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A trade-off between farm production and flood alleviation using land use tillage preferences as a natural flood management (NFM) strategy

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ABSTRACT

Trade-off studies effectively compare rational decisions when choosing alternatives. This study utilizes a Bayesian belief network (BBN) model to analyse land use tillage practices for flood management, considering climate, soilscape, slope, and farming systems. The BBN comprises three sub-models using soil samples, farm surveys, synthetic datasets, and literature review data. In one scenario, conventional tillage on a 3° slope increased the net value of crop yield (50.85 %) and positive farm effects (49.64 %) but increased surface runoff (66.24 %) and reduced flood alleviation benefits (58.56 %). On the other hand, conservational tillage on a 3 ° slope yielded lower crop yield increase (14.11 %) and farm production effects (13.80 %) but reduced surface runoff (51.05 %) and increased flood alleviation benefits (45.06 %). Similarly, conventional tillage on a 12 ° slope showed similar crop yield and farm production effects, with slightly higher surface runoff (66.88 %) and reduced flood alleviation benefits (59.13 %). Conversely, adopting conservational tillage on a 12 slope resulted same extent of reduction in crop yield increase band (14.11 %) and farm production effects (13.80 %) but effectively reduced surface runoff (50.42 %) and improved flood alleviation benefits (44.49 %). Therefore, a trade-off between farm production and flood alleviation was identified when tillage preference was applied as a natural flood management strategy. Results showed this trend was particularly pronounced amongst soils on slopes. The model can help users in informed decisions on tillage for sustainable farming, with the potential for improvement through additional variables and farm-specific data.

Introduction

Tillage as farm management practice

Tillage practices are essential for crop production management, involving seedbed preparation, weed control, residue management, crust breaking, and water infiltration improvement. These adaptations contribute to efficient planting, reduced weed competition, and improved crop emergence [1]. Tillage promotes organic mineralization, nutrient release, and spring warming. It incorporates fertilizer nutrients, disrupts insects & pest habitats, and reduces soil compaction [2]. Tillage practices support crop plant protection, weed control, and insect pest management [3]. They also assist in water harvesting and residue management through manual and mechanical operations [4].

Several approaches were used to model the impact of tillage implements on soil physical and nutrient properties in different agro-ecosystem models. The researchers team evaluated 16 different models to simulate the impact of tillage on soil physical properties such as bulk density, texture distribution, hydraulic properties, *etc.* and reported gaps for improvement in tillage components for interacting factors [5]. "Researchers also proposed the Tillage Operations Quality Optimization (TOQO)" model to enhance efficiency with real-time online recommendations on parameters like vibration, bulk density, slippage ratio, fuel consumption, tillage depth, and field efficiency. This model demonstrates that tillage practices are essential tools in farm management for achieving efficient production [6].

In a study on field operations with high traffic at the farm, different tillage methods (no-tillage, disc tillage, and spring-time tillage) were tested in sandy loam soils, emphasizing the need to prevent soil compaction caused by wheel traffic after tillage [7]. Soil compaction, erosion, organic carbon depletion, and structural changes hinder sustainable production by reducing soil water permeability, retention, and storage [8,9]. In future, these factors do not facilitate flood alleviation during seasonal rainfall generally and in extreme rainfall events particularly.

A team of researchers explored the impact of vehicular traffic on soil compaction in agricultural fields, finding that historical increases in compaction led to a significant decrease in hydraulic conductivity and

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water storage capacity in subsoils [10]. They emphasized the estimated compaction costs, including agricultural production loss and flooding damage, and warned about the potential compounding effect of heavier farm machinery and extreme weather events. Finally, they stressed the importance of considering soil's mechanical limits in future agricultural operations. Heavy field traffic is due to the exploitation of farm mechanization, which is linked with tillage frequency and intensity that could impact flood management because extreme weather events are occurring more frequently over time [11].

Tillage preference as natural flood management (NFM) strategy

Tillage techniques are also practised as a natural flood management (NFM) strategy to create soil surface roughness, especially across the slope of farmland, improving water absorption, infiltration, and storage in the soil profile [12]. However, the mechanical working of soils can damage soil structure. A team of scientists emphasized Best Management Practices (BMPs), including reduced tillage, can potentially support flood loss reduction [13]. They found a modest reduction in peak discharge and economic loss, which exhibited a substantial loss reduction where high-valued assets were located downstream in their studied watersheds. Another study explored reduced tillage (RT) and conventional tillage (CT) in wheat and maize crops for two cropping seasons in a set-up of rainfall-runoff plots 5 m^2, 30 m^2, and 180 m^2 plot sizes. Their results showed an average reduction in runoff coefficients of RT compared to CT, and there was an overall runoff coefficient affected by crop type, with winter wheat 1.7–30 times lower than maize [14].

Importantly, the phenomena of soil structural changes to adverse soil conditions are developed over a period with less awareness of causal indicators to exhibit their pronounced effects into observable evidence with the changing climate in due course. This fact is important to explore tillage practices for their rational and sustainable levels to achieve farming without compromising the ecological objectives.

Decision support tools

Decision support systems are crucial in various fields, including education, medicine, business, and agriculture, with modules like databases, models, knowledge bases, and user interfaces. They have become integral to decision-making [15]. Few researchers used a participatory approach to design a user-friendly decision support tool for non-farm microbial risk assessment involving regulators, catchment managers, farmers, scientists, and industry staff [16]. This support is crucial for formulating targeted policies and domain-specific programs. The study assessed the effects of government programs on tillage practices and substitutes. Examining country-level data from Iowa, Nebraska, and South Dakota, it was found that producers affected by drought and floods preferred conservation tillage. The study also highlighted the unintended consequences of agricultural policies, such as disaster payments and crop insurance, on-farm conservation practices [17]. Researchers proposed a classification for hydrogeological instability risks in Western Sicily and identified four main types. They highlighted the importance of educating farm owners and managers about specific risks and implementing best practices like conservative soil tillage to mitigate them [18].

Developing decision-support tools addressing farming & environmental risks is crucial and timely precious. A valued study explored decision-support tools in agriculture for enhancing productivity and environmental outcomes by emphasizing the importance of reliable information sources. In addition, the study employed a mixed methods approach to identify factors influencing farmers and advisors in utilizing these tools, underscoring their potential for effective design in the future of agriculture [19]. Hence, the need for potential decision support tools to achieve the above goals has emerged.

Bayesian networks as a decision support tool

Several modelling approaches are used in agroecological studies. Bayesian networks are famous tools for modelling uncertainty in complex domains of ecosystems and environments in a mathematical framework [20]. A review study categorized application of Bayesian networks in agricultural domain based on solving problems into following categories *e.g.*, automated monitoring (making inferences involving automated data generated through installed sensors for crops, livestock, natural resources, and storage environment control), prediction (making inferences based on set conditions for crop yields, crop diseases, their evolution & transmission, effects of climate change, profitability/ viability of farms, agricultural policies, agricultural economics), cause identification (identifying breeding success or failure, pathology, weeds invasion, pest & parasitoids, plant growth, farmer engagement) and lastly, classification purposes such as Bayesian Networks and the related BAN – Augmented Bayesian network classifier & Tree Augmented Naïve Bayes classifiers (strategizing classification for agricultural problems such as land classification, weed-crop competitiveness, disease identification, animal parentage classification and spraying strategies) ([21–37]).

Few researchers reviewed integrative quantitative systems of modelling approaches in France, Germany, and The Netherlands, assessing the challenges and differences amongst countries in agricultural land-use systems. They highlighted the importance of bridging the gap between knowledge and technology using the flexible Bayesian network modelling approach, which incorporates qualitative and quantitative inputs for decision-making [38]. A novel approach through a Bayesian Belief Network model was applied to assess the impacts of land use and identify adaptation strategies, including low or no tillage, in Malawi. They incorporated climate projections, local data, literature, and expert opinion to quantify biophysical adaptation benefits from Climate-Smart agricultural activities [39]. Bayesian networks have been used for decision support in land use modelling, integrating quantitative and qualitative data [40].

Decision support tools like Bayesian networks are crucial for stakeholders in addressing tillage as a farm management practice and flood risk management. They enable informed decision-making, analysing potential management choices and their impact on farm production through probability inferences and graphical representations [41]. A modeller defined Bayesian networks as graphical models that encode probabilistic relationships, providing benefits such as handling missing data, predicting the consequences of interventions, combining prior knowledge and data, and avoiding overfitting through Bayesian statistical methods [42]. Bayesian network models are powerful graphical tools to reflect data and decision-support inferences.

A researchers team described integrating qualitative and quantitative operational risk data using a Bayesian approach [43]. A survey also highlighted combining synthetic data generation and generative adversarial networks for learning models [44]. Much work has been published that involved generating synthetic datasets from various crop models (given within the tool as prototype models) based on an algorithm, resulting in a series of published works. Modellers highlighted numerous crop models provided with the DSSAT tool [45]. Minimum data requirements for input variables are pre-requisite to execute simulations to have outputs of response variables [46]. This approach is favourable when no or limited data are available for specific locations under study. Factors like regulatory restrictions, COVID-related scenarios, and time constraints drive the adoption of data simulation techniques as alternative data representation methods, enabling practice runs and comparable results before using real data. Synthetic data generated through simulations can effectively meet the minimum requirements when empirical datasets are limited. However, integrating various datasets at different levels in a Bayesian model remains a challenge in agroecological domains.

Although several approaches were developed to explore the relationships between tillage, soil variables and their impacts on related phenomena for farm production [5], few others used Bayesian network models, which delivered valuable decision analysis for integrated river basin management [1]. However, a huge potential exists to model tillage-related aspects for catering to flood risk management through sustainable farm production [6]. There is a gap in the development of a tool especially in addressing situations where trade-offs exist between competing choices in agroecological domains. This challenge becomes very significant when information is available in diverse forms and can be utilized for useful inferences. For instance, considering the challenges posed by climate change phenomena, a decision-support tool to enable informed choices amongst competing interests is the need of the hour. Hence, a prototype model should be developed to mitigate flood risks without compromising sustainable production. This model should illustrate the most pertinent variables representing the associated scientific phenomena and be compatible with integrating various input data types to enable the right choices.

What preferences should tillage practices be for sustainable farm production while facing compaction, runoff generation, and flood risk management in local catchment areas in the UK? This question highlights adopting tools for sustainable resolutions using tillage preference as a natural flood management (NFM) strategy.

The following are the main objectives of this study:-

Ø To develop a decision support tool, *e.g.*, Bayesian Belief Network (BBN) model for tillage modification as an NFM strategy.
Ø To quantify the variables in the BBN model exhibiting their strength and sensitivity towards variables of interest.
Ø To highlight the relationship between flood alleviation and farm production using land use tillage preference as an NFM strategy.

Materials and methods

Case study area and data

The Thames River Basin District has twenty (20) management catchments defined by the Environmental Agency, UK (United Kingdom) [47]. These include Cherwell and Ray, Colne, Cotswolds, Darent and Cray, Essex South, Gloucestershire, and the Vale, Kenneth and Trib, Kent North, Lee Upper, Loddon and Trib, London, Maidenhead and Sunbury, Medway, Mole, Roding Beam and Ingrebourne, Thames AWB, Thames GW, Thames TraC, Thames and Chilterns South, and Way and Trib. In addition, Thames Valley consists of several smaller catchments administered through numerous water bodies. The Thames River basin district covers over 16,200 km^2. The management catchments include rivers, lakes, groundwater, estuarine and coastal waters. The river basin district is around 17 % urbanised, and the rural land is predominantly arable grassland and woodland. The valley has a history of flash flooding and has a variety of land-use farming systems in the catchment area. A few important catchments & web-catchment areas are highlighted based on their location within flood risk zones and boundaries in the map shown in Fig. 1.

Climate change phenomena pose significant challenges that must be tackled to mitigate flooding and address food shortages effectively. This study investigated the interactions between climate, soilscape, slope, and farming systems, utilizing a working-with-nature approach for effective flood management in alignment with the study's objectives. Then, a Bayesian network model was constructed, representing the relationships between interacting variables. Step-wise procedure was followed for synthesising a Bayesian Belief Network model: construction methodology, structural learning, and network or system evaluation [21]; guidelines for Bayesian network model development, testing, and updating BBNs are also available [48].

