Detlefsen (2006)										•		
CropScape Han et al. (2012)						•	•					
SIMAGRI Han et al. (2019)				•	•	•		•		•		
FDSSFIS Yang et al. (2017)						•		•				
MOTIFS Meul et al. (2008)			•	•								
CarrotAge Le Ber et al. (2006)			•			•						
AgriSensor Kubicek et al. (2013)				•			•			•		
CognitiveInputs Devitt et al. (2017)				•		•		•		•		
Ruß et al. Ruß et al. (2009b)				•	•						•	
Tan et al. Tan et al. (2012)							•					
INT-VIS Gibbs et al. (2015)								•		•		
Piplani et al. Piplani et al. (2015)							•		•			
HyperTree de Souza et al. (2003)		•										
iGreen Ebert et al. (2011)							•					
Munro et al. Munro et al. (1996)						•	•					
DEVA Reed et al. (2001)							•				•	
Zhong-Xiao Leng and Yimit (2009)							•					
Fegraus et al. Fegraus et al. (2012)				•			•		•	•		

(continued on next page)

Table 8 (*continued*)

	flux	*domain ontology*	*landscape*	*soil*	*yield*	*crop*	*location*	*rainfall*	*water supply*	*weather*	*vegetation*	*biomass*
LandEx Stepinski et al. (2014)							•					
RF-CLASS Zhang et al. (2013)						•	•		•		•	
FluxDataONE Yan et al. (2014)	•											
Mudisshu et al. Mudisshu et al. (2016)										•		
CLIMSAVE Savin (2015)					•					•		
Zheng et al. Zheng and Altamimi (2017)					•	•						
SMAP Hu et al. (2017)						•	•		•		•	
Num. Papers:	1	1	12	25	14	25	42	13	4	20	8	2
Percent (%):	2	2	20	41	23	41	69	21	7	33	13	3

	water quality	*fertilisation*	*irrigation*	*bio-index*	*pollution*	*soil temp.*	*humidity*	*wind speed*	*sensor*	*economy*	*pest data*	*livestock data*	*env. risk*
AgMine Armstrong and Nallan (2016)													
AgriAG Stojanovic et al. (2017b)													
AgriSuit Yalew et al. (2016)													
AgroDSS Rupnik et al. (2019)											•		
AquaGIS Lorite et al. (2013)													
ATLAS Thierry et al. (2017)													
Blauth et al. Blauth and Ducati (2010)													
Byishimo et al. Byishimo and Garba (2016)			•						•				
CAMDT Han et al. (2017)		•											
CropGIS Machwitz et al. (2019)													
CropSAT Lundström and Lindblom (2018)		•											
DIDAS Friedman et al. (2016)			•										
DyNoFlo Dairy Cabrera et al. (2005)										•			
Galindo et al. Aragó Galindo et al. (2012b)		•											
GeoVisage Jarvis et al. (2017)						•	•	•	•				
Geovit Terribile et al. (2017)	•								•				
GramyaVikas Adinarayana et al. (2008)													
HydroQual Accorsi et al. (2014)	•			•	•								
Li et al. Li et al. (2017)						•	•						
LMTool Falloon et al. (2018)								•					
Luvisi et al. Luvisi et al. (2011)									•				
mDSS Mysiak et al. (2005)			•										
SmartScape Tayyebi et al. (2016)										•			
VBoxReporting Bimonte et al. (2016)									•				
Vite.net Rossi et al. (100 (2014))	•										•		
visualizeR Frías et al. (2018)													
ViPER Oliver et al. (2017)												•	
Ochola et al. Ochola and Kerkides (2004)	•									•			•
Falcao et al. Falcao et al. (2006)													
LandCaRe Wenkel et al. (2013)												•	
ValorE Acutis et al. (2014)												•	
Agroland Laudien et al. (2010)		•											
Gandhi et al. Gandhi et al. (2016)													
CaNaSTA O'Brien (2008)													
eFarmer Pettit et al. (2007)													
FARMERS Río et al. (2011)													•
PlanteInfo Thysen and Detlefsen (2006)		•	•								•		
CropScape Han et al. (2012)													
SIMAGRI Han et al. (2019)													
FDSSFIS Yang et al. (2017)													
MOTIFS Meul et al. (2008)	•									•	•		
CarrotAge Le Ber et al. (2006)													

(*continued on next page*)

Table 8 (*continued*)

	water quality	*fertilisation*	*irrigation*	*bio-index*	*pollution*	*soil temp.*	*humidity*	*wind speed*	*sensor*	*economy*	*pest data*	*livestock data*	*env. risk*
AgriSensor Kubicek et al. (2013)						•	•	•	•				
CognitiveInputs Devitt et al. (2017)													
Ruß et al. Ruß et al. (2009b)		•											
Tan et al. Tan et al. (2012)									•				
INT-VIS Gibbs et al. (2015)		•										•	
Piplani et al. Piplani et al. (2015)													
HyperTree de Souza et al. (2003)													
iGreen Ebert et al. (2011)													
Munro et al. Munro et al. (1996)													
DEVA Reed et al. (2001)													
Zhong-Xiao Leng and Yimit (2009)			•										
Fegraus et al. Fegraus et al. (2012)	•								•				
LandEx Stepinski et al. (2014)													
RF-CLASS Zhang et al. (2013)													
FluxDataONE Yan et al. (2014)													
Mudisshu et al. Mudisshu et al. (2016)													
CLIMSAVE Savin (2015)													
Zheng et al. Zheng and Altamimi (2017)													
SMAP Hu et al. (2017)													
Num. Papers:	6	7	5	1	1	3	3	3	8	4	4	4	2
Percent (%):	10	11	8	2	2	5	5	5	13	7	7	7	3

are often measured by sensors. Following weather data, *rainfall* (13 tools) and it crop yield (14 tools) have been used most frequently. *Rainfall*, like weather data, is vital for crops. However, rainfall alone does not determine crop development; *humidity*, it soil temperature, etc. are also important for crops. Thus, weather data is more commonly used than rainfall alone. For instance, AquaGIS (Lorite et al., 2013) uses both rainfall and weather predictions to show water levels in an area of interest, allowing for selection of a field. it Crop yield, as seen in 14 tools, is often used as a metric to measure return and farm performance. In addition, four tools have also used economy data to be able to optimise resources and leverage profit.

