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A system approach towards prediction of food safety hazards: Impact of climate and agrichemical use on the occurrence of food safety hazards

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ABSTRACT

In this study, we aimed to demonstrate the aptness of a system approach to predict the level of contamination in a given agricultural product. As a showcase, the impact of climate and agrichemical use on the occurrence of food safety hazards in feed of dairy cows in the Netherlands was used. Data on chemical hazards in dairy cows' feed in the Netherlands for the years 2000 to 2013 were retrieved from the Dutch monitoring program KAP (Quality Program for Agricultural Products). Climate data (17 variables) and agrichemical usage figs. (6 variables) for the Netherlands were obtained from the NOAA's National Centers for Environmental Information, the European Commission Joint Research Center's Agri4Cast database, and FAO's FAOSTAT. A Bayesian Network (BN) was constructed with this data and optimized for the prediction of the contamination level. The overall accuracy of prediction of the level of contamination in feed was 90.3%. Sensitivity analysis demonstrated that many climate and agrichemical variables contributed to the prediction; however, their individual contribution was generally small. The applicability of the BN was demonstrated in more detail for grass and maize as feed components. The observed trends in contamination of these crops were accounted for by climate and agrichemical variables, with the impact varying amongst the specific variables and commodities. The variables with the highest impact were "days of precipitations in a month with $\geq$ 2.5 mm" and "annual use of herbicides".

The results demonstrate that data-driven BNs can capture complex interactions, thereby enabling high-accuracy predictions. Whilst the applicability of this approach to the safety of dairy cows' feed in the Netherlands has thus been demonstrated, it can also be applied to other areas of food safety when a systems approach is needed. Such models can support risk assessors and risk managers in their understanding of the impacts of a given factor on food and feed safety, and inform the latter's decisions to mitigate potential risks.

1. Introduction

The performance of a food supply chain, including the levels attained for food safety and nutritional impact, is affected directly and/or indirectly by many factors such as climate, economy, and human behavior. It has been argued that a systems approach is needed that takes all of these interactions into account to optimize the safe operation of food supply chains and to enable mitigation actions when needed (Kendall et al., 2018; Marvin et al., 2016, 2009, 2013). In particular, climate has been indicated as a driver of food safety risks and predictive models for food safety have been developed that included climate parameters but these models are generally limited to the prediction of the occurrence of mycotoxins in various agricultural crops such as maize, wheat, and tomato (Nešić, 2018).

Recently, using food fraud as an example, Bayesian Network (BN) has been advocated as a methodology to integrate the various effects of drivers of change in food safety, hence allowing for a systems approach towards achieving food safety (Marvin et al., 2016). BNs are cause-effect prediction models belonging to the family of probabilistic graphical models, which combine principles from graph theory, probability theory, computer science and statistics. Their outcomes present probabilistic relationships between the variables selected based on current knowledge. This allows for bidirectional reasoning (i.e. prediction and interpretative inference) under uncertainty, and for drawing conclusions based on the information available (Cheng et al., 2002). BNs have been used in several research domains such as ecological risk assessment (Lee and Lee, 2006; Pollino et al., 2007), medical image analysis (Arias et al., 2016), herbs and spices sampling (Bouzembrak et al., 2018), nanomaterials risk assessment (Linkov et al., 2015; Low-Kam et al., 2015; Money et al., 2014; Winkler et al., 2014), and natural gas stations safety assessment (Sohn et al., 2017; Zarei et al., 2017).

Food safety hazards in milk primarily enter the dairy production

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chain at the feed production and dairy farm stages, either by digestion of contaminated feed (e.g. compound feed, silage and grass) and/or by administration of veterinary medicines (Asselt et al., 2016). Climate change has been suggested as a driver of change in many factors present in these two stages, affecting the development of known and emerging hazards (van der Spiegel et al., 2012). Safefood (Safefood, 2017) studied the influence of climate change on the dairy chain of the island of Ireland and identified a number of food safety risks that are like to be impacted, which includes pathogens, chemical contaminants and natural toxins.

In this study, we aimed to demonstrate the aptness of a system approach to predict the level of contamination in an agricultural product using the BN approach in which the relationships between the variables are calculated using machine learning algorithms and historical data. As a showcase, the impact of climate and agrichemical use on the occurrence of food safety hazards in feed of dairy cows in the Netherlands was used.

2. Materials and methods

2.1. Bayesian network approach

The BN approach consists of three distinctive steps being i) data collection and processing, ii) BN model construction and, iii) BN model validation.

2.1.1. Data collection and processing

2.1.1.1. Monitoring data from dairy feed in the Netherlands. Data on chemical food safety hazards in dairy cows feed in the Netherlands was retrieved from the Dutch monitoring programme KAP (Quality Program for Agricultural Products)[1] for the years from 2000 to 2013. Data in KAP was obtained from the Dutch dairy organization and the Dutch food and consumer product safety authority (NVWA). In total 109,350 analytical results were retrieved for dairy feed products that are on the market in the Netherlands. The data collected from KAP was processed before it was used for the BN modelling step. The following preliminary treatments of the collected monitoring data were conducted:

- Removal of extra text and symbols. For instance, values of the sample contain text or symbols.
- Removal of all products that are not grown or produced in the Netherlands (e.g. soy, rice). This step yielded in total 54,806 individual analytical results, which were used for the model development. The following parameters were taken from the raw data: day, month, year, country of origin, country of control, product name, hazard category, limit of detection (LOD), hazard name and hazard concentration. The LOD depends on the analytical method applied and it is provided in KAP for each analytic report. Contamination level was calculated for each case, which is the difference between the hazard concentration and the LOD. It can be negative or positive, negative means that no contamination was found in that sample (zero values) or that all concentrations were below LOD and positive means that a concentration above LOD was found. The range of the LODs of each hazard category is provide in Table 1.

Table 1
Range of LODs for each hazard category.

Hazard category	LOD range	Unit
Biotoxins	0–25	mg/ Kg
Composition	0–1	g/Kg
Heavy metals	0–500	mg/Kg
Industrial contaminants	0–70,000	pg TEQ/G
Migration	0–2.5	mg/Kg
Mycotoxins	0–7400	µg/Kg
Pesticides	0–10	mg/Kg
Radiation	0–2520	Bq/Kg
Veterinary residues	0–30	mg/Kg

2.1.1.2. Climate data. The main climate data such as temperature and precipitation for the Netherlands was retrieved from the National Oceanic and Atmospheric Administration's (NOAA) website,[2] which is maintained by National Centers for Environmental Information (NCEI). The data related to soil evaporation, water evaporation, plant transpiration, and snow depth in the Netherlands for the period 2000–2013 was collected from the European Commission Joint Research Center's Agri4Cast[3] database. Agri4Cast engenders Agro-Meteorological Data in Europe, where meteorological data are available on a daily basis from 1975 to the last calendar year completed, covering the EU Member States, neighbouring European and Mediterranean countries.

2.1.1.3. Use of agrichemical. The use of agrichemicals (herbicides, insecticides, fungicides, rodenticides, and pesticides) in the Netherlands was collected from the United Nations Food and Agriculture Organization's (FAO) Corporate Statistical Database (FAOSTAT). The FAO Pesticides Use database included data on the use of major pesticide groups (herbicides, insecticides, fungicides, rodenticides, pesticides and plant growth regulators) and of relevant chemical families. Data report the quantities (in tonnes of active ingredients) used in or sold to the agricultural sector for crops and seeds. Information on quantities applied to single crops was not available.