The research question has hypothesized whether the "use of tillage

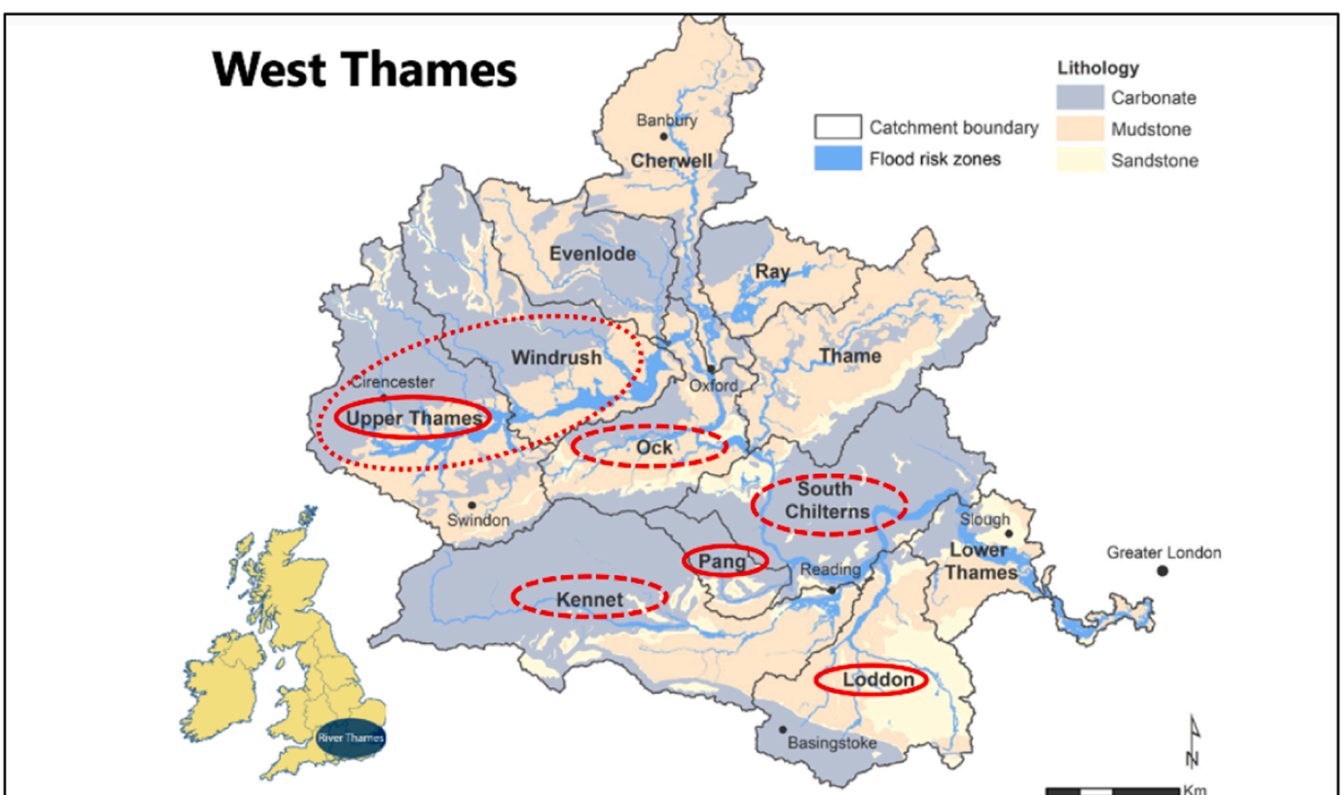

Fig. 1. Catchment areas showing their locations within flood risk zones and boundaries.
([2]Source: www.landis.org.uk).

preferences as a natural flood management (NFM) strategy affects flood alleviation and farm production; the model structure should provide an understanding of how tillage preferences can influence flood alleviation alongside farm yield for food production. The study defined clear model objectives, scope, and conceptualization of model structure, which are vital in the modelling process [49]. This research has examined tillage preference as an independent variable, while flood alleviation and farm production were dependant variables. This study used a Bayesian Belief Network (BBN) model to account for uncertainties and interdependencies amongst the variables of interest, effectively addressing mutual concerns and interactions. By modifying tillage operations (conventional tillage, conservational tillage), the results have anticipated conditional relationships between intermediate variables impacting flood alleviation and farm production. The model has assumed that local tillage preferences have a trade-off effect on flood alleviation and farm production.

The model design was anticipated to capture uncertainties related to soil texture, soil water retention range, soil organic matter/ carbon contents, surface runoff amounts, conventional and conservational tillage preferences, etc. However, the focus remained on ensuring relationships presented in the model structure were real and that the best would be causal. Therefore, the priority was to identify and include the most appropriate variables meeting the same in the model for tillage preference.

Synthesis of network model structure

Synthesis of model structure can be achieved using three frequent methodologies: manual construction, data-driven (automatic) construction, and a combination of both earlier [21]. A scholastic approach was adapted to construct a basic Bayesian network structure based on a published scientific literature (PSL) review. This technique is being published as a research article in a peer-reviewed journal. The process involved practising a literature review to identify causal or conditional relationships reported in published scientific literature. The step-wise approach is to incorporate them in the given templates of the spreadsheets. Identified variables are systematically stored in rows and columns and also remain traceable. Then, they are connected using the Netica interface to denote variables as nodes and relationships as links or arcs between any two variables identified. Further details about the PSL method are beyond the scope of this paper.

Nonetheless, the final Bayesian model structure is built on key variables established in that research (Table 1). This powerful PSL method has unveiled a network of seventeen interactions, unravelling the intricate web of cause-and-effect relationships. These twelve variables have served as the foundation for gaining insights into tillage management's effects on flood alleviation and farm production, as shown in Table 1.

Table 1
Variables and their relationships were identified using the PSL approach.

Twelve (12) Variables were identified using the Published Scientific Literature (PSL) approach.	
Soil Texture	Weeds
Infiltration	Erosion
Drainage	Effect on flood alleviation
Tillage practices	SOM/ SOC
Soil Compaction/ H. Bulk Density	Surface Runoff
Nutrients Loss	Effect on-farm yield
Seventeen (17) relationships were identified using the PSL approach.	
Soil texture type to tillage	Weeds to nutrients loss
Tillage practices for weeds	Erosion to nutrients loss
Tillage to erosion	Runoff to nutrients loss
Tillage to compaction	Runoff to erosion
Tillage to SOM/ SOC	Runoff to drainage
SOM/ SOC to infiltration	Nutrients loss farm yield
Compaction to runoff	Drainage to flood alleviation
Compaction to infiltration	Infiltration to runoff
Compaction to erosion	

Initially established using the PSL approach, the BBN model structure has undergone structural improvements through expert knowledge elicitation. I employed Six (6) domain experts to conduct semi-structured interviews after seeking ethical clearance from the school's designated committee. As a result, experts contributed unique adaptations to enhance the BBN model structure (refer to Table 2).

Ten variables have consistently emerged through the PSL approach and expert elicitation. These commonly identified variables were integrated into the final version of the BBN model structure (refer to Table 3).

Identification and inclusion of pertinent variables for enhanced model structure I extended the model comprising three sub-models

The sub-model 1

The sub-model 1 has focused on temporal factors (*e.g.*, climatic variables) and their influence on key variables involved in the natural processes of plant growth stages during seasonal crop production. All variables used in sub-model one comprised measurement axioms with quantitative (continuous) data types. Input variables, *e.g.*, soil type, average daily rainfall (mm), and daily mean temperature (C°), responded to water uptake demand ratio (water stress), total water in the soil profile (storage in mm), and total biomass (kg/ ha).

However, selecting independent variables, including climatic data, temperature, precipitation, and soil parameters, presented challenges [50]. Including weather variables, specifically daily precipitation and temperature, in the basic model structure was crucial for considering the impact of climatic factors and their interrelated variables on cereal crop production. These variables provided quantitative data representations within the Bayesian network model [51].

The scarcity of data and the spatiotemporal effects of weather and other covariates on yields and technological change posed further difficulties in drawing inferences [52]. This research utilized a tool for crop growth simulation modelling tool, "Decision Support System for Agrotechnological Transfer (DSSAT)" (https://dssat.net/about/), to address that. I introduced tillage preference options in the X-build module of DSSAT in the crop management section and shown in supplementary data, *e.g.*, Table S3. The study also considered slope amongst soil profile types with varying degrees (*e.g.*, 3 ° & 12 ° angle to represent regular and steep slopes). These slope angles were incorporated into the DSSAT tool using s-module data input, and I executed simulations for individual soilscapes as listed in Table 4. I utilized this spatial correlation for suggested yields with the help of DSSAT. This concept was realized by employing local soilscape in the s-module, climatic data in Weatherman, and crop phenology data from the given prototype experiment in DSSAT version 4.7. Technological tools, holistic approaches, and conditional yield distributions improve understanding of crop yield behaviour. This model integrated key influencing variables such as root water uptake, soil water content, crop biomass, product weight, and plant residues. Supplementary material includes pertinent datasets and essential details utilized in the modelling work.

The S-build module of the DSSAT tool was introduced with forty dominant soil profiles (individually) to accurately reflect actual weather data from a local weather station and tillage preferences while keeping all other environmental and management measures unchanged in seasonal wheat crop growth models for the RORO7401 standard experiment provided with DSSAT software version 4.8. A single simulation was run for 46 years, and a list of all simulations is given below in Table 4. Soil category assessment is described in supplementary documents, *e.g.*, annexes Table S1 and S2.

DSSAT determines two stress factors, *e.g.*, potential root uptake using "TURFAC" and "SWFAC," affecting crop phenology, growth, and biomass activated when potential transpiration demand equals or exceeds potential root water uptake, as shown in Fig. 2. Nodes represented as

Table 2
Several variables and relationships were identified by various experts/ specialists during expert knowledge elicitation and through the Published Scientific Literature (PSL) approach for structural construction of the BBN model for tillage preferences.

Expert	Expertise/ Specialization	Variables Identified	Interactions Identified
1	*A hydrologist* specialising in water pollution at ecosystem, catchment and continental scale.	15	28
2	*An environmental & social scientist* for land uses, communities and policies involving local decision-making.	15	31
3	*An environmental scientist* for carbon and water cycles in ecosystems domains from test tube to catchment scale.	14	26
4	*A crop scientist* for plant physiology, biology, and genetics research in biodiversity, crops, and agroecosystems.	14	27
5	*A soil scientist* specialising in soil biochemistry in rural agricultural, natural, and polluted environments.	14	25
6	*Practising farmer* managing a farmhouse practising mix farming of raising livestock and arable crops.	18	49
Source	Study Domains	Variables Identified	Interactions Identified
*PSL Method	Agriculture, Ecology, Agri-Environment, Climate Change.	12	17

* **PSL** = "Published Scientific Literature".

Table 3
Commonly identified variables by all experts/ specialists.

Ten variables were commonly identified using the PSL approach & knowledge elicitation from all experts.	
Tillage practices	Expert 1 *(A hydrologist)*
Soil texture type	Expert 2 *(An environmentalist)*
*Soil cover/ Weeds cover	Expert 3 *(A social scientist)*
*Soil organic matter/ Soil organic carbon	Expert 4 *(A crop scientist)*
*Soil compaction/ Bulk density	Expert 5 *(A soil scientist)*
Erosion	Expert 6 *(A practising farmer)*
Surface runoff	
*Nutrients (loss/ competition/ leaching/ access)	
Effect on flood alleviation	
Effect on-farm yield	

* Some of the variables with related phenomena were grouped for interchangeable uses.

continuous variables carrying quantitative datasets were discretised in the BBN model for tillage for meeting compatibility with a software application.

This sub-model provided output variables such as biomass, product weight, water uptake demand ratio, total water in a soil profile, daily surface runoff, and senesced organic matter to the soil. In addition, the study considered physiological characteristics, growth, and biomass production responsive to water stress effects [53]. Similar aspects were experimented with in a study on increasing water-competing aspects of agriculture and eco-environment and developed a hybrid Bayesian network. Results found a strong relationship between available water supply, water storage, and production reduction. The same was experienced in another Bayesian network for wheat, maize, cotton, *etc.* [54]. They recommended a trade-off framework about the water-use conflict between agricultural and eco-environmental. Table 5 and S7(a) show the variables and relationships included in sub-model 1.

The sub-model 2

In this sub-model, a few variables were grouped by considering the list of identified variables from Table 3 and the availability of datasets. The selection of variables in the sub-model was prioritized on the commonly identified variables by the domain experts and through published literature. These were six variables (*e.g.*, tillage, texture, bulk density, soil structure, organic matter, and farming systems) with fifteen identified interactions (Table 6). Four of them were identified by all experts consulted for individual adaptations. The practising farmer specially endorsed the fifth variable (farming systems). The availability of survey data results for farming systems was also considered. Another domain expert recommended a sixth variable (soil structure). Access to pertinent data scores, such as a visual evaluation of soil structural (VESS), was also available to include this variable in the BBN model structure. More importantly, sub-model 2 focused on relevant datasets derived from local surveys and empirical datasets analysis to assess the impact on interdependent variables, as shown in Fig S1 [70]. Variables and their interactions in sub-model two are enlisted below in Table 6 and Table S7(b).

The sub-model 3

This sub-model selected variables based on their relevance and significance linked to farming issues. Catchment managers have many challenges dealing with ecological assets and environmental management [55]. Few variables exist as a point of concern in local farm management. These are erosion, nutrients (loss + competition) and weeds ([58,60,98,99]). The selection of these variables is mainly based on the common recommendation made by the consulted experts, which was established through literature citation. All experts endorsed their inclusion as part of the BBN model structure amongst individual adaptations, as enlisted in Table 3. The only challenge was data availability, which was addressed by consulting published literature and domain knowledge. They are enlisted below in Table 7 & S7(c).

Model parametrization

In the parameterisation process, I first parametrized the model in Netica software using a case file comprising 1927 cases. A breakdown of cases is given below in Table 8. Then, I used domain knowledge and literature base data to parameterize the remaining nodes in the model.

A single case file with 1927 cases was used during the model parameterisation process by combining cases from sub-models 1 and 2. However, the nodes in the third sub-model required knowledge elicitation through domain expert opinion and data from existing literature. A screenshot of specimen Excel spreadsheets for processing cases to parameterize the model is supplied in Table S4 and S5 of supplementary material. The case files comprising cases with simulated datasets for training and testing the BBN model with no missing and 25 % missing data are also provided in the supplementary material.