Next, we found that *landscape data* is also used as an input in 12 different DSSs. The ability to hold water, for example, is greatly defined by the shape of a landscape. This, in turn, has an impact on irrigation requirements of the farm. In a few cases, it irrigation data has also been used as an input for decision support. We discovered five tools that used irrigation data as an input. As discussed in Section 3.1.5, irrigation data is often used in irrigation management systems, together with additional data such as soil, location, crop type, rainfall and weather predictions (see Table 8). Similarly, there are tools designed for fertiliser management (7 tools) and live stock management (4 tools) which keep track of crop *fertilisation* and it live stock data, respectively. These management tools usually illustrate the current status of a farm, allowing farmers to keep track of the impact on crops and environment. ViPER (Oliver et al., 2017), for example, illustrates the risk of microbial pollution (e.g. E. Coli) on a land using livestock data. Pest control is also an important aspect of agriculture. However, we found only four tools that used it pest data for decision support with pest and disease control. Interestingly, the use of it pest data is only found in DSSs that are designed to assist with whole-farm management (e.g. Vite.net Rossi et al., 100 (2014) and MOTIFS Meul et al., 2008).

Tools designed for other stakeholders in addition to farmers, such as farm advisers, agronomists, policymakers and academic researchers, tend to use different sets of data compared to those designed for farmers only. These data include: *vegetation* (8 tools), it water quality (6 tools), it water resources (4 tools), *biomass* (2 tools), it environmental risk (2 tools), it biological index (1 tool), *pollution* (1 tool), it flux data (1 tool) and it domain ontology (1 tool). However, as can be observed in Section 3.2, not many of the tools are designed for farm advisers, agronomists, policymakers and academic researchers; the majority of the tools are designed for farmers.

3.7. Uncertainty

Large amounts of unstructured data and complex predictive models are known to lead to uncertainty (Daradkeh et al., 2010). Given the concerns regarding trust and technology adoption in PA, the study of uncertainty assessment through visualisation is relevant to our research (Marra et al., 2003). Visualisation mechanisms for communicating uncertainty have proven to be successful gaining trust particularly for non-expert users (Kay et al., 2016). The incorporation of uncertainty into the decision-making process is crucial for making decisions and maximising benefits (Daradkeh et al., 2017). Only two out of the 61 papers considered the communication of uncertainty through visualisation: CropGIS (Machwitz et al., 2019) and visualizeR (Frías et al., 2018). CropGIS (Machwitz et al., 2019) uses a time-series to show information about biomass development of maize with a range of uncertainty describing various meteorological scenarios (see Fig. 15a). visualizeR (Frías et al., 2018) uses a bubble plot together with a map to visualise seasonal forecasting of climate, where the colour and size of the bubble are used to encode different levels of probability (see Fig. 15b). Such uncertainty representations better reflect the reality compared to static forecasts, making the prediction more reliable for farmers.

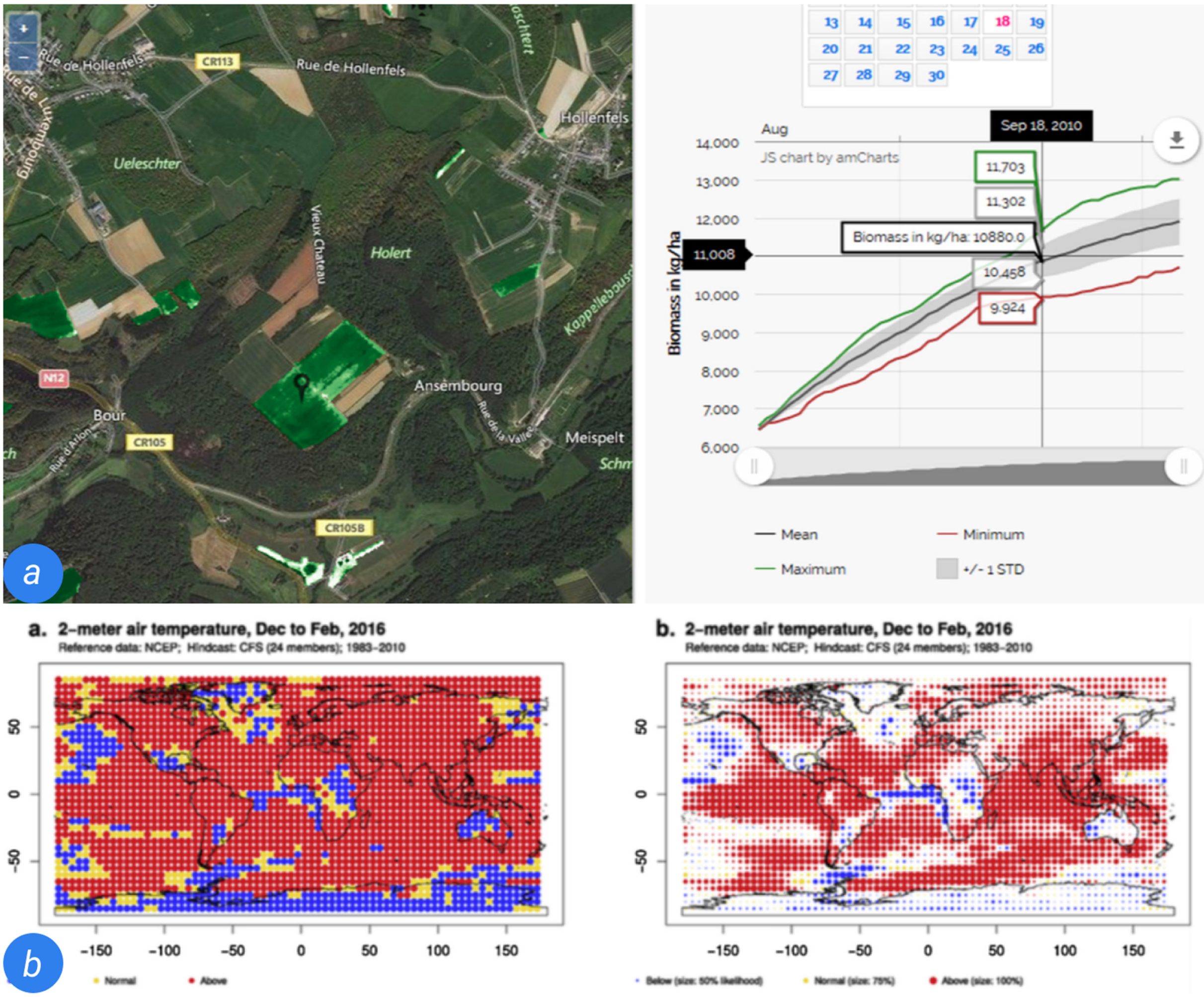

Fig. 15. Visualisation of uncertainty: (a) CropGIS (Machwitz et al., 2019) shows the variability of biomass estimation over time. (b) visualiseR (Frías et al., 2018) uses bubble plot to communicate uncertainty in climate change scenarios.