The description of the parameters and the data source used to collect data for the parameter are listed in Table 2.

2.1.2. The construction and validation of the BN model

A BN structure is composed of nodes, arcs and probabilities. The value of the nodes may be discrete or continuous, but the most widely used are the discrete nodes. In this study, discrete nodes were used in a similar manner as reported in previous studies for BN models to predict food fraud (Bouzembrak and Marvin, 2016; Marvin et al., 2016). In total, 44,115 different cases selected randomly from the total dataset (i.e. 80% of the total dataset) were used for learning by the model. The BN model was built using the Tree-Augmented Naive Bayes algorithm of Hugin 8.4 software (Heckerman, 2008; Marcot et al., 2006; Nyberg et al., 2006) and optimized for the node "contamination level". The validation of the developed BN was conducted with the remaining 20% (10,691 cases) of the total dataset (Bouzembrak and Marvin, 2016; Marvin et al., 2016). The validation cases were not used in the development of the BN. The validation was performed for each case, where the contamination level (positive or negative) was predicted using all input parameters. It was assumed that the prediction made by the BN based on these input values was correct when the contamination level with the highest probability given by the BN matched the contamination level given in the validation case.

2.2. Sensitivity analysis

To determine which of the parameters in the BN contributed most to the contamination level (hence the parameter for which the BN model was optimized), a sensitivity analysis was performed. Two different methods were used, namely the entropy function (method 1) and parameter sensitivity analysis (method 2).

[1] https://chemkap.rivm.nl/

[2] https://www.ncdc.noaa.gov/cdo-web/datasets/GSOM/locations/FIPS:NL/detail#stationlist

[3] http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx

Table 2
Description of the defined parameters and their data source.

Model variables	Description	Units	Data source
Year	Year	–	KAP*
Origin country	Country of origin	–	KAP
Product	Product name	–	KAP
Product category	Product category	–	KAP
Month	Month	–	KAP
Notifying country	Notifying country	–	KAP
Hazard category	Hazard Category	–	KAP
Hazard	Hazard	–	KAP
Days precipitation (0.1)	Days of precipitation with precipitation ≥0.1 in. (2.54 mm)	Days	NOAA**
Days precipitation (1)	Days of precipitation with precipitation ≥1 in. (25.4 mm)	Days	NOAA
Days precipitation (0.5)	Days of precipitation with precipitation ≥0.5 in. (12.7 mm)	Days	NOAA
Precipitation (M)	Total month precipitation	Inch	NOAA
Max temperature(M)	Mean max monthly temperature	°C	NOAA
Min temperature(M)	Mean min monthly temperature	°C	NOAA
Mean temperature(M)	Mean month temperature	°C	NOAA
Meanmax temperature(M)	Mean max month temperature	°C	NOAA
Soil evaporation	Potential evaporation from a moist bare soil surface - monthly average	mm/day	Agri4Cast***
Water evaporation	Potential evaporation from a free water surface - monthly average	mm/day	Agri4Cast
Plant transpiration	Potential evapotranspiration from a crop canopy - monthly average	mm/day	Agri4Cast
Snow depth	Snow depth – monthly average	cm	Agri4Cast
Days Max temperature (32)	Number of days in month with maximum temperature ≥ 32 °C	Days	NOAA
Days Max temperature (0)	Number of days in month with maximum temperature ≤ 0 °C	Days	NOAA
Days Min temperature (0)	Number of days in month with minimum temperature ≤ 0 °C	Days	NOAA
PG Regulators	Yearly Plant Growth Regulators use	Tonnes	FAOSTAT****
Pesticides	Yearly pesticides use	Tonnes	FAOSTAT
Contamination level	Contamination level: (Pos (> LOD) or Neg (< LOD))	Pos or Neg	–
Herbicides	Yearly herbicides use	Tonnes	FAOSTAT
Insecticides	Yearly insecticides use	Tonnes	FAOSTAT
Fungicides	Yearly fungicide use	Tonnes	FAOSTAT
Rodenticides	Yearly rodenticides use	Tonnes	FAOSTAT

* KAP: Dutch monitoring programme KAP (Quality Program for Agricultural Products).
** NOAA: National Oceanic and Atmospheric Administration's National Centers for Environmental Information.
*** Agri4Cast: European Commission Joint Research Center's Agri4Cast database.
**** FAOSTAT: United Nations Food and Agriculture Organization's (FAO) Corporate Statistical Database.

2.2.1. Method 1: entropy function

In the literature, the entropy function has been used to analyse the sensitivity of BN models. Entropy is a measure of how much the probability mass is scattered over the states of a variable. Since entropy can be used as a measure of the uncertainty in the distribution of a variable in a network, it is used to identify and rank the most important parameter (Kjærulff and Madsen, 2008). It consists of calculating the function H(X) of a node X:

$$H(X) = -\sum_{X} P(X) \log P(X)$$

where P(X) is the probability distribution of X. In this study, we calculated the entropy values for the node "contamination level".

2.2.2. Method 2: parameter sensitivity analysis

This is another type of sensitivity analysis that is supported by probabilistic networks such as BN. Parameter sensitivity analysis belongs to the class of the one-factor-at-a-time methods, where sensitivity measures are usually calculated when one factor is changed and all other factors are constant (Saltelli, 1999). The aim of this method is to show in more detail the effect of the selection of a specific condition (state of a parameter) on the direction of change of the probability of the output parameter. In this way, the impact on the output parameter of a parameter with a low entropy can be shown. In this study, the probability of the node "contamination level" was assessed when the value of one parameter was changed (i.e. select different states of the node) and all other parameters were fixed. Only the effect of climate and agricultural parameters were tested in this way, since the aim is to analyse the impact of climate and agrichemical use on the occurrence of food safety hazards in dairy cows feed.

2.3. Trend analysis

The chemical food safety hazards monitoring data of dairy cows feed products produced or grown in the Netherlands in the period 2000–2013 was used to build the BN. This BN linked these analytical results with climate and agricultural parameters relevant for the Netherlands. To demonstrate the application of the BN in trend analysis, we focused on two main feed products, namely grass (e.g. grass bits, grass hay and fresh grass) and maize (e.g. green maize ensiled or fodder, maize flour and maize corn). Fresh, dried or ensiled forages such as grass, maize and alfalfa constitute 50–70% of the diet of dairy cattle and the forages are generally grown and processed on the dairy farm itself (Driehuis et al., 2008b). A trend analysis was conducted for the contamination level of maize and grass by selecting these products in the "product category" node and consequently recording the probabilities of the "positive" state of the "contamination level" when selecting a year in the "year" node and a month in the "month" node. In this way, the probabilities of detecting a contamination for the two product categories for the period 2000–2013 for each month was obtained. To estimate the positive contamination level for years following 2013, a best-fitted logarithmic regression was conducted using Microsoft Excel software (supplement Fig. 1). For this exercise, the average per year was used and only the last 4 years (2010 − 2013) because for both product categories the level of positive contamination was much (> 2 times; see supplement Fig. 2) higher in the previous period (2000–2009) resulting in a poor fitting and unreliable prediction for 2014, 2015 and 2016.

