

Article

Visualizations of Uncertainties in Precision Agriculture: Lessons Learned from Farm Machinery

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Abstract: Detailed measurements of yield values are becoming a common practice in precision agriculture. Field harvesters generate point Big Data as they provide yield measurements together with dozens of complex attributes in a frequency of up to one second. Such a flood of data brings uncertainties caused by several factors: accuracy of the positioning system used, trajectory overlaps, raising the cutting bar due to obstacles or unevenness, and so on. This paper deals with 2D and 3D cartographic visualizations of terrain, measured yield, and its uncertainties. Four graphic variables were identified as credible for visualizations of uncertainties in point Big Data. Data from two plots at a fully operational farm were used for this purpose. ISO 19157 was examined for its applicability and a proof-of-concept for selected uncertainty expression was defined. Special attention was paid to spatial pattern interpretations.

Keywords: yield measurements; point Big Data; uncertainty expression; interactive 3D visualization; ISO 19157

1. Introduction

The period of the past twenty years can be characterized by a shift from conventional agriculture through precision agriculture [1] towards the latest innovations in the form of data-driven agriculture [2]. A crucial part of precision agriculture is estimating crop yield. Information on yield is important for two main reasons: it can be used to maximise economic profitability and to reduce the environmental burden caused by agricultural activities [3,4]. Both objectives need as much precise information on yield as possible. It has been defined, for example, by Auernhammer [5], that a yield in a plot is not homogeneous owing to variable soil conditions, weather, climate, and so on. Consequently, all plots have their strong and weak zones in terms of crop yield. Data from field harvesters represent the most detailed, as well as the most credible, source of yield information. On the other hand, field harvesters provide measurements with a bias. Conventional approaches of reducing these biases through filtering the data were described, for example, in Blackmore [6], Arslan and Colvin [7], Lyle et al. [8], Reznik et al. [9], Vega et al. [10], and Reznik et al. [11].

A different approach relies on so-called Big Data, which is more than a term for vast volumes of data, equivalent to Terabytes of memory and larger in the context of geoinformatics. Big Data approaches also process all the available data, while conventional approaches usually deal with only a subset of data (e.g., a representative and random sample; a subset without erroneous data) [12] (pp. 19–25). Processing of all available data is related to ‘veracity’, which is considered “the fourth V (volume—velocity—variety—veracity)” and seems to be the most relevant in the agricultural domain [13].

Processing and visualization of all the available data from farm machinery forms the basic premise of the presented paper, with its main objective being an innovative approach to dealing with visualization of uncertainties of point Big Data. In this context, the term “point Big Data” is defined as all the available farm machinery measurements of yield and uncertainty thereof in the Rostěnice pilot farm in the Czech Republic (see Section 2.1 for details). Point data were selected for the purpose of this paper as they are the original source of uncertainty, in contrast to more common visualizations of interpolated and/or density surfaces as described by Jezek et al. [14], Charvat et al. [15], Mezera et al. [16], Netek et al. [17], and Reznik et al. [18]. Interpolated/density surfaces add an additional level of uncertainty during their creation.

Data quality and uncertainty are crucial issues in geographical information science (GIS), because uncertainties occur in the real world and at each stage of knowledge extraction from spatial data, as well as from Big Data in general [19]. The quality definition started with the positional errors and topology at the early stage of GIS development, and both concepts developed with an increasing interest in the use of spatial data in decision-making processes [20,21].

There exist several definitions of both concepts, although international standards have only evolved with respect to the quality. In the following text, we use the definition by Longley et al. [22]: “uncertainty is the difference between a real geographic phenomenon and the user’s understanding of the geographic phenomenon”. The quality of data can be generally defined as “the degree to which a set of inherent characteristics fulfils requirements” [23]. This definition was further developed and consistently used in ISO (International Organization for Standardization) standards 19101 [24], 19157 [25] and 19158 [26] for geographical information.

The history of uncertainty visualization is connected with the National Center for Geographic Information and Analysis (NCGIA) [27,28]. The NCGIA Research Initiative on “Visualization of Spatial Data Quality” stressed the necessity of properly communicating the information about data quality and uncertainty. Alternatively, quality can be described as “fitness for use” [29] or, in other words, the ability to comply with the user’s needs. Therefore, for a reasonable quality definition, we need to know the intended use of data and the users. Regarding the farm machinery data mentioned above, the point geometry representing the data uncertainty and the user group of farmers and agricultural specialists frame the context of the study.

The primary objectives of this paper are to address certain outstanding aspects as follows:

1. Propose a method of uncertainty expression of measured yield data;
2. Apply means of cartographic visualization of uncertainties to measured point Big Data based on existing cartographic recommendations and empirical studies.

In situ sensor measurements of yield from field harvesters were used as input data for the presented proofs of concept.

1.1. Data Quality and Uncertainty

The issue of data quality and uncertainty as a general phenomenon in the natural world has been at the centre of the geospatial community since the beginning of geographic data quality research. Moellering [30] introduced a broader framework for evaluating geographic data quality and proposed several measures (accuracy, consistency, completeness, and lineage) as essential components to be used as possible dimensions describing geographic data. Other quality dimensions representing particular

characteristics of quality have been proposed by scholars [31–33] and standardisation organisations for both data and services. ISO, OGC (Open Geospatial Consortium), and W3C (World Wide Web Consortium) have agreed on ISO 19157 as a common standardization framework for geographic data quality [25,34,35]. In summary, the dimensions of quality depend on the application domain. Feiden et al. [36] discusses these dimensions in the context of agriculture and the soil in general.

The international standard ISO 19157:2013 [25] establishes the principles for describing the quality of geographic data. Among others, it defines components for describing data quality (also known as data quality elements and sub-elements) and a set of data quality measures for use in evaluating and reporting data quality. A variety of measures are based on counting erroneous items, such as if ‘number of missing objects in the dataset’ equals ‘5’. However, there are also several measures dealing with the uncertainty of numerical values. The uncertainty-related data quality basic measures according to ISO 19157 are based on the concept of modelling the uncertainty of measurements with statistical methods. None of the uncertainty concepts/expressions presented in ISO 19157 are applicable to the measured point Big Data with respect to the scope presented in this study. The elementary premise of all ISO 19157 uncertainty measures, that is, reference values (‘ground truth’) to quantify the derivations with a certain probability, is not met.

