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Embedding expert opinion in a Bayesian network model to predict wheat yield from spring-summer weather

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ABSTRACTS

Wheat yield is highly dependent on weather, Therefore, predicting its effect can improve crop management decisions. Various modelling approaches have been used to predict wheat yield including process-based modelling, statistical models, and machine learning. However, these models typically require a large data set for training or fitting. They often also have a limited ability in capturing the effects of small-scale variability, time, and duration of extreme weather events. Here, we develop a Bayesian Network (BN) model by interviewing experts including farmers, embedding their knowledge from years of experience within a quantitative model. These experts identified the period from the beginning of anthesis to the end of grain filling stage as a critical period and maximum temperature, mean temperature and precipitation as key weather variables for inclusion in the BN. To keep the time input from experts manageable, the conditional probability table for the BN was constructed based on their anticipated impact on the mean yield of different weather conditions. The model predicted the yield in the same or neighbouring class (very low, low, medium, high and very high) as the reported yield with low error rate ranging from 9.1 to 15.2% and, when used to estimate the median predicted yield, R^2 ranging from 41 to 52%. Interestingly, model successfully predicted the yield in years 1998, 2007, 2012 and 2020 which had the most extreme weather events. Additionally, the more recent data, from 2012 to 2022 was predicted more accurately, especially 2022 season which was not sown yet when eliciting information and recently added to the testing data. Little difference was observed between the predictions made using model parameters based only the opinion of the farm manager from which the test data originated, and the predictions made using the average opinion of a group of 9 experts. The inclusion of causal variables in the model also provided insight into the experts' rationale, allowing unexpected results to be explored. This methodology provides a means to rapidly develop a successful predictive model of wheat yield with limited (or no) data using expert understanding. This model could be tuned and updated with data as it becomes available.

1. Introduction

Weather conditions affect crop yield at different phenological stages and are therefore a key driver of the spatial and temporal variability in crop yield [1]. Amongst weather variables, temperature and precipitation are the most influential variables affecting the yield of winter wheat. Extreme weather events such as drought and heat stress during anthesis and grain filling can significantly reduce the yield of wheat crop [2–4], while very wet conditions late in the season can cause lodging, reduction in grain yield and quality and prevent harvesting the crop in appropriate time [4–6]. In addition, variability in weather events between and within seasons is considered to be the main source of uncertainty in predicting crop yield [3,7] and accounts for about 50% of the variability in wheat yield [8]. Using summary weather variables for the late season instead of entire season avoids the confounding effect of weather variables between early and late in the season. For example, there might not be an obvious relationship between temperature and wheat yield during winter, but high temperature might have a negative impact during spring-summer [9,10] and vice versa for precipitation [3]. In addition, decisions on fertilizer application, especially variable

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rate application are usually made after observing the spatial variability in crop biomass early in the construction phase, which is usually in late February to early March in most of Europe. Therefore, the focus should be on the influence of weather events from the beginning of anthesis to the end grain filling stage since the effect of weather condition from sowing to the beginning of anthesis is already reflected by the crop biomass.

Many machine learning approaches have been developed to predict the effect of weather variables on wheat yield, however, the relatively low performance of these approaches has always been controversial and the variables affecting yield vary by region, crop variety and season [11], as they were developed based on statistical relationship between historical yield and weather data [3,12,13]. The main limitations of these approaches are that they learn from patterns, but these patterns may not hold in future. There may also be a requirement for more data than is available [3]. In addition, other drivers of inter-annual variability may be neglected - e.g. a change in management practice, effect of weeds, use of different fields with different potential yield [14], therefore, developing model based on average national or regional yield and weather data might underestimate the effect of weather variables on wheat yield [15–17]. Most of the models describe the effect of temperature on crop development in different ways such as thermal time, vernalisation, and day length [7]. In addition, these models may attribute crop damage caused by high temperature to a short period of drought, since positive temperature anomalies can behave as a proxy for short dry spells not captured by seasonal precipitation variables [18,19].

The impact of extreme weather event on crop yields is poorly simulated in previous yield forecasting systems since they were based on simulating crop response to environment which are often designed for seasonal patterns of temperature and precipitation [13]. Thus, they can satisfactorily predict the average yield, but not the intra-annual variability in yield, because they are not capable to handle extreme weather events [20,21]. Recently, some crop modelling approaches considered the negative effect of extreme events to improve yield prediction [6,13], but these models were built to predict the future effect of climate change on crop yield at national scales. The frequency of extreme weather events negatively impacting agriculture is expected to increase due to climate change [22] suggesting a significant threat to winter wheat production worldwide [23]. Therefore, wheat growers require timely and reliable crop production forecasting and early warning systems to change their management to face that [24,25], Since farmers frequently witnessed yield losses due to extreme weather events, it is essential to consider their views and understanding about the negative effect of extreme weather events when planning adaptation and policies [26]. Exploiting in-field knowledge and experience can provide an opportunity to inform future research about yield losses due to extreme weather events.

Bayesian Networks (BNs) are probabilistic models that can deal with the issue of uncertainty associated with other models, as they link variables with probabilities based on a direct acyclic graph [27–29] which represent the qualitative part of BNs and the predictive power of casual variables is quantified by the quantitative part of BNs represented by a Conditional Probability Table (CPT) [30].The ability of BNs models to make inference, deal with missing data and integrate new data make them ideal models for agricultural studies [31]. On the other hand, using BNs in agriculture modelling can sometimes be challenging, due to lack of available data for calibrating the model [29]. However, the main feature of BN model is that it allows manual intervention by embedding expert knowledge to fill the gap in information, especially for capturing the effect of extreme weather event on crop yield.