To test the performance of the BN, data of the variables contributing to the prediction of the contamination level as determined in the sensitivity method 1 were collected from the identified data sources. These figures were used as input for the BN and the probabilities of the "Pos"

Table 3
The most common food safety hazard categories and products reported in KAP (2000–2013) for dairy cow feed in the Netherlands.

The most common food safety hazard categories		The most common products	
Hazard category	%	Product	%
Mycotoxins	34	Grass	11
Industrial contaminants	24	Maize	10
Biotoxins	12	Alfalfa	7
Heavy metals	10	Feed for bovine	7
Radiation	8	Wheat	7
Pesticides	7	Soy	5
Veterinary drugs	6	Feed for ruminants	4

(positive) state in the contamination level node recorded and compared with the value obtained from the calculation using the best-fitted logarithmic regression curve.

3. Results

3.1. Data collection and processing

3.1.1. Monitoring data of dairy feed in the Netherlands

The following hazard categories were reported in KAP (2000 – 2013) (see Table 3): mycotoxins (34%), industrial contaminants (24%), biotoxins (12%), heavy metals (10%), radiation (8%), pesticides (7%), veterinary drugs (6%). More than 110 feed products had been tested for KAP, of which the main ones were, in decreasing order: Grass (11.4%), maize (10%), alfalfa (7%), feed for bovine (7%), wheat (7%), soy (5%) and feed for ruminants (4%). Note that for the model development, only products were included that are grown or produced in the Netherlands, hence soy and rice had been removed from the data set.

3.1.2. Agricultural data

Fig. 1 shows the variation of use over the years of the agrichemicals and it is clear that agrichemicals (i.e. use of fungicides, herbicides, rodenticides, pesticides and plant growth regulators) remained rather constant, except for insecticides, which dropped after 2010 to a very low level. An explanation for this decline may be related to shifting EU policies on pesticides including the adoption of a new regulation [i.e. Regulation (EC) No 1107/2009] on innovation and development of alternatives, which was implemented in 2011, and to an increasing use of seed treatment agents such as neonicotinoïds (Oppewal, 2017). The most used agrichemical category is pesticides followed by fungicides, herbicides, insecticides and plant growth regulators. The use of rodenticides was low (< 1 t) and no data was available after 2010.

3.2. Construction and validation of the BN

The BN model is shown in Figs. 2 and 3. In Fig. 3, the nodes (i.e. variables) are shown as ellipse and the states (i.e. different data classes within a variable) are given in the squares. In each square, the probability of each specific state is shown in percentages and is presented as a green bar. For clarity, the states are not shown for all nodes. Since, the BN was optimized for the "contamination node", this node is centralized and is connected by an arc to all other nodes. An arc may connect other nodes but this depends on their quantitative relationship. The contamination level gave the following probabilities for the states: "Neg" (78.1%) and "Pos" (21.9%). Hence, only in a small portion (i.e. 21.9%) of the analytical results in KAP were above the LOD ("Pos"). The BN was validated with the dataset that was randomly extracted from the total data set and not used for the model development. The accuracy of the prediction of the contamination level overall was equal to 90.3%. The model validation results, as based on 10,691 records, are presented in Table 4. Differences of accuracy were observed for the two states of the contamination level node. The accuracy for the "Neg" state was 94.0% and for the "Pos" state 78.0%. This difference is due to the large difference in the number of records between both groups (see Table 4).

3.3. Sensitivity analysis

To determine the contribution of the parameters present in the BN to the level of contamination (below or above the LOD) with a particular contaminant (hazard), a sensitivity analysis based on entropy calculation was performed for these two nodes.

The following parameters had the highest contribution to the contamination level node (in decreasing order): hazard (0.27), hazard category (0.1), product (0.1), product category (0.07), year (0.06), insecticides (0.03), herbicides (0.02), rodenticides (0.01) and many climate parameters with values between 0 and 0.01 as shown in Table 5. The following parameters had the highest contribution to the hazard node (in decreasing order): hazard category (1.4), year (0.8), product (0.8), insecticides (0.4), herbicides (0.3), PG regulator (0.3), contamination level (0.3), pesticides (0.1), rodenticides (0.1), and fungicides (0.1). Several climate parameters showed entropy values

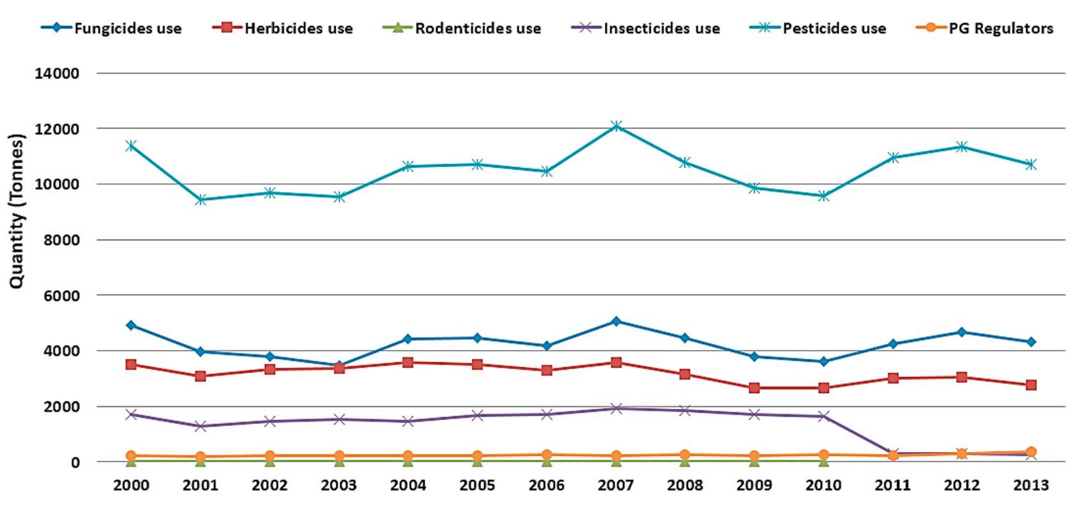

Fig. 1. The yearly use of fungicides, herbicides, rodenticides, insecticides, pesticides and plant growth regulators in the Netherlands in the period 2000–2013 as reported through FAOSTAT.

