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Automated food safety early warning system in the dairy supply chain using machine learning

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Abstract

Traditionally, early warning systems for food safety are based on monitoring targeted food safety hazards. Therefore, food safety risks are generally detected only when the problems have developed too far to allow preventive measures. Successful early warning systems should identify signals that precede the development of a food safety risk. Moreover, such signals could be identified in factors from domains adjacent to the food supply chain, so-called drivers of change and other indicators. In this study, we show for the first time, using the dairy supply chain as an application case, that such drivers and indicators may indeed represent signals that precede the detection of a food safety risk. Using dynamic unsupervised anomaly detection models, anomalies were detected in indicator data expected by domain experts to impact the development of food safety risks in milk. Detrended cross-correlation analysis was used to demonstrate that anomalies in various indicators preceded reports of contaminated milk. Lag times of more than 12 months were observed. Similar results were observed for the 6 largest milk-producing countries in Europe (i.e., Germany, France, Italy, the Netherlands, Poland, and the United Kingdom). Additionally, a Bayesian network was used to identify the food safety hazards associated with an anomaly for the Netherlands.

These results suggest that severe changes in domains adjacent to the food supply chain may trigger the development of food safety problems that become visible many months later. Awareness of such relationships will provide the opportunity for food producers or inspectors to take timely measures to prevent food safety problems. A fully automated system for data collection, processing, analysis and warning, such as that presented in this study, may further support the uptake of such an approach.

***Keywords**:* anomaly detection, emerging risk, Bayesian network, dynamic unsupervised anomaly detection, detrended cross-correlation analysis.

1 Introduction

Food safety, which is enforced by national and international legal requirements, is an important element to consider to ensure a safe and sufficient supply of food. Control and prevention measures are implemented to detect potential food safety risks, including chemical, biological and physical risks. Most of the implemented systems are symptom based (they check for the presence of a hazard or disease) and should therefore be considered reactive systems (H. Marvin & Kleter, 2014; H. Marvin, et al., 2009). Such systems consequently detect food safety issues only when these issues have already developed and may pose a risk to human and/or animal health. An analysis of food safety incidents concluded that a wider recognition of the environment in which food is being produced is needed to ensure that a similar incident will not occur in the future (Costa, et al., 2017; Kleter & Marvin, 2009; Maeda, et al., 2005; H. Marvin & Kleter, 2014; H. Marvin, et al., 2009). Approaches and procedures towards such proactive systems have been developed, including systems for the early detection of food safety issues or food fraud in (social) media using text mining (Kate, et al., 2014) and ontologies (Luijckx, et al., 2016; Van de Brug, et al., 2014), system approaches to integrate data impacting drivers and food safety monitoring data using Bayesian networks (BNs) (Marvin & Bouzembrak 2020, Marvin et al. 20120, 2016, Bouzembrak & Marvin 2019) and artificial neural networks (ANNs) (Lin, et al., 2019), and anticipation systems for food safety issues using autoregression-based screening tools (Verhaelen, et al., 2018) and support vector machines (SVMs) (Zhang, 2020). Although these systems have shown great potential, successful future warning of food safety risk has been difficult to demonstrate. Recently, the usefulness of anomaly detection to identify risks was demonstrated in various studies (Li, et al., 2016; Ryan, et al., 2019; Salehi & Rashidi, 2018). Anomaly detection can not only detect the outliers of sample sets but also recognize rare events in nature as preliminary signals of risks (Rembold, et al., 2019).