The quality of data also plays a crucial role in agriculture. Food and Agriculture Organisation (FAO) stressed the importance of data quality measures (completeness, precision, consistency) for collecting and combining heterogeneous land use data [37]. The FAO has further developed procedures for using statistical techniques and integrating data sources from different regions of the world [38]. The CountrySTAT framework [39], serving as an integration platform for agricultural statistics, has defined the following six dimensions of data quality: relevance and completeness, accessibility and clarity, timeliness, comparability, subjectiveness, and coherence. Ouma et al. [40] downsized the quality measures from global to national perspective and proposed an alternative set of quality dimensions encompassing both quantifiable and subjective ones. Malaverri and Medeiros [41] developed a meta-study surveying the use of quality measures/dimensions in agricultural applications as well as the context of use. Their observations revealed that the most often mentioned (and probably used) dimensions are accuracy, timeliness, and completeness, followed by consistency and relevancy. The same authors also pointed out that particular measures vary according to the spatial scale (local to global), measured factors (natural and human—soil management practices), and types of devices. Nevertheless, none of the analysed studies dealt with uncertainty of spatially-located data in (precision) agriculture in general and farm machinery in particular.

1.2. Uncertainty Visualization

The revised and modified spatial data quality research agenda proposed by National Center for Geographic Information and Analysis (NCGIA) [28] also included a role of data quality visualization in decision-making and dispute resolution. This agenda established grounds for further research and strongly influenced activities in data quality visualization for the next decades, including conceptual models, computation of uncertainties, as well as the investigation and evaluation of visualization methods themselves [42].

MacEachren et al. [43] stated that most research directed towards uncertainty visualization had focused on developing representation methods [44,45], on software applications for the display of uncertainty [46], and on developing the uncertainty visualization theory [47,48]. Less has been done on the empirical evaluation of the role of uncertainty in geographic decisions and, more specifically, on the role of maps and uncertainty representation in that decision making. Zhang and Goodchild [49] have demonstrated that visual form can improve the communication about spatial data uncertainty within spatial analysis and spatial decision support. On the basis of their review and synthesis of the literature on uncertainty visualization, MacEachren et al. [43] identified seven core challenges requiring an interdisciplinary effort to be accomplished. One of these challenges dealt directly with the understanding of how knowledge of information uncertainty influences information analysis,

decision making, and decision outcomes. Despite reasonable amounts of work done in the field of uncertainty visualization methods [50–61] and the testing of the impact of visualization on decision making [62–68], there is still a wide gap between the uncertainty visualization theory and widely accepted use of uncertainty representation within the decision-making process. The same conclusions have been reached in the field of visualization of special data uncertainties related to precision agriculture [69–72]. Specifically, uncertainty visualizations were applied in tasks such as the sustainability of tropical fodder cultivation [69], in support of weed management [70], seasonal climate estimates on a global scale [71], and estimating the amount of biomass in individual fields [72].

To overcome the gap between the theory of data quality visualization and real use, several authors have proposed visualization typologies for spatial data in general [48,73] and for selected contexts of use [47,74,75]. Senaratne et al. [64] evaluated the usability of visualization methods and proposed a methodology and a web-based tool (uncertainty visualization selector) to determine suitable methods. The selection is a decision tree process based on the following parameters: data type, data format, uncertainty type, and interaction.

If the “fitness of use” concept is accepted (see above), we need to focus on the current use of uncertainty visualization in the area of interest. Gutierrez et al. [76] elaborated a meta-analysis focusing on the role of visualizations in agricultural decision support systems (DSSs). They included several types of supportive visualization techniques including maps and uncertainty/quality visualization, aiming at design guidelines for a better and more user-optimised concept of DSS. Generalising their findings, the display of uncertainty is rather exceptional in agricultural data and, if applied, it should be provided in a cognitively plausible way. In other words, it is crucial to display the quality data in a way the end users can find the added value in terms of their decision making.

When visualizing uncertainty, we are no longer limited only by the classic 2D cartographic visualization. Several approaches and techniques have been proposed for 3D visualization of phenomena related to the precision agriculture domain (e.g., [9,15,77–81]). However, only a few studies have considered the problem of visualizing thematic data, such as yield, in 3D, and the uncertainty/data quality simultaneously. In 3D visualization, the additional graphic variable—the perspective height (introduced by Slocum et al. [82])—is usually used to express terrain conditions, but alternatively, it can also be used to represent thematic data like yield or even the uncertainty. Dübel et al. [60] described the topic of 3D visualization of terrain and uncertainty in detail, but this study was not focused directly on precision agriculture, so the only relevant exception is Pettit et al. [83]. Naturally, 3D visualization is not always beneficial and, when using it, it is necessary to follow certain principles; this topic is discussed, for example, by Ware and Plumlee [84], Wood et al. [85], Jobst et al. [86], and Shepherd [87]. A considerable importance in the application of 3D visualization lies in its interactivity, which, compared with a static visualization, delivers better usability. This was theoretically discussed by Shephard [87] and also empirically documented (e.g., [88,89]).

Traditional cartographic techniques using visual variables were defined by Bertin [90] and elaborated by MacEachren [91] and Slocum et al. [82], who provided nine visual variables, as depicted in Figure 1. Slocum et al. [82] defined visual variables together with an example to increase understandability. So far, applicability of visual variables to uncertainty of point Big Data has not been sufficiently addressed as no specific proposal is available. Figure 1 proposes the general (in)applicability of visual variables to the uncertainty of point Big Data.

Visual variable	Example	Example on Point Big Data	Applicability to Qualitative Point Big Data	Applicability to Quantitative Point Big Data	
Spacing			not applicable	not applicable	
Size			not applicable	not applicable	
Perspective Height			applicable*	applicable*	* The 'perspective height' visual variable is applicable to point Big Data under the condition of interactivity and colour/greyscale differentiation.
Orientation			not applicable	not applicable	
Shape			not applicable	not applicable	
Arrangement			not applicable	not applicable	
Lightness			applicable**	applicable**	** The 'lightness' visual variable is applicable only under certain conditions of base map (e.g. orthophoto vs. grey-scale topographic map) or used color scheme (avoiding lightness close to white color when using light background and vice-versa).
Hue			applicable***	not applicable	*** Traffic light metaphor, basic (three colors) or extended (five colors) is one of the common approaches (for more details see section 2.3).
Saturation			applicable	applicable	

Figure 1. Applicability of visual variables to uncertainty of point Big Data.

2. Materials and Methods

2.1. Study Site

Farm data on yield measurements were provided by the Rostěnice Farm in the Czech Republic. Data on crops, agronomic practices, and yield measurements were provided for the purposes of this paper.

The farm, Rostěnice a.s. (N 49.105 E 16.882; see Figure 2), manages over 10,000 ha of arable land in the South Moravian Region of the Czech Republic. The average annual rainfall is 544 mm and the average annual temperature is 8.8 °C. Within the managed land, the most prevalent soil types are Chernozem; Cambisol; haplic Luvisol; Fluvisol near to water bodies; and, occasionally, also Calcic Leptosols. The main programme is plant production, where the main focus is on the cultivation of malting barley, maize for grain and biogas production, winter wheat, oilseed rape, and other crops and products such as soybean and lamb.