There are three approaches for constructing BN model; 1. Automatically from data, 2. Manually where both network and CPT are based on expert knowledge, and 3. Hybrid approach by constructing the graphical part from expert knowledge and learning the model from the data [29,31]. Constructing BNs from data without human intervention is the most popular approach for various applications [31]. The hybrid approach is commonly used to deal with unavailable or partially available data in agriculture modelling studies. For example, the hybrid approach was adopted to improve the prediction of corn yield in Iowa state from partial data [32], to predict the response of winter wheat to different fungicide spray programmes in England and Wales with missing data [29], and to predict wheat yield under future scenarios of climate change and production costs in Russia [30]. The manual approach (network and CPT based on expert knowledge) which is adopted in this study is rarely used in agricultural studies, especially for capturing the effect of extreme weather events on crop yield. It has been used for some other areas of land management and provided promising results with absence of empirical data such as estimating the impact of land management change on weed invasion potential [33]; developing flood risk management options with stockholders [34], for water resources management [35] and for assessing of agri-environmental measures [36]. The main limitations of manual approach in agricultural studies are that it could be more prone to human bias, knowledge of group of experts might not be enough to represent a region and lack of specialized experts for a particular region [31]. However, increasing the number of internal experts (key farmer), involving some external experts (experts with strong knowledge but not directly involved in yield production such as academic) with using more efficient methods of eliciting information (direct interviews and workshops) can overcome these limitations. The information provided by the internal or local experts found to be more reliable than information provided by the adjacent or external experts [37]. Of course, manual models can also be tested against smaller available datasets to identify if a bias exists. Integrating expert knowledge in BN models can have some advantages; for example, it avoids attributing variability in the annual yield due to sources other than the weather, captures experts understanding of the causal interactions and increases their understanding of the model [7], and help scientists and policy makers in developing strategies and plans for farm level adaptation [26]. It is also useful to understand how farmers deal with risks and opportunities induced by the climate, process, adaptation options and outcome [38], understand both social and physical influence of adverse weather events [39]. In addition, it can be used to consider intra-annual variability which could be informed by short term weather forecasts to help farmers to change their management practices and crop varieties to cope with likely effect [40,41].

In this study we aim to develop new Bayesian network model based on expert knowledge for capturing the negative effect of weather events on winter wheat and test the model for a case study in Thames Valley, England. Expert knowledge used in this study to develop model structure, CPT, identify key weather variables, and their thresholds, timing, and probable yield losses. The primary aim is to introduce a new yield forecasting system that does not require empirical data to predict the influence of weather on winter wheat yield which affect within season nutrient demand. It can be used with short term weather forecasts to allow predictions of within season management decision to avoid potential yield losses.

2. Methodology

The modelling approach used in this study is Bayesian network. Expert knowledge about the effect of extreme weather events on wheat yield used to determine the structure and parameters. To elicit the key weather variables affecting winter wheat yield and their threshold, the five step of elicitation protocol (motivating, structuring, conditioning, encoding and validation) described by Fenton and Neil [42] were followed. Eliciting information from experts can be either during a meeting, workshop and/or through distributing a questionnaire. However, workshop participants might disagree, and this can cause conflict, and the limitation of questionnaire is that it requires some pre identification of expert response [31]. The hybrid approach that consists of more than one method is the typical approach [36] and is the one adopted in this study. Opinion and knowledge of five experts (2 key farmers, 1 agronomist and 2 academics) obtained *via* a Microsoft Team interview and a written questionnaire distributed to four other experts (3 farmers and one academic) in a workshop. Five of those experts were farmers who are the proximate witnesses of adverse weather impact on their crops [26,43].Two of the interviewed farmers one in Oxfordshire, UK and one from Rheinland-Pfalz, Germany are the key farmers who are fully engaged with the project and provided access to their farms and data, but only yield data from the UK key farmer was used for testing the model. The other three farmers were from UK, Thames Valley-farmers, and they filled out a questionnaire during the workshop. In addition to farmers, the opinions of some external experts were also included. The external experts were Three academics and one agronomist for the University of Reading who have strong knowledge and experience on crop-weather relation over many years of scientific research and modelling the effect of weather condition on wheat growth and yield. This small number of experts with relevant knowledge and experience was optimum for the approach we used, as increasing the number of experts might reduce the improvement in model accuracy [44].

2.1. Key questions

Farmers were given a series of questions to answer considering their farm context. These questions focused on the effect of weather variables on wheat yield from the beginning of anthesis to the end of grain filling stage, since this is the critical period during wheat growth season to weather conditions [5,10,45] and is also a time at which yield predictions are useful to inform fertiliser applications. To include the effect of weather before this period, crop biomass (indicated by NDVI) in March used as a starting point, as it reflects the key effect of sowing date and weather condition from sowing to the time at which NDVI has been measured NDVI [46]. In order to structure the model with definite weather variables, it was important to ask experts first to identify the key weather factors affecting wheat during this period. Experts were then asked to specify the threshold of each weather variable, the magnitude of yield losses if it exceed or below threshold, duration of adverse event to affect yield, the combined effect of different weather variables, ideal and worst-weather scenarios in relation to wheat yield. Experts were also asked to define yield classes t/ha, since the meaning of yield categories (very low, low, average, high and very high) might vary amongst regions or even farms, due to the variability in pedoclimatic condition and agronomic practices, which might affect the performance of the model [5,9,14]. As the crop biomass is set as a starting point, they were asked for their opinion on the response of low, medium, high, or very high crop biomass in March to adverse weather events.

2.2. Key weather factors and modelling structure

The network was based on a minimum set of weather variables which were considered the most influential to avoid confounding effects of similar variables. Including large number of weather variables might lead to strong collinearity between variables such as mean temperature and sunshine duration [7]. In this study, most of experts agreed on three weather factors as a key factor significantly affecting wheat yield: rainfall, maximum air temperature and mean air temperature. These identified weather factors along with NDVI in March and Yield which is the average wheat yield they can expect under certain weather conditions used to build a BN (Fig. 1). Yield, NDVI in March and each of weather variables were divided into different classes and the expert were asked to provide ranges or limits for each class based on their experience (Fig. 1).