Model's learning relied on its algorithm for the crop model to generate synthetic datasets by running simulations in the DSSAT. A simple and effective algorithm was developed for learning the BBN model using data inconsistent with a given node ordering search [65]. This means ordering base search is competitive in performing well. Similarly, the DSSAT model executes variable interactions hierarchically, giving variables responses following crop growth stages. Given the study objective, the variable of interest was selected, and their responses were applied in the respective nodes in the first sub-model. Evidence found a similar approach applied to create synthetic datasets through a process that simulated the evolution of pasture growth over 30 years. They trained the DeepPaSTL model on these datasets, which predicted pasture growth for short and long-horizon predictions with missing and irregular historical measurements [66,67].

A case file was generated, which is provided in the supplementary material. The Bayes net parametrized conditional probability tables (CPTs) of nodes (variables) using two algorithms in Netica software. Firstly, the *counting algorithm* is the most straightforward algorithm for parameter learning of CPTs from a case file and is called counting learning and known as a true Bayesian learning algorithm. This procedure starts in ignorance, provided no previous learning or prior probabilities are defined by an expert, no missing data, and no latent

Table 4
Dominant soils & slopes were introduced in the S-module, with 40 experiments conducted in DSSAT for tillages. A single simulation (each experiment) was executed for 46 years using DSSAT software v4.8.

Tillage management	Slope angle	Soil ID: RDPG	Texture code	Clay	Silt	OC
Conservational tillage (Minimum/ zero tillage)	3°	307603	SLOP 300003	22	56	7.6
	3°	507603	SLOP 300005	27	56	7.4
	3°	602603	SLOP 300006	13	29	2.6
	3°	704403	SLOP 300007	23	42	4.4
	3°	803903	SLOP 300008	21	47	3.9
	3°	102903	SLOP 300010	7	12	2.9
	3°	145803	SLOP 300014	2	20	5.8
	3°	184403	SLOP 300018	30	41	4.4
	3°	209003	SLOP 300020	69	26	9
	3°	223503	SLOP 300022	12	31	3.5
	12°	307603	SLOP 120003	22	56	7.6
	12°	507603	SLOP 120005	27	56	7.4
	12°	602603	SLOP 120006	13	29	2.6
	12°	704403	SLOP 120007	23	42	4.4
	12°	803903	SLOP 120008	21	47	3.9
	12°	102903	SLOP 120010	7	12	2.9
	12°	145803	SLOP 120014	2	20	5.8
	12°	184403	SLOP 120018	30	41	4.4
	12°	209003	SLOP 120020	69	26	9
	12°	223503	SLOP 120022	12	31	3.5
Conventional tillage (Traditional tillage practices throughout cropping season)	3°	307603	SLOP 300003	22	56	7.6
	3°	507603	SLOP 300005	27	56	7.4
	3°	602603	SLOP 300006	13	29	2.6
	3°	704403	SLOP 300007	23	42	4.4
	3°	803903	SLOP 300008	21	47	3.9
	3°	102903	SLOP 300010	7	12	2.9
	3°	145803	SLOP 300014	2	20	5.8
	3°	184403	SLOP 300018	30	41	4.4
	3°	209003	SLOP 300020	69	26	9
	3°	223503	SLOP 300022	12	31	3.5
	12°	307603	SLOP 120003	22	56	7.6
	12°	507603	SLOP 120005	27	56	7.4
	12°	602603	SLOP 120006	13	29	2.6
	12°	704403	SLOP 120007	23	42	4.4
	12°	803903	SLOP 120008	21	47	3.9
	12°	102903	SLOP 120010	7	12	2.9
	12°	145803	SLOP 120014	2	20	5.8
	12°	184403	SLOP 120018	30	41	4.4
	12°	209003	SLOP 120020	69	26	9
	12°	223503	SLOP 120022	12	31	3.5

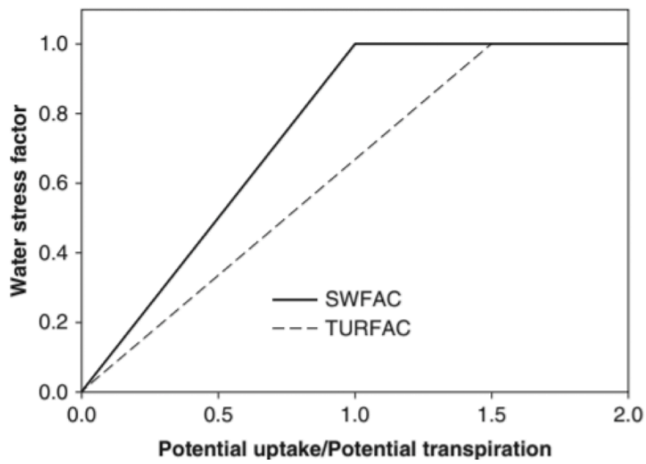

Fig. 2. The graph between water stress factor and potential uptake/potential transpiration.
The value of both stress factors ranges from zero to one, where one represents no stress and zero represents maximum stress.

Table 5
Variables (nodes) and relationships (arcs) are included in the first sub-model.

Nine (9) Variables are recognized and included in sub-model 1	
Slope (SLOPE) Rainfall (PRED) Temperature (TMEAN) Total water in the soil profile (SWTD) Water uptake demand ratio (WUPRD) Senesced organic matter to soil (SNSWD) Daily surface runoff (ROFC) Total weight – Biomass (TWAD) Product weight – crop yield (HWAD)	
Eleven (13) relationships are recognized amongst variables in sub-model 1	
Temperature to water uptake demand ratio	Total water in the soil profile to daily surface runoff
Temperature to the total weight (biomass)	H_2O uptake demand ratio to the total weight (biomass)
Rainfall to water uptake demand ratio	The total weight (biomass) to senesced OM to soil
Rainfall to the total weight (biomass)	Total weight (biomass) to product weight (yield)
Rainfall to total water in the soil profile	Slope to daily surface runoff
Rainfall to daily surface runoff	Senesced OM into the soil to SOMC
Senesced OM into the soil to total water in the soil profile	

Table 6
Variables (nodes) and relationships (links/ arcs) are included in the second sub-model.

Six (6) Variables recognized and included in sub-model 2	
Tillage (TILLAGE) Texture (TEXTURE) Bulk density (BULKDENSITY) Soil structure (VESS) Organic matter (SOMC) Farming system (LANDUSE)	
Fifteen (15) relationships identified & recognized for sub-model 2	
Texture type to Tillage	Land use farming System to Tillage preferences.
Texture type to Bulk density	Land uses the farming system to Bulk density.
Texture type to Soil organic matter/ carbon	Land uses the farming system to Soil organic matter/ carbon
Texture type to Soil structure	Land uses the farming system to Crop yield.
Tillage to Bulk density	Tillage to Soil organic matter/ carbon
Tillage to Weeds	Tillage to Total water in the soil profile
Tillage to Erosion	SOMC to Soil structure
Bulk density to Soil structure	

Table 7
Variables (nodes) and relationships (arcs) are included in the third sub-model.

Three (3) Variables categorized for sub-model 3	
Weeds Erosion Nutrients (Loss + Competition)	
Three (3) relationships identified & recognized for sub-model-III	**References**
Erosion to Nutrients (loss + competition)	[56] Quinton, *et al.*, 2010. [57] Visser, et al., 2007. [58] Barrows, *et al.*, 1963.
Weeds to Nutrients (loss + competition)	[59] Harre, *et al.*, 2020. [60] Jane, *et al.*, 2007. [61] Lambert, *et al.*, 1986.
Nutrients (Loss + Competition) to Crop Yield	[62] Ciampitti, *et al.*, 2014. [63] Tan, *et al.*, 2005. [64] Bindraban, *et al.*, 2000.

Table 8
Number of cases included in the final case file.

Sub-model number	Number of cases	Origin of cases (Nature of Data)
Sub-model 1	1840	Synthetic data by simulations
Sub-model 2	87	Survey data & empirical data
Sub-model 3	0	Elicited knowledge & literature data
Total	1927	–

node exists. This method is applied to the Bayes net's first sub-model nodes (variables). Secondly, the expectation maximization (EM) algorithm is used where missing data exist in the case file. This Bayes net also includes a small amount of missing data, which was observed during the extraction of survey datasets. During parameterisation, these missing data points were processed into the final Bayes net using a single case file that compared cases for all nodes (variables) of the first and second sub-models. Hence, the more robust EM algorithm is applied to the case file using Netica software to process the cases. This method finds the maximum *likelihood of Bayes net,* the net which is the given data. If N is the net and D is the data, finding the N gives the highest probability, *e.g.*, P(N|D).

Using Bayes rule, P(N|D) = P(D|N) (PN)/ P(D). Since P(D) stays the same for all candidate nets, an attempt should be made to find probability with maximize P(D|N) P(N); this is maximizing its logarithm: log(P (D|N) P(N)). This is good where more data is available, which allows more importance for the first term to be comparable to the second. As the case file contains much data for entire variable nodes in the first and second sub-models, hence EM algorithm is applied efficiently where small missing data points exist for learning the Bayes net ([67,68,69]).

The second sub-model is populated mainly with survey datasets to parametrize this section of the BBN model. Variables were selected considering data availability and their direct relationships with variables of interest. And applied this as the Bayesian network uses survey data to train a learning algorithm [70]. They implemented different strategies in different agent-based models and found the probabilistic-directed graphical model stands out. They differentiated training Bayesian networks before using survey data or during simulation runs alone. Each variable (node) in the network contains conditional probability tables (CPT) depending upon its parent nodes. CPT exhibits the probability that an event will occur relying on combinations of their linked nodes and the values of their states.

The first sub-model has variables that learnt their conditional probability table (CPT) from simulated datasets specimen shown in Table S4.

In contrast, the second sub-model has variables that learnt their CPT from extracted data from the survey and empirical datasets collected from field samples. Empirical datasets were acquired from soil sampled from various farms for measuring bulk density, soil structure aggregates, and soil organic matter/ carbon contents by the Landwise project partner in the Thames Valley area. In addition, different datasets were also extracted from experimental trials, interviews & surveys conducted by project partners (*e.g.,* Landwise NFM, QNFM, University of Reading, University of Gloucestershire, *etc.*) in the Thames Valley catchment areas. These were chosen to parametrize the second sub-model of the BBN model for tillage preferences, and related data are shown in Table S5.

Some data were qualitative and discrete, while the others were continuous variables with quantitative ranges. However, such continuous variables were discretised for meeting compatibility with the Netica software application used for BBN model synthesis. This sub-model-II included variables, *e.g.*, land use farming systems, tillage preferences, soil texture types, bulk density, soil structure, and soil organic matter/carbon, which resulted in their impacts on variables, *e.g.*, organic matter, soil compaction, and crop yield. In addition, a study explored soil functions such as water retention, carbon sequestration, organic matter cycling, and plant growth [71]. Soil structure is strongly affected by bioturbation, tillage, and compaction concerning land use. They explored differences in soil structural changes caused by soil functions. They examined soil structural and microbial activity from all land use types, such as conventional and organic farming, meadows, and pastures. They found a significant difference between land use variations based on microstructural properties. Larger macropore diameters were noticed in grassland soils containing particulate organic matter, including root biomass, and better microbial activity than croplands. They stated that land use affects carbon mineralization in aerated soils comparatively well than others. The CPTs in this sub-model were learnt through a case file with several cases processed through Netica software using the EM algorithm for parametric learning, as explained in the above section. Variables and their identified interactions are shown below in Table 6, and Table S5 depicts a case file used to parametrize nodes linked in sub-model 2.

The third sub-model used elicited knowledge acquired from literature and domain expert opinion for parametrization. Knowledge elicitation is widely used to parametrize BNs based on highly qualitative data, which is considered a complex, time-consuming process. The best would be to parametrize BNs using data where possible; however, where limited or no data are available, domain knowledge elicitation is used to estimate the parameters to specify conditional probability tables (CPTs) between interacting variables in this sub-model. This stage involved steps undertaken for model development using a knowledge or data-based approach [72]. Therefore, parameter estimates can be learned from data and experts. However, BN development is an iterative process, so estimates could not be exact in early prototypes with uniform probabilistic distributions. A data-driven approach combined expert knowledge elicitation with an applied parameterization for the same Bayesian Network (BN) model [73]. Hence, the expert knowledge elicitation approach was used to parametrise the third sub-model-III of BBN of tillage. States of variables were categorized into the binary function to enable them to be coupled with the rest of sub-model-1 & 2. And parametrization of sub-model three was done at last after having impacts of variables from the rest of the two sub-models. This method helped incorporate prior beliefs with minimum, maximum, and plausible values for defining each instantiation of two interacting variables in the BN model. The probability distributions of each interacting variable reflected direct influence based on the strength of conditional relationships in respective instantiation. For example, at the coupling node of surface runoff, probability distributions representing bulk density, soil structure, weeds, and daily surface runoff provide an instantiation of the highest daily surface runoff where a sloped gradient interacts with highly increased compaction in soil structures and higher bulk density. Sub-models are coupled at the coupling nodes [74,75,76]. A summary of coupling nodes (variables) and their links (interactions) in the BBN model are shown in supplementary material in Table S8, and conditional probability tables (CPTs) for coupling nodes, *e.g.*, surface runoff and crop yield, are shown in Table S9 & S10. Moreover, the CPTs for coupling nodes of erosion, nutrients (loss & competition), and weeds are elaborated in Fig S2 & S3.

Different methods of BBN discretization are used for continuous variables, with none being superior to others because there is a risk of information loss amongst all of them. However, discretization is necessary for representing factorisations of joint probability distributions over finite sets of discrete random variables [1]. Therefore, the discretization approach was applied to such variables. The combination of discrete and continuous variables provides a hybrid Bayesian network, which reduces the loss of information compared to all discrete variables ([77, 78]). Discretization of all variables was done before parameterisation, where continuous data were discretised into sub-groups defining the ranges in the datasets. This helps simplify the parameterisation process to facilitate the expert elicitation procedure. Node states were established for each variable because thresholds, means, and standard deviations from mean values of data and discretization were adopted, as defined in Table S6(a) and measured statistics mentioned in Table S6(b). And coupling nodes are highlighted in Table S8 of the supplementary material.