In this study, we aimed to explore this potential of anomaly detection for future food safety risks. Since indicators of drivers of changes are expected to affect the development of food

safety risk, we anticipated that an anomaly in an indicator may be a signal for a future food safety risk. As a test case, the milk supply chains of the six largest milk-producing countries in Europe (i.e., Germany, France, the UK, the Netherlands, Italy and Poland) were considered. Milk, as an outstanding nutrient source for various population groups (from infants to the elderly), is one of the most important foods worldwide (Papademas & Bintsis, 2010). In 2018, 683 million tons of milk was produced, 32% of which came from Europe (FAOSTAT, 2020). Europe plays an important role in the world dairy market due to its production yield and export volume (Van Asselt, et al., 2017). In Europe, the six largest milk-producing countries contributed more than 50% of the total European production (Eurostat, 2020). Nevertheless, during the period of 2010 to 2019, 627 notifications related to milk and milk products were reported in the European Rapid Alert for Food and Feed system (RASFF, 2015). The dairy supply chain is complex: it involves feed production, raw milk production, processing by dairy companies, etc. (Van Asselt, et al., 2017). Hazards can enter various stages and cause food safety issues. Therefore, it is essential to obtain advance alert signals and take appropriate measures to prevent a crisis.

We explore the potential of an early warning system for food safety risks by statistically linking anomalies of indicators in the drivers of change to food safety reports in monitoring programmes. For each indicator in the drivers of change, a dynamic unsupervised anomaly detection (DUAD) model was developed to detect anomalies in the collected data. In addition, a BN model that integrates all the indicators and the food safety monitoring data was built to predict the probability of contamination in a product if any anomaly is detected in one of the indicators. Furthermore, a detrended cross-correlation analysis (DCCA) was conducted to investigate whether significant correlations and time lags existed between the time series, the anomalies detected and the time series of the number records in the food safety monitoring databases. The developed early warning system of food safety risks was implemented in a

KNIME[1] workflow to allow automatic real-time data extraction from different data sources, data processing and running of the developed models. The workflow generates automatic warnings for potential future food safety risks, thereby providing risk managers time to implement preventive actions.

In this study, we show for the first time that an anomaly in specific indicators of the drivers of change, such as milk price, feed price, and average monthly precipitation, can be statistically linked to a food safety hazard reported by monitoring programmes many months later. Furthermore, we predicted the specific type of hazards associated with such anomalies, thereby enabling stakeholders to take preventive actions.

2 Materials and methods

The applied approach consists of five distinct steps, as shown in Figure 1: (1) identification of the main drivers and indicators of emerging and existing food safety risks in the dairy supply chain for the six largest milk-producing countries in Europe, including the Netherlands, Italy, Germany, France, United Kingdom, and Poland, (2) identification of data sources of the selected indicators, including a quality assessment, (3) creation of KNIME workflows to automatically retrieve, process and integrate the data of the indicators from the data sources, (4) development of an anomaly detection model for each indicator and (5) development of an automated BN model to predict the probability of contamination (on hazard type level) in milk.