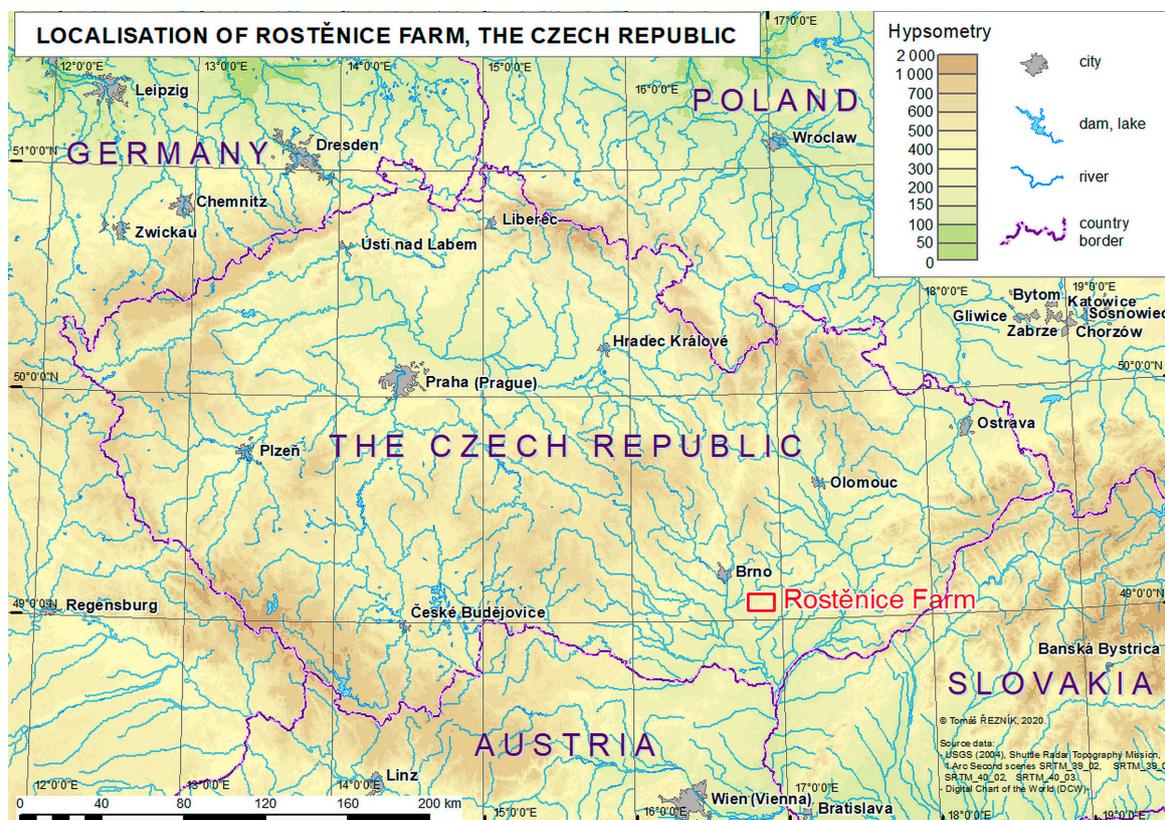


Figure 2. Geographical location of the Rostěnice Farm.

Plots “Pivovářka” and “Přední prostřední”, with an acreage of 44.5 ha and 61.2 ha, respectively, were selected for the pilot study. These plots are located in sloping terrain; for this reason, conservation practices with respect to soil tillage have been implemented to reduce soil water erosion. The farm has applied long-term soilless cultivation (mostly choppers) on its land, leaving all straw after harvest on the land. The high spatial variability of soil conditions has led to the adoption of precision farming practices, such as the variable application of fertilizers (since 2006) and crop yield mapping by harvesters (since 2010).

The farm machinery measurements are collected by field harvesters with time resolution of one second at the average harvesting speed of 1.55 ms⁻¹; the mean value is thus 370 points per hectare. The pilot study included tens of thousands of points per average plot. The spatial resolution is a result of a combination of harvesting speed and the width of a cutting bar (9.15 m). A visualization of

this point Big Data is a challenge as it entails approximately a distance of 0.16 mm between points in a row and 0.46 mm between lines at the 1:10,000 scale, or approximately the distance equal to 0.31 mm between points in a row and 0.92 mm between lines at the scale of 1:5000.

2.2. Uncertainty Expression

As stated in Blackmore [6], Arslan and Colvin [7], Lyle et al. [8], and Reznik et al. [9], several sources of uncertainty can be identified for farm machinery field measurements:

- harvesting dynamics:
 - lag time;
 - filling time and emptying time of the combine harvester;
- measurement errors:
 - related directly to yield;
 - related to moisture observations;
- accuracy of the positioning system:
 - collocated observations;
 - outliers;
- harvesting strategy (decisions and actions of the harvester operator):
 - higher than the recommended harvesting speed;
 - sudden changes of speed;
 - harvest turns and headlands;
 - overlapping (crossings) and partially overlapping trajectories;
 - raising the cutting bar due to obstacles or unevenness of terrain.

The computation of uncertainty for the purposes of this paper was defined according to the following equation:

$$N0 = \left| \left(1 - \frac{v}{x_1} \right) \right| + \left| \left(1 - \frac{v}{x_2} \right) \right| \quad (1)$$

where

$N0$: index of uncertainty variation in a given point;

v : value of yield production in a given point;

x_1 : mean value of yield production of predeceasing n points (field measurements);

x_2 : mean value of yield production of following n points (field measurements);

n : defined as 1/20 of relative density of measurements per hectare (see the more detailed explanation below).

Equation (1) was defined based on the following process:

- This analysis is preconditioned on the fact that the variation of yield production is a continuous process that follows environmental and soil characteristics; therefore, sudden and small coverage area differences in yield production compared with the surrounding areas are not probable/expected, that is, are considered an uncertainty.
- An analysis of yield variations for 15 crossings of farm machinery trajectory when taking into account variable rates of preceding and following points (see Figure 3). Crossings were used as a model owing to the known uncertainty in those areas.

- On the basis of the analysis, it was discovered that the suitable area for calculating uncertainty is mainly dependent on the frequency of measurements and distance. Both of these variables are included in the density of measurements per hectare. The value of 1/10 of the density (i.e., half of that on each side of the point) was taken into account as representative surroundings. Other environmental aspects (relief, water distribution, soil conditions, and so on) of the plot might be taken into account as well.
- Values of preceding and following points are calculated separately owing to different possible behaviour on each side. For example, in Figure 3, points at the beginning and at the end of the “U” shape are affected by uncertain values only from one side, while the other is balancing the final uncertainty towards a lower value. On the other hand, a point in the middle of the “U” shape is different from the neighbours on both sides and, additionally, emphasizes the final value of uncertainty.
- Absolute values are taken into account owing to possibly overestimated uncertain values (above the mean value of surroundings).