In the final BBN model, variables as part of the first and second sub-models were parameterized using a single case file containing synthetic datasets (simulated data), empirical datasets (field data of soil samples), and broad-scale survey datasets. The case file comprises cases following the same order/ sequence, although Netica is not sensitive towards the order of cases in a case file. Variables of the third sub-model were parameterized at last as a part of the final model using a knowledge base from literature and domain experience. So, responses in final output variables could have comprehensive effects of uncertainties of all variables in the full BBN model for land use and tillage preferences as an NFM strategy. The full model is shown with all three sub-models, as shown in Fig 3.

Results and discussion

Evaluating the BBN model of tillage preferences

The model needed evaluation and validation. Model validation means describing the output and mechanism of generating a system's output, and the model's performance meets its acceptance. BBN model for tillage is subject to validation based on data availability for the catchment area, and the model has the flexibility to upgrade for similar catchment areas. Data availability can also deliver model validation. However, BBNs are commonly used where no or limited datasets are available. A common technique of BBN model validation is to use expert opinion to find their agreement with model structure, discretisation, and parametrization [63]. Validation tests, such as D-separation analysis, are also performed [79]. Causal independence-based tests are structural tests measuring consistency as a reliability criterion [80].

However, evaluation of BBN models is applied for this model to consider other limitations of datasets and experts' availability. Model evaluation delivers credibility, acceptance, and efficient applications. Different metrics are used to gauge the performance and uncertainty of Bayesian network models. These include metrics of model sensitivity & influence, metrics of model complexity, metrics of BN model prediction performance, metrics of uncertainty in posterior probability distributions, and metrics for comparing alternative posterior probability distributions [81]. Most of these evaluation metrics are tool-specific. The following approaches are applied using the Netica software tool, as mentioned below.

Bayesian networks used in environmental modelling are not routinely validated, with over 37.7 % receiving no validation [82]. The current work's evaluation of the model CPTs involved quantitative and subjective reviews, allowing for complete model validation. Model structural evaluation and validation performed by six domain experts expressed their adaptations to the basic BBN model for tillage. Commonly identified variables were included in the final model structure. In addition, domain expertise validated the aggregated distributions through face validity. It has been established that expert

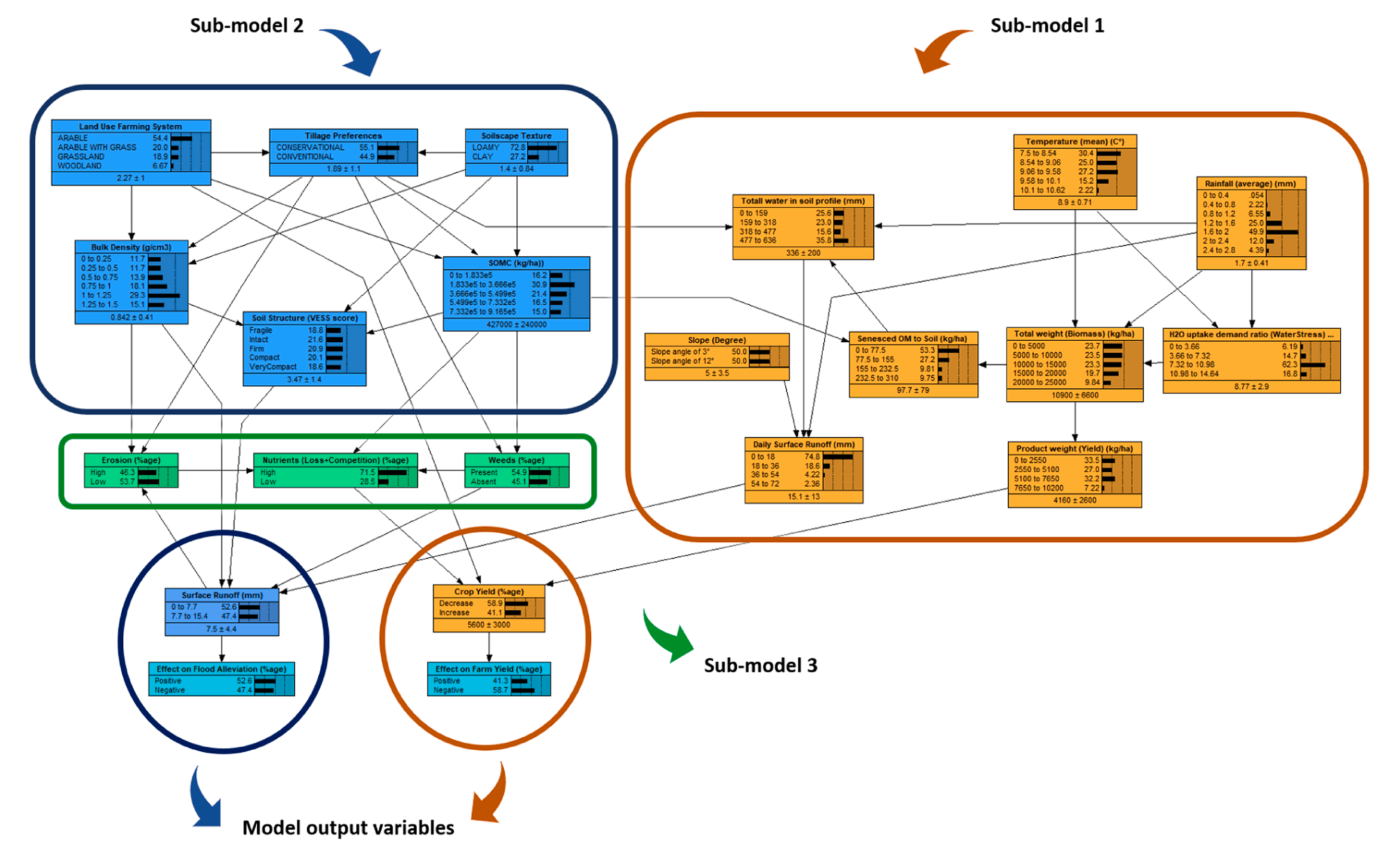

Fig. 3. The consolidated final version (qualitative & quantitative data-driven) of the BBN model for tillage preferences as an NFM strategy.

probability elicitation for Bayesian networks contains issues related to human capabilities [83], where evaluation relies on personal knowledge, commercial pressures, and other factors [84].

Additionally, variables based on measurement axioms in the model have valid interactive relationships depicted through crop model algorithms used in the DSSAT software. The simulated datasets used to learn the CPTs also reflected their impact on model performance at the model testing stage and sensitivity to findings. Netica can efficiently measure the degree to which findings at any node can influence the beliefs at another node, given the findings currently entered. The measures can be in mutual information (entropy reduction) or the expected reduction of real variance. Sensitivity analysis in Bayesian network modelling helped determine the extent to which related variables highlight a new finding in a target node. This analysis illustrated the underlying probability structure of a model given prior probability distributions [85]. Model sensitivity can be determined as variance reduction for continuous variables or entropy reduction for categorical variables [81]. Sensitivity to finding and sensitivity to parameters are the methods of validity for expert-elicited networks [68]. The model was tested for its sensitivity to key variables of interest. Sensitivity to finding at node "Effect on flood alleviation" is prescribed under Table 9.

Table 9
Sensitivity of “Effect on Flood Alleviation” to a finding at another node.

Sr. no.	Node	Mutual info	Per cent	Variance of Beliefs
1	Effect on Flood Alleviation	0.99809	100	0.2493374
2	Surface Runoff (mm)	0.91729	91.9	0.2394374
3	Weeds (%age)	0.25808	25.9	0.0838819
4	Tillage Preferences	0.22460	22.5	0.0736358
5	Erosion (%age)	0.21263	21.3	0.0699184
6	Nutrients (Loss+Competition)	0.02273	2.28	0.0078249
7	Bulk Density (g/cm^3)	0.01776	1.78	0.0060903
8	Soil Structure (VESS score)	0.00929	0.931	0.0031977
9	Land Use Farming System	0.00775	0.777	0.0026567
10	Crop Yield (%age)	0.00508	0.509	0.0017550
11	Effect on Farm Yield (%age)	0.00487	0.488	0.0016834
12	Soilscape Texture	0.00225	0.225	0.0007749
13	SOMC (kg/ha)	0.00131	0.131	0.0004510
14	Senesced OM to Soil (kg/ha)	0.00022	0.0217	0.0000746
15	Daily Surface Runoff (mm)	0.00012	0.0125	0.0000430
16	Total water in the soil profile	0.00001	0.00096	0.0000033
17	Rainfall (average) (mm)	0.00001	0.000825	0.0000028
18	Slope (Degree)	0.00001	0.000705	0.0000024
19	The total weight (Biomass) (kg/ha)	0.00000	2.84e-05	0.0000001
20	Product weight (Yield) (kg/ha)	0.00000	1.67e-05	0.0000001
21	H_2O uptake demand ratio	0.00000	0	0.0000000
22	TMEAN	0.00000	0	0.0000000

This showed a sensitivity of variable of interest, *e.g.*, "Effect on Flood Alleviation" could have from a list of variables in the network with their order of influence and the extent of variance in beliefs that could be expected. This also highlights the most relevant information expressing how much the target node’s beliefs, mean value, *etc.*, could be influenced by a single finding at each of the other nodes in the net and its significance in the network. In this case, surface runoff is the most critical variable affecting flood alleviation, and mean temperature is the least significant in the network. The table’s mutual information value of listed variables highlights the uncertainty reduction or expected reduction of real variance towards the objective variables, *e.g.*, the effect on flood alleviation. More sensitive variables to finding variables (Effect on Flood Alleviation) have higher sensitivity values in the table for mutual information (entropy reduction/ variance reduction) and variance of belief in the list. Similarly, the extent of variance in belief amongst variables reduces in the list where sensitivity to the finding variable reduces. Sensitivity to finding at node "Effect on-farm yield" is prescribed as in Table 10.

Table 10
Sensitivity of "Effect on Farm Yield" to a finding at another node.

Sr. no.	Node	Mutual info	Per cent	Variance of Beliefs
1	Effect on Farm Yield	0.97795	100	0.2423976
2	Crop Yield (%age)	0.89716	91.7	0.2324977
3	Nutrients (Loss+ Competition)	0.10682	10.9	0.0357140
4	Land Use Farming System	0.06307	6.45	0.0204222
5	Weeds (%age)	0.01387	1.42	0.0046589
6	Tillage Preferences	0.01063	1.09	0.0035736
7	SOMC (kg/ha)	0.00987	1.01	0.0033106
8	Erosion (%age)	0.00638	0.652	0.0021422
9	Surface Runoff (mm)	0.00507	0.519	0.0017042
10	Product weight (Yield) (kg/ ha)	0.00502	0.513	0.0016856
11	Effect on Flood Alleviation	0.00487	0.498	0.0016365
12	The total weight (Biomass) (kg/ha)	0.00391	0.399	0.0013108
13	Bulk Density (g/cm3)	0.00201	0.206	0.0006738
14	Senesced OM to Soil (kg/ha)	0.00197	0.201	0.0006553
15	Soilscape Texture	0.00018	0.0184	0.000603
16	Total water in the soil profile (mm)	0.00012	0.0126	0.0000415
17	Soil Structure (VESS score)	0.00011	0.0108	0.0000356
18	H2O uptake demand ratio	0.00008	0.0086	0.0000282
19	TMEAN	0.00004	0.00396	0.0000130
20	Rainfall (average) mm	0.00004	0.00389	0.0000128
21	Daily Surface Runoff (mm)	0.00001	0.00146	0.0000048
22	Slope (Degree)	0.00000	0	0.0000000

This showed a sensitivity of variable of interest, *e.g.*, "Effect on Farm Yield" could have from a list of variables in the network with their order of influence and the extent of variance in beliefs that could be expected. This also highlights the most relevant information displaying how much the target node's beliefs, mean value, etc., could be influenced by a single finding at each of the other nodes in the net and its significance in the network. In this case, crop yield is the most critical variable affecting farm yield, and the slope is the least significant in the network. The table's mutual information value of listed variables highlights the uncertainty reduction or expected reduction of real variance towards target variables, *e.g.*, the effect on farm yield. More sensitive variables to finding variables (Effect on Farm Yield) have higher values for mutual information (entropy reduction/ variance reduction) and variance of belief in the list. In Table 10, sensitivity towards "Effect on Farm Yield" is influenced most by the variable "crop yield," the slope is the least significant in the network.

Testing model performance evaluation through 5000 simulated cases with no missing data compared to 5000 simulated cases with 25 % missing data for the BBN model for tillage modification

The final BBN model generated 5000 simulated cases with no missing data to find the model's performance first. And later, the same was done with 25 % of missing data. The following results were found. Testing models with test cases is not a unique approach but instead tried in several domain studies. A comparable approach also introduced test data generation and model checking [86]. For example, the medical sector used a similar approach ([87,88]). Researchers also used Bayesian networks to create synthetic datasets and compared inferences from simulated data by a single BBN and Bayesian model averaging over a set of networks [89]. This approach is useable in model scenarios, expecting the BBN model to match reality. Hence, the below model testing technique was applied for performance evaluation for its sensitivity to findings using simulating random cases [90].