The nodes were defined using thresholds for each weather variable from beginning of anthesis to end of grain filling stage, generated from expert opinion and literature evidence as follows:

2.2.1. Maximum air temperature (Temperature stress)

Experts expressed their concerns about the negative effect of temperature stress on winter wheat yield during the period from anthesis to end of grain filling. Their concerns agree with findings of some recent research [5,15,47,48], this can cause a significant reduction in the yield of winter wheat even in regions where temperature is currently favourable [23].

The effect of maximum temperature divided into three classes,

a Low or no stress when the maximum temperature not reaching this threshold
b Medium stress when the maximum temperature >25 for at least one week anytime during anthesis and grain filling stages
c High stress when the maximum temperature is 30 °C or more for at least two consecutive days and was not less than 27 °C in the preceding and following 2 days during anthesis and grain filling stages.

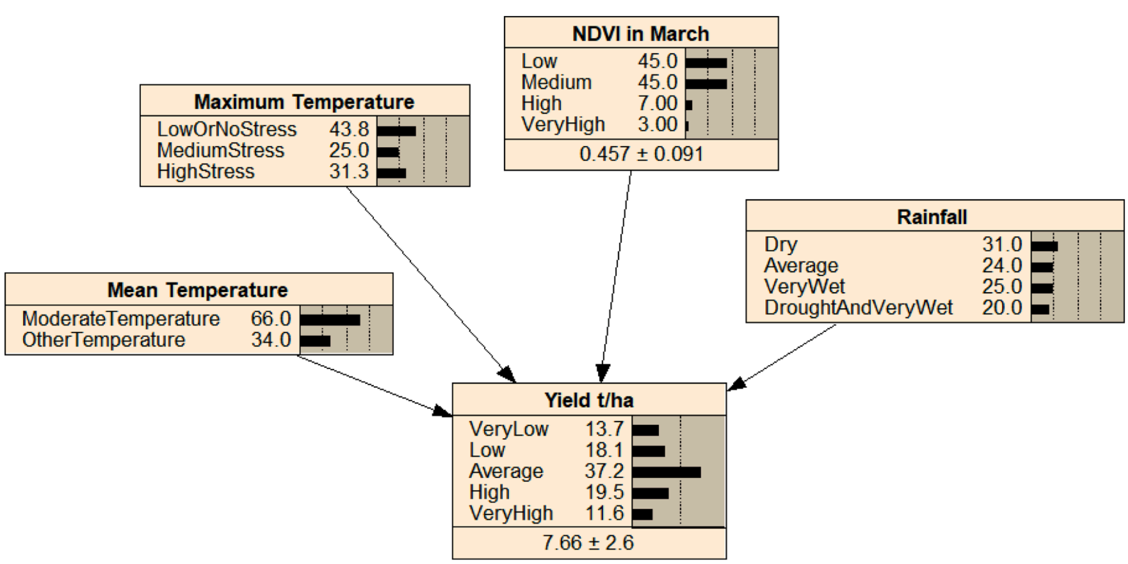

Fig. 1. Model structure showing the categories of crop biomass (NDVI) in March and weather variables from beginning of anthesis to the end of grain filling stage and categories of simulated wheat yield. The numbers in parent nodes represent%probabilities of those weather conditions from 1990 to 2021. In the child node (Yield) the numbers next to yield classes are the probabilities for achieving certain yield under certain weather condition and the number in the bottom of the node refer to average yield and standard deviation.

The threshold for high temperature stress identified by experts in this study aligns with some literature studies [5,9,49] who found that high temperature stress occurs at >30 °C, however, the threshold was slightly higher>34 or 35 °C in some other studies [50,51].

2.2.2. Rainfall

Rainfall or precipitation can affect winter wheat yield from beginning of anthesis and grain filling stages in different ways: As low rainfall or drought during anthesis and grain filling stages can significantly reduce the yield [5], a significant reduction in yield might occur if precipitation exceed the relevant range [4,5,8], therefore, four conditions related to rainfall were created though a discussion with experts and then justified using the literature as follows:

a Drought: a drought event is identified for any season when there were 14 days without rainfall (0 mm) and rainfall was less than 3 mm in the previous three days any time from anthesis to end of grain filling. This can cause irreversible damage to crop tissues [2,4], permanent abortion of florets and sterility resulting in fewer grains [5,52,53] and reduce the grain size [6,54].
b Very wet (Flood): If the rainfall is more than 40 mm in three consecutive days or more than 30 mm in 2 consecutive days and was not less than 5 mm in the previous 3 days. Very wet conditions can cause Oxygen deficit due to water logging [55], affect harvest process and grain quality [6] cause soil erosion and nutrient leaching [51] and together with higher temperature can increase pest and disease infections [5].
c Average: when there is no two consecutive weeks with 0 mm rainfall and not more than 40 mm in 3 days or 30 in 2 days.
d Drought and very wet: When a period of drought followed by a period of very wet or vice versa from anthesis to end of grain filling. The effect of this event is expected to be higher than other rainfall related events, as the crop experience unfavourable condition twice during the same season.

2.2.3. Mean temperature

According to our experts, moderate or favourable temperature for wheat yield is between 10 and 23 °C from anthesis to end of grain filling, anything outside this range for more than one week is considered as other temperature or unfavourable. These thresholds are in conformity with [48,56] who reported a significant positive correlation between yield and thermal time during grain filling stage, but that might shorten grain filling duration and consequently the yield if it exceeds the relevant range [47], and it can influence floret fertility if it exceeds 24 °C for short period at the start of heading [57].