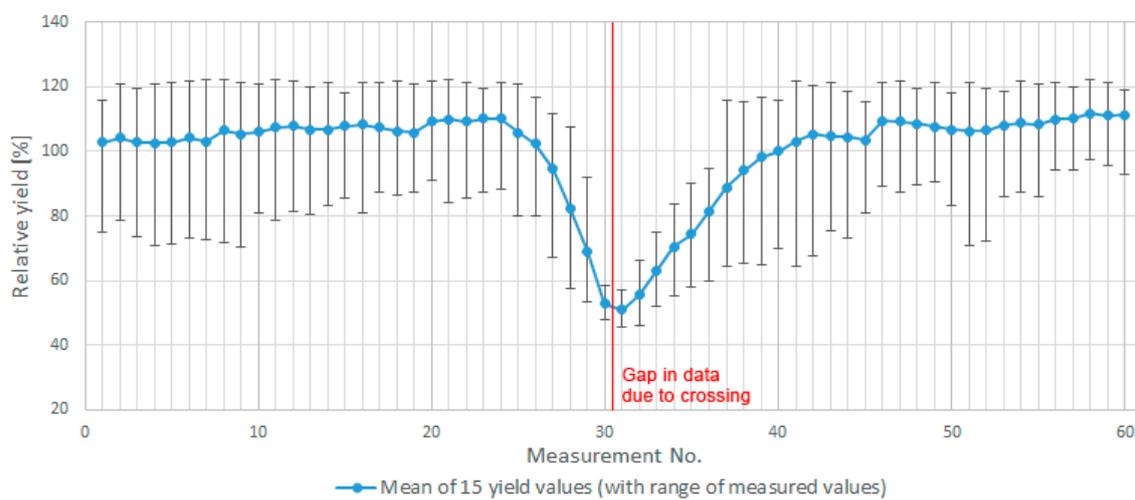


Figure 3. The mean and the range of yield values in crossings of a farm machinery trajectory: a demonstration of point measurements for a proof-of-concept uncertainty definition.

Figure 4 presents some of the situations that affected uncertainty owing to the harvesting strategy: crossings, overlapping and partially overlapping trajectories, raising the cutting bar causing gaps in data, harvester turns, and headlands (beginning of a new row).

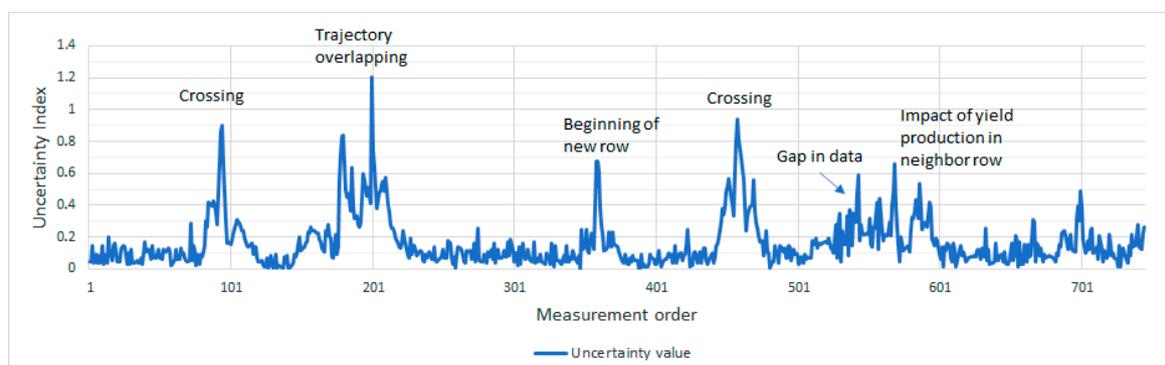


Figure 4. The mean and the range of yield values in crossings of problematic parts of farm machinery trajectory: a demonstration of point measurements for proof-of-concept uncertainty definition.

2.3. Uncertainty Visualizations

As depicted in Figure 1, four methods of cartographic visualization are applicable for the visualization of uncertainty values in the chosen context. All the following four methods of cartographic visualization of yield data from field harvested were selected as a proof-of-concept within this study:

- colour hue in the form of an extended traffic lights metaphor;
- lightness;
- saturation;
- perspective height.

The methods using colour hue, lightness, and saturation represent intrinsic techniques, while the perspective height is considered extrinsic in the sense of Kinkeldey and Senaratne [61]. Application of hue, lightness, and saturation requires a classification scheme to be used. The Jenks natural breaks classification method [92] was used homogeneously in those cases.

Colour hue refers to the dominant wavelength of visible light. Colour hue is the only colour variable that is suitable for representing qualitative data [93]. The (extended) “traffic lights” metaphor is based on colour hue variations, and it is often used and discussed as an alternative for data quality visualization [55,56,59,73]. Humans often integrate their external knowledge into a decision-making process. Utilising the information from everyday experience (traffic lights) helps users to decode the red-orange-green categories more intuitively (see Figure 5). It is also an easy to understand solution for new and inexperienced users [73]. Moreover, this metaphor enables the “fitness for use” classification [54] and users’ adjustment using different data representation and contexts.

Lightness is also known as a colour value, a light or dark variation of one single hue. Lightness is commonly associated with quantitative data [82,93]. When only grayscale is available, lightness can be applied to shades of grey. The number of colour values used in a scheme, and the perceptual distance between each lightness value, affect how efficiently a reader can interpret depicted values [94]. Saturation is the purity or intensity of a single hue of colour. Fully saturated colours appear vivid or bold, while fully desaturated hues appear grey. Usually, colour saturation is associated with ordinal data as well as with uncertainty [82,93]. Both lightness and saturation have been recommended for uncertainty visualization based on user preferences [53,58] and intuitiveness [57,58]. Besides the intuitiveness of methods, several scholars addressed the uncertainty level match with higher or lower lightness and saturation. Empirical studies supported higher lightness and lower saturation for higher uncertainty [57,63].

There are more graphic variables available in 3D visualizations compared with 2D. Locations on the horizontal axis level in 3D can be used for expressing attribute values. This additional graphic variable is known as perspective height [82]. Perspective height serves for the depiction of quantitative data. The perspective height can be combined with the above-mentioned colour graphics variables. Both colour and perspective height can display the same phenomenon, or two different phenomena, in which case users can compare the individual variables (phenomena). Uncertainty can be one such phenomenon.