Testing model performance evaluation for its sensitivity to findings with 5000 cases with no missing data

- For Effect on Flood Alleviation: Predicted

The model is tested with 5000 cases with no missing data, resulting in the below outcomes.

Table 11 shows that the model performs very well for its predicted accuracy, *e.g.*, it predicted 2624 times positive when these were actually positive. However, the model predicted 26 times positive when these were actually negative. On the other hand, the model predicted 2328 times negative when they were actually negative, but the model predicted 22 times negative when they were actually positive. Hence, the error rate was lower to 0.96 %, which means model performance is good [81]. This matrix means model evaluation performance remained excellent with a lower error rate of 0.96 % when tested with 5000 simulated cases with no missing data.

As Table 12 shows, the test quality with a higher AUC may be considered better, and the area under the receiver operating characteristics curve (ROC), found above 0.9, means the model has outstanding diagnostic test performance [91]. This suggests a 99.03 % chance that model prediction for the effect on flood alleviation will correctly distinguish a normal effect on flood alleviation from an abnormal effect on flood alleviation based on the ordering of test ratings.

- For Effect on Farm Yield: Predicted

The model is tested with 5000 cases with no missing data; the results are in Table 13.

This table shows that the model performs well for its predicted accuracy, *e.g.*, the model predicted 2061 times positive when these were actually positive about the effect on farm yield. However, the model predicted 19 times positive when these were actually negative. On the other hand, the model predicted 2886 times negative when these have actually negative effect on farm yield. Still, the model predicted 34 times negatives but actually had a positive effect on farm yield. Hence, an error rate lower than 1.06 % means model performance is good [81]. This matrix means model evaluation performance remained excellent with a low error rate of 1.06 % when tested with 5000 simulated cases with no missing data. Therefore, model predictive accuracy is better for the effect on flood alleviation than the effect on farm yield.

The test with a higher AUC may be considered better, and the area under the receiver operating characteristics curve (ROC), found above 0.9, means the model has outstanding diagnostic test performance [91]. This suggests a 99.86 % chance that model prediction for effect on farm yield will correctly distinguish a normal effect on farm yield from an abnormal effect on farm yield based on the ordering of test ratings. This is highlighted in Table 14.

Testing model performance evaluation for its sensitivity to findings with 5000 cases with 25 % missing data

- For Effects on Flood Alleviation: Predicted

The model is tested with 5000 cases with 25 % missing data, resulting in the below outcomes.

Table 15 shows that the model performs well for its predicted accuracy, *e.g.*, the model predicted 1879 times positive when these were

Table 11
Confusion Matrix.

	Predicted Positive	Predicted Negative
Actually Positive	2624	22
Actually Negative	26	2328

Error rate = 0.96 %.

Table 12
Quality of Test for the state "Positive":.

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg.	Error-Rate
0	100	0.00	52.92	100.00	47.08
1	99.17	98.77	98.91	99.06	1.02
99.5	0.00	100.00	100.00	47.08	52.92
100	0.00	100.00	100.00	47.08	52.52

Gini Coeff = 0.9806 Area under ROC = 0.9903.

Table 13
Confusion Matrix.

	Predicted Positive	Predicted Negative
Actually Positive	2061	34
Actually Negative	19	2886

Error rate = 1.06. %

Table 14
Quality of Test for the state "Positive.".

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg.	Error-Rate
0	100	0.00	41.90	100.00	58.10
1	98.38	99.21	98.90	98.83	1.14
99.5	0.00	100.00	58.10	58.10	41.90
100	0.00	100.00	58.10	58.10	41.90

Gini Coeff = 0.9772 Area under ROC = 0.9886.

Table 15
Confusion Matrix.

	Predicted Positive	Predicted Negative
Actually Positive	1879	103
Actually Negative	118	1604

Error rate = 5.967 %.

actually positive effects on flood alleviation. However, the model predicted 118 times negative when these were actually positive. On the other hand, the model predicted 1604 times negative when these had actually negative effect on flood alleviation. Still, the model predicted 103 times negative when these had actually positive effects on flood alleviation. Hence, the error rate found 5.967 % means model performance is good [86]. Furthermore, this matrix means model evaluation performance remained good, with an error rate of 5.967 % when tested with 5000 simulated cases with 25 % missing data.

The test quality for the positive state of flood alleviation with a higher AUC may be considered better, and the area under the receiver operating characteristics curve (ROC), found above 0.9, means the model has outstanding diagnostic test performance [91]. This suggests a 97.9 % chance that model prediction for the effect on flood alleviation will correctly distinguish a normal effect on flood alleviation from an abnormal effect on flood alleviation based on the ordering of test ratings. Test findings are mentioned in Table 16.

- For Effects on Farm Yield: Predicted

Table 17 shows that the model performs well for its predicted accuracy, *e.g.*, the model predicted 1270 times positive when these were actually positive effects on farm yield. However, the model predicted 241 times negative when these were actually positive effects. On the other hand, the model predicted 2199 times negative when these were actually negative, but the model predicted 241 times negative but had actually positive effect on farm yield. Hence, the error rate found 7.911 % means model performance is not bad [81]. This matrix means model evaluation performance remained not too bad with a low error rate of 1.911 when tested with 5000 simulated cases with 25 % missing data. Model predictive accuracy is not better for the effect on farm yield than that of the effect on flood alleviation because the error rate of 5.967 % for the effect on flood alleviation is lower than that of the error rate of 7.911 % for the effect on farm yield.

Table 16
Quality of Test for the state "Positive.".

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg.	Error-Rate
0	100	0	53.51	100	46.49
1	99.34	67.25	77.73	98.89	15.58
2	99.29	74.85	81.97	98.93	12.07
10	99.29	76.48	82.93	98.95	11.31
15	98.94	79.09	84.49	98.48	10.29
20	97.68	84.61	87.96	96.94	8.4
25	96.77	88.15	90.39	95.95	7.24
30	95.86	90.82	92.32	95.02	6.48
40	95.06	92.86	93.87	94.23	5.97
70	92.53	94.31	94.93	91.65	6.64
75	89.71	95.88	96.16	89.00	7.42
80	84.21	97.56	97.55	84.3	9.58
85	80.37	98.49	98.39	81.34	11.2
90	77.45	98.61	98.46	79.16	12.72
95	75.98	98.84	98.69	78.15	13.39
99.5	0	100	100	46.49	53.51
100	0	100	100	46.49	53.51

Gini Coeff = 0.958.
Area under ROC = 0.979.

Table 17
Confusion Matrix.

	Predicted Positive	Predicted Negative
Actually Positive	1270	241
Actually Negative	57	2199

Error rate = 7.911 %.

Table 18 shows the test quality for the positive state effect on farm yield with a higher AUC may be considered better, and the area under the receiver operating characteristics curve (ROC), found above 0.9, means the model has outstanding diagnostic test performance [91]. These statistics suggest a 97.6 % chance that model prediction for effect on farm yield will correctly distinguish a normal effect on yield from an abnormal effect on yield based on the ordering of the test ratings.

In a comparative analysis, the model performed better with 5000 test cases with no missing data, where the confusion matrix for the effect on flood alleviation and the effect on farm yield showed s error rates of 0.96 % and 1.06 %, respectively. Contrarily, the model tested with 5000 test cases with 25 % missing data as per the confusion matrix report showed an error rate of 5.967 % for the effect on flood alleviation and

Table 18
Quality of Test for the state "Positive."

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg.	Error-Rate
0	100	0.00	40.11	100.00	59.89
1	99.01	70.61	69.29	99.07	18.00
2	98.87	77.26	74.44	99.03	14.07
15	98.68	78.15	75.15	98.88	13.62
20	98.35	79.52	76.28	98.63	12.93
25	97.62	82.71	79.09	98.11	11.31
30	95.37	85.95	81.97	96.52	10.27
40	89.15	93.88	90.71	92.81	8.02
50	84.05	97.47	95.70	90.12	7.91
60	82.59	98.45	97.27	89.41	7.91
70	80.87	99.11	98.39	88.55	8.20
90	79.55	99.29	98.69	87.88	8.63
98	74.52	99.42	98.86	85.35	10.57
99.5	0.00	100.00	100.00	59.89	40.11
100	0.00	100.00	100.00	59.89	40.11

Gini Coeff = 0.9513 Area under ROC = 0.9756.

7.911 % for the effect on farm yield, respectively. Hence, less missing data would lead to better model performance in the given circumstances. Furthermore, in comparison, the area under the receiver operating characteristics curve (ROC) was found to be above 0.9, which means the model has outstanding diagnostic test performance institutions [91].

Validation of BBN model for tillage

A comparative statistical analysis was executed for logistic regression following a frequentist approach, as the original BBN model contains three sub-models with a range of discrete to continuous dataset types to parameterize the model. Hence, only those parameters abundant in quantitative or numerical datasets (*e.g.*, 1927 cases) were used in this process. To perform this, the runoff and yield were used as dependant variables in respective analyses by defining them in appropriate nominal classes/ categories. This part is included as enclosure S1 in the supplementary material for detailed insights where desired.

However, the BBN model for tillage can also be validated by exploring scenarios favouring flood alleviation or farm yield in the network model. This aspect could reflect how individual expert reflects one's intuition in model performance evaluation. The change in probabilities could be highlighted as a graphical comparison by reflecting certain aspects of the model that are more sensitive to a variable of interest than others. Therefore, scenario exploration can play a vital role in highlighting vital inferences that will help evaluate the model and suggest valuable insights [92]. For example, in the BBN model of tillage, a scenario-based relative probability change about the impact of land use type, *e.g.*, farming systems could be favoured by a practising farmer to seek healthy returns comparative to an environmentalist would like to support no or limited exposures to their soils *etc*. This aspect could also help highlight priority preferences over neglected areas to focus on better decision support towards informed choices. Hence, this study emphasizes influence analysis using scenarios assessment of the BBN.

This model delivered meaningful inferences, analysed through influence analysis against varying scenarios against established phenomena. These scenarios have been highlighted with associated concerns [93]. The approach highlights the probabilistic estimates by exemplifying specific scenarios which are significantly important towards likely preferences and decision shifts that could face probabilistic estimates of the associated eventualities in slope farmland. These scenarios especially denote the impact of decision choices attached to higher yield, which are inclined to a large pro-production shift towards arable farming systems. Such choices will bring more land under cultivation involving conventional or conservational tillage. Whereby tillage preferences have their implications attached with conditional probabilistic estimates of the effect on flood alleviation as a criterion variable. This research is influenced by conservation assessment outcomes, which were explored against the impact of weather and climate scenarios and the impacts of agricultural change on farmland biodiversity in the UK ([94,95]). These aspects become crucial in a catchment area with slopy land features, soil compaction and other concerned land cover preferences as predictive variables [96]. Hence, the following scenarios are illustrated to depict model inferences.

Scenario-1

When arable farming (at the slope of 3° degree) with conventional tillage as the exclusive land-use tilling system selected in the model, the model resulted in probabilistic estimates for crop yield "increase" from 41.1 % to 62 % (with a net increase of 50.85 %), and this caused a "positive" effect on farm yield rising from 41.3 % to 61.8 % (with a net increase of 49.64 %). But surface runoff was found in a higher band of "7.7 to 15.4 (mm)," raised from 47.4 % to 78.8 % (net increase of 66.24 %), which causes flood alleviation impact in the "positive" band, reducing it from 52.6 % to 21.8 % (with a net decrease of 58.56 %) [14,97]. Furthermore, probabilistic estimates of bulk densities were also observed moving towards the highest bands, *e.g.*, "1.25–1.5 g/cm^3" from 15.1 % to 23.3 %, with a net increase of 54.3 %.

In the first sub-model, probabilistic estimates for the senesced organic matter in soil were found in a decreasing trend towards its highest band, "232.5 to 310 Kg/ha", from 9.75 % to 7.73 % (with a net decrease of 20.72 %). However, total soil water in the soil profile was found to have an increasing trend towards its highest band, "477 to 636 mm", from 35.8 % to 36.2 % (with a net increase of 1.12 %). In the third sub-model, erosion estimations were found to increase in its "high" band from 46.3 % to 95.9 % (with a net increase of 107.13 %) [98]. Still, weeds' "presence" reduced from 54.9 % to 3.43 % only (with a net decrease of 93.75 %), and these affected reducing the nutrient losses in its "high" band from 71.5 % to 57.1 % (with a net decrease of 20.14 %). These are shown in Fig 4.

This aspect shows that overall, arable farming with conventional tillage systems does not favour reducing surface runoff and flood alleviation but supports crop yield and farm production. However, the inclined trend of higher production could endanger the increased risk of exposure to a higher surface runoff, which could not help flood alleviation. Similar findings were reported in a field experiment that traffic and tillage affect runoff and crop performance on heavy clay soils. Annual mean runoff amounts were 44 % greater in trafficked plots than those with controlled traffic and 24 % greater in stubble mulch-tilled plots than in zero-tilled plots [97].

Scenario-2

Contrarily, when arable farming (at the slope of 3° degree) with conservational tillage as the exclusive land-use tilling system selected in the model. The model resulted in probabilistic estimates with a slight rise in the crop yield "increase" band from 41.1 % to 46.9 %, with a net increase of 14.11 %). However, the band "positive" effect on farm yield increases from 41.3 % to 47 % (raising the net positive effect by 13.80 %). This response could be due to nutrient loss caused by weeds remaining on the field in the conservational tillage system. Surface runoff was found comparatively at reduced levels within a higher band ("7.7 to 15.4 mm") by reducing it from 47.4 % to 23.2 % (with a net reduction of 51.05 %), which causes flood alleviation impact in the "positive" band, rising from 52.6 % to 76.3 % (with a net increase of 45.06 %), this is undoubtedly a far better impact than that observed in the first scenario which showed the flood alleviation benefits in "positive" band reduced by 58.56 %. Bulk densities observed in the "higher" bands, *e.g.*, "1.25–1.5 g/cm^3", reduced from 15.1 % to 9.75 % with a net decrease of 35.43 %. Comparable results about reduced tillage tend to decrease overall levels of runoff coefficients [97].