The frequency of occurrence of each of these incidents calculated from weather data from 1990 to 2021 and converted to probabilities (Table 1)

2.4. Model parameterisation using expert opinions

Eliciting a CPT for a Bayesian Network can be a time-consuming process prone to misunderstanding from the experts. We used a light touch approach to elicit the influence of the model variables on the mean yield inspired by previously suggested approaches [58,59]. We then asked experts to identify any key interactions and their impact.

1 A standard distribution was defined using yield ranges normalised relative to the field average. As our distribution was discretised, the ranges for the yield wereset (e.g. the answers of one expert) as 0–0.56, 0.56–0.81 0.81−1.25, 1.25–1.5, and 1.5–2 (Fig. 2). The distribution was simulated as a skew normal distribution with a standard deviation of 0.2 and a skew parameter of −2. The standard deviation represented the most certainty that could be achieved, whilst the skew represents the negative skew typically observed in wheat yield distributions. In future models these aspects could be elicited from experts more explicitly.
2 A 'high reference yield' (HRY) was taken at a value of 1.5, to represent a typical high yield that participants were comparing other outcomes to.
3 The experts' statements about the impact of the model variables on yield were used to define the mean yield the experts expected for each category of each variable individually (e.g. Table 2). Generally, these means were below the HRY, with one exception for the condition in which warm temperatures throughout the summer produced excellent conditions which were assumed to increase the yield slightly beyond the high value that experts were conceptualising for comparison.
4 One interaction effect was specifically noted by one expert: the interaction between high temperatures and rain, thus the means of these combined conditions were implemented explicitly.
5 All other interaction effects were implemented by applying each of the conditions sequentially, assuming that a second impact that reduced the yield had a proportional effect rather than an absolute effect. Additionally, if after the simulated effect of the previous conditions had reduced the mean yield to less than 1, the proportional impact of any further negative effect on mean yield was multiplied by 0.3, and by 0.2 if the previous mean yield was less than 0.7 (Appendix 1). Whilst these thresholds and proportions were arbitrary, they were implemented because the effects of the weather conditions are not additive, thus a yield that is already reduced due to negative conditions is likely less influence by other conditions that are not ideal.
6 This resulted in a mean value for each combination of model conditions (e.g. weather plus NDVI) which was used along with the standard deviation and skew to calculate the probability distribution for each line of the CPT (Appendix 2).
7 Two CPT tables were generated one based on the opinion of key farmer alone and other based on average opinion of all 9 experts (average CPT). For average CPT, expert statements about yield ranges, optimum NDVI value, expected yield under individual and combination of weather variables were averaged across all experts and used to calculate the probability distribution for each line of the CPT

2.5. Prediction and model performance

Yield was predicted using the Bayesian network (BN) developed which has selected weather variables and NDVI in March as the parent nodes and yield as the child node. This was implemented in Netica 607 (Fig. 1). The Conditional Probability Table (CPT) generated by MATLAB from expert opinion was used to inform the model about yield probabilities under different weather scenarios and crop. The nodes for each variable were created with different states and the probability of occurrence of each weather conditions added manually to the table of relevant node. Daily weather data from January 1990 to August 2022 downloaded from Met-department data server, weather measurement field located at the University of Reading which is located 6 miles from

Table 1
The probability and the number of years that each of these events occurred from 1990 to 2021.

Events	Number of Years	Probabilities
Low Or No Temperature Stress	14	0.44
Medium Temperature Stress	8	0.25
High Temperature Stress	10	0.31
Drought	10	0.31
Average	7	0.22
Very Wet (flood)	8	0.25
Drought And Flood	7	0.22
Moderate Temperature	21	0.66
Other Temperature	11	0.34

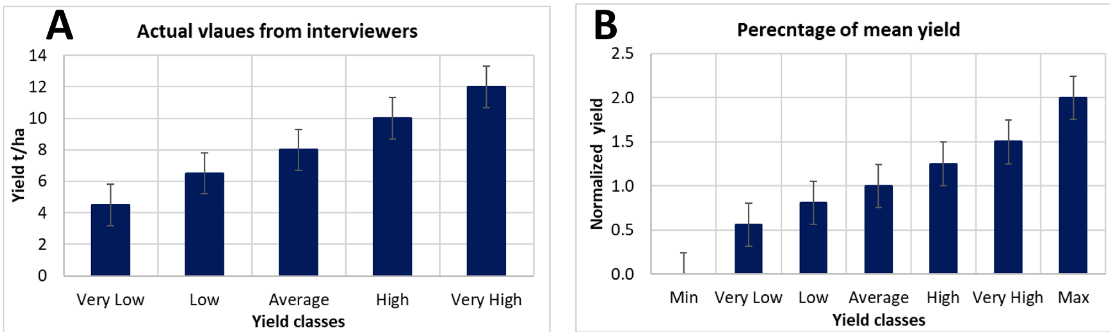

Fig. 2. Values of yield obtained from the interview (A) Actual and (B) as a percentage of mean.

Table 2
An example of how a potential effect of any weather variable based theexpert opinion one of the experts converted to values. Numbers are displayed as a percentage of mean. High reference yield is the maximum yield expected under favourable weather condition. The yield then decreases by a specific magnitude based on the severity of the stress.

Variables	Potential effect based on Expert opinion	Expected Yield
Maximum Temperature (Heat stress)	High temperature stress can bring the yield down from high reference to average,	Low or No Temperature Stress = Wheat Yield High Reference = 1.5 Medium Stress = 1.2 High stress = 1
Rainfall (drought and flood)	Drought conditions can bring the yield down from very high to lower end of low, flood or very wet condition can bring the yield down from very high to high and drought and very wet condition can bring the yield down from very high to just above	Drought = 0.75 Average = Wheat Yield High Reference Flood = 1.2 Flood and Drought= 1.1
Mean temperature (Thermal time)	Mean temperature outside the range of 10–23 °C from beginning of anthesis and grain filling stages will have an impact on yield	Moderate Temperature = Wheat Yield High Reference + 0.1 Other temperature = Wheat Yield High Reference – 0.2
Crop Biomass (NDVI)	The ideal crop biomass is high, which is more preferred than very high biomass	Low Biomass= 0.9 Medium = 1.2 High = Wheat Yield High Reference Very High = 1.1

the field site at which its yield data were used for testing the model.