3.8. Design and evaluation

Despite the potential of visualisation, many approaches are poorly received by end-users, which is attributed to a lack of engagement in the design process of the tools (Whitman et al., 2015). To tackle this gap between complex scientific tools and more "user-friendly" systems, a human-centred approach is desired. In this review, we found a total of 11 articles that followed a user observation approach (see Table 9). The majority of these articles (10 out of 11) also reported using questionnaires for evaluation. In total, we found 12 articles that used questionnaires to evaluate their DSSs. Besides, we found that nine out of 61 articles reported using interviews as a feedback method during evaluation. Amongst these articles that used observations, questionnaires and interviews, only one (i.e. Geovisage Jarvis et al., 2017) reported the use of a qualitative analysis method, thematic analysis, to analyse feedback from end-users. Finally, we found four articles that declared the use of workshops to obtain feedback from end-users.

Participatory design has been identified as an important methodology in the design and development of tools used by end-users in the agriculture domain, with the purpose of gaining trust and technology acceptance, increasing adoption with end-users. However, only 11 out of 61 articles reported using a participatory design approach. Meanwhile, three articles used a focus group approach during the design process, and four reported the use of an iterative design approach.

4. Discussion

The results presented have many implications to consider for many future research directions. Here, we discuss the results around the research questions presented in Section 1.

4.1. RQ1: What visualisation techniques are being used across different domains in agriculture?

As presented in Section 3.3, the vast majority of visualisations in agriculture used a 2D map to provide an overview of the landscape to the user with a few attempts of 3D maps to provide more detail about the terrain. On top of these maps, the use of heatmaps is relevant, which are often layered over the maps to highlight different kinds of data for the user. Time-series are commonly used to display information over time, such as daily data coming from sensors. Histograms are also often used to provide information coming from sensors to show the distribution of data over time. Clustering visualisations, radar and pie charts were used to compare metrics from data in the map. Dashboards are relevant since they provide immediate access to various interactive components to monitor and display data, offering a set of visual tools to the decision-maker for interaction and exploration. We also discovered that dashboards are being used in a wide variety of application domains such as land suitability assessment, crop biomass analysis, crop control, wheat production, fertiliser management, pest control, dairy farming and vineyard management. In a number of other domains that we

Table 9
The visualisation tools categorised by evaluation methods and design approach. Empty row within a category means "unclear" or "not mentioned" by the paper.

	evaluation					*design*		
	user observation	*questionnaire*	*interview*	*workshops*	*qualitative analysis*	*focus group*	*iterative process*	*part. design*
AgriAG Stojanovic et al. (2017b)	•	•						
CropSAT Lundström and Lindblom (2018)	•	•	•					
DyNoFlo Cabrera et al. (2005)	•	•	•			•	•	•
Galindo et al. Aragó Galindo et al. (2012b)								•
GeoVisage Jarvis et al. (2017)	•	•	•		•			•
Geovit Terribile et al. (2017)								•
HydroQual Accorsi et al. (2014)	•	•	•					
LMTool Falloon et al. (2018)	•	•	•	•			•	•
mDSS Mysiak et al. (2005)			•				•	•
SmartScape Tayyebi et al. (2016)								•
Vite.net Rossi et al. (100 (2014))	•	•						•
visualizeR Frías et al. (2018)		•						
ViPER Oliver et al. (2017)	•	•		•				•
Ochola et al. Ochola and Kerkides (2004)	•					•		
Agroland Laudien et al. (2010)	•	•	•					
eFarmer Pettit et al. (2007)	•	•						
MOTIFS Meul et al. (2008)								•
Piplani et al. Piplani et al. (2015)		•	•			•	•	•
Zhong-Xiao Leng and Yimit (2009)			•	•				
CLIMSAVE Savin (2015)				•				
Num. Papers:	11	12	9	4	1	3	4	11
Percent (%):	18	20	15	7	2	5	7	18

looked at, such as livestock management, aquaculture analysis, cotton production, rice production and soil-moisture analysis (see Table 4), dashboards are not yet introduced. We believe that these domains (but not limited to) can also greatly benefit from a dashboard. Uncertainty visualisation is another aspect that many existing DSSs have ignored, but can unquestionably improve user understanding of the decisions provided by the system. The role of uncertainty visualisation is further discussed in RQ3.

4.2. RQ2: How are these visualisations being used by end-users to make decisions?

Most of the applications discovered in this review are intended for farmers for various activities in the field, ranging from land suitability assessment to livestock and crop management. Some others are used by advisers and agronomists to provide feedback to farmers in their decision-making. A few of these applications are designed for policymakers who use systems to simulate conditions and plan ahead on how policies can affect particular environments. For instance, visualisation of crop status in maps allows the farmer to know the right amount of fertiliser, irrigation water or pesticide needed to achieve the optimum yield at a particular location within a parcel. Overall, three different types of DSSs were observed: those designed for a particular farming requirement, simulation and whole-farm management (see Section 3.5 for details). Unfortunately, while whole-farm management is a difficult task and is often engaged by farmers nearly every day, not many tools are currently available to support such a task. More tools should provide farmers with various plug-and-play components allowing them to perform planning for whole-farm management or individual farming requirements. Similarly, with the growth in agricultural operations over the years, we should consider designing tools that are scalable and support multiple devices (i.e. desktop and mobile) for on-the-fly access and in-field decision-making.