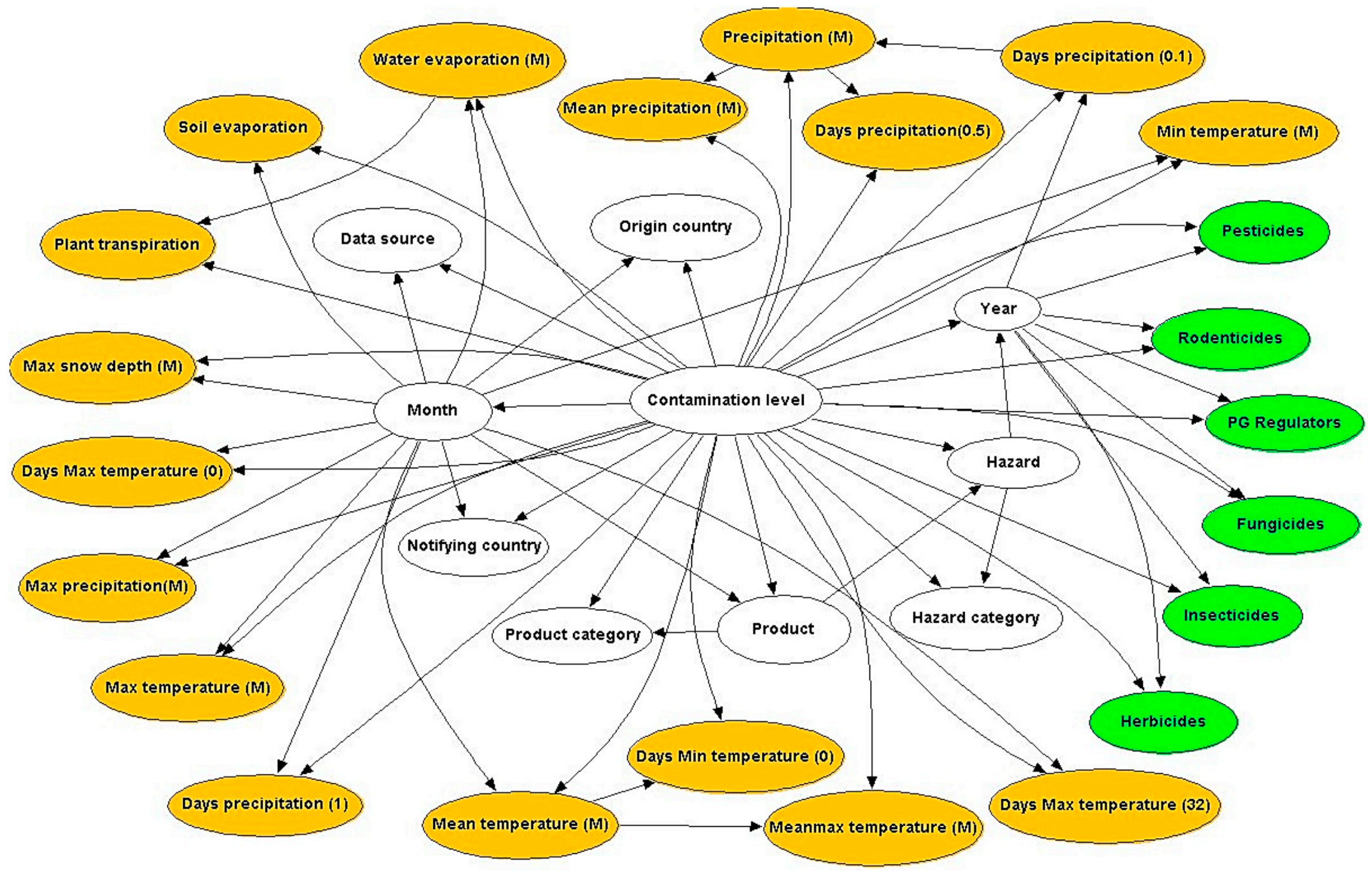

Fig. 2. BN optimized for contamination level. The white ellipses are variables derived from the Dutch KAP database containing monitoring data on feed products used by dairy farms in the Netherlands. The orange ellipses are climate variables containing data derived from the NOAA database and Agri4cast database and the green ellipses the agrichemical variables containing data derived from FAOSTAT. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

between 0 and 0.1 (Table 5).

A parameter sensitivity analysis was performed and the results are shown in Table 5. As can be seen in the table all parameters (climate and agricultural) had an effect on the contamination level node, albeit differences in the extent and direction were observed. A clear explanation of the observed trends is not always easy to understand because of lack of knowledge of a variable on the output parameter (e.g. the effect of “max snow depth” on the level of contamination). However, the aim of method 2 was to demonstrate that variables with low entropy could have an impact on the level of contamination, which was observed. Furthermore, the probability of a positive contamination was generally 3–4 times higher for grass compared to maize.

3.4. Trend analysis

To illustrate how the BN could be used to show impacts and relationships between model variables, grass (e.g. grass bits, grass hay, fresh grass) was selected for further, in-depth analysis. The main contaminant categories found in grass were industrial contaminants, heavy metals and biotoxins. Most climate variables had no or very little impact on the probability of occurrence of hazards in grass except the variable “days of precipitation (0.1)” [i.e. days of precipitation with precipitation ≥ 0.1 in. (2.54 mm)]. There was a particularly high impact of this variable on the occurrence of biotoxins and heavy metals. The effect of this variable was less pronounced (and in opposite direction), though, for industrial contaminants. The main feed commodities used on the dairy farm and grown in the Netherlands, usually on the farm itself, are maize, grass and alfalfa (Driehuis et al., 2008b). These products are subject to contamination induced by climate or due to the use of agrichemicals. To show the contamination that had been found in maize and grass using the BN, these commodities were selected in the product node and the probabilities of the positive findings (e.g. “Pos” state) were recorded in the contamination level node, under varying the years and months in the respective nodes. The results are shown in Fig. 4A, B for the years 2000 to 2013. The inter-monthly contamination pattern was different between the two forages but consistent for either forage across all years. The probability of a positive finding of contamination in maize was lower than what was found in grass and in most years showed a peak in August and December (see Fig. 4A). For grass, the probability of positive contamination started high in January and dropped to a minimum in April followed by an increase until October.

3.4.1. Forecasting the potential of contamination in maize or grass

3.4.1.1. Calculation using the regression equation. Using the regression equation as described in section 2.3 in M & M, we calculated the probabilities of positive findings of contamination (with contaminant levels above LOD) of grass and maize for the years 2014, 2015 and 2016 (see Table 6). The probability of a positive contamination in grass was almost twice as high compared to that of maize and for both forages, the probability of contamination increased in years.

3.4.1.2. Calculation using the BN and new input values. The underlying predictors were, in decreasing order: hazard, hazard category, product, product category, year, insecticides herbicides and rodenticides. The variables having an insignificant contribution to the prediction accuracy (e.g. variable with an entropy < 0.01, such as the climate variables) were not taken into account although they were shown to