In the first sub-model, probabilistic estimates for senesced organic matter in soil were found in a decreasing trend towards its highest band ("232.5 to 310 Kg/ha") from 9.75 % to 8.51 % (with a net decrease of 12.72 %). However, total water in the soil profile was found to have an increasing trend towards its highest band ("477 to 636 mm") from 35.8 % to 36.4 % (with a net increase of 1.68 %). In the third sub-model, erosion was found to decrease in its "high" band from 46.3 % to 6.41 % (with a net decrease of 86.16 %), but weeds "presence" increased from 54.9 % to 96.7 % (with a net increase of 76.14 %), and these affected the nutrient losses in its "higher" band rising from 71.5 % to 81.6 % (with a net increase of 14.13 %). This is shown in Fig 5.

This response shows conservational tillage preference could help to reduce pressure on higher soil bulk density and increase surface runoff. Hence, these will have favourable effects on flood alleviation. A study also highlighted that conservational (NT) tillage reduces up to 50 % in runoff [20] and 50–95 % sediment losses [98].

Scenario-3

When arable farming (at the slope of 12° degree) with conventional tillage as the exclusive land-use tilling system selected in the model, the model resulted in probabilistic estimates for net change in crop yield "increase" band rising from 41.1 % to 62 % (with a net increase of 50.85), and this

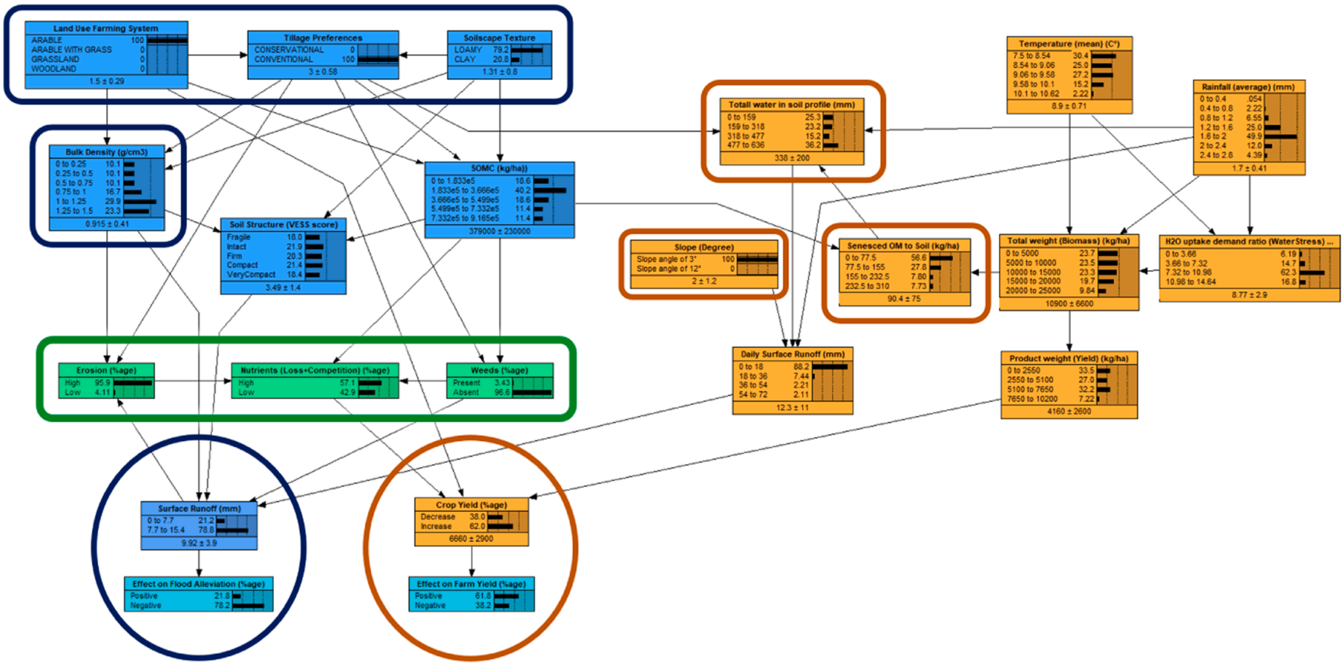

Fig. 4. Bayesian Belief Network (BBN) model for tillage preference with arable farming (at slope of 3° degree) with conventional tillage as the exclusive land-use tilling system.

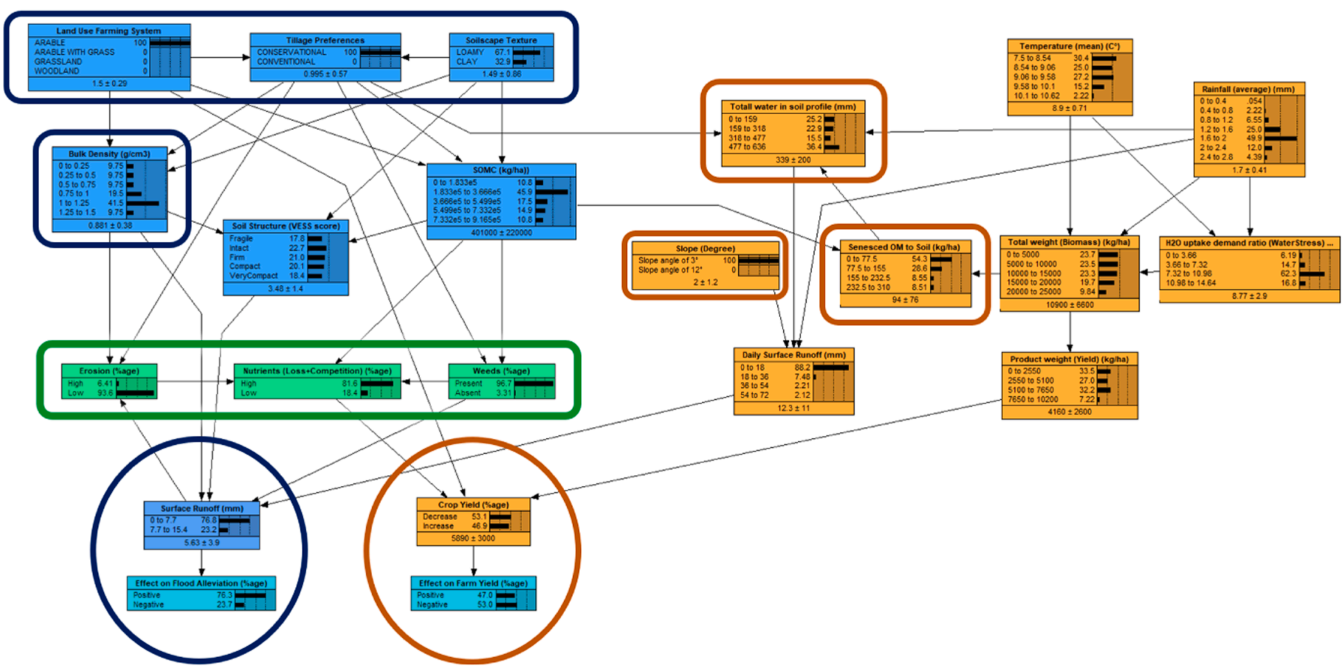

Fig. 5. Bayesian Belief Network (BBN) model for tillage preference with arable farming (at slope of 3° degree) with conservational tillage as the exclusive land-use tilling system.

caused a "positive" effect on farm yield rising from 41.3 % to 61.8 % (with a net increase of 49.64). They were the same as found in scenario 1. But surface runoff was found a little more in a higher band of "7.7 to 15.4 (mm)," rising from 47.4 % to 79.1 % (with a net increase of 66.88 %), which causes flood alleviation impact in the "positive" band, sharply decline in it from 52.6 % to 21.5 % (with a net decrease of 59.13 %). In addition, bulk densities observed an increase in the highest band, *e.g.*, "1.25–1.50 g/cm^3", from 15.1 % to 23.3 % (with a net increase of 54.3 %).

In the first sub-model, probabilistic estimates for senesced organic matter in soil were found to have a decreasing trend towards its highest band ("232.5 to 310 Kg/ha") from 9.75 % to 7.73 % (with a net decrease of 20.72 %). However, total soil water in the soil profile was found to have an increasing trend towards its highest band ("477 to 636 mm") from 35.8 % to 36.2 % (with a net increase of 1.12 %). In the third sub-model, erosion was found to increase in the "high" band from 46.3 % to 95.9 % (with a net increase of 107.13 %), but weeds' "presence" reduced from 54.9 % to 3.43 % only (with a net decrease of 93.75 %), and these affected reducing the nutrient losses in its "higher" band from 71.5 % to 57.1 % (with a net decrease of 20.14 %) [88]. This aspect means a slope angle of 12 ° in full land use arable farming systems with conventional tillage will not impact in comparison with that of statics for the same variables responses on non-sloppy except for increased runoff because of the increased slop angle.

This aspect also showed arable farming with conventional tillage systems does not favour reducing surface runoff and flood alleviation with slopes over 12 ° But no minor crop yield change was found, hence the farm production. However, the inclined trend of attaining higher crop production could further endanger the increased risk of higher runoff generation in sloppy areas. It could not help in flood alleviation at all. These results are displayed in Fig 6. Similar observations were reported in a watershed-based study using the SWAT model to simulate runoff and sediment yield. Model results produced an annual soil loss rate of 24.2 Mg/ha/year, with 95.2 % of the watershed experiencing moderate to severe soil loss rates. They highlighted that soil, land use, land cover, and slope positions are critical. Their observed changes could lead to land degradation and negative implications for stakeholders [99].

Scenario-4

Contrarily, when arable farming (at the slope of 12 ° degree) with conservational tillage as the exclusive land-use tilling system selected in the model. The model resulted in probabilistic estimates for net change rise in crop yield in the "increase" band from 41.1 % to 46.9 % (with a net increase of 14.11 %), causing a slight rise in the 'positive' band of effect on farm yield rising from 41.3 % to 47 % (with a net increase of 13.8 %). Surface runoff was found lower in a higher band of "7.7 to 15.4 (mm)," reducing from 47.4 % to 23.5 % (with a net decrease of 50.42 %), which also affected flood alleviation in its "positive" band by increasing from 52.6 % to 76 % (with a net increase of 44.49 %). Bulk densities declined in the highest band, *e.g.*, "1.25–1.50 g/cm^3", from 15.1 % to 9.75 % (with a net decrease of 35.43 %).

In the first sub-model, probabilistic estimates for senesced organic matter in soil were found to have a decreasing trend towards its highest band ("232.5 to 310 Kg/ha") from 9.75 % to 8.51 % (with a net decrease of 12.72 %). However, total soil water in the soil profile was found to have an increasing trend towards its highest band ("477 to 636 mm") from 35.8 % to 36.4 % (with a net increase of 1.68 %). In the third sub-model, erosion was found to decrease in the "high" band from 46.3 % to 6.43 % (with a net decrease of 86.11 %), but weeds' "presence" increased from 54.9 % to 96.7 % only (with a net increase of 76.14 %), and these affected reducing the nutrient losses in its "higher" band from 71.5 % to 81.6 % (with a net increase of 14.13 %). Similar studies found comparable results [100].

This result means slope angle is exceptionally critical; even choosing conservational tillage will not help. However, this could be a little helpful in reducing erosion as found in its "higher" band lowering from 46.3 % to 6.43 % with a net decrease of 86.11 %, which is observed in complete arable farming systems with conservational tillage preferences at a slope of 12 ° angle [25]. However, this could increase chances for higher weed presence, impacting higher nutrient losses. Hence, a trade-off relationship exists between losses by erosion and weeds presence using conservational tillage. This aspect shows conservational tillage preferences at sloppy farms could have limited help in reducing the surface runoff and the effect on flood alleviation with a focus on obtaining farm yield. These inferences are revealed in Fig 7. A study reported similar findings about tillage preference in field experiments with farming at the land of a 15°-degree slope. Tillage modification at the slope reduced runoff by 11.5–64.5 %, but sediment yield increased by 59.2–132.1 % [101,102].