[1] https://www.knime.com/

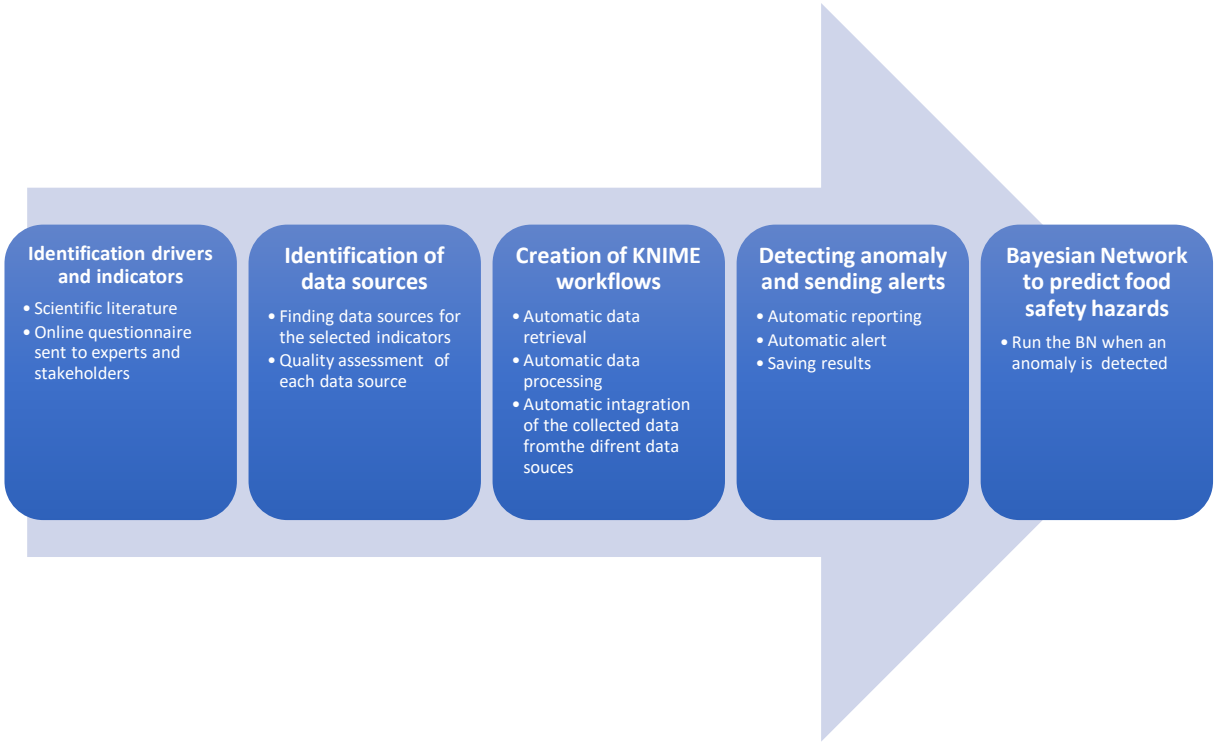


Figure 1: Districts steps in the automated food safety early warning system.

2.1 Identification of drivers and indicators of emerging and existing food safety risks

In our research, four drivers of change and associated indicators (39 in total) that have a direct and/or indirect impact on the development of a food safety hazard in the diary supply chain were obtained from two early studies (SANC, 2013; van der Spiegel, et al., 2012) and are presented in Table 1. An online questionnaire was designed to determine the three most important indicators for each driver. The draft questionnaire was tested for clarity, completeness and completion time by three dairy experts from Wageningen University and Research who were not members of the research team. Based on the feedback received, the questionnaire was modified and sent by email to 73 European dairy experts. These experts were identified based on a literature study, web search and consultation with various food safety authorities in Europe. The final questionnaire is attached in Supplementary 1.

Table 1. Drivers and candidate indicators of emerging and existing food safety risks in dairy milk supply chain.

Drivers	Candidate indicators
Economic	Energy prices (e.g. electricity and petrol) in your country
	Feed prices (e.g. hay, straw, grains, proteins, concentrate) in your country
	Fertiliser prices in your country
	Raw cow milk prices in your country
	Farm land prices in your country
	Income of dairy farms in your country Labours costs on dairy farms in your country
	Labours costs on dairy farms in your country
	Market shares of plant-based milk in your country
	Global demands for cow milk
	Cow milk consumption in your country
	Economic growth in your country
	Frequency of fraud in dairy sector in your country
	Transportation costs in your country
	Market share of the biggest dairy company in your country
	Dairy farm size (number of cows per farm) in your country
	Production of industrial dairy compound feed in your country
Environmental	Average temperature in your country
	Average precipitation in your country
	Share of land area used for pastures in your country
	Total renewable water resources in your country (km^3)
	Fertilizer consumption in your country
	Methane emission of dairy cattle in your country
	Manure production of dairy cattle in your country
	Nitrogen excretion by dairy cattle in your country
	Phosphorus excretion by dairy cattle in your country
	Usage of pesticides in dairy sector
	Usage of herbicides in dairy sector
	Usage of antibiotics in dairy sector
Social	Population
	Inflows of foreign population into your country
	Agriculture share of GDP in your country
	Urban population in your country
	Average age of dairy farmers in your country
Technological	Area cultivated with biotech/GM crops in your country
	Number of transferrable embryos used in dairy sector in your country
	Investments in R&D related to dairy sector in your country
	Number of patents related to dairy sector in your country
	Level the of adoption of technology on dairy farms in your country
	Percentage of dairy farms using an automated milking system in your country