Two-dimensional cartographic representations were conducted using ESRI (Environmental Systems Research Institute) ArcMap software in version 10.6 (ESRI, Redlands, CA, USA), while 3D cartographic visualizations were conducted utilising the Plotly JavaScript library (version 1.54.7; Plotly Technologies Inc., Montreal, Canada) [96]. Spatial reference properties were set equally for all the visualizations conducted. The coordinate reference system with code ‘32633’ was used as defined in the EPSG (European Petroleum Survey Group) Geodetic Parameter Registry [97]. To be more specific, universal transverse mercator (UTM) projection of zone 33 N on WGS (World Geodetic System) 1984 coordinate system with Greenwich prime meridian was used as a common reference. Linear units used for expression to a user were set up to meters, while angular units were degrees. Note that the Plotly JavaScript library presents for the visualization purposes coordinates in the cartesian coordinate system

owing to on-the-fly conformal transformation that sets the new origin (with X as well as Y equal to 0) instead of the original UTM coordinates.

Extended traffic light metaphor (hue)		Lightness			Saturation		
Colour	Hexidecimal	Colour	Hexidecimal	Lightness	Colour	Hexidecimal	Saturation
	#1a9641		#e5e5ff	95		#dcdcf5	10
	#a6d96a		#b3b3ff	80		#b8b8f5	25
	#ffffbf		#3333ff	60		#8787f5	45
	#fdae61		#0000cc	40		#6262f5	60
	#d7191c		#000080	25		#0000f5	100

Figure 5. Colour scales for colour hue in the form of the extended traffic light metaphor, lightness, and saturation. Colours were optimised in ColorBrewer [95].

3. Results

The results achieved during the study are presented in Sections 3.1 and 3.2 according to the cartographic visualization method used. Figures 6–11 present the results processed according to the methodology described in Section 2.2. As depicted in Table 1, uncertainty values lower than 0.2 appear at 67% for the Přední prostřední plot and 43.9% for the Pivovárka plot.

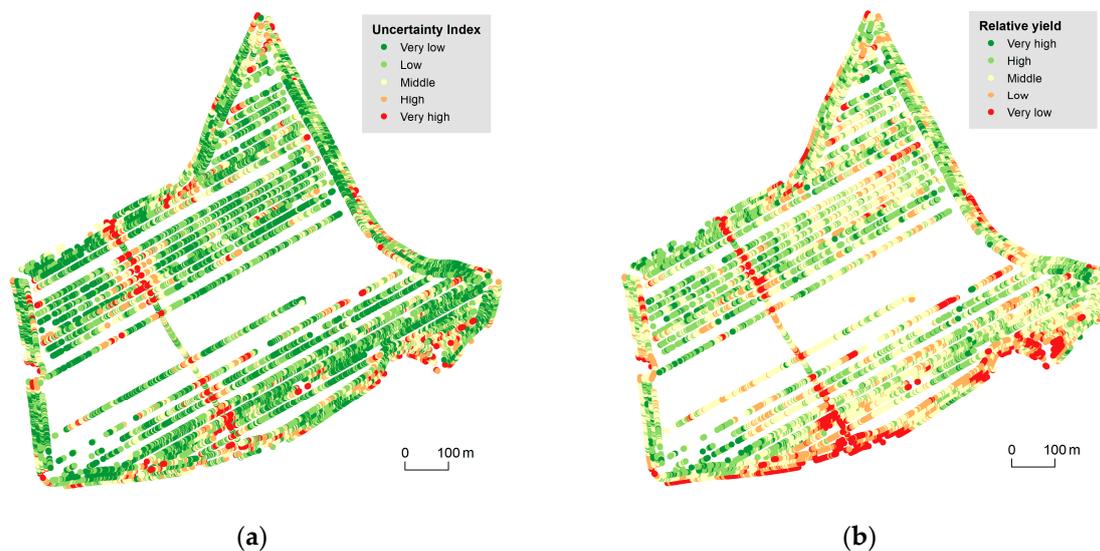


Figure 6. The extended traffic light metaphor for qualitative data on uncertainty (a) and yield (b) for the Přední prostřední plot.

3.1. 2D Cartographic Methods

The extended traffic light metaphor for five classes was used for presenting qualitative data on uncertainty and relative yield. As depicted in Figures 6 and 7, quantitative data were classified into five qualitative classes: from very low, through low, middle, and high to very high. Note that the extended traffic light metaphor was used inversely in Figures 6 and 7 in the cases of uncertainty index and relative yield owing to associativeness: red is used for very high uncertainty index, while red is also used for very low relative yield. The motivation is the same in both cases, as the red colour evokes a negative perception (of low yield and/or high uncertainty). Figures 6 and 7 were used to demonstrate various spatial patterns:

- The plot “Přední prostřední” in Figure 5 demonstrates crossing in point measurements;
- The plot “Pivovárka” in Figure 6 demonstrates the influence of terrain on uncertainty and yield measurements.

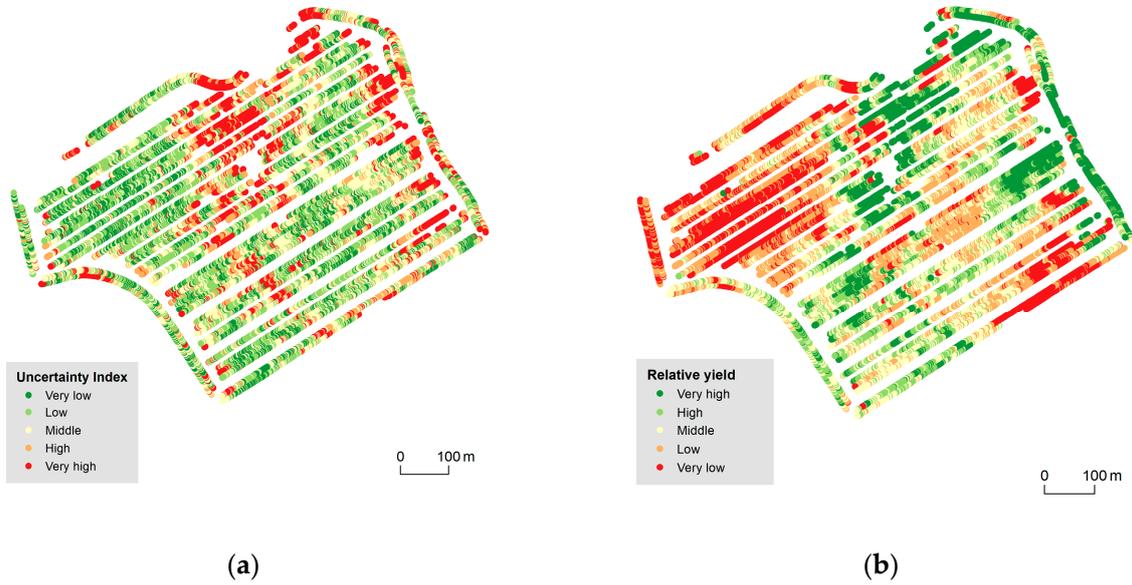


Figure 7. The extended traffic light metaphor for qualitative data on uncertainty (a) and yield (b) for Pivovárka plot.