4.3. RQ3: What is the role of uncertainty in the visualisation tools that support decision-making?

Despite the importance of illustrating uncertainty in visualisations, the agriculture domain has not yet seen many applications of uncertainty visualisations. In this review, only two tools reported communication of uncertainty through visualisation. We claim that representation of uncertainty provides higher reliability and better reflection about the reality, making predictions more reliable for end-users (Sacha et al., 2016) and producing high quality and informed decisions (Fernandes et al., 2018). While many of the DSSs analysed in this review presented visualisations to aid stakeholders in their decision-making, they often lack an appropriate representation of uncertainty, despite this being an essential part of the decision-making process. Moreover, uncertainty has to be represented in a way that corresponds to the user's expectations and knowledge in a way that is easy to understand (Kwon et al., 2011). We believe that visualisation should be used to support the fundamental parts of the analysis, especially during uncertain scenarios, allowing users to control and evaluate data at all stages and empowering their decision-making process (John et al., 2015). Presentation of uncertainty to non-expert users can be helpful, but to maximise its effectiveness it must be displayed in a way that reveals its advantages to end-users (Kinkeldey et al., 2015).

4.4. RQ4: What is the role of HCI in the design and development of visualisation tools to support end-user decisions?

As presented in Section 3.8, only a few tools included a report about the usability evaluation or a participatory design process. Although we have discovered a great amount of visualisation tools in agriculture, it is still a difficult task to select the most suitable visualisation and interaction techniques for end-users. Feedback from end-users is an important aspect in developing tools that are usable in practical settings (Saizmaa and Kim, 2008; Rose et al., 2018).

A lack of uptake of agricultural DSSs has been noted previously by researchers as a major challenge in the field (Rose et al., 2018). The "problem of implementation" is based on the knowledge that participatory strategies during the design and development stages are the most critical factors to build technology adoption (Lindblom et al., 2017). In fact, there is a significant effort to adopt a more user-centred approach in the design of DSS applications (Parker, 1999). A user-centred approach in the design and development of DSSs has shown to have a positive influence, for instance, in crop production (Parker and Sinclair, 2001), being seen as a beneficial method for transferring knowledge from scientists to farmers. One of the main reasons on low adoption and acceptance is because most of the existing DSSs are based on what scientists and developers consider as the necessary knowledge that should be implemented in the tool, but in reality, they fail to capture the expertise and practical needs of the farmers. In this review, the System Usability Scale (SUS), focus groups and semi-structured interviews appeared in some of the design and development stages of applications. In particular, the case of VisAdapt presented a collaborative and interactive design process, leading to satisfactory results towards the development of the tool. Focus groups and semi-structured interviews are well-established methodologies for exploring perceptions and gathering ideas from the stakeholders which are developed as a result of the social and interactive nature of the process.

5. Limitations

There are some limitations to this systematic review study that should be articulated. First, our included studies were limited to those written in English, meaning that relevant studies written in other languages may have been excluded. Second, even though an extensive scope search was conducted in scientific databases and most relevant journals of the agriculture domain, some relevant literature in other domains might have been excluded. Third, we may have missed some tools that are used in practice, but that are not reported in scientific literature. Finally, some of the categories we used in this review could not be clearly identified in the papers we analysed. For example, a few papers did not clearly state the development status of the tools being presented.

6. Conclusion

This systematic review presents a comprehensive report on the use of visualisation techniques in the field of agriculture. We have discussed the most used visualisation techniques considering end-users, data sources, representation of uncertainty and evaluation methods. Based on this analysis, we have also provided design guidelines towards the implementation of interactive visual DSSs. We found that while the vast majority of applications are intended to use maps for visualisation together with satellite imagery, there is a significant opportunity of using dashboards to support farmers and advisers with more interactive components and dashboards to handle and interact with uncertain data. We also recommend the use of participatory design research, that has been successfully applied to increase the usability of applications for farmers. In addition, we highlight the role of representing uncertainty to increase user confidence and trust. The extensive body of analysed tools provide rich examples of how DSSs for agriculture can be designed on top of a variety of data sources involving different stakeholders in the design process, and representing both the data as well as underlying uncertainty to support informed decision making. We hope that this review will inspire and motivate many researchers and practitioners towards creating dashboards and visualisations following participatory research methods and uncertainty representations in future design and developments of agricultural DSSs.

Acknowledgements

Funding for this research has been provided by the European Union's Horizon 2020 research and innovation programme (grant agreement number 780751).

References

Accorsi, P., Lalande, N., Fabrègue, M., Braud, A., Poncelet, P., Sallaberry, A., Bringay, S., Teisseire, M., Cernesson, F., Ber, F.L., 2014. Hydroqual: visual analysis of river water quality. In: 2014 IEEE Conference on Visual Analytics Science and Technology (VAST), pp. 123–132. https://doi.org/10.1109/VAST.2014.7042488.

Acutis, M., Alfieri, L., Giussani, A., Provolo, G., Di Guardo, A., Colombini, S., Bertoncini, G., Castelnuovo, M., Sali, G., Moschini, M., et al., 2014. ValorE: an integrated and GIS-based decision support system for livestock manure management in the Lombardy region (northern Italy). Land Use Policy 41, 149–162.

Adinarayana, J., Azmi, S., Tewari, G., Sudharsan, D., 2008. Gramyavikas: a distributed collaboration model for rural development planning. Comput. Electron. Agric. 62 (2), 128–140. https://doi.org/10.1016/j.compag.2007.12.008.

Aragó Galindo, P., Granell, C., Molin, P.G., Huerta Guijarro, J., 2012a. Participative site-specific agriculture analysis for smallholders. Precision Agric. 13 (5), 594–610. https://doi.org/10.1007/s11119-012-9267-4.

Aragó Galindo, P., Granell, C., Molin, P.G., Huerta Guijarro, J., 2012b. Participative site-specific agriculture analysis for smallholders. Precision Agric. 13 (5), 594–610. https://doi.org/10.1007/s11119-012-9267-4.

Armstrong, L.J., Nallan, S.A., 2016. Agricultural decision support framework for visualisation and prediction of western australian crop production 1907–1912. https://ieeexplore.ieee.org/document/7724598/.

Best, S., León, L., Claret, M., 2005. Use of precision viticulture tools to optimize the harvest of high quality grapes. In: Proceedings of the Fruits and Nuts and Vegetable Production Engineering TIC (Frutic05), pp. 249–258.

Bimonte, S., Naoufal, E., Gineste, L., 2016. A system for the rapid design and implementation of personalized agricultural key performance indicators issued from sensor data. Comput. Electron. Agric. 130, 1–12. https://doi.org/10.1016/j.compag.2016.09.010.