2.2 Identification and quality assessment of data sources

The data sources, which represented the selected indicators in step 1, were either provided by experts or found by the authors. All the selected data sources were open source. If multiple data sources represented the same indicator, a quality assessment was performed according to the method described by Rodgers and colleagues (Rodgers, et al., 2011). This quality assessment consisted of nine parameters: relevance, timeliness, updated frequency, accuracy, edition, accessibility, clarity, comparability and coherence. Only data sources that were relevant to the topic were fully assessed. The overall quality score (QS_i) of each data source i was therefore represented as the weighted sum of these eight criteria, according to the following formula:

$$\mathrm{QS_i} = \sum_{\mathrm{j}=1}^{8} \alpha_{\mathrm{j}} \cdot \mathrm{S_{ij}} \tag{1}$$

where α_{j} is the weight of each criterion and $\mathrm{S_{ij}}$ is the score of data source i in criterion j.

2.3 Data collection and integration in workflows

KNIME workflows were built for each indicator and associated data source to automate the data collection, processing, integration, analysis and visualization. Different data retrieving nodes (e.g., file reader, csv reader, and get request) were used depending on the type of data source (Warr, 2012). For each of the six countries, raw data from different sources were formatted into an integrated dataset X by means of a series of file handling and manipulation nodes to remove irrelevant columns and rows and structure the data indexed by time. Therefore, the series data ($\mathrm{X_i^k}$) of indicator i in country k can be represented by the following formula:

$$X_i^k = \begin{pmatrix} x_{i,1}^k \\ x_{i,2}^k \\ \vdots \\ x_{i,t}^k \end{pmatrix} \tag{2}$$

where $x_{i,t}^{k}$ is the datum of indicator *i* in country *k* at time point *t*.

In this way, both historical and new data, once available in the data sources, were collected and processed automatically and made available for further analysis in the KNIME workflows. All workflows are available in Supplementary 2.

2.4 Detecting anomalies

2.4.1 Dynamic unsupervised anomaly detection

DUAD models were developed for each indicator to detect anomalies in the collected data (Winters, et al., 2014). The DUAD model of indicator *i* was developed as follows:

- A training set Y with the customized time window width (n) and lag interval (l) was constructed.
- An autoregressive model M_i was trained on the training set.
- The standard deviation (σ) of the absolute values of ε ($|\varepsilon|$) was calculated, where the letter E is interpreted to mean the expected value:

$$\sigma = \sqrt{\frac{1}{m}\sum_{k=1}^{m}(|\varepsilon_k| - E)^2} \quad (3)$$

- The confidential interval (CI) of 'normality' was defined with a one-tailed p value (p=0.05):

$$CI = [0,\ 1.64 * \sigma) \quad (4)$$

- $x_{i,t}$ was predicted and the absolute value of the prediction error ($|\varepsilon_t|$) was calculated, where c is a real variable:

$$|\varepsilon_t| = x_{i,t} - (c + \sum_{k=1}^{n} \varphi_{n-k+1} x_{i,t+(k-n-1)*l}) \quad (5)$$

- $|\varepsilon_t|$ was compared with CI: if $|\varepsilon_t| \notin CI$, an anomaly of indicator *i* at time point *t* was detected.
- $p_{i,t}$ was calculated as the probability of $|\varepsilon_t| \in |\varepsilon|$, which represents the probability of record t of indicator i being normal:

$$p_{i,t} = \frac{1}{\sqrt{2\pi}\sigma} exp(-\frac{(x_{i,t}-\mu)^2}{2\sigma^2}) \quad (6)$$

$$\mu = \frac{1}{t}\sum x_{i,t} \quad (7)$$

Seasonal trends should be considered before detecting anomalies; therefore, a seasonality test was conducted on the datasets of monthly or quarterly updated indicators. For the indicators with significant seasonality, the DUAD models were trained with the data of the same month for the past ten years, while the models of the indicators without significant seasonality impact were built using data from the past ten months. The DUAD models of all the yearly and quarterly updated indicators were trained with the data from the past three years or quarters.