Comparative analysis to examine variable responses and their impacts across different scenarios

Scenario 1 vs. scenario 2

The probabilistic estimates as a net increase effects on farm production ("increase" = band) (49.64 %), crop yield ("increase" = band) (50.85 %), surface runoff ("7.7–15.4 mm – higher band") (66.24 %), bulk density ("1.25–1.50 g/cm^3" = band) (54.30), total water in soil profile ("477–636 mm = highest band") (1.12 %), and erosion ("high" = band) (107.13) were found to be higher while the more significant estimation of net decrease were found on effects on flood alleviation ("increase" = band) (58.56 %), senesced OM to soil ("232.5–3.10 kg/ha" = highest band) (20.72 %), weeds presence ("presence" = band)

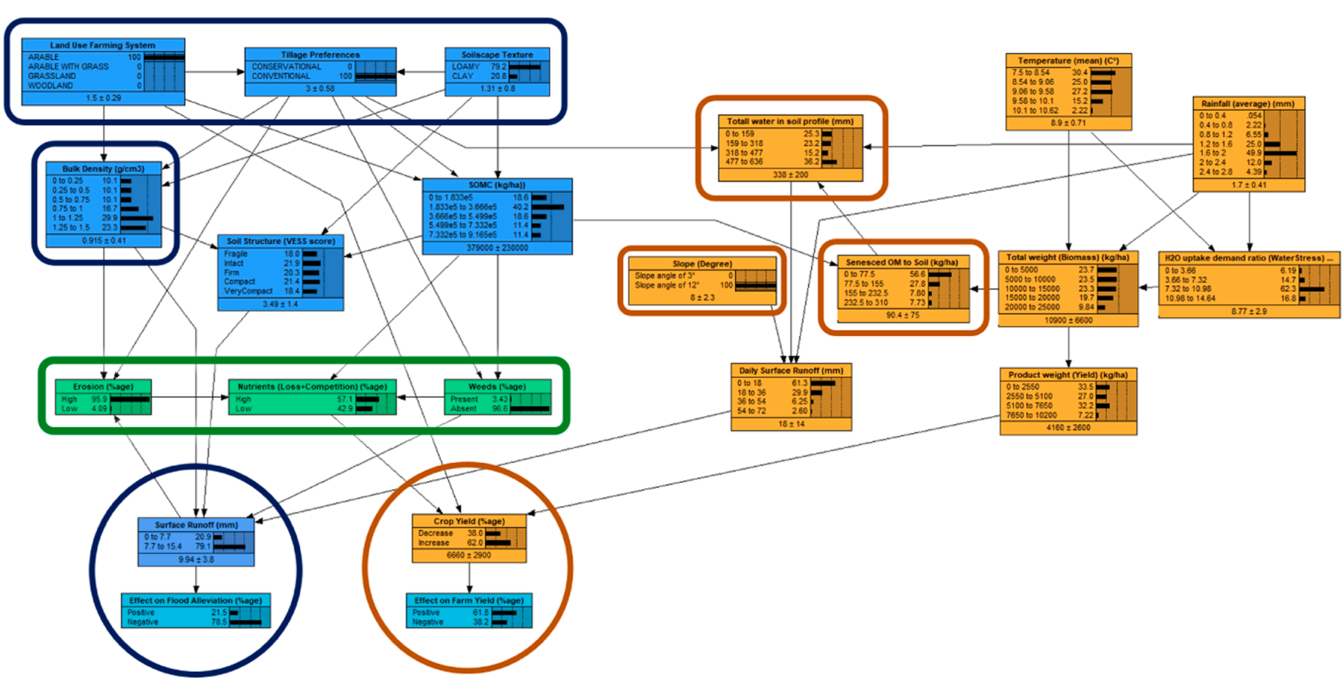

Fig. 6. Bayesian Belief Network (BBN) model for tillage preference with arable farming (at slope of 12° degree) with conventional tillage as the exclusive land-use tilling system.

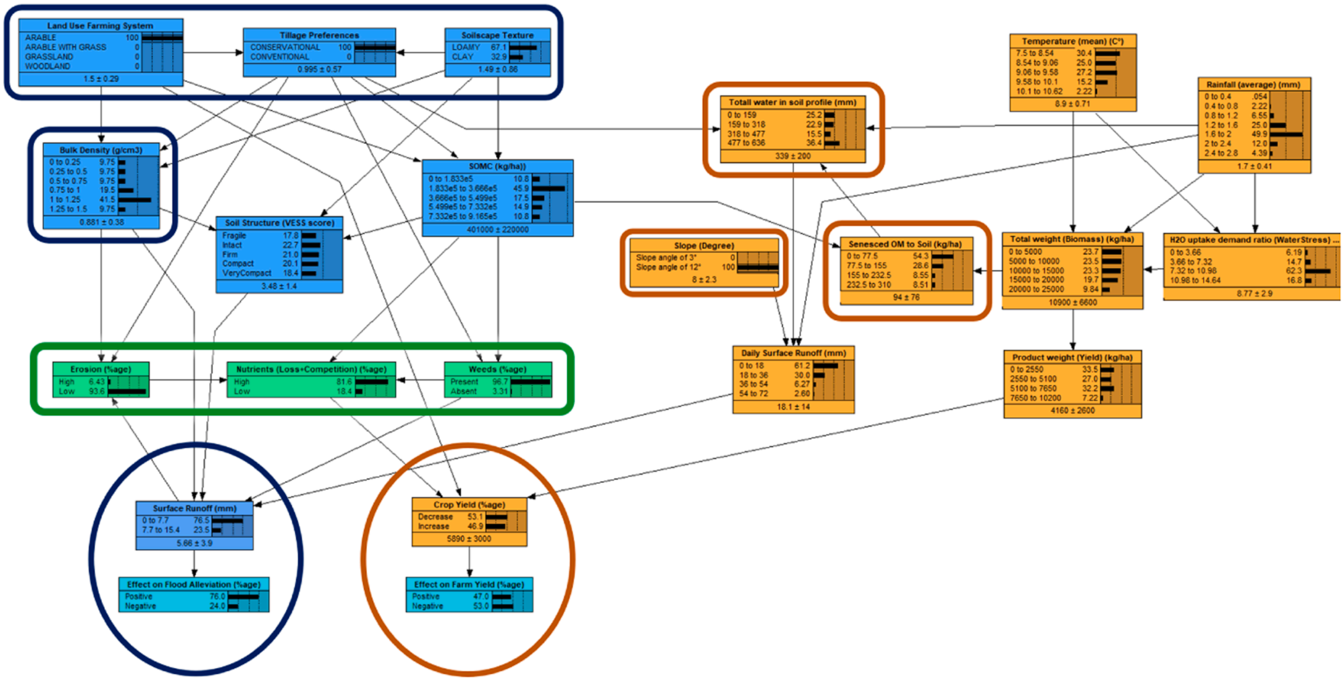

Fig. 7. Bayesian Belief Network (BBN) model for tillage preference with arable farming (at slope of 12° degree) with conservational tillage as the exclusive land-use tilling system.

(93.75 %), and nutrient loss ("higher" = band) (20.14 %) in conventional tilled arable cropping systems at a slope of 3° angle (Fig 4 & Table S11a in supplementary material).

Contrarily, the probabilistic estimates for a net increase found on the effects on farm production ("increase" = band) (13.80 %), crop yield ("increase" = band) (14.11 %), effects on flood alleviation ("positive" = band) (45.06 %), total water in soil profile ("477–636 mm" = highest band) (1.68 %), weeds presence ("presence" = band) (76.14 %) and nutrient loss ("higher" = band) (14.13 %), while the more significant estimation of net decrease were found in surface runoff ("7.7–15.4 mm – higher band") (51.05 %), bulk density ("1.25–1.50 g/cm^{3}" = band) (35.43 %), senesced OM to soil ("232.5–3.10 kg/ha" = highest band) (12.72 %), erosion ("high" = band) (86.16 %) in conventional tilled arable cropping systems at a slope of 3° angle (Fig 5 & Table S11b in supplementary material).

Hence, the first scenario is inclined towards higher farm production but less attractive for flood alleviation with increased yield ("increase" = band) (50.85 %) and increasing effect on farm production ("increase" = band) (49.64 %) [103]. At the same time, the second scenario is more centric towards flood alleviation by reducing runoff ("7.7–15.4 mm – higher band") (51.05 %) and increasing effect on flood alleviation ("increase" = band) (45.06 %) but less attractive for returns from gaining higher farm yields [104]. These highlights are shown in Fig 8.

Scenario 3 vs. scenario 4

The probabilistic estimates as a net increased effects on farm production ("increase" = band) (49.64 %), crop yield ("increase" = band) (50.85 %), surface runoff ("7.7–15.4 mm = higher band") (66.88 %), bulk density ("1.25–1.50 g/cm^{3}" = band) (54.30), total water in soil profile ("477–636 mm" = highest band) (1.12 %), and erosion ("high" = band) (107.13) were found to be higher while the more significant estimation of net decrease were found on effect on flood alleviation ("positive" = band) (59.13 %), senesced OM to soil ("232.5–3.10 kg/ha" = highest band) (20.72 %), weeds presence ("presence" = band) (93.75 %), and nutrient loss ("higher" = band) (20.14 %) in conventional tilled arable cropping systems at a slope of 12° angle [105] (Fig 6& Table S11c in supplementary material).

Contrarily, the probabilistic estimates for a net increase found on the effects on farm production ("increase" = band) (13.80 %), crop yield ("increase" = band) (14.11 %), effects on flood alleviation ("positive" = band) (44.49 %), total water in soil profile ("477–636 mm" = highest band) (1.68 %), weeds presence ("presence" = band) (76.14 %) and nutrient loss ("higher" = band) (14.13 %) were found to be higher while the more significant estimation of net reduction were found surface runoff ("7.7–15.4 mm = higher band") (50.42 %), bulk density ("1.25–1.50 g/cm^{3}" = band) (35.43 %), senesced OM to soil ("232.5–3.10 kg/ha" = highest band) (12.72 %), and erosion ("high" = band) (86.11 %) in conservational tilled arable cropping systems at a slope of 12° angle [106] (Fig 7 & Table S11d in supplementary material).

Therefore, the third scenario is inclined toward higher farm production with increased yield ("increase" = band) (50.85 %) and increasing effect on farm production ("increase" = band) (49.64 %) [103] but less attractive for flood alleviation due to the probabilistic estimation of a net runoff ("7.7–15.4 mm = higher band") rise of 66.88 %. At the same time, the forth scenario is more centric towards flood alleviation by reducing runoff ("7.7–15.4 mm – higher band") (50.42 %) and increasing effect on flood alleviation ("increase" = band) (44.49 %) but less attractive for returns from gaining higher farm yields ([104,107, 108]). These inferences are shown in Fig 9.

Summary of scenarios analysis

The summary for variable responses for all scenarios is mentioned in table 19, and how these variations (calculations) appear is highlighted in tables S11 (SS11a-S11d) in the supplementary material. These tables described how the probabilistic estimates for the net change in values of variable responses were shifted over various scenarios. These variations were quite prominent when comparing the conventional against conservational tillage preference at the same or diverse slope angles. However, these fluctuations are not obvious if compared against the same kind of tillage preference against two different slopes of 3 ° and 12 ° angles. For instance, probabilistic estimates in conventional tillage preferences in arable farming systems exhibited no comparative variations in variable responses except for surface runoff ("7.7–15.4 mm =

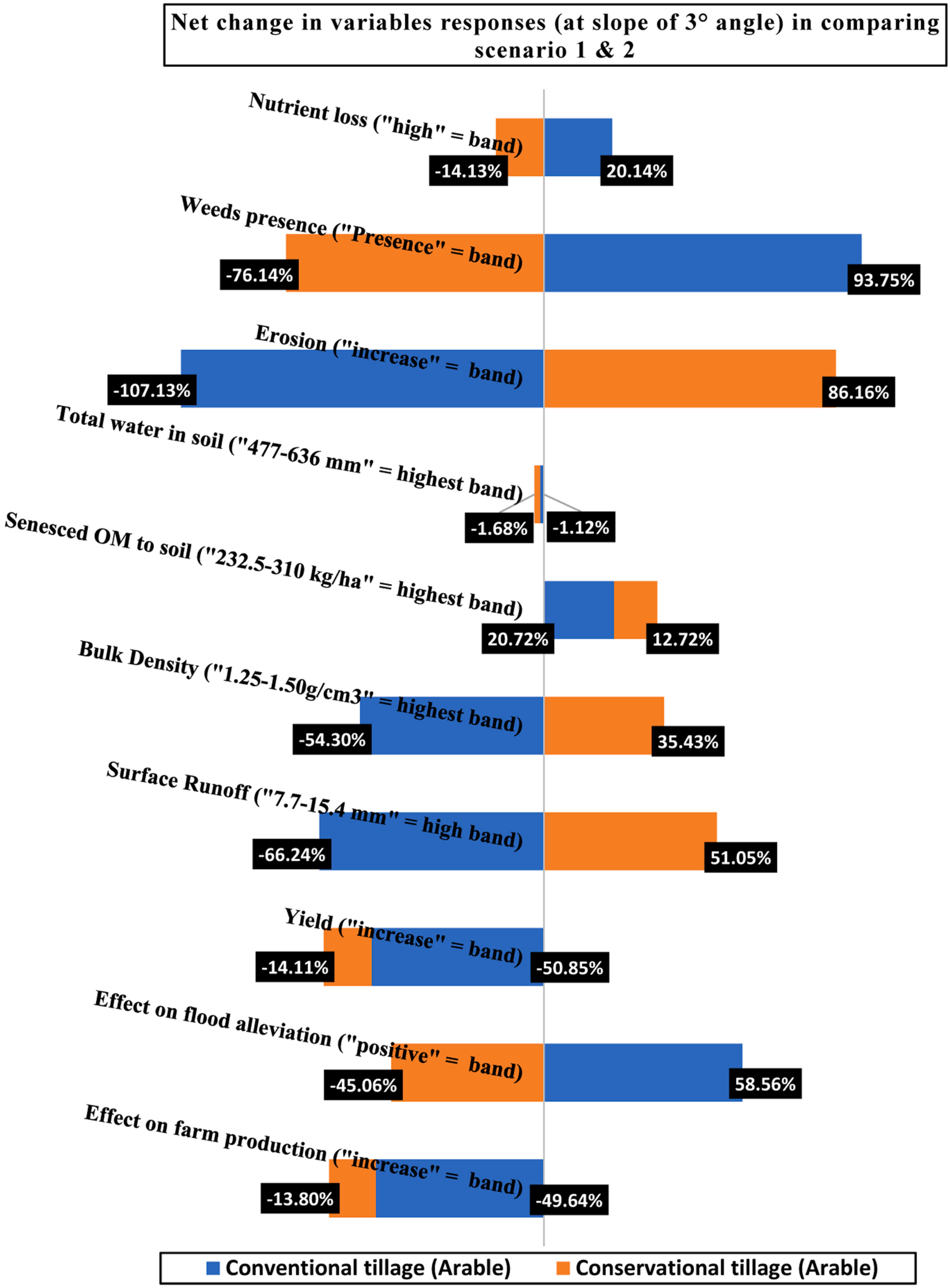

Fig. 8. Comparative analysis of conventional & conservational tillage impacts in Scenario 1 vs. Scenario 2.