Blauth, D.A., Ducati, J.R., 2010. A web-based system for vineyards management, relating inventory data, vectors and images. Comput. Electron. Agric. 71 (2), 182–188. https://doi.org/10.1016/j.compag.2010.01.007.

Byishimo, A., Garba, A.A., 2016. Designing a farmer interface for smart irrigation in developing countries. In: Proceedings of the 7th Annual Symposium on Computing for Development, ACM DEV '16. ACM, New York, NY, USA, pp. 30:1–30:3. https://doi.org/10.1145/3001913.3006639.

Cabrera, V.E., Breuer, N.E., Hildebrand, P.E., Letson, D., 2005. The dynamic North Florida dairy farm model: a user-friendly computerized tool for increasing profits while minimizing n leaching under varying climatic conditions. Comput. Electron. Agric. 49 (2), 286–308. https://doi.org/10.1016/j.compag.2005.07.001.

Daradkeh, M., Abul-Huda, B., 2017. Incorporating uncertainty into decision-making: an information visualisation approach. In: Linden, I., Liu, S., Colot, C. (Eds.), Decision Support Systems VII. Data, Information and Knowledge Visualization in Decision Support Systems. Springer International Publishing, Cham, pp. 74–87.

Daradkeh, M., McKinnon, A., Churcher, C., 2010. Visualisation tools for exploring the uncertainty-risk relationship in the decision-making process: a preliminary empirical evaluation. In: Proceedings of the Eleventh Australasian Conference on User Interface, vol. 106. Australian Computer Society Inc, pp. 42–51.

del Águila, I.M., Cañadas, J., Túnez, S., 2015. Decision making models embedded into a web-based tool for assessing pest infestation risk. Biosyst. Eng. 133, 102–115. https://doi.org/10.1016/j.biosystemseng.2015.03.006.

de Souza, K.X., dos Santos, A.D., Evangelista, S.R., 2003. Visualization of ontologies through hypertrees. In: Proceedings of the Latin American Conference on Human-computer Interaction. ACM, pp. 251–255.

Devitt, S.K., Perez, T., Polson, D., Pearce, T.R., Quagliata, R., Taylor, W., Thornby, D., Beekhuyzen, J., 2017. A cognitive decision tool to optimise integrated weed management. In: International Tri-Conference for Precision Agriculture 2017, Hamilton, New Zealand. Springer.

Diehl, A., Pelorosso, L., Delrieux, C., Matković, K., Ruiz, J., Gröller, M. E., Bruckner, S., 2017. Albero: a visual analytics approach for probabilistic weather forecasting. In: Computer Graphics Forum, vol. 36, no. 7, 2017, pp. 135–144. https://doi.org/10.1111/cgf.13279.

Dolinska, A., 2017. Bringing farmers into the game. strengthening farmers' role in the innovation process through a simulation game, a case from tunisia. Agric. Syst. 157, 129–139.

Ebert, A., Deller, M., Thelen, S., Scheler, I., 2011. igreen: non-formal modelling in practice. In: Proceedings of the 29th Annual European Conference on Cognitive Ergonomics. ACM, pp. 283–284.

Falcao, A.O., dos Santos, M.P., Borges, J.G., 2006. A real-time visualization tool for forest ecosystem management decision support. Comput. Electron. Agric. 53 (1), 3–12.

Falloon, P., Soares, M.B., Manzanas, R., San-Martin, D., Liggins, F., Taylor, I., Kahana, R., Wilding, J., Jones, C., Comer, R., de Vreede, E., de Cerff, W.S., Buontempo, C., Brookshaw, A., Stanley, S., Middleham, R., Pittams, D., Lawrence, E., Bate, E., Peter, H., Uzell, K., Richards, M., 2018. The land management tool: developing a climate service in southwest uk. Clim. Serv. 9, 86–100. https://doi.org/10.1016/j.cliser.2017.08.002. climate services in practice: what we learnt from EUPORIAS.

Fegraus, E.H., Zaslavsky, I., Whitenack, T., Dempewolf, J., Ahumada, J.A., Lin, K., Andelman, S.J., 2012. Interdisciplinary decision support dashboard: a new framework for a tanzanian agricultural and ecosystem service monitoring system pilot. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 5 (6), 1700–1708.

Fernandes, M., Walls, L., Munson, S., Hullman, J., Kay, M., 2018. Uncertainty displays using quantile dotplots or CDFs improve transit decision-making. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM, pp. 144.

Few, S., 2006. Information Dashboard Design. O'Reilly Sebastopol, CA.

Frías, M., Iturbide, M., Manzanas, R., Bedia, J., Fernández, J., Herrera, S., Cofiño, A., Gutiérrez, J., 2018. An r package to visualize and communicate uncertainty in seasonal climate prediction. Environ. Model. Softw. 99, 101–110. https://doi.org/10.1016/j.envsoft.2017.09.008.

Friedman, S.P., Communar, G., Gamliel, A., 2016. Didas – user-friendly software package for assisting drip irrigation design and scheduling. Comput. Electron. Agric. 120, 36–52. https://doi.org/10.1016/j.compag.2015.11.007.

Gandhi, N., Armstrong, L.J., Petkar, O., 2016. Proposed decision support system (DSS) for