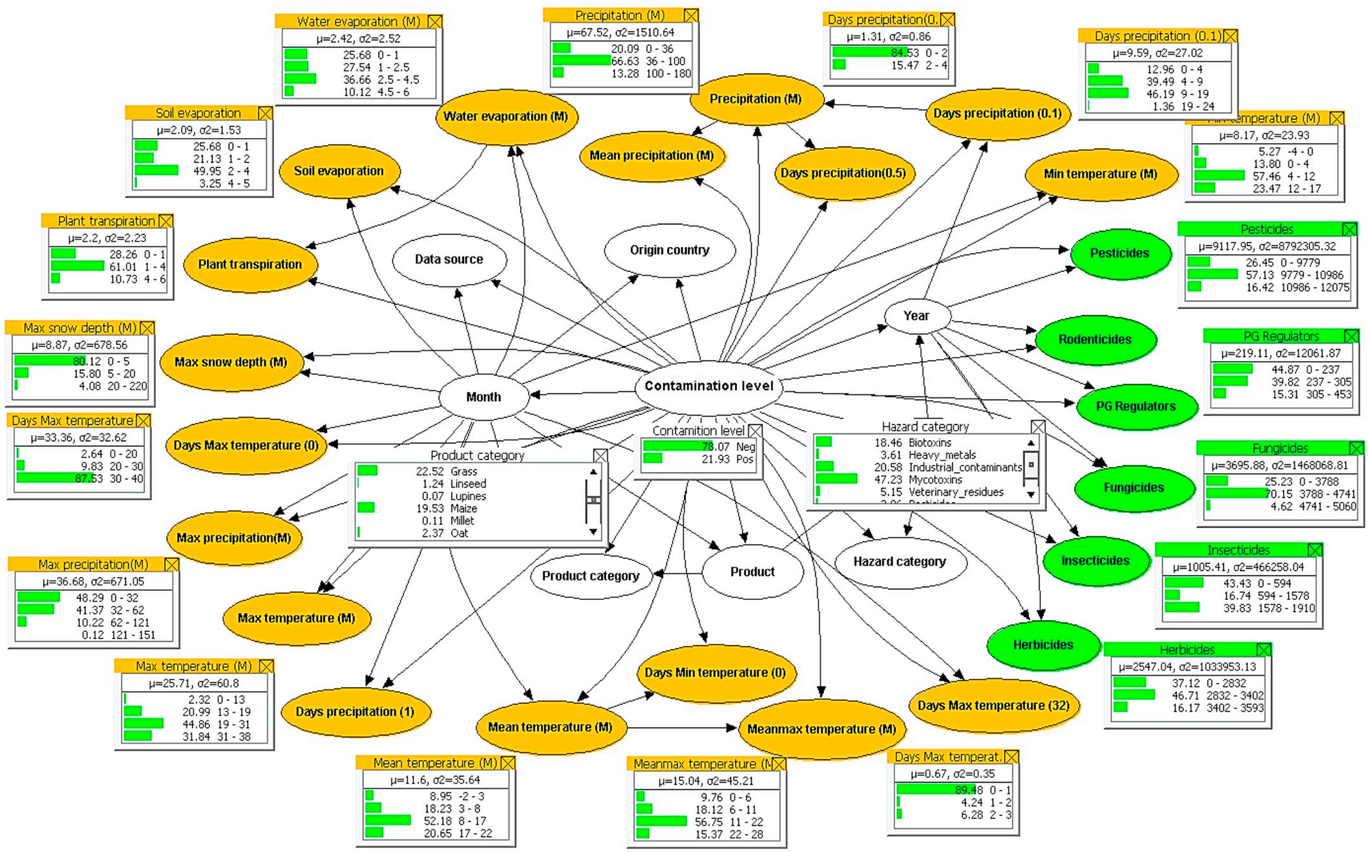

Fig. 3. BN optimized for contamination level showing the states (squares) and probabilities (green bars) of some variables (nodes). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
The validation results of the BN model.

Contamination level	Neg	Pos	Total	Accuracy (%)
Neg	7762	504	8266	94%
Pos	504	1893	2425	78%

have an impact on the contamination level (see results sensitivity method 2).

To compare the prediction of the probability of positive findings of contamination between the BN and the extrapolation approach for the years 2014 to 2016, similar conditions should be used. Since, the extrapolation was done on the overall contamination for grass or maize but not for a specific hazard, hazard category or detailed product, no selection was made in the BN for these nodes either, although these three nodes contributed most to the prediction of the contamination level as judged from the sensitivity analysis. As input, maize or grass was selected in the product category node of the BN and the annual use of insecticides, herbicides and rodenticides in 2014, 2015 and 2016 as collected from the data sources FAOSTAT and used. FAOSTAT, however, did not contain data on the use of agrichemicals in 2016 and no data was available either for rodenticides. The annual use of insecticide in 2014 and 2015 was 297 and 326 t, respectively, and that of herbicides 3266 t and 2881 t, respectively. The probability in the “Pos” state of contamination of grass or maize was recorded using only the input variables insecticides and herbicides, and the results are shown in Table 5. The predicted levels showed the same trend as was observed with extrapolation (grass higher than maize and increasing by the year) but the levels are 50–40% lower than those obtained with extrapolation. We expect that the outcomes could converge if more input variables with a high contribution to the prediction accuracy were used. Furthermore, each of the individual states of the agrichemical nodes includes a certain range and hence a change may not be visible if it still falls within the same state. This situation occurred with herbicide use in 2015. In 2014, it equated 3266 t and 2881 t in 2015. Both values fell in the same state (2nd) but the 2015 value was almost in the 1st state (lower state). If the lower state was used as input than higher probabilities were obtained which were closer to the values obtained through extrapolation (e.g. 20–40% lower, see asterisk values in Table 6).

3.5. Examples of BN model use

3.5.1. Maize

For maize in many years, the highest probability of positive contamination was found in August. The positive contamination in August can be assessed in the hazard category node when selecting August in the month node and maize in the product category node. The main hazards thus observed for maize were mycotoxins (85.5%) followed by heavy metals (5.9%) and industrial contaminants (4.4%). To determine the probability of positive contaminations with mycotoxins of maize in August over the years, “maize” was selected in the product category node,” mycotoxins” in the hazard category node, and "8" in the month node and recorded the probability of positive findings in the contamination level node by varying the years. The results are shown in Fig. 5 and show that the positive contamination level was high in 2000 to 2007 with a peak in 2006 (57.0%) and 2007 (56.8%) followed by a sharp decrease, with a very low value in 2010 (7.8%) and a subsequent slow increase to 19.1% in 2013.

The probability of finding mycotoxins in maize in August in a given year can be retrieved from the hazard node and is shown in Table 6 for four years with high probabilities (2002, 2004, 2005 and 2007), and for

Table 5
Parameter sensitivity analysis of climate variables and use of agrichemicals on contamination level for all products, maize and grass.