2.4.2 Hazard monitoring data

The output of the DUAD models was compared with notifications of hazards in milk reported in the European Rapid Alert for Food and Feed (RASFF)[2] database to test whether an anomaly can be used as an early warning for a potential food safety risk. Notifications with the product category of 'milk and milk products' and notification country of Germany, France, Italy, the Netherlands, Poland or the United Kingdom from 2005 to 2019 were extracted from the RASFF. Irrelevant notifications related to different dairy products (e.g., cheese, ice cream and yoghurt) were removed. The counts of the notifications in each country were summed by month and year. Consequently, for each country, two time series (counts of the notifications per month and per year) were constructed. In addition, for the Netherlands, official monitoring records of milk were obtained from the Quality Program for Agricultural Products database (KAP) (Marvin & Bouzembrak 2020) based on the keywords 'raw milk' and the time period of 2005 to 2018. This data set contains all records of milk analysis and therefore provides an accurate representation of the safety level of milk in the Netherlands as obtained based on RASFF. Each record in KAP contains the name of a hazard, the concentration of the hazard, the

[2] https://ec.europa.eu/food/safety/rasff_en

corresponding limit of detection (LOD), and the hazard category. Records with hazard concentrations higher than their LODs were listed separately (5096 of 122299) and summed yearly and monthly, such as the notification counts in RASFF.

2.5 Detrended cross-correlation analysis

Based on the normal probability ($p_{i,t}$) of indicator *i* at time *t* from the DUAD model, the level of the anomaly ($LA_{i,t}$) of indicator *i* (monthly updated) at time *t* was calculated as:

$$LA_{i,t} = ln(1 - p_{i,t}) \quad (8)$$

A DCCA was conducted to investigate whether there were significant correlations and time lags between the time series of LA and the time series of the number of RASFF records per month. The detailed steps of DCCA can be found in Zebende (2011). DCCA defines correlation coefficients based on different time lags and time windows. In our case, the time lags refer to the number of months offset between the anomaly level and RASFF notifications, while time windows refer to the number of data points used in each pairwise analysis. For instance, $R_{(lag=5, window=10)}$ = 0.4 means that the correlation coefficient between the anomaly levels in months 1-10 and the number of RASFF notifications in months 6-15 is 0.4. To determine when the coefficients are significant, a threshold $R_{0\ (lag,\ window)}$ was calculated using random data by repeating the calculations 500 times and taking the value at the 0.975 quantile. If the correlation $R_{(lag=l,\ window=j)}$ is larger than R_0, then the cross-correlation is significant at the specific lag and window. A similar DCCA analysis was performed between the time series of LA and the time series of the number of KAP records above LOD to explore whether there were correlations and time lags between these values.

According to on the power test (Cohen, 1977), the data sizes of yearly updated indicators were not adequate; hence, DCCA was applied on monthly updated indicators only.