indian rice crop yield prediction. In: Technological Innovations in ICT for Agriculture and Rural Development (TIAR), 2016 IEEE. IEEE, pp. 13–18.
Gibbs, S., Cromie, K., Pellow, R., 2015. An interactive spreadsheet model for visualizing dairy farm data. In: Proceedings of the 15th New Zealand Conference on Human-Computer Interaction. ACM, pp. 51–55.
Han, W., Yang, Z., Di, L., Mueller, R., 2012. CropScape: a web service based application for exploring and disseminating us conterminous geospatial cropland data products for decision support. Comput. Electron. Agric. 84, 111–123.
Han, E., Ines, A.V., Baethgen, W.E., 2017. Climate-agriculture-modeling and decision tool (CAMDT): a software framework for climate risk management in agriculture. Environ. Model. Softw. 95, 102–114. https://doi.org/10.1016/j.envsoft.2017.06.024.
Han, E., Baethgen, W.E., Ines, A.V., Mer, F., Souza, J.S., Berterretche, M., Atunez, G., Barreira, C., 2019. Simagri: An agro-climate decision support tool. Comput. Electron. Agric. 161, 241–251. https://doi.org/10.1016/j.compag.2018.06.034. Issn: 0168-1699.
He, C., Parra, D., Verbert, K., 2016. Interactive recommender systems: a survey of the state of the art and future research challenges and opportunities. Expert Syst. Appl. 56, 9–27.
Hertem, T.V., Rooijakkers, L., Berckmans, D., Fernández, A.P., Norton, T., Berckmans, D., Vranken, E., 2017. Appropriate data visualisation is key to precision livestock farming acceptance. Comput. Electron. Agric. 138, 1–10. https://doi.org/10.1016/j.compag.2017.04.003.
Higgins, J., Green, S., Handsearching, 2005. In: Higgins, J., Green, S. (Eds.), Cochrane Handbook for Systematic Reviews of Interventions, Cochrane (Chapter 6).
Hu, L., Di, L., Yu, E., Yue, P., Tang, J., Lin, L., Zhang, C., Sun, Z., Hu, R., Shrestha, R., et al., 2017. Developing geospatial web service and system for SMAP soil moisture monitoring. In: Agro-Geoinformatics, 2017 6th International Conference on. IEEE, pp. 1–5.
Imam, S.A., Choudhary, A., Sachan, V.K., 2015. Design issues for wireless sensor networks and smart humidity sensors for precision agriculture: a review. In: 2015 International Conference on Soft Computing Techniques and Implementations (ICSCTI). IEEE, pp. 181–187.
Ingram, J., 2008. Agronomist–farmer knowledge encounters: an analysis of knowledge exchange in the context of best management practices in England. Agric. Hum. Values 25 (3), 405–418. https://doi.org/10.1007/s10460-008-9134-0.
Jarvis, D.H., Wachowiak, M.P., Walters, D.F., Kovacs, J.M., 2017. Adoption of web-based spatial tools by agricultural producers: conversations with seven northeastern Ontario farmers using the geovisage decision support system. Agriculture 7 (8). https://doi.org/10.3390/agriculture7080069.
John, M., Koch, S., Heimerl, F., Müller, A., Ertl, T., Kuhn, J., 2015. Interactive visual analysis of german poetics. Digital Humanities.
Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., Keating, B.A., Munoz-Carpena, R., Porter, C.H., Rosenzweig, C., Wheeler, T.R., 2017. Brief history of agricultural systems modeling. Agric. Syst. 155, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014.
Kamilaris, A., Kartakoullis, A., Prenafeta-Boldú, F.X., 2017. A review on the practice of big data analysis in agriculture. Comput. Electron. Agric. 143, 23–37.
Kay, M., Kola, T., Hullman, J.R., Munson, S.A., 2016. When (ish) is my bus?: User-centered visualizations of uncertainty in everyday, mobile predictive systems. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, CHI '16. ACM, New York, NY, USA, pp. 5092–5103. https://doi.org/10.1145/2858036.2858558.
Kinkeldey, C., Schiewe, J., Gerstmann, H., Götze, C., Kit, O., Lüdeke, M., Taubenböck, H., Wurm, M., 2015. Evaluating the use of uncertainty visualization for exploratory analysis of land cover change: a qualitative expert user study. Comput. Geosci. 84, 46–53. https://doi.org/10.1016/j.cageo.2015.08.007.
Kubicek, P., Kozel, J., Stampach, R., Lukas, V., 2013. Prototyping the visualization of geographic and sensor data for agriculture. Comput. Electron. Agric. 97, 83–91. https://doi.org/10.1016/j.compag.2013.07.007.
Kwon, B.C., Fisher, B., Yi, J.S., 2011. Visual analytic roadblocks for novice investigators. In: 2011 IEEE Conference on Visual Analytics Science and Technology (VAST), pp. 3–11. https://doi.org/10.1109/VAST.2011.6102435.
Laudien, R., Pofagi, M., Roehrig, J., 2010. Development and implementation of an interactive spatial decision support system for decision makers in Benin to evaluate agricultural land resources—case study: Agroland. Int. J. Appl. Earth Obs. Geoinf. 12, S38–S44.
Le Ber, F., Benoˇt, M., Schott, C., Mari, J.-F., Mignolet, C., 2006. Studying crop sequences with CarrotAge, a HMM-based data mining software. Ecol. Model. 191 (1), 170–185.
Le Gal, P.-Y., Dugué, P., Faure, G., Novak, S., 2011. How does research address the design of innovative agricultural production systems at the farm level? A review. Agric. Syst. 104 (9), 714–728.
Leng, Z.-X., Yimit, H., 2009. Decision support systems for improving irrigation scheme management in arid area. In: Education Technology and Computer Science, 2009. ETCS'09. First International Workshop on, vol. 3. IEEE, pp. 332–335.
Li, M., Chen, S., Liu, F., Zhao, L., Xue, Q., Wang, H., Chen, M., Lei, P., Wen, D., Sanchez-Molina, J.A., Bienvenido, J.F., Li, Z., Yang, X., 2017. A risk management system for meteorological disasters of solar greenhouse vegetables. Precision Agric. 18 (6), 997–1010. https://doi.org/10.1007/s11119-017-9514-9.
Lindblom, J., Lundström, C., Ljung, M., Jonsson, A., 2017. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. Precision Agric. 18 (3), 309–331. https://doi.org/10.1007/s11119-016-9491-4.
Lorite, I., García-Vila, M., Santos, C., Ruiz-Ramos, M., Fereres, E., 2013. AquaData and AquaGIS: two computer utilities for temporal and spatial simulations of water-limited yield with AquaCrop. Comput. Electron. Agric. 96, 227–237. https://doi.org/10.1016/j.compag.2013.05.010.