Parameter (node)	States	Probability (%) of state "Pos" of contamination level			Entropy	
		All products	Maize	Grass	Contamination level	Hazard
Days Max temperature (0)	0–20	14.0	8.3	37.7	6.76×10^{-4}	3.66×10^{-3}
	20–30	24.1	14.1	53.0		
	30–40	21.9	11.2	38.4		
Days Min temperature (0)	0–6	22.2	11.1	38.6	3.48×10^{-4}	4.6×10^{-3}
	6–12	18.5	11.6	38.8		
	12–24	22.6	14.3	51.4		
	24–29	21.3	13.2	50.8		
Days Max temperature (32)	0–1	22.8	11.6	41.7	2.79×10^{-4}	2.58×10^{-3}
	1–2	18.9	7.6	29.2		
	2–3	11.2	7.6	21.7		
Max temperature (M)	0–13	17.2	11.1	44.5	7.16×10^{-4}	6.78×10^{-3}
	13–19	20.8	12.7	46.1		
	19–31	21.2	11.0	41.7		
	31–38	24.0	11.0	35.3		
Mean temperature (M)	− 2-3	24.8	15.7	55.7	1.5×10^{-3}	10×10^{-3}
	3–8	18.0	12.0	34.7		
	8–17	21.8	10.2	39.1		
	17–22	24.6	16.3	38.2		
Mean max temperature (M)	0–6	24.0	15.0	54.3	1.43×10^{-3}	9.47×10^{-3}
	6–11	17.6	11.7	33.5		
	11–22	22.3	10.5	39.4		
	22–28	24.2	16.1	37.8		
Min temperature (M)	− 4-0	13.9	8.5	35.4	1.5×10^{-3}	10×10^{-3}
	0–4	25.0	15.4	58.2		
	4–12	20.3	10.0	37.0		
	12–17	26.0	17.2	39.6		
Days precipitation (0.1)	0–4	12.3	7.6	24.2	0.00	0.00
	4–9	24.2	12.0	40.7		
	9–19	22.7	12.4	40.7		
	19–24	21.9	12.2	49.9		
Days precipitation (0.5)	0–2	20.5	10.5	37.7	3.05×10^{-3}	2.11×10^{-3}
	2–4	29.7	16.6	49.8		
Max precipitation (M)	0–32	18.5	10.2	38.2	3.52×10^{-3}	4.48×10^{-3}
	32–62	25.5	13.8	41.0		
	62–121	24.0	10.3	40.0		
	121–151	3.9	3.1	10.3		
Mean precipitation (M)	0–2	20.9	10.8	40.3	9.09×10^{-4}	8.68×10^{-3}
	2–5	22.0	11.5	39.2		
	5–6	38.9	23.5	60.8		
Precipitation (M)	0–36	16.3	8.7	33.0	2.42×10^{-3}	20×10^{-3}
	36–100	23.3	12.1	40.6		
	100–180	23.4	12.9	42.7		
Max snow depth (M)	0–5	22.0	11.0	38.4	8.59×10^{-3}	8.54×10^{-3}
	5–20	14.9	9.9	34.6		
	20–220	46.7	28.1	73.0		
Plant transpiration	0–1	22.4	13.2	48.0	1.19×10^{-3}	6.29×10^{-3}
	1–4	20.7	10.1	37.9		
	4–6	27.5	15.6	35.6		
Soil evaporation	0–1	20.4	12.5	44.5	4.45×10^{-4}	7.84×10^{-3}
	1–2	21.1	9.5	50.0		
	2–4	23.1	11.6	36.2		
	4–5	20.5	14.1	28.2		
Water evaporation (M)	0–1	20.4	12.5	44.5	6.47×10^{-4}	10×10^{-3}
	1–2.5	22.4	10.0	48.1		
	2.5–4.5	21.5	11.3	34.9		
	4.5–6	25.9	13.7	33.4		

(*continued on next page*)

Table 5 (*continued*)

Parameter (node)	States	Probability (%) of state "Pos" of contamination level			Entropy	
		All products	Maize	Grass	Contamination level	Hazard
Fungicides	0–3788	20.8	8.8	41.9	3.57×10^{-3}	120×10^{-3}
	3788–4741	21.2	10.6	37.8		
	4741–5060	38.9	37.9	51.9		
Herbicides	0–2832	14.5	7.0	18.7	20×10^{-3}	330×10^{-3}
	2832–3402	21.6	9.9	47.6		
	3402–3593	40.0	31.5	54.7		
Insecticides	0–594	12.1	7.0	11.0	30×10^{-3}	420×10^{-3}
	594–1578	37.0	20.7	56.1		
	1578–1910	26.3	17.8	40.9		
Pesticides	0–97,779	21.6	9.2	43.5	6.55×10^{-4}	140×10^{-3}
	9779–10,986	22.9	11.7	38.5		
	10,986–12,075	18.8	12.8	35.9		
Rodenticides	0–0.3	14.7	6.7	24.7	10×10^{-3}	140×10^{-3}
	0.3–0.6	27.6	16.6	47.7		
	0.6–1	25.4	11.6	48.0		
PG Regulators	0–237	28.3	15.3	52.1	9.75×10^{-3}	290×10^{-3}
	237–305	16.9	8.5	29.5		
	305–453	16.3	8.4	11.6		

the year with the lowest probability (2010). In this setting, the following input parameters were selected: "maize" in product category node, "mycotoxin" in the hazard category node, month "8" in the month node, "Pos" in the contamination level node and "a year" in the year node. The mycotoxins found can be obtained in the hazard node, including the linked probabilities (i.e. representing the frequency). For all years, the main mycotoxins in maize (in August) were zearaleone and deoxynivalenol. It is apparent that the likelihood of occurrence of these two mycotoxins in maize was much lower in 2010, whilst in that particular year, also considerably more mycotoxins were reported than previously (see Table 7).

3.5.2. Grass

The main hazard categories with positive findings in grass in the period analysed (2000–2013) were industrial contaminants (84.0%), heavy metals (10.3%), biotoxins (3.6%) and mycotoxins (1.2%). The industrial contaminants encompass hazards such as PCBs and PBDE and heavy metals include arsenic (24.1%), lead (31.2%), cadmium (28.5%) and mercury (16.2%).

As stated, the BN allowed to analyse the effect of the climate and agricultural parameters on the presence of hazards in grass (i.e. positive samples). To this end, "grass" was selected in the product node, "Pos" in the contamination level node and a state in the climate or agricultural parameters was selected while recording the probabilities of the hazard categories. All temperature-related climate parameters, plant transpiration, max snow depth, soil and water evaporation, precipitation (0.5), and precipitation had no or a minor effect ($< 5\%$) on the probabilities of the hazard category. Interestingly, the climate parameter "precipitation (M) (i.e. total month precipitation)" had a significant effect, changing the probabilities with 3% to 7.5% but the strongest effect of the climate parameters was found for "days of precipitation (0.1)" [i.e. days of precipitation with precipitation ≥ 0.1 in. (2.54 mm)]. These results are shown in Table 8. The climate parameter "days of precipitation (0.1)" was also the climate parameter scoring the highest (although low) in the sensitivity analysis, hence contributing the most to the prediction of positive contamination in grass (data not shown).

A larger impact was observed for the agricultural parameters, as illustrated by the results for herbicides and insecticides presented in the next tables (Tables 9 and 10).

4. Discussion

Food supply chains are vulnerable to many drivers (such as climate, agricultural practices, economy, human behavior) that directly and/or indirectly affect their performance and thereby influence the quantity and quality of the food being produced. A better understanding of these complex interactions may help to minimize the loss due to contamination with hazards and thereby contribute to an improvement in food security.

In this study, we showed that BNs could be used to integrate data covering both climate parameters and usage of agrichemicals, to predict the occurrence of food safety hazards. For the climate parameters, we extracted data on temperature, precipitation, evaporation, plant transpiration and snow fall in the Netherlands during the period studied (2000–2013) from the NOAA and Agri4Cast websites. These parameters are generally accepted to have an impact on the plant growth, disease development and use of agrichemicals (Bouzembrak and Marvin, 2019). In addition, also the yearly use of agrichemicals in the Netherlands was collected and used as variable in the model. It should be noted that these figures were for the Netherlands as a whole and hence were not confined solely to feed production for dairy cows. Each analytical result (positive or negative) for feed products grown or produced in the Netherlands in the period 2000–2013 was linked to a climate report for the month in which the sample for the analytical measurement was taken and to the use of agrichemicals in that particular year. We aimed to predict the occurrence of chemical food safety hazards and to show the impact of climate and agrichemicals on this contamination and therefore a BN was developed optimized for the variable "contamination level".