The model is designed in a way that it can be used to predict yield of winter wheat anywhere in western Europe using weather data and NDVI during these sensitive growth stages in that region. However, the model performance was assessed at both farm and field levels using historical yield and NDVI data from the farm of one of the key farmers located in Oxfordshire in UK. At farm level, average wheat yield for the farm was available from 1990 to 2022, but NDVI data were only available from 2016. At field level average yield and NDVI were available for 131 fields on winter wheat crop from 2016 to 2021 (18–28 winter wheat fields per year) (Table 3). Crop biomass (NDVI) was calculated from clear sky Sentinel-2 images available for around the middle of March as follows:

NDVI= (Near Infrared – Red) / (Near Infrared + Red). These data along with weather data described in Section 2.3 for each season were processed to identify the relevant category for each node of the Bayesian network in each year. The model was tested using average CPT for all interviews and CPT from the interview with key farmer.

Yield data in the testing dataset was categorised into 5 classes based on expert opinion: very low < 6 t/ha, low 6–7 t/ha, average 7–8.5 t/ha, high 8.5–10 and very high > 10 t/ha.

Table 3
Number of wheat fields in each season, mean, maximum, minimum and standard deviation of wheat yield.

Season	Number of Fields	Mean t/ha	Min t/ha	Max t/ha	Sd t/ha
2016	19	8.7	7.75	10.95	0.84
2017	28	8.1	8.1	13.38	1.66
2018	19	6.6	4.11	9.75	1.63
2019	20	9.8	6.62	12.8	1.58
2020	18	5.1	2.1	8.7	1.44
2021	27	7.3	4.85	10.86	1.61

The accuracy of model performance was assessed from a confusion matrix showing the frequency predicted vs observed categorisation by calculating: (1)level I error rate for true classes (in the same class of the reported yield), false classes (not in the same class of reported yield) and their sum and (2) level II error rate by increasing the acceptable threshold of level I error to ±1 “bin” [28]. The predicted yield at farm and field (estimated as the median of the predicted distribution) was plotted against actual yield and R^2 and Mean Squared Error (MSE) calculated.

3. Results

3.1. Average yield per year from 1990 to 2022

The model predicted the average yield in most seasons from the period 1990–2022 in the right classes. Predicted yields based on the expert knowledge fall in the same class as observed yield for 18 seasons out of 33 seasons with relatively high Level 1 error rates 45.5% for bot CPTs (Table 4A). Most of the uncertainty in the prediction was around the yields in the average categories, as the model classified yield as low in 4 years which had average observed yield based on both CPTs (Table 4A). While most of the data in the diagonal (correct class), precited yields fall in the wrong class in 13–15 years (Table 4A). However, the mispredictions in most cases (10–12 years) fall in the neighbouring classes suggesting small error rate (Table 4A). Therefore, Level 2 error rate (±1 class) was much lower 9.1 and 15.2% than Level 1 error rate (Table 4A). In general, the model performed well in predicting wheat yield under different weather condition. As predicted yield falls in the same class as observed yield (Very High) under favourable weather condition for wheat growth (e.g. 2017 and 2019; Fig. 3); it classified the predicted yield in the same class of observed yield (Very Low) in years experienced high temperature stress and both drought and very wet condition during anthesis and grain filling stages (e.g. 1998 and 2020; Fig. 3). Interestingly, the model successfully predicted the yield under extreme weather condition such as sever flood causing significant yield losses in affected area (e.g. 2007 and 2012; Fig. 3). Although, the expert knowledge was obtained and the model developed in 2021, predicted yield for 2022 season was classified in the same class as reported (Fig. 3). Higher overestimation occurred in early years (1991, 1992, 1996 and

Table 4
Confusion matrix of validating the model using yield and NDVI data from the selected farm (A) Average farm yield per year from 1990 to 2022 and (B) Individual fields per year 2016–2021.

		Observed Yield t/ha									
		CPT based on interview with key farmer					Average CPT of all interviews				
		A- Average yield at farm level 1990–2022									
		VeryLow	Low	Average	High	Very High	Very Low	Low	Average	High	Very High
Predicted Yield, 50% Probability	Very Low	2	0	0	0	0	2	0	0	0	0
	Low	0	5	2	1	0	0	5	3	1	0
	Average	0	4	6	0	0	0	4	6	0	0
	High	0	2	5	4	1	0	0	2	3	0
	Very High	0	0	0	0	1	0	2	2	1	2
	Level I error = 45.5%			**Level II error =9.1%**			**Level I error = 45.5%**			**Level II error =15.2%**	
	B- Average yield of individual fields 2016–2021 (131 fieldsat the selected farm).										
	Very Low	10	0	0	1	0	10	0	0	1	0
	Low	3	6	3	2	0	3	6	3	2	0
	Average	5	3	11	4	4	0	2	11	6	1
	High	0	1	6	20	15	5	1	6	16	11
	Very High	0	1	6	8	22	0	2	6	10	29
	Level I error = 47.3%			**Level II error =15.3%**			**Level I error = 45%**			**Level II error =13.7%**	