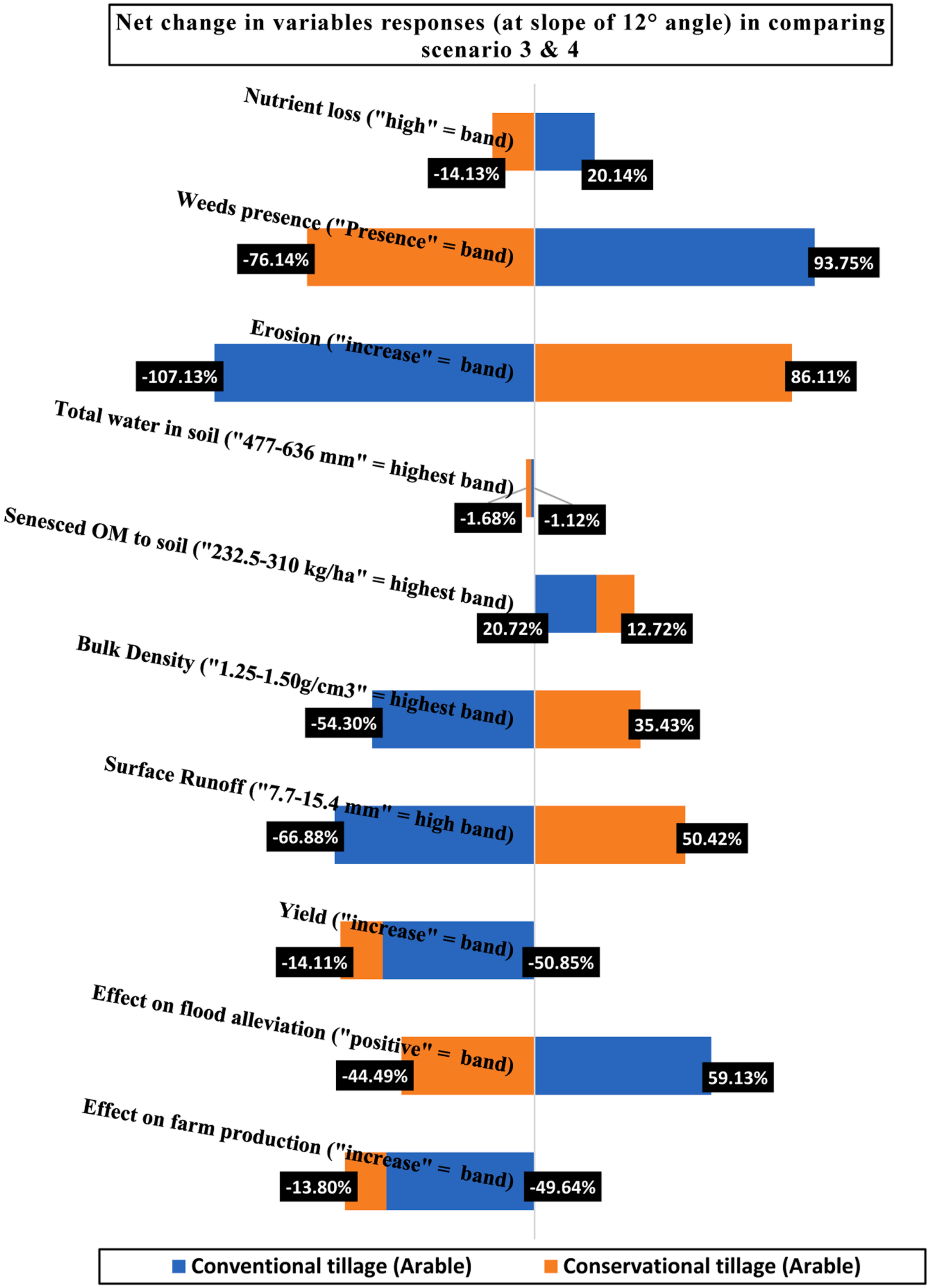

Fig. 9. Comparative analysis of conventional & conservational tillage impacts in Scenario 3 vs. Scenario 4.

Table 19
Summary of the probabilistic estimates with comparative net change in variables response adapting four scenarios.

Variables of interest	Scenario 1 Conventional tillage - Arable farming - (@ 3° slope) Net Change		Scenario 2 Conservational tillage - Arable farming - (@ 3° slope) Net Change		Scenario 3 Conventional tillage - Arable farming - (@ 12° slope) Net Change		Scenario 4 Conservational tillage - Arable farming - (@ 12° slope) Net Change	
Effect on farm production ("increase" = band)	-49.64%	increase	-13.80%	increase	-49.64%	increase	-13.80%	increase
Effect on flood alleviation ("positive" = band)	58.56%	decrease	-45.06%	increase	59.13%	decrease	-44.49%	increase
Yield ("increase" = band)	-50.85%	increase	-14.11%	increase	-50.85%	increase	-14.11%	increase
Surface Runoff ("7.7-15.4 mm" = high band)	-66.24%	increase	51.05%	decrease	-66.88%	increase	50.42%	decrease
Bulk Density ("1.25-1.50g/cm^3" = highest band)	-54.30%	increase	35.43%	decrease	-54.30%	increase	35.43%	decrease
Senesced OM to soil ("232.5-310 kg/ha" = highest band)	20.72%	decrease	12.72%	decrease	20.72%	decrease	12.72%	decrease
Total water in soil ("477-636 mm" = highest band)	-1.12%	increase	-1.68%	increase	-1.12%	increase	-1.68%	increase
Erosion ("increase" = band)	-107.13%	increase	86.16%	decrease	-107.13%	increase	86.11%	decrease
Weeds presence ("Presence" = band)	93.75%	decrease	-76.14%	increase	93.75%	decrease	-76.14%	increase
Nutrient loss ("high" = band)	20.14%	decrease	-14.13%	increase	20.14%	decrease	-14.13%	increase

higher band") (net increase of 66.24 % at 3 ° slope and 66.88 % at 12 ° slope) and the effect on flood alleviations ("positive" = band) (net decrease of 58.56 % at 3° slope and 59.13 % a 12° slope) (Table 19). This response seems correct as the slope angle cannot solely influence comparative crop yield, bulk density, senesced OM, *etc*., but can influence runoff to generate and accelerate along the gradient.

Similarly, probabilistic estimates in conservational tillage preferences in arable farming systems at both slope angles also displayed no variation amongst most variable responses except for erosion (net decrease of 86.16 % at 3 ° slope and 86.11 % at 12 ° slope), surface runoff ("7.7–15.4 mm = higher band") (net increase of 66.24 % at 3 ° slope and 66.88 % at 12 ° slope) and the effect on flood alleviations ("positive" = band) (net increase of 45.06 % at 3 ° slope and 44.49 % a 12 ° slope) were observed (Table 19) ([100,110]). These inferences show that conservational tillage is the response to reducing runoffs and increasing the positive effects on flood alleviation. However, the net change rate is insignificant for these sensitive variables' responses at increased slopes amongst conservational tillage preferences. However, conservational tillage preferences are better than conventional tillage in arable farming systems to cater to flooding risks. This helps in the reduction of runoff generation, and favours flood alleviation benefits.

Trade-off relationship between flood alleviation and farm yield using tillage as NFM strategy

There is a trade-off between farm production and flood alleviation in the Thames Valley catchment areas, especially in slope farmlands with intensive arable farming systems. However, the combination of no-tillage and agroforestry has shown significant potential in reducing soil erosion on vulnerable farmlands [109].

Considering the landscape's spatial characteristics and high groundwater tables in the catchment area, traditional tillage practices solely aimed at maximizing crop yield are not advisable. Instead, strategic land use and management practices must be employed when deciding how to till the land. Steep slopes exceeding 12° can lead to runoff generation, and improper tilling practices in such areas can worsen the problem. Therefore, exploring alternative land use and tillage methods that minimize adverse effects is essential. A field experiment also supported this approach [110]. For example, conservational tillage methods, which involve maintaining vegetation, crop residues, and plant stubbles as land cover, create resistance to runoff flow, promote rainfall infiltration, and increase water storage in the soil profiles ([111,112]).

Conclusions

The BBN model for tillage preferences was constructed using key variables impacting flood alleviation and farm yield through tillage as a natural flood management (NFM) strategy. The PSL approach identified influential variables, and interviews with domain experts further enriched the model. The final Bayesian Belief Network (BBN) model highlighted three sub-models, with an interface for climate, topography, Spatio-temporal factors and diverse data types. Sub-model 1 was parametrised using quantitative datasets with Gaussian distribution, sub-model 2 was populated by survey and empirical data, and sub-model 3 employed the literature and domain knowledge. Parametrization employed simulated datasets from DSSAT for sub-model one and discretized datasets for conditional probability tables (CPTs). The executed BBN model displayed the trade-off relationship between flood alleviation and farm yield with tillage modifications as an NFM strategy.

This BBN depicted the following inferences.

- The BBN model for conventional tillage preferences with intensive arable farming systems at a 3 ° slope resulted in a crop yield "increase" band with a net rise of 50.85 % and "positive" effects on farm yield with a net increase of 49.64 %. But surface runoff was found to be "high" with a net increase of 66.24 %, whereas flood alleviation impacted "negatively" with a net decrease of 58.56 % in flood alleviation benefits. This preferred choice of farming at the slope of 12 ° angle also showed a similar influence on farm yield and effect on farm yield. However, the surface runoff found excessive in higher band and was up to 66.88 %, which further lessened the flood alleviation benefits by 59.13 %.
- BBN model for conservational tillage preferences with full arable farming systems at 3 ° slope resulted in a minor growth in the "increase" band of crop yield with a net rise of 14.11 % that caused a "positive" effect on farm yield with a net increase of 13.80 %. However, surface runoff showed a considerable decline in its higher band

with a net reduction of 51.05 %. This runoff reduction causes flood alleviation's "positive" band, rising with a net increase of 45.06 % in benefiting flood alleviation. This preferred choice of farming at the slope of 12° angle resulted in the same level of a net increase of 14.11 % in crop yield that caused "positive" effects on farm yield with a net increase of 13.8 %. However, surface runoff decreased in the higher band, with a net decline of 50.42 %, which caused the flood alleviation positive band with a net increase of 44.49 % in flood alleviation benefits.

- Propensity to conventional tillage practices in arable farming systems tends to increase farm yield for seasonal crop gains but favours higher runoff risks due to reducing the land cover intermittently. This approach resultantly does not support the effect of flood alleviation, but vice versa if conservation tillage opts.
- Tendency to increase arable & arable with grassland farming systems also increases the farm yield through tempted frequent tillage operations, which provide soil mechanical interface for soil disturbance and beyond. However, these actions also cause increased farm trafficking and could trigger higher runoff risks due to reduced land cover during wet weather spells. Therefore, a little to no reduction in flood alleviation will result.

A trade-off relationship exists between flood alleviation and farm yield using intense arable farming systems with conventional tillage preference as an NFM strategy.

The model can be further upgraded and customized to meet specific farm requirements. Improved performance relies on the availability of high-quality datasets with spatial-temporal factors. Incorporating catchment-specific datasets can highlight land use and tillage policy trends. The model's sensitivity to spatiotemporal factors, such as groundwater table, historical flooding, and nutrient losses, can be addressed. Enhancing the model with tailored data sources for specific study areas can improve its performance.

Author contributions

Qaisar Ali contributed to the study conception, design, and completion of the work and wrote this paper draft of the manuscript. He performed material preparation, data compilation, and analysis following guidance from the Department of Sustainable Land Management, School of Agriculture, Policy, and Development, University of Reading, UK.

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Institutional review board statement

Study involved the participation of domain experts/ professionals from the UK for their semi-structured interviews. As a result, the School of Agriculture, Policy, and Development research ethics committee granted appropriate institutional approval vide 'Form 2′. MSc PhD Staff Ethical Clearance Submission 'Form' vide ref. No. 001,604, dated Jun 26, 2021.

Declaration of Competing Interest

"The authors declare no conflict of interest. The funders had no role in the study's design; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results."

Data availability

Data will be made available on request.

Informed Consent Statement

I obtained "informed consent from all participants involved in the study". However, no minor was a part of the study at any stage.

Ethical statement

I declare that I have not used any generative artificial intelligence (AI) and AI-assisted technologies in the writing process of this manuscript.

This study involved the participation of domain experts/ professionals from the UK for their semi-structured interviews. As a result, appropriate institutional approval was granted by the research ethics committee of the School of Agriculture, Policy, and Development through 'Form 2′. MSc PhD Staff Ethical Clearance Submission Form' vide ref. No. 001604 dated 26 June 2021.

Patents

This work does not report patent rights at the time of publication. However, enhanced future work could attract patents and will be updated accordingly.

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Supplementary materials

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