4.1.1. Model development and performance

The Tree-Augmented Naive Bayes algorithm (Friedman et al., 1997) has demonstrated excellent classification performance (Madden, 2009)

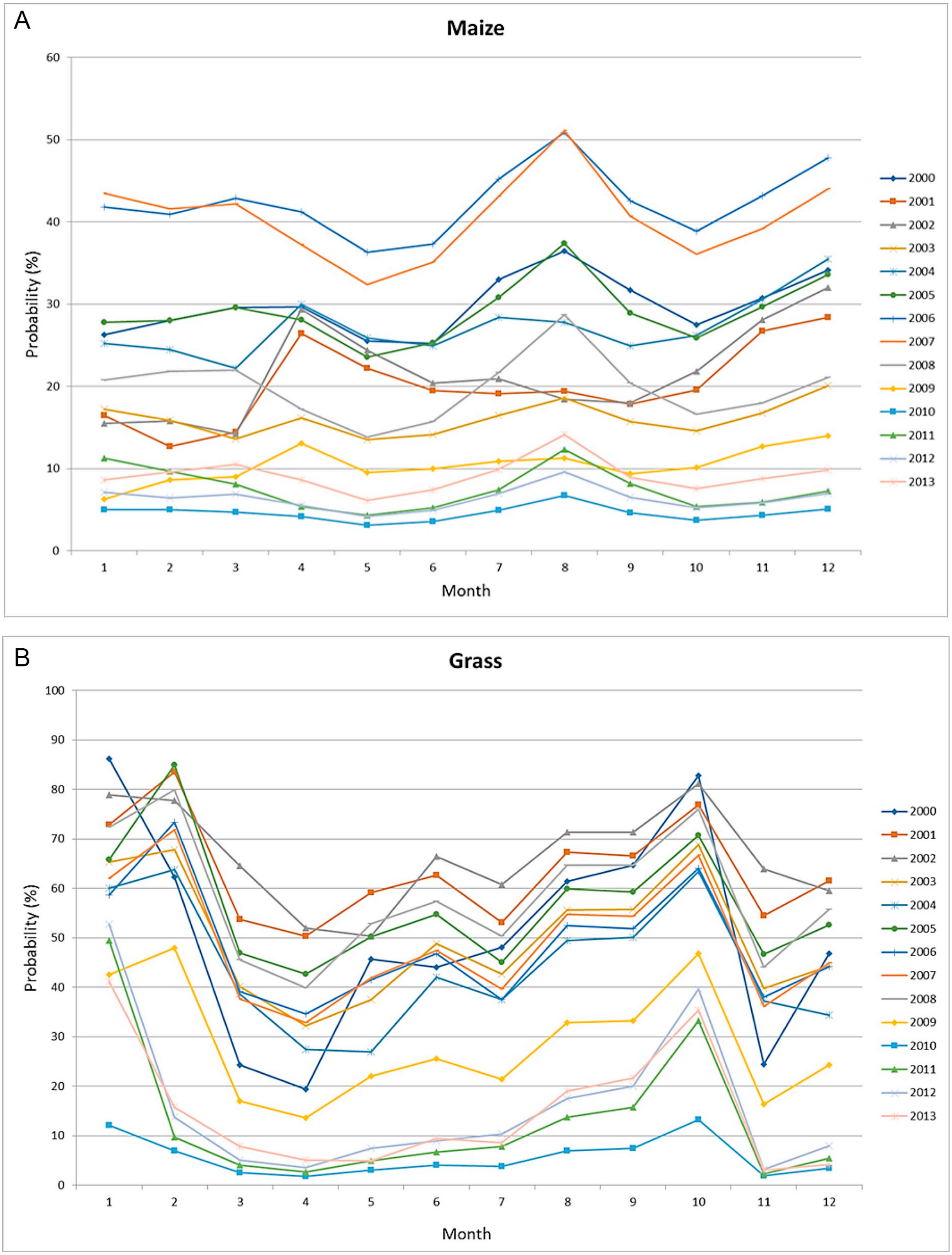

Fig. 4. A, B Probabilities of positive contamination ("Pos" state in the contamination level node) per month for maize (A) and grass (B) in the Netherlands in the years 2000–2013.

in terms of classification accuracy while maintaining efficiency and simplicity (Jiang et al., 2012). It is obvious that the conditional independence assumption in naive BN is rarely true in reality. However, it was demonstrated in literature that the naive BN based on the typically false assumption that the predictor variables are independent, can be highly effective, and often more effective than sophisticated rules (Hand and Yu, 2001; Jiang et al., 2012).

In the validation step, difference of accuracy was observed between the two classes of the contamination level node (i.e. "Pos" vs "Neg"). The positive class had a lower accuracy compared to the negative one

Table 6
Predicted probability (%) of positive findings of contamination of grass and maize using the regression equation and BN.

		Years		
		2014	2015	2016
Grass	Extrapolation	18.1	19.4	20.5
	BN	10.3	10.3 (11.6*)	Not available
Maize	Extrapolation	9.1	9.6	10.0
	BN	6.1	6.1 (8.4*)	Not available

* Values obtained when the 1st state of herbicide use was used instead of the 2nd state.

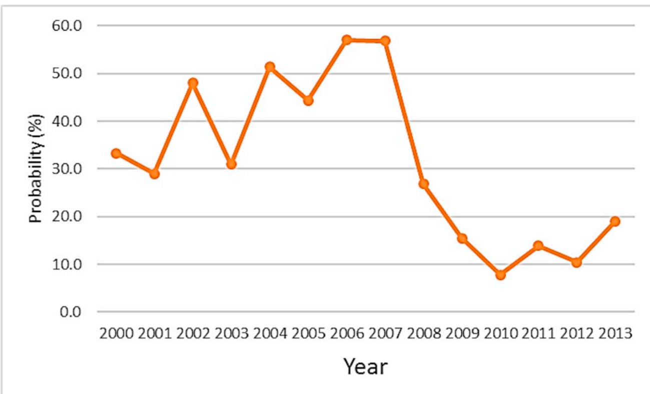

Fig. 5. Trend of positive contamination of mycotoxin in maize in August over the period 2000–2013.

Table 7
Probability (%) of occurrence of mycotoxins in maize in August of selected years.

	Years				
Mycotoxins	2002	2004	2005	2007	2010
Zearaleone	62.8	39.9	39.8	45.7	19.8
Deoxynivalenol	37.2	55.1	52.3	48.8	18.5
Aflatoxin B1	0	3.2	0	1.9	0
Nitropropionic acid	0	0	0	0	0.7
Fumonisin B1	0	1.8	0	2.2	13.5
Fumonisin B2	0	0	0	1.0	6.6
Fumonisin B3	0	0	0	0	3.2
Moniliformin	0	0	0	0	6.4
Alterriol-methylether	0	0	0	0	2.8
Beauvericin	0	0	0	0	17.6
3–15-acetyl-DON	0	0	7,6	0	4.9
HT-2 toxin	0	0	0	0.4	3.3
T-2 toxin	0	0	0	0	1.0
Alterriol	0	0	0	0	1.0
Roquefortine C	0	0	0	0	0.7

Table 8
Effect of "days of precipitation (0.1)" on the probabilities (%) of a positive finding of contamination of grass with various hazard categories.

	Days of precipitation (0.1)			
Hazard categories	0–4	4–9	9–19	19–24
Biotoxins	19.9	3.0	3.7	1.3
Heavy metals	15.9	8.7	11.3	17.0
Industrial contaminants	69.4	86.2	83.0	81.1
Mycotoxins	2.8	1.1	1.1	0.6
Pesticides	1.0	0.7	0.6	0
Radiation	0	0.2	0.3	0
Veterinary residues	0.08	0.06	0.04	0

Table 9
Effect of "herbicides" on the probabilities (%) of a positive finding of contamination of grass with various hazard categories.