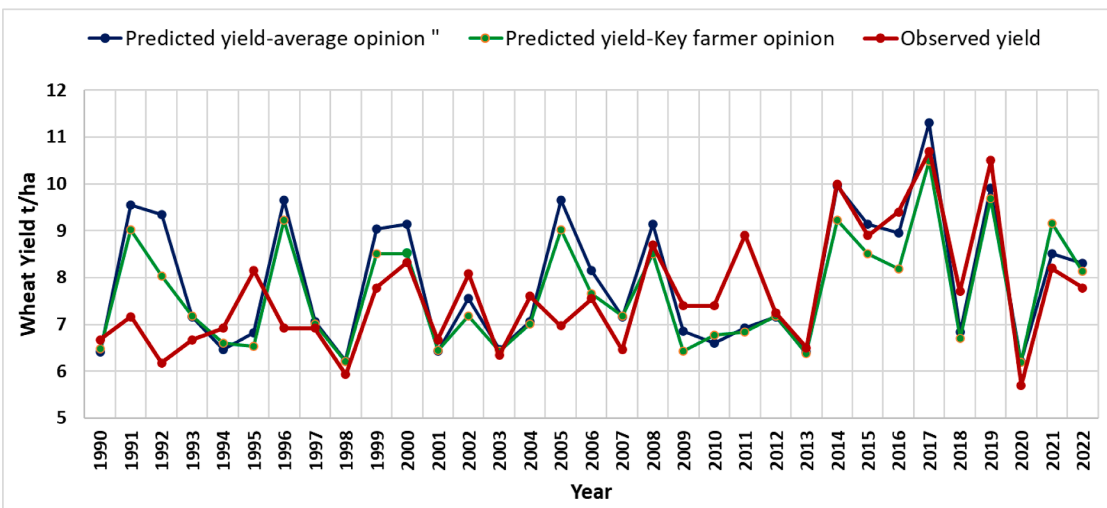

Fig. 3. Actual wheat yield per year recorded at the testing farm from 1990 to 2022, predicted yield based on key farmer opinion and average opinion of all participants.

2005; Fig. 3). Those four years had a same favourable weather condition for winter wheat crop from beginning of anthesis to the end of grain filling stage, but the recorded yield was low; this could be due to some other factor such as crop variety and/or agronomic practices in the farm of which the testing dataset is based.

Prediction made based on key farmer opinion did not differ from prediction made based on average opinion of all participants with 45.5% Level I error rate for both predictions based on key farmer and average opinion of all participants (Table 4A). However, predicted yield for only three seasons fall outside ±1 bin of observed yield based on key farmer compared to five fields for average opinion of all participants; therefore, Level II error rate was much lower 9.1 compared to 15.2 respectively (Table 4A). The predicted yield based on both CPTs followed similar patterns over the period from 1990 to 2022 with slight changes in over or underestimating the observed yield (Fig. 3).

Based on linear regression using the median yield from the predicted probability distribution, the model successfully predicted 43% and 41% of temporal variability in the recorded wheat yield from 1990 to 2021 for both key farmer and average opinion of all participants respectively (Fig. 4A and B). The regression line slightly departure form 1:1 line indicating to slight overestimation in low yielding years and underestimation in high yielding years. Despite the higher level I error rate of the confusion matrix (Table 4A), MSE value were small (1.02) especially for key farmer opinion compared to 1.37 average opinions of all participants (Fig. 4A and B). This indicate that although the predicted yield is in not classified in the same class as the recorded yield, the median yield might be in upper end of lower class or in the lower end of upper class which result in lower yield difference.

3.2. Yield of individual fields per year from 2016 to 2021

For individual fields, NDVI in March was also available for 131 fields on winter wheat crop as well as average yield per field from 2016 to 2021.This was the only variable between fields which reflect sowing date, soil properties and weather condition over winter. Although, predicting average yield per year based on key farmers opinion outperformed the prediction based on average opinion of all participants concerning Level II error (Table 4A), for field level prediction based on average opinion of all participants slightly outperformed the prediction based on key farmers opinion. Prediction based on average opinion of all participants classified the yield of 72 fields in the same class as recorded yield over 6 growing seasons compared to 69 fields based on key farmers opinion (Table 4B). Therefore, Level I error rate was slightly lower 45% average opinion of all participants compared to 47.3for key farmer's