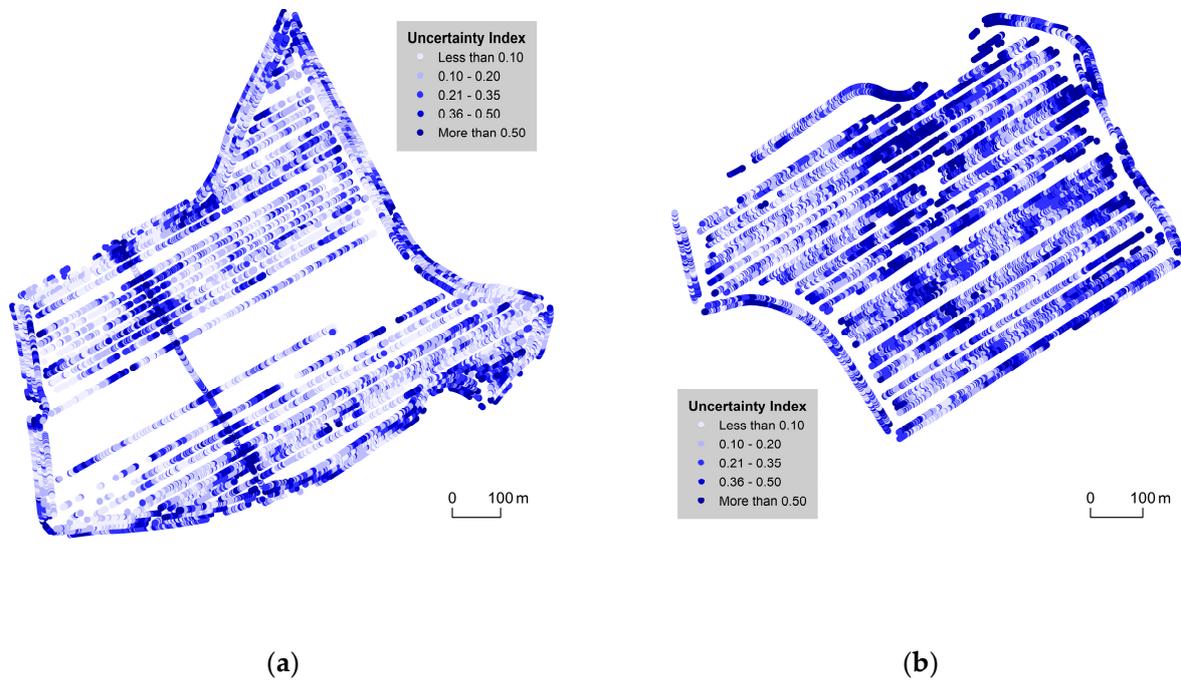


Figure 8. Lightness applied to quantitative data on uncertainty for Přední Prostřední (a) and Pivovárka (b).

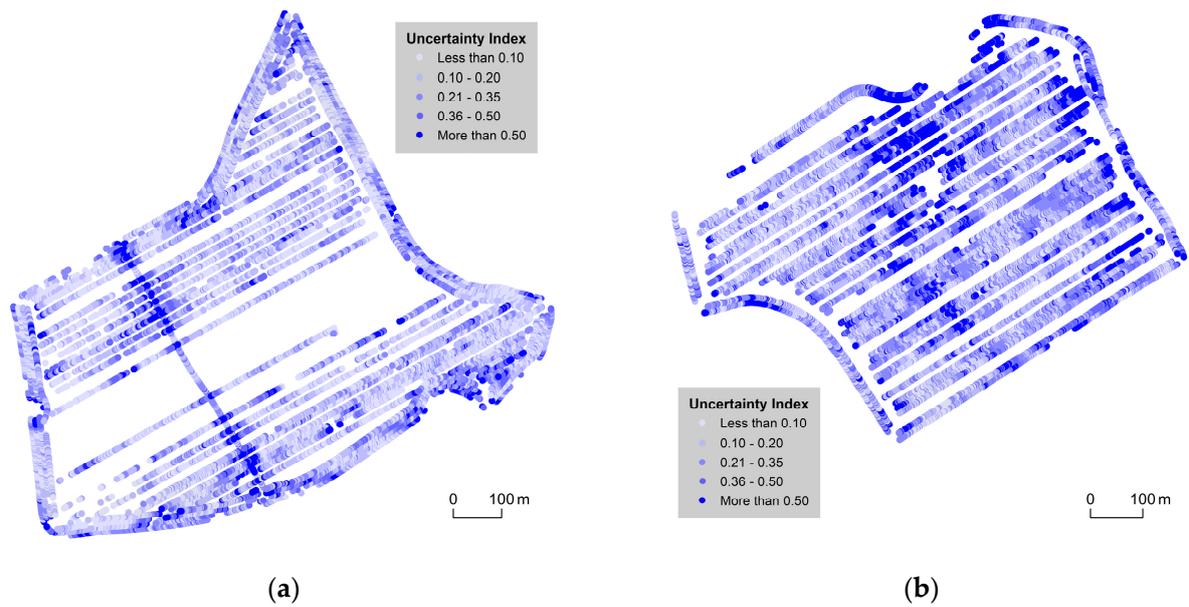


Figure 9. Saturation applied to quantitative data on uncertainty for Přední Prostřední (a) and Pivovárka (b).

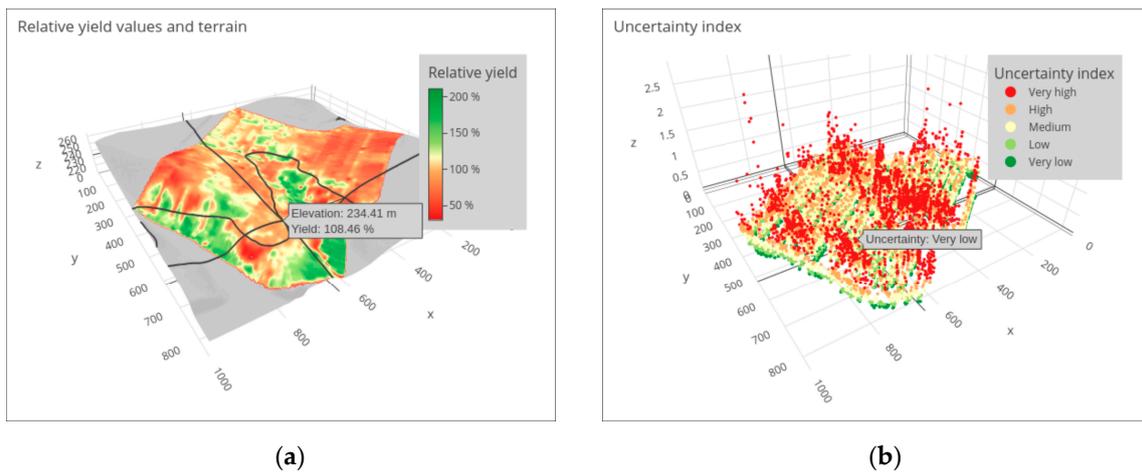


Figure 10. Application of the perspective heights method to uncertainty values and the measured data on relative yield (a) and uncertainty index (b). Three slicing lines were applied for the visualization of relative yield (X, Y, Z), while two slicing lines were applied for the visualization of the uncertainty index (X, Y). Note, the interactive version is available at https://bl.ocks.org/SLeitgeb/raw/5ebc03f461b79386002cdeca308c09ac/?fbclid=IwAR1mvLHOib5NM3JWDZssNuGRq4SiDPB6-9MPnqIFWzN3LxcvDP2uQZRLL_s.