Lundström, C., Lindblom, J., 2018. Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to Foster farming practices: the case of CropSAT. Agric. Syst. 159 (C), 9–20. https://doi.org/10.1016/j.agsy.2016.09.01.
Luvisi, A., Pagano, M., Bandinelli, R., Rinaldelli, E., Gini, B., Scartòn, M., Manzoni, G., Triolo, E., 2011. Virtual vineyard for grapevine management purposes: a RFID/GPS application. Comput. Electron. Agric. 75 (2), 368–371. https://doi.org/10.1016/j.compag.2010.12.013.
Machwitz, M., Hass, E., Junk, J., Udelhoven, T., Schlerf, M., 2019. CropGIS – a web application for the spatial and temporal visualization of past, present and future crop biomass development. Comput. Electron. Agric. https://doi.org/10.1016/j.compag.2018.04.026.
Manos, B.D., Ciani, A., Bournaris, T., Vassiliadou, I., Papathanasiou, J., 2004. A taxonomy survey of decision support systems in agriculture. Agric. Econ, Rev. 5 (389-2016-23416), 80.
Marra, M., Pannell, D.J., Ghadim, A.A., 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? Agric. Syst. 75 (2), 215–234. https://doi.org/10.1016/S0308-521X(02)00066-5.
McBratney, A., Whelan, B., Ancev, T., Bouma, J., 2005a. Future directions of precision agriculture. Precision Agric. 6 (1), 7–23. https://doi.org/10.1007/s11119-005-0681-8.
McBratney, A., Whelan, B., Ancev, T., Bouma, J., 2005b. Future directions of precision agriculture. Precision Agric. 6 (1), 7–23.
McHugh, M.L., 2012. Interrater reliability: the kappa statistic. Biochem. Medica: Biochem. Medica 22 (3), 276–282.
Meul, M., Van Passel, S., Nevens, F., Dessein, J., Rogge, E., Mulier, A., Van Hauwermeiren, A., 2008. Motifs: a monitoring tool for integrated farm sustainability. Agron. Sustain. Develop. 28 (2), 321–332.
Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., the PRISMA Group, 2009. Preferred reporting items for systematic reviews and meta-analyses: the prisma statement. Ann. Int. Med. 151 (4), 264–269. https://doi.org/10.7326/0003-4819-151-4-200908180-00135.
Mudisshu, A., Murase, T., Otsuka, S., 2016. Meteorological data visualization application for mandarin farmers support. In: Advanced Applied Informatics (IIAI-AAI), 2016 5th IIAI International Congress on. IEEE, pp. 900–903.
Munro, H., Novins, K., Benwell, G., Mowat, A., 1996. Interactive visualisation tools for analysing NIR data. In: Computer-Human Interaction, 1996. Proceedings., Sixth Australian Conference on. IEEE, pp. 19–24.
Mysiak, J., Giupponi, C., Rosato, P., 2005. Towards the development of a decision support system for water resource management. Environ. Model. Softw. 20 (2), 203–214. https://doi.org/10.1016/j.envsoft.2003.12.019. policies and Tools for Sustainable Water Management in the European Union.
O'Brien, R., 2008. Visualising uncertainty in spatial decision support. In: 8th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, June 2008, Shanghai, PR China.
Ochola, W., Kerkides, P., 2004. An integrated indicator-based spatial decision support system for land quality assessment in Kenya. Comput. Electron. Agric. 45 (1–3), 3–26.
Odom, W., 2010. "mate, we don't need a chip to tell us the soil's dry": opportunities for designing interactive systems to support urban food production. In: Conference on Designing Interactive Systems. https://doi.org/10.1145/1858171.1858211.
Oliver, D.M., Bartie, P.J., Heathwaite, A.L., Pschetz, L., Quilliam, R.S., 2017. Design of a decision support tool for visualising e. coli risk on agricultural land using a stakeholder-driven approach. Land Use Policy 66, 227–234.
Parker, C., 1999. A user-centred design method for agricultural dss. In: EFITA-99: Proceedings of the Second European Conference for Information Technology in Agriculture. Bonn, Germany, pp. 27–30.
Parker, C., Sinclair, M., 2001. User-centred design does make a difference. the case of decision support systems in crop production. Behav. Inform. Technol. 20 (6), 449–460.
Paustian, M., Theuvsen, L., 2017. Adoption of precision agriculture technologies by german crop farmers. Precision Agric. 18 (5), 701–716. https://doi.org/10.1007/s11119-016-9482-5.
Pearson, K., 1895. Contributions to the mathematical theory of evolution. II. Skew variation in homogeneous material. Philos. Trans. R. Soc. Lond. 186 (Part I), 343–424.
Pettit, C., Bishop, I., Cartwright, W., Park, G., Kemp, O., 2007. Enhancing web-based farm management software through the use of visualisation technologies. In: Proceedings of the MODSIM07: International Congress on Modelling and Simulation, Citeseer.
Pham, X., Stack, M., 2018. How data analytics is transforming agriculture. Bus. Horiz. 61 (1), 125–133. https://doi.org/10.1016/j.bushor.2017.09.011.
Piplani, D., Singh, D.K., Srinivasan, K., Ramesh, N., Kumar, A., et al., 2015. Digital platform for data driven aquaculture farm management. In: Proceedings of the 7th International Conference on HCI, IndiaHCI 2015. ACM, pp. 95–101.
Reed, B., Swets, D., Bard, L., Brown, J., Rowland, J., 2001. Interactive visualization of vegetation dynamics. In: Geoscience and Remote Sensing Symposium, 2001. IGARSS'01. IEEE 2001 International, vol. 1. IEEE, pp. 210–212.
Rind, A., Wang, T.D., Aigner, W., Miksch, S., Wongsuphasawat, K., Plaisant, C., Shneiderman, B., 2013,,. Interactive information visualization to explore and query electronic health records. Found. Trends Hum.-Comput. Interact. 5(3), 207–298. https://doi.org/10.1561/1100000039.
Río, M., Franco-Uría, A., Abad, E., Roca, E., 2011. A risk-based decision tool for the management of organic waste in agriculture and farming activities (farmers). J. Hazardous Mater. 185 (2–3), 792–800.
Rose, D.C., Parker, C., Fodey, J., Park, C., Sutherland, W.J., Dicks, L.V., 2018. Involving stakeholders in agricultural decision support systems: improving user-centred design. Int. J. Agric. Manage. 6 (3–4), 80–89.