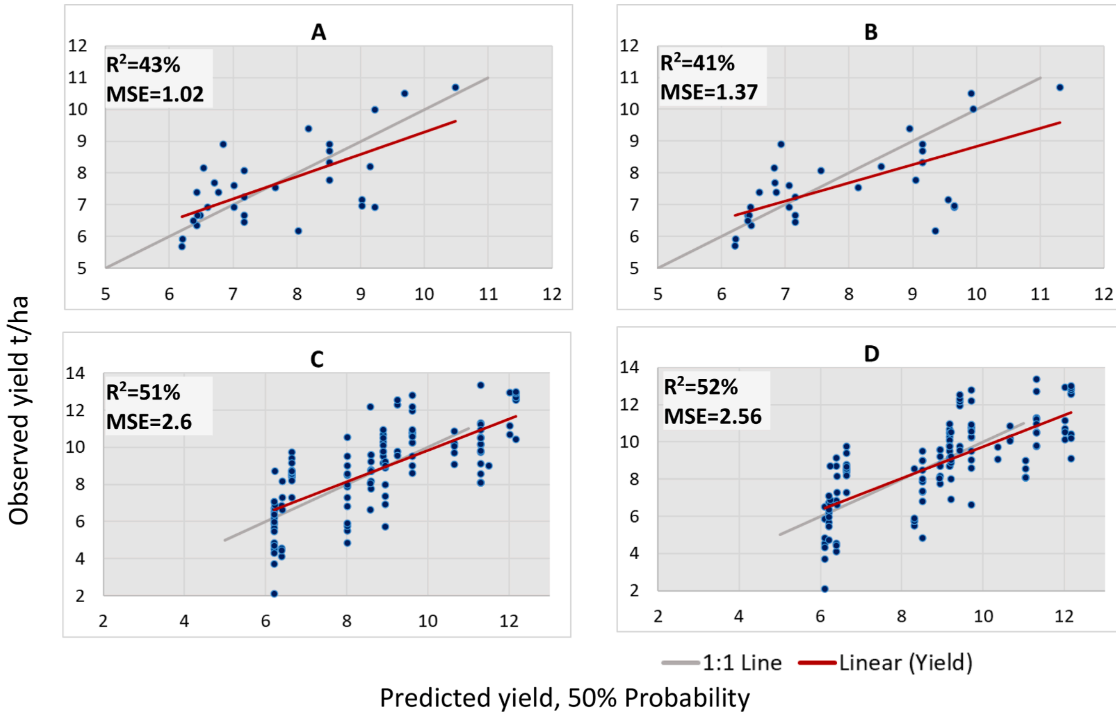

Fig. 4. Linear regression between actual wheat yield of selected farm and predicted yield at farm level 1990–2022(A and B) and field level 2016–2021 (C and D) based on CPT from key farmer interview (A and C) and average CPT of all interviews (B and D).

opinion (Table 4B). The misprediction fall in the neighbouring class for 42 fields for prediction based on both CPTs. Therefore, Level II error was notably reduced to 13.7 and 15.3% for prediction made based on average opinion of all participants key farmer's opinion respectively (Table 4B).

Linear regression model did show notable difference between prediction based on key farmer's opinion and key farmer's opinion and accounted for 52 and 51% of temporal variance in recorded yields of 131 fields from 2016 to 2021 (Fig. 4C and D). There were also no significant differences in MSE between predictions made based on key farmer's opinion and average opinion of all participants which were 2.6 and 2.65 respectively (Fig. 4C and D). Overall percentage of variance account was higher for individual fields from 2016 to 2021 compared to average yield per farm/year from 1990 to 2022, but MSE was also higher for both opinions. Although, regression line is close to 1:1 relationship, higher MSE indicate to the variability between individual fields each year (Fig. 4C and D). Most of overestimation occurred in 2021 season for both opinions, as the recorded yield in 5 fields were very low, but the model classified them as average and high which resulted in higher error rate (Table 4B). On the other hand, most of underestimation occurred in 2017 and 2019 seasons, as the yield was very high, but the model classified as high (Table 4B).

4. Discussion

The annual increase in wheat yield is slowing in most of wheat production area around the world due to changes in weather condition [23] especially in late 20th and early 21st Century [47] and a further reduction is expected in the future [23], due to expected changes in climate [22].Farmers and agronomist have already witnessed this decline in agriculture production over this period due to warming and erratic rainfall [26]. The approach presented in this study differ from previous approaches, as it embeds expert opinions and knowledge in a quantitative framework; especially farmers who hold different opinions about crop-weather relationships [26], to capture the effect of adverse weather events on wheat yield. One of the important steps of eliciting protocol is external validation of information gathered from experts against literature [42]. Therefore key weather variables affecting wheat yield during critical stage (beginning of anthesis to end of grain filling) and their thresholds identified by participants compared to those reported in previous studies and were consensus to some extent with them such as maximum temperature [5,9,23,50,60], drought and very wet conditions [2,4–6,8,52–54,61], mean temperature [47,48,57] and using crop biomass in March as a starting point consensus with findings of [46].

Following Fenton and Neil [42], another external validation of model performance was performed against yield data reported at one of the selected farms for this study from 1990 to 2022. Overall, the model classified the predicted yield exactly in the same classes of reported yield for most years from 1990 to 2022 and fields from 2016 to 2021 with acceptable error rate (Level-I error) and R^2 (Table 4 and Fig. 4). However, most of mis-prediction fall in the neighbouring classes, therefore, ranges of error rate significantly declined from 45% to 9.1–15.2% (Table 4) which called Level-II error rate when the range of prediction changed to ±1 of actual classes of reported yield. This is in part because the yield prediction is in fact a probability distribution, with the confusion matrix based on the most likely category; Thus, although one category is most likely, the probability might not be much higher than for another neighbouring category. The probability distribution reflects the experts' uncertainty in a prediction based on the model variables, and some uncertainty is to be expected as there are other weather and management interactions that also affect yield. Chawla [32]similarly considered Level II error rate for a model predicting corn yield at county level of in the state of Iowa, USA, using BN with expert knowledge. In decision analysis, taking level II error rate by increasing the acceptable threshold of level I error to ±1 "bin" depends on decision maker to set the threshold of prediction and acceptable error rate [28]. Level II error rate is especially important for this model due the fact that, yield variability is not due to weather conditions only, as soil properties and management practice can either mitigate or amplify the adverse effect of weather [62].

It is interesting that the model provided a particularly good prediction for the last eleven years (Fig. 3), especially in 2022 season, as the expert knowledge was obtained and the model built in 2021 when experts had no idea about weather condition and crop performance in 2022, demonstrating the validity of the model for future predictions. There could be various contributing reasons for this such as changes in data collection methods with digitisation potentially providing more accuracy in data from later years, the conditions from the last ten years may be fresher in experts' memories and the management practices are more similar in recent years. These influences warrant further investigation in future studies and highlight considerations as to how the experts' experience may influence the approach, in turn affecting how the resulting model should be used. For example, the approach is unlikely to produce a model that performs well in weather conditions that the experts have not experienced, nor is the approach likely to be robust to a significant change in management practices.

The model and data also provide an insight into the effects of recent climate extremes. Indeed, the highest and lowest yield values for both the observed and predicted yields occur during the last six years (Fig. 3). As there is a low chance of observing the two most extreme yields within the last five years of a 33-year time series, this suggests that recent weather conditions are having more impact on yield volatility, as has been suggested elsewhere [10]. However, whilst the increase in the variability of the observed yield suggests that this volatility has increased greatly (e.g. mean of 6.36 t/ha and standard deviation of 0.63 t/ha from 1990 to 1999, compared to 8.01 t/ha 1.36 from 2002 to 2022) this change is more subtle for the predicted data (7.2 and 1.36 t/ha for 1990–1999 compared to 8 and 1.44 t/ha for 2002–2022)..