221 *2.6 Bayesian network model to predict food safety hazards*

222 BNs are suitable for integrating data from indicators, and such models often have high
223 prediction accuracy for the factor for which they have been optimized (Bouzembrak & Marvin,
224 2019; Marvin & Bouzembrak, 2020; Marvin, et al., 2016). A similar approach was followed in
225 this study using a naïve BN module available in KNIME. Since detailed monitoring data on milk
226 were available only for the Netherlands (through the KAP database), a BN model was prepared
227 for the Netherlands. The objective was to trigger a BN analysis when an anomaly was observed
228 in any of the indicators using the latest data. In this way, the probability of having contamination
229 in milk above a certain threshold (i.e., LOD) that is associated with this anomaly was obtained.
230 To this end, records related to milk were extracted from the KAP database (described in 2.4.2).
231 Based on the concentrations of the hazard reported and the LOD, all records were labelled
232 with the corresponding 'risk class': (1) '<LOD' (i.e., hazard concentration was below the LOD);
233 (2) '>LOD' (i.e., hazard concentration was above the LOD). To prepare the input dataset for
234 the BN model, the monitoring dataset was integrated with the indicator dataset.
235 In the period of 2005 to 2017, 122299 records were extracted from KAP, of which 5096 records
236 were positive (i.e., LOD > 0) and 117203 were negative (i.e., LOD < 0). The BN prediction
237 model was trained with 80% of the collected records, which were randomly extracted from the
238 total dataset. The remaining 20% were used to validate the model. In the BN model, the input
239 parameters, including all the identified indicators, were used to predict the levels ('<LOD' or
240 '>LOD') of the related records. The BN model was developed with 'Numeric Binner', 'Naïve
241 Bayes Leaner', and 'Naïve Bayes Predictor' from KNIME. Three performance indicators were
242 used to evaluate the BN model performance: accuracy (percentage of records labelled
243 correctly), sensitivity (percentage of '>LOD' records classified correctly) and specificity
244 (percentage of '<LOD' records classified correctly).

3 Results and discussion

3.1 Indicator selection and data collection

In total, 16 completed questionnaires were received (i.e., response rate of 21.9%), of which seven (43.8%) came from experts working in the dairy industry, four (25%) came from public research institutes and three (18.8%) came from academia. The countries of residence of the respondents were the Netherlands (six respondents, 37.5%), Italy (three respondents, 18.8%), the United Kingdom (three respondents, 18.8%), Germany (two respondents, 12.5%), France (one respondent, 6.3%), and Ireland (one respondent, 6.3%). The three indicators with the highest votes per driver were considered the most important indicators and were included in this study (presented in Table 2).

As shown in Table 2, for each driver, the differences between the votes of the first and second indicators were larger than those between the second and third indicators per driver (except for the differences in technological indicators, which were the same). The results suggest that the respondents tended to reach agreement on the most important indicator while remaining divided over the second and third most important indicators.

Table 2. Indicators selected by experts and descriptions of related data sources.

Drive	Indicator	Rank	Votes	Data sources	Available countries	Update frequency	Time range	Data format
Economic	Raw milk price	1st	10	EU commodity price dashboard	FR, DE, IT, NL, PL, UK	Monthly	2005-2019	CSV file
	Feed price*	2nd	6	EU commodity price dashboard	FR, DE, IT, NL, PL, UK	Monthly	1991-2019	CSV file
	Income of dairy farms	3rd	6	European Statistical Office	FR, DE, IT, NL, PL, UK	Every two years	2005-2016	JSON file
Environmental	Usage of antibiotics	1st	8	Kerkgenootschap der Zevende-dags Adventisten Rapport, UK Veterinary Antibiotic Resistance and Sales Surveillance Report	NL, UK	Yearly	2009-2017	PDF file
	Share of land area used for pasture	2nd	5	Food and Agriculture Organization	FR, DE, IT, NL, PL, UK	Yearly	1992-2015	ZIP file
	Average temperature	3rd	4	Koninklijk Nederlands Meteorologisch Instituut	NL	Monthly	1906-2019	Generic data file
	Average precipitation	3rd	4	Koninklijk Nederlands Meteorologisch Instituut	NL	Monthly	1951-2019	Generic data file
Social	Total population	1st	9	European Statistical Office	FR, DE, IT, NL, PL, UK	Yearly	2000-2018	JSON file
	Average age of dairy farmers	2nd	5	European Statistical Office	FR, DE, IT, NL, PL, UK	Every four years	2005-2013	JSON file
	Urban population	3rd	3	Food and Agriculture Organization	FR, DE, IT, NL, PL, UK	Yearly		ZIP file
Technological	Investment in R&D related to dairy sector	1st	10	European Statistical Office	NL, PL, UK	Quarterly	2015-2019	JSON file
	Level of adoption of technology	2nd	7	European Statistical Office	FR, DE, IT, NL, PL, UK	Yearly	2005-2017	JSON file
	Number of patents related to dairy sector	3rd	4	European Patent Office	FR, DE, IT, NL, PL, UK	Yearly	1980-2019	Linked open data