Rossi, V., Salinari, F., Poni, S., Caffi, T., Bettati, T., 2014). Addressing the implementation problem in agricultural decision support systems: the example of vite.net. Comput. Electron. Agric. 100, 88–99. https://doi.org/10.1016/j.compag.2013.10.011.
Rupnik, R., Kukar, M., Vracar, P., Košir, D., Pevec, D., Bosnic, Z., 2019. AgroDSS: a decision support system for agriculture and farming. Comput. Electron. Agric. https://doi.org/10.1016/j.compag.2018.04.001.
Ruß, G., Kruse, R., Schneider, M., Wagner, P., 2009a. Visualization of agriculture data using self-organizing maps. In: Allen, T., Ellis, R., Petridis, M. (Eds.), Applications and Innovations in Intelligent Systems XVI. Springer London, London, pp. 47–60.
Ruß, G., Kruse, R., Schneider, M., Wagner, P., 2009b. Visualization of agriculture data using self-organizing maps. In: Allen, T., Ellis, R., Petridis, M. (Eds.), Applications and Innovations in Intelligent Systems XVI. Springer London, London, pp. 47–60.
Sacha, D., Senaratne, H., Kwon, B.C., Ellis, G., Keim, D.A., 2016. The role of uncertainty, awareness, and trust in visual analytics. IEEE Trans. Visualiz. Comput. Graphics 22 (1), 240–249.
Saizmaa, T., Kim, H.-C., 2008. A holistic understanding of hci perspectives on smart home. In: 2008 Fourth International Conference on Networked Computing and Advanced Information Management, vol. 2. IEEE, pp. 59–65.
Saket, B., Endert, A., Demiralp, C., 2019. Task-based effectiveness of basic visualizations. IEEE Trans. Visualiz. Comput. Graphics 25 (7), 2505–2512. https://doi.org/10.1109/TVCG.2018.2829750. ISSN: 1077-2626.
Savin, C., 2015. Embedding sectorial models in an integrated platform for assessing climate change impacts. In: Modelling Symposium (EMS), 2015 IEEE European. IEEE, pp. 37–42.
Spiegelhalter, D., Pearson, M., Short, I., 2011. Visualizing uncertainty about the future. Science 333 (6048), 1393–1400.
Stepinski, T.F., Netzel, P., Jasiewicz, J., 2014. LandEx—a GeoWeb tool for query and retrieval of spatial patterns in land cover datasets. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 7 (1), 257–266.
Stojanovic, V., Falconer, R.E., Isaacs, J., Blackwood, D., Gilmour, D., Kiezebrink, D., Wilson, J., 2017a. Streaming and 3d mapping of agri-data on mobile devices. Comput. Electron. Agric. 138, 188–199. https://doi.org/10.1016/j.compag.2017.03.019.
Stojanovic, V., Falconer, R.E., Isaacs, J., Blackwood, D., Gilmour, D., Kiezebrink, D., Wilson, J., 2017b. Streaming and 3d mapping of agri-data on mobile devices. Comput. Electron. Agric. 138, 188–199. https://doi.org/10.1016/j.compag.2017.03.019.
Tan, L., Haley, R., Wortman, R., Zhang, Q., 2012. An extensible and integrated software architecture for data analysis and visualization in precision agriculture. In: 2012 IEEE 13th International Conference on Information Reuse Integration (IRI), pp. 271–278. https://doi.org/10.1109/IRI.2012.6303020.
Tayyebi, A., Meehan, T.D., Dischler, J., Radloff, G., Ferris, M., Gratton, C., 2016. Smartscape: a web-based decision support system for assessing the tradeoffs among multiple ecosystem services under crop-change scenarios. Comput. Electron. Agric. 121, 108–121. https://doi.org/10.1016/j.compag.2015.12.003.
Terribile, F., Bonfante, A., D'Antonio, A., Mascellis, R.D., Michele, C.D., Langella, G., Manna, P., Mileti, F., Vingiani, S., Basile, A., 2017. A geospatial decision support system for supporting quality viticulture at the landscape scale. Comput. Electron. Agric. 140, 88–102. https://doi.org/10.1016/j.compag.2017.05.028.
Thierry, H., Vialatte, A., Choisis, J.-P., Gaudou, B., Parry, H., Monteil, C., 2017. Simulating spatially-explicit crop dynamics of agricultural landscapes: the atlas simulator. Ecol. Inform. 40, 62–80. https://doi.org/10.1016/j.ecoinf.2017.05.006.
Thysen, I., Detlefsen, N.K., 2006. Online decision support for irrigation for farmers. Agric. Water Manag. 86 (3), 269–276. https://doi.org/10.1016/j.agwat.2006.05.016.
Wachowiak, M.P., Walters, D.F., Kovacs, J.M., Wachowiak-Smolíková, R., James, A.L., 2017. Visual analytics and remote sensing imagery to support community-based research for precision agriculture in emerging areas. Comput. Electron. Agric. 143, 149–164. https://doi.org/10.1016/j.compag.2017.09.035.
Wenkel, K.-O., Berg, M., Mirschel, W., Wieland, R., Nendel, C., Köstner, B., 2013. LandCaRe DSS–an interactive decision support system for climate change impact assessment and the analysis of potential agricultural land use adaptation strategies. J. Environ. Manage. 127, S168–S183.
Whitman, C.J., Armijo, G., Schiappacasse, L.N., 2015. Methodology for informed design of sustainable tourism accommodation in Chile's 9th region the gateway to Patagonia. Energy Procedia 78, 267–272. https://doi.org/10.1016/j.egypro.2015.11.633. 6th International Building Physics Conference, IBPC 2015.
Yalew, S., van Griensven, A., van der Zaag, P., 2016. Agrisuit: a web-based GIS-MCDA framework for agricultural land suitability assessment. Comput. Electron. Agric. 128, 1–8. https://doi.org/10.1016/j.compag.2016.08.008.
Yan, A., Lv, B., Liu, F., Li, Q., Lin, G., Bai, Y., 2014. FluxDataOne: an integrated solution for the management, visualization, and analysis of flux data for agricultural and ecological studies. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 7 (11), 4523–4529.
Yang, G., Liu, L., Guo, P., Li, M., 2017. A flexible decision support system for irrigation scheduling in an irrigation district in china. Agric. Water Manage. 179, 378–389.
Zhang, B., Di, L., Yu, G., Shao, Y., Shrestha, R., Kang, L., 2013. A web service based application serving vegetation condition indices for flood crop loss assessment. In: Agro-Geoinformatics (Agro-Geoinformatics), 2013 Second International Conference on. IEEE, pp. 215–220.
Zheng, Y., Altamimi, T., 2017. Innovative mobile visualization platform: specification on a prototype mobile application for agriculture, in: Cybernetics. In: (CYBCONF), 2017 3rd IEEE International Conference on. IEEE, pp. 1–6.
Zudilova-Seinstra, E., Adriaansen, T., Van Liere, R., 2009. Overview of interactive visualisation. In: Trends in Interactive Visualization. Springer, pp. 3–15.