When the model was used for field level predictions, the difference in the predicted yield for the different fields was much smaller than the observed variability. For these predictions, the within a year weather condition for all fields were the same (with minor adjustments for sowing date), thus any differences in weather due to micro-climate were not considered. As the main influence on the prediction for different fields was the NDVI in March, the lack of variability thus suggests that the parameters for the influence of this variable do not adequately capture the differences between the fields. This could be because the influence of this aspect was not well understood by farmers, perhaps because it is a more unusual variable to consider. Alternatively, the model structure may require additional variables to capture the differences between fields, such as an interaction effect between weather conditions and soil type. These are all potential areas of improvement in the model.

BN with expert knowledge improved the prediction of winter wheat in previous studies [29,30], but after the model calibrated with historical agroclimatic data. The full manual approach of BN has been used in some other studies for managing water resources, flood risks and agronomic managements [33–36]. Therefore, there is lack of studies on embedding expert opinion into BN to precited the yield of winter wheat in relation to weather with no empirical data available. The performance of the model based on reasonable weather variables and early crop biomass sounds acceptable suggesting that embedding expert knowledge was effective approach to capture specific time, duration, and thresholds of adverse weather events. This is poorly captured by some of previous approaches which rely on seasonal or monthly accumulation of weather variables [13,63], as wheat yield more sensitive to within-season variability in rainfall [46,64] and temperature stress for a very short period during anthesis and grain filling can cause yield losses [3,9,47]. Most interestingly, the model successfully captured the effect of extreme events happened in notable years in UK; for example, predicted yield was in the same class as the recorded yield for years 2007, 2012 which had a severe flooding causing significant yield losses in affected areas [5,65,66], and years 1998 and 2020 which had very wet winter causing lodging followed by drought period in spring and very wet condition late in the season preventing harvest in appropriate time [67]. Overestimation occurred in earlier years such as1991, 1992, 1996 and 2005, which could be due the management practice, and crop variety, which have changed recently(personal communication with farm manager), as farmers are adopting new crop varieties and management practices to adapt to changes in weather patterns [40,41], in addition to sowing and harvest dates which might have been improved due to warmer and drier summer [5]. Including spatial and temporal information on management practice, crop variety, sowing and harvest dates can therefore improve model performance and overcome the uncertainty in spatiotemporal prediction. Although this might be difficult for other approaches and for prediction at regional or national scales, due to variability between farms [3,15], it is possible to obtain this information from farmers and agronomists and integrated in this modelling approach.

The error rate of the model was better for extreme low and high yields, but accuracy decreased for years in which yield was in the intermediate range. For example, the recorded yield was very high in 2017 and 2019 which were very wet years with higher maximum temperature and the model well predicted the yields in those years at farm level. This is in conformity with [56] who indicated that the yield tends to increase with higher temperature associated with higher rainfall. It is possible that the higher error rate for intermediate ranges of yield was because the yield under these conditions was less influenced by the other conditions not included in this model.

Little difference observed between prediction made based on key farmers opinion and average opinion of all participants indicating the importance of local information for yield predictions, as it was in line with average information. The mean reason could be that the knowledge of most experts involved in this study limited to the study area (Thames Valley farmers) where they based. Local information can be more valuable for integrating some other variables such as agronomic practice and soil types. Previous studies suggested looking at crop response to weather at small spatial scales, as they observed variation between sites within the same region [3,5,15].

In this study, the result of our new approach confirmed the importance of embedding in-farm knowledge into machine learning for simulating the effect of weather condition on winter wheat yield especially for small scales prediction. Its performance can further be improved by integrating some local or farm level information such soil types and spatiotemporal changes in agronomic practices, crop varieties and sowing date. Using crop biomass in March with three-month weather forecast in this approach could provide some, albeit uncertain, information to wheat growers about expected yield losses due to anticipated adverse weather events. This can be used as an early warning system for wheat growers to change their management, especially fertilizer application to face the expected extreme weather events. In addition, including time series satellite vegetative and drought indices can also improve the prediction.

5. Conclusion

This new approach, which relies on embedding expert opinion in machine learning, proved to be successful in simulating the yield of winter wheat in relation to spring-summer weather conditions. The most interesting feature of this approach was its ability to capture, with no model calibration, the effect of extreme weather events occurred in notable years1998, 2007, 2012 and 2020, as predicted yield matched the recorded yield in those years. In addition, the model successfully predicted the yield in 2022 season, which was after the development of the model and elicitation of opinion from the expert group, demonstrating its power in predicting future wheat yields. It is evident that experts who participated recognized the effect of erratic precipitation, heat stress and required thermal time. They efficiently identified the critical time, duration, and thresholds of selected weather variables affecting the yield of winter wheat which might be difficult to be captured by other approaches. Changes in agronomic practices, crop variety sowing, and harvest dates could be the main causes of uncertainty in model performance, as most of overestimation occurred in earlier years which might have different agronomic practices. Using site specific knowledge (key farmer opinion) in this kind of modelling approach proved to be as efficient as using general knowledge such as average opinion of all participants for small scale predictions. In general, this approach can potentially overcome some of uncertainty associated with other approaches, such as the inadequate data available for calibration, small scales variability, capturing adverse weather events at specific times and flexibility for parametrizations. With increasing availability of three-month weather forecasts, this approach can predict yield losses due to any adverse weather events and so inform in-season management or to predict the likely impact of climate change. Including site-specific agronomic and soil information as well as the temporal changes in agronomic practices could significantly improve the performance of this approach.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2023.100224.

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