Both Figures 6 and 7 depict two plots, Přední Prostřední and Pivovárka at Rostěnice farm. Figures 5 and 6 show contradicting spatial patterns for uncertainty on the one hand and measured yield on the other hand. In other words, Figure 6 depicts similar spatial patterns between the measured yield and low uncertainty. Figure 7 depicts the opposite, that is, a contradicting spatial pattern.

Lightness and saturation methods are depicted in Figures 8 and 9, respectively. Both methods are primarily applicable to quantitative data, in these cases, to the uncertainty index. The presented results follow the same classification scheme as in the case of qualitative data presented in Figures 6 and 7 (in both cases, only their left parts) in order to enable comparability. The applied 2D visualization methods confirmed high uncertainty values of overlapping (crossings) and partially overlapping trajectories.

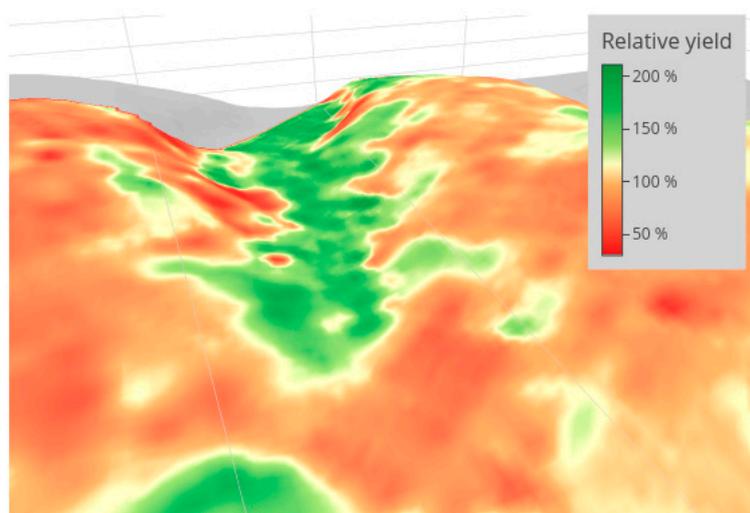


Figure 11. Detail of a ‘supernormal strip of fertile land’ in a form of a valley where relative yield reaches up to 180% of the mean yield for the whole plot.

Table 1. Representation of the percentage of uncertainty values per field.

Value	Přední Prostřední [%]	Pivovárka [%]
less than 0.10	36.2	16.8
0.10–0.20	30.8	27.1
0.21–0.35	21.1	29.2
0.36–0.5	7.8	13.4
more than 0.5	4.1	13.5

3.2. 3D Cartographic Method

Figure 10, as well as Supplementary Material S1 depict the application of the perspective heights method to uncertainty values and the measured data on yield. Moreover, the 3D terrain is visualized at the same time. The Plotly JavaScript library [96] was used to generate 3D scenes following the principles of perspective height as a graphic variable. The multiple coordinated views principle was applied as well to visually link data on both uncertainty and yield. The reference frame and slicing lines (Figure 10 and Supplementary Material S1) support obtaining the exact values of uncertainty/yield data. Interactivity is applied as well with the same objective as the reference frame; zoom and pan are used to support obtaining exact uncertainty/yield values.

The following spatial pattern was revealed thanks to a combination of uncertainty visualization together with yield values and terrain, as depicted in Figure 11. Valleys as supernormal strips of fertile land [9] are characterized by above average uncertainty values (classes of “high” and “very high” uncertainty) in the study area.

4. Discussion

The discussion follows the main objectives of the study and details the results in the following parts:

- (un)feasibility of uncertainty expression according to ISO 19157;
- applicability of the cartographic methods used in general;
- a confrontation of the achieved results with similar studies.

4.1. Uncertainty Expressions and ISO 19157

Uncertainty concepts/expressions/measures as presented in ISO 19157 [25] are not generally applicable to the point Big Data measured. ISO 19157, as a common standardization framework for ISO,

OGC, and W3C, relies on a comparison with a dataset with a higher quality of the measure in question (e.g., positional accuracy, thematic classification correctness, the accuracy of time measurement). A dataset with higher quality with respect to yield in the given time and space was not available for our study. None of the following ways could be implemented: another Big Data measurement with more precise yield values or (as foreseen by ISO 19,157 [25]) its subset with more detailed sample field measurements. For that reason, the concept of uncertainty expression was developed by the authors in this paper.

Transferability, scalability, and extensibility of the uncertainty expressions developed to other applications are some of the advantages of this approach. The uncertainty expression developed is a proof-of-concept that was successfully tested on the point Big Data obtained from yield measurements on two plots at a fully operational Czech farm. Uncertainty expressions, as well as their cartographic visualization, were verified using a total of 32,625 points displayed to a user at the same time. The presented uncertainty expression could be further developed:

1. If an aspect(s) of uncertainty other than the one used in this study is to be presented (a sudden change of measured yield).
2. If the objective is to express, relativize, and combine partial uncertainties.
3. If the objective is to present point Big Data of a different nature than the data measured by field harvesters.

4.2. Applicability of Used Cartographic Methods

Big Data visualization is a distinct approach as its primary goal is to visualize the whole dataset, while 'traditional' cartographic methods [82,90,91] deal with aggregations/generalizations or interpolation. As demonstrated in this paper, there are challenges such as displaying the full density of points. Uncertainty, in general, originates at the following two levels in the scope of 'traditional' cartographical visualization methods:

1. uncertainty of input information intended for a cartographic visualization;
2. processing of input data through (cartographic) methods of aggregation, generalization, and interpolation, as well as interpretations thereof.

Cartographic visualization of Big Data uncertainties eliminates the level (2) as map-maker processing of input data is suppressed. At the same time, visualization of a whole dataset brings new possibilities, such as a novel approach to uncertainty expression and visualization.