	Herbicides		
Hazard categories	0–2832	2832–3402	3402–3593
Biotoxins	14.4	2.8	0
Heavy metals	6.7	10.8	11.3
Industrial contaminants	70.2	85.5	88.0
Mycotoxins	4.7	0.6	0.4
Pesticides	3.8	0.05	0.04
Radiation	0	0.3	0.3
Veterinary residues	0.3	0	0

Table 10
Effect of "insecticides" on the probabilities (%) of a positive finding of contamination of the various hazard categories in grass.

	Insecticides		
Hazard categories	0–594	594–1578	1578-1910
Biotoxins	48.7	0	2.2
Heavy metals	7.0	9.1	11.5
Industrial contaminants	13.8	90.0	85.9
Mycotoxins	18.1	0.2	0.3
Pesticides	11.4	0	0.1
Radiation	0	0.7	0
Veterinary residues	1.0	0	0

(78% vs 94%), which is often observed when large difference exists between the number of cases for each group in the training dataset.

The validity of the BN was further confirmed by the comparison of the BN output with observations published in the scientific literature. Driehuis and colleagues (Driehuis et al., 2008a) analysed various feedstuffs used for dairy cows in the Netherland in 2002 to 2005 for the presence of mycotoxins and observed that the main mycotoxins were deoxynivalenol (DON) and zearalenone. The number of positive samples and the concentrations founds depended on the year and feed product. For maize silage, the number of positive samples with these mycotoxins was higher in 2004 compared to 2002 and 2003 (Driehuis et al., 2008b). The BN confirmed a higher probability of DON contamination in 2004 compared to 2002 and 2003 in maize silage (data not shown) but a higher prevalence of zearalenone in 2004 was not shown. This difference may be due to the specificity of the various sample sets (KAP vs the samples collected by (Driehuis et al., 2008b).

4.1.2. Applications of the BN

Climate has a direct and indirect impact on the occurrence of food safety hazards on agricultural products (Miraglia et al., 2009). Recently, (Kos et al., 2017) observed in a study in Serbia that raining conditions were favourable for high contamination of maize with DON. It is commonly known that temperature, relative humidity, drought, insect attack, and use of fertilizers have an impact on mycotoxin production by fungi (Paterson and Lima, 2010) but each fungus will have its own optimum for mycotoxin production. It is advocated and shown in this research that the complex interaction between environmental conditions (climate), agricultural practices and the presence of food safety hazards can be captured by BNs. Agrichemicals such as pesticides, insecticides and herbicides are used in grassland management to combat weeds, insects and fungi that produce harmful compounds to dairy animals such as pyrrolidizidine alkaloids (Dreger et al., 2009; Edgar, 2004). Interesting, the simulation with the BN as shown in Tables 8 and 9, demonstrated that that the probability of contamination with biotoxins (mainly alkaloids) and mycotoxins strongly drops when the applied amounts of these agrichemicals increases (compare state 1 and state 2 in Tables 8 and 9). Hence, with low application levels of agrichemicals, apparently more toxin-producing fungi and weeds are present in the grass products.

Trend analysis of positive contaminations in grass and maize using the BN (as shown in Fig. 4A B) provides an overview of the probability of occurrence (i.e. finding) of a hazard on these feed products during the season. It is apparent that yearly trends are similar but the level between the years significantly differs. Hence, some years have a higher probability of the occurrence of a hazard than others do. Such year difference most probably is due to climate difference between years, which affects the use of agrichemicals, and presence of mycotoxins and plant toxins (Paterson and Lima, 2010) (Bryden, 2012). Mycotoxins (i.e. main hazards on maize), may contaminate before and after harvest of the crop in the autumn. At storage, mycotoxin producing fungi may grow depending on large number of factors including climate (Bryden, 2012; Miraglia et al., 2009) and this may explain the increase of the probability of contamination in maize during the year, peaking in August (see Fig. 4A). Similar effects may occur for grass as well. The sharp drop observed after month 10 (October) most probably is due to differences in grass products being tested. The majority of the samples tested in the grass category reported in KAP are grass bits (59%), followed by grass hay (32%). However, this ratio was quite different between month 10 and month 11. In month 10, 87% of the samples tested were grass bits (87%) and 11% grass hay, while in month 11, 21% were grass bits and 72% grass hay. For the Netherlands, it was shown that the main contamination in grass (industrial contaminations such as dioxins) decreases from April to August due to dilution (grass growth) (Traag et al., 2006) and therefore may explain the observed drop in Fig. 4B.

In this study, we used food safety in feed of dairy cows in the Netherlands as a case to demonstrate the applicability of BN to integrate data from various sources and origins. In a similar manner, other data can be integrated that have an impact on food safety such as production volumes, farm practices, soil conditions, trade, and prices. Furthermore, BN allows the integration of expert judgement as a variable thereby expanding its potential use.

The results demonstrated the applicability of data-driven BNs to capture complex interactions of parameters. We advocate the use of BNs, which allow to address food safety problems in a holistic manner, thereby helping to understand the complex interactions that exists between the drivers of change acting upon food production systems. This understanding will support risk managers and risk assessors in their efforts to mitigate and assess potential risks, respectively.

4.1.3. Model limitations

The BN model was based on records reported in the Dutch KAP database, and therefore the model is restricted to the information provided within this database. Because of this limitation, the current BN was only applicable for the Netherlands and was limited to chemical hazards and feed products. Fortunately, results of all analytical measurements (above and below LOD) were reported in KAP, which allowed the construction of a BN that could predict the chance of finding a contamination in a feed product. For this study, records were available from 2000 until 2013. It is expected that the BN model accuracy will improve if data from more years are included (Banko and Brill, 2001; Friedman and Yakhini, 1996).

The BN model developed used a range of historical data to calculate the probabilities, which may affect the detection of the new cases. BN can easily be adapted to new cases by selecting only the latest year in the prediction. For instance, the node “year” can be used to select data from 2013 to be included in the prediction, for example, if the user would like to use only data from this year. In addition, BNs are easily adaptable to new data when they become available, and the model can be updated continuously to reflect any new information and new developments. Therefore, it is recommended that the new cases should be added to the model as they are reported in the different data sources.

In the model, several data sources used were only updated annually making their contribution to the BN limited. For instance, the use of agrichemicals was given as an average value for an entire country for a specific year. This means there is a lack of more detailed information related to the data sources.

5. Conclusions

A BN model was constructed to predict the contamination level in dairy feed products in the Netherlands. The model was based on official monitoring data, climate variables and use of agrichemicals for the Netherlands over a 14-year period. A high accuracy of prediction (90.3%) was achieved. An impact of climate parameters on the prevalence of contamination was demonstrated but their contribution to the accuracy of prediction was limited. The variables having the highest impact on the level of contamination were: hazard, hazard category, product, product category, year, insecticides, herbicides and rodenticides.

This study sends some light over the impact of climate and agrichemical use factors on food safety issues, but it also raises the following insights for future research. Our model was based mainly on feed of dairy cows samples recorded in KAP monitoring database, which is limited to the monitoring data of one country (i.e. The Netherlands). More data sources incorporating expert judgements and global monitoring data such as WHO Global Environmental Monitoring System (GEMS)/Food contaminants database and the European Food Safety Authority (EFSA) data warehouse could be included.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2019.102760.

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