*: the 'Feed price' including the feed barley price, feed maize price and feed wheat price

262 For the driver “economy”, the indicator ‘raw milk price’ ranked highest. Clearly, milk price and
263 quality parameters, such as the levels of fat and protein percentages (Dommerholt & Wilmink,
264 1986), are related, but a relationship between food safety hazards such as total bacteria counts
265 and aflatoxin M1 has also been reported (Hoffmann & Moser, 2017; Lindahl, et al., 2018;
266 Popescu & Angel, 2019). Regarding the environmental indicators, ‘usage of antibiotics’ was
267 the most important indicator. Antibiotics, especially those with a broad antibacterial spectrum,
268 can be applied to treat acute diseases in cows. However, these drugs can be deposited in
269 cows’ mammary glands and milk and eventually ingested by humans (Sachi, et al., 2019). Most
270 respondents selected ‘population’ as the most important social indicator of existing and
271 emerging risks in the dairy supply chain. A growing population would result in a higher demand
272 for milk and consequently a demand for more farmland. Competition with other land uses may
273 pose constraints on the dairy supply chain and eventually lead to new or known food safety
274 risks (Huws, et al., 2018).

275 *3.2 Identification and quality assessment of data sources*

276 In total, 60 related data sources were identified by the authors and interviewed experts. Among
277 them, 20 were classified as relevant by an expert panel. The total quality of these 20 data
278 sources was scored, and all the relevant data sources received full scores on accuracy,
279 accessibility and clarity but varied in timeliness. The Koninklijk Nederlands Meteorologisch
280 Instituut (KNMI)[3] and European Patent Office (EPO)[4] data sources had the highest timeliness
281 scores, followed by the EU commodity price dashboard. The data sources with the highest
282 total quality scores per indicator are listed in Table 2. Four of the selected data sources were
283 updated monthly, and one was updated quarterly. The update frequencies of the other data
284 sources were equal to or longer than one year. The values of all the indicators except ‘usage

[3] https://www.knmi.nl/over-het-knmi/about

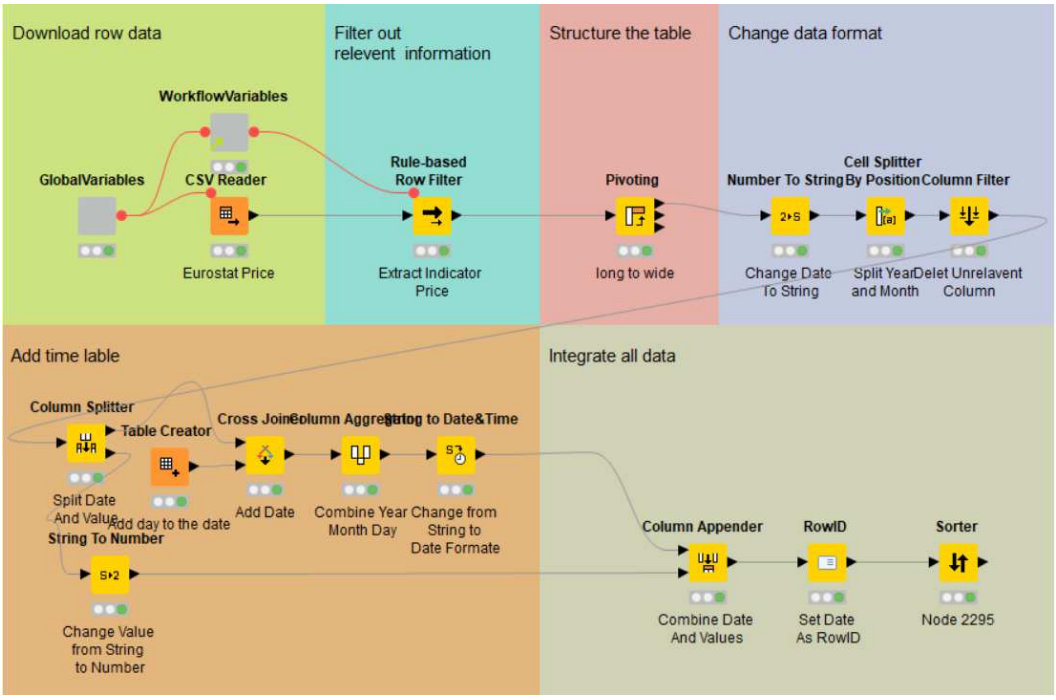
[4] https://www.epo.org/

of antibiotic' could be extracted directly using modules available in KNIME. The data source of 'usage of antibiotic' was a PDF file; therefore, value extraction required additional text mining techniques. Thus, a script was written in R and inserted into the KNIME workflow.

3.3 Collecting and integrating data automatically via workflows in KNIME

A KNIME workflow was built for each indicator and data source; in total, 15 KNIME workflows were developed. Figure 2 presents an example of a workflow of extraction and processing of the milk price and integration of the dataset. As shown in Figure 2(a), the extraction of the milk price from the EU commodity price dashboard consists of six steps: (1) download raw data; (2) filter out relevant information; (3) structure the data in a table; (4) change the data format for further analysis; (5) add a time label; and (6) integrate all the data. These six steps were realized by means of a series of KNIME nodes. These steps were repeated for each country, and the results were combined in a single table. The result of this workflow (i.e., a table with milk prices per country per month) is presented in Figure 2(b).

a.



b.

Row ID	S Date	D DE	D FR	D IT	D NL	D PL	D UK
2018-12-01	2018-12-01	36.47	36	37.2	37.25	33.2	32.9
2018-11-01	2018-11-01	37.16	36.73	37.08	37.25	32.85	34.8
2018-10-01	2018-10-01	36.63	36.71	36.81	38	32.57	34.6
2018-09-01	2018-09-01	35.43	35.98	35.44	37	31.6	34.3
2018-08-01	2018-08-01	33.83	34.63	35.26	35.75	30.72	33.09
2018-07-01	2018-07-01	33.19	33.7	35.25	35.75	30.38	31.26
2018-06-01	2018-06-01	32.56	32.63	34.86	34.25	30.4	30.06
2018-05-01	2018-05-01	32.38	32.43	34.89	34	30.69	29.63
2018-04-01	2018-04-01	32.99	32.9	35.24	34.5	31.96	30.51
2018-03-01	2018-03-01	34.21	33.85	35.81	35.5	32.41	31.32
2018-02-01	2018-02-01	34.88	35.04	35.98	35.75	32.95	32.31
2018-01-01	2018-01-01	36.76	35.27	36.57	37.5	34.02	33.35
2017-12-01	2017-12-01	39.96	36.01	38.08	41.5	36.07	34.79
2017-11-01	2017-11-01	40.52	36.4	38.02	41.75	35.8	34.92
2017-10-01	2017-10-01	40.34	36.17	37.68	41.75	34.46	34.52
2017-09-01	2017-09-01	39.39	36.6	37.7	40.5	33.71	32.82
2017-08-01	2017-08-01	37.44	35.11	37.15	38.5	32.57	30.97
2017-07-01	2017-07-01	35.89	34.04	36.78	37.25	31.61	30.53
2017-06-01	2017-06-01	34.38	32.32	36.62	36.75	31.25	29.64

Figure 2. An example workflow of data extraction and processing from the EU commodity price dashboard (a) and the dataset obtained after the integration (b).

3.4 Anomaly detection

A significant seasonal impact was observed only for the indicators ‘average temperature’ and ‘average precipitation’ ($P<0.05$). Therefore, the DUAD models of these two indicators were trained with the data of the same month from the past ten years, while the models of the other

monthly updated indicators were trained with the data from the past ten months. The DUAD models developed to detect anomalies were integrated in KNIME, and the resulting workflow is shown in Figure 3.