Both 2D and 3D cartographical methods for uncertainty visualization have been developed [50–52,60,69–72]. Cartographical methods have the following similarities when applied to point Big Data, no matter which 2D cartographic method was used. These similarities include the following:

- Point size: remains the same, no matter whether qualitative or quantitative data are being visualized.
- Spatial pattern: overall picture is clear to a user when the values are not affected by any other characteristics and/or dimensions.
- Point density: conflicts of points tend to be common as each application needs to strike a balance between the following contradicting requirements:
 - the need to maintain readability of a symbol, which pushes for larger symbols, as opposed to the following:
 - the need to provide an overview that enables to clearly see spatial patterns in the whole dataset, which pushes for smaller symbols;
 - both contradicting requirements above are tightly connected to a scale that is being used for a cartographic presentation.

The following similar aspects of 3D cartographic visualizations in comparison with their 2D counterparts can be identified:

- perspective height as an additional graphic variable brings a possibility to combine the presented value(s) (i.e., yield, in our study) and uncertainty value in one cartographic visualization [85].
- Scale variations across a 3D scene, which complicates readability in comparison with 2D: value depicted as perspective height changes according to the perspective projection distortion [86,87].
- In the case of interactive perspective heights, the previously mentioned disadvantages can be overcome using cutting planes (Figure 10a) and other interactive functions [87].

4.3. Comparison with Similar Studies

The existing research aims at the visualization of uncertainty in (precision) agricultural data primarily beyond (geo)spatial visualizations (e.g., [70,72]). In such cases, visualization of uncertainty was expressed in a graph rather than on a map. O'Brien [69] used an approach similar to Figure 10 of this paper, that is, two map windows: one for the presented values and the second for the expression of uncertainty. From a cartographic perspective, uncertainty was visualized through saturation, and this was used in this paper as well. O'Brien [69] also foresees a presentation of the uncertainty layer as a semi-transparent one together with the primary information layer.

Recently, a study on a similar topic was conducted by Frías et al. [71] with a focus on uncertainty expressions on a global seasonal climate prediction. Frías et al. [71] distinguish between the following methods: bubble plot (that equals the combination of colour hue, size, and saturation methods presented in this paper), pie charts (where saturation is used for uncertainty), and reliability categories (colour hue in a form of a modified traffic light metaphor). The main differences between Frías et al. [71] and the results presented in this paper are the following:

- The extended/modified traffic light metaphor uses six colour hues for five classification classes (note that the 'marginally useful' class is presented by two distinct colour hues). Moreover, only the hues on both ends of the spectrum (red and green) are compliant with traffic lights. The remaining four hues (yellow, light brown, cyan) lie outside the traditional traffic light scheme and are also perceptually demanding. Potential users must use the legend to define the order of hues and their corresponding meanings (perfect—dangerously useless). Strictly sticking to the traffic lights hues (green, orange, and red and their lightness) as used in our study helps users make more intuitive decisions.
- Frías et al. [71] employed size and transparency to express uncertainty in a regular grid that avoided overlaps. Such a method was not feasible within our study as a consequence of spatial closeness of the measured data. However, the use of transparency for uncertainty visualization is considered highly intuitive [57]. On the other hand, only three transparency levels have been empirically tested and using more categories could complicate map reading.

Three-dimensional uncertainty visualizations have so far been used only rarely in the agriculture domain [76], with a primary goal to provide information about the terrain. Dübel et al. [60] presented a sophisticated tool for 3D visualization of terrain, data, and associated visualization in a single map window. They also stressed the importance of scenario-aware visualization highlighting either the data or uncertainty in more detail. Unlike Dübel et al. [60], we used two parallel plots—one for terrain and data and the other for the associated uncertainty. Both plots are connected and changes in detail (zoom in and out, pan) and directions (rotate, tilt) are automatically performed in both windows. Parallel interactivity supports the possibility of prioritisation in detail in both the data/terrain and uncertainty views.

A combination of 2D and 3D visualization of agricultural data was presented by Stojanovic et al. [80], who also performed a subjective qualitative empirical testing of applications on a mobile platform. The users praised the 3D visualization for the portrayal of terrain and other 3D objects (buildings), but their personal preferences varied depending on age and technological skills. The possibility to

choose a data presentation according to the users' preference and practice is a consideration we pay attention to in preparing our visualizations.

The achieved results are in line with Shepherd [87], who concluded that 2D maps support more accurate estimations of relative sizes and distances, while 3D visualizations enable complex and, in some cases, also a more natural view of data values and their combination with depictions of other phenomena (i.e., terrain).

5. Conclusions

The 'traditional' cartographic methods usually rely on nine visual variables of a symbol, out of which four were identified as applicable to the visualization of point Big Data uncertainty in precision agriculture. Only a single visual variable (saturation) is generally applicable, while perspective height, lightness, and colour hue are applicable only under certain conditions with respect to interactivity support, the base map, and the colour scheme used (e.g., the extended traffic light metaphor). Alternatively, three visual variables (perspective height, saturation, and lightness) are applicable to quantitative uncertainties, while the remaining variable (hue) is applicable only to qualitative uncertainties.

All four applicable visual variables (perspective height, saturation, lightness, and hue) were demonstrated on a cartographic visualization of 32,625 points at the same time that comprise second-by-second measurements by field harvesters at two plots of a fully operational farm. Static maps of hue, saturation, and lightness were developed for 2D and interactive maps for perspective height for 3D. In the case of visualization using perspective height—and 3D visualization in general—the interactivity is appropriate. Interactive functions make it possible to read the values of yield and uncertainty, and the dependence of these phenomena on the terrain. All graphic variables used can also be combined with each other, which was tested on a 3D visualization.

Data quality measures for uncertainties of point Big Data need to be elaborated in the geospatial domain. The existing measures included in ISO 19157 [25] are not applicable even though this standard has been recognized as a common standardization framework by ISO, OGC, and W3C. The authors developed a proof-of-concept algorithm for the expression of uncertainties that is applicable to yield measurements by field harvesters. Further development of the proof-of-concept algorithm for uncertainty expression is a key for automation of the point Big Data filtration procedure in precision agriculture, as well as in other domains.

The ongoing work should also deal with the following user testing aspects:

- A comparison of the level of individual visual variables (hue, saturation, lightness, perspective height) in particular contexts;
- a comparison of user performance when working with 3D versus 2D visualizations;
- usability of interactive visualizations versus non-interactive (static) visualizations;
- the effect of user expertise on user performance when working with the proposed visualizations.

User verification relying on appropriate research methods will prove the suitability of the cartographic visualization methods described and demonstrated above. User testing should also indicate the contexts in which these methods can be used correctly by various users.

Supplementary Materials: The following are available online at https://bl.ocks.org/SLeitgeb/raw/5ebc03f461b79386002cdeca308c09ac/?fbclid=IwAR1mvLHOib5NM3JWDZssNuGRq4SiDPB6-9MPnqIFWzN3LxcvDP2uQZRLL_s, Supplementary Material S1: Interactive application of the perspective heights method to uncertainty values and the measured data on relative yield and uncertainty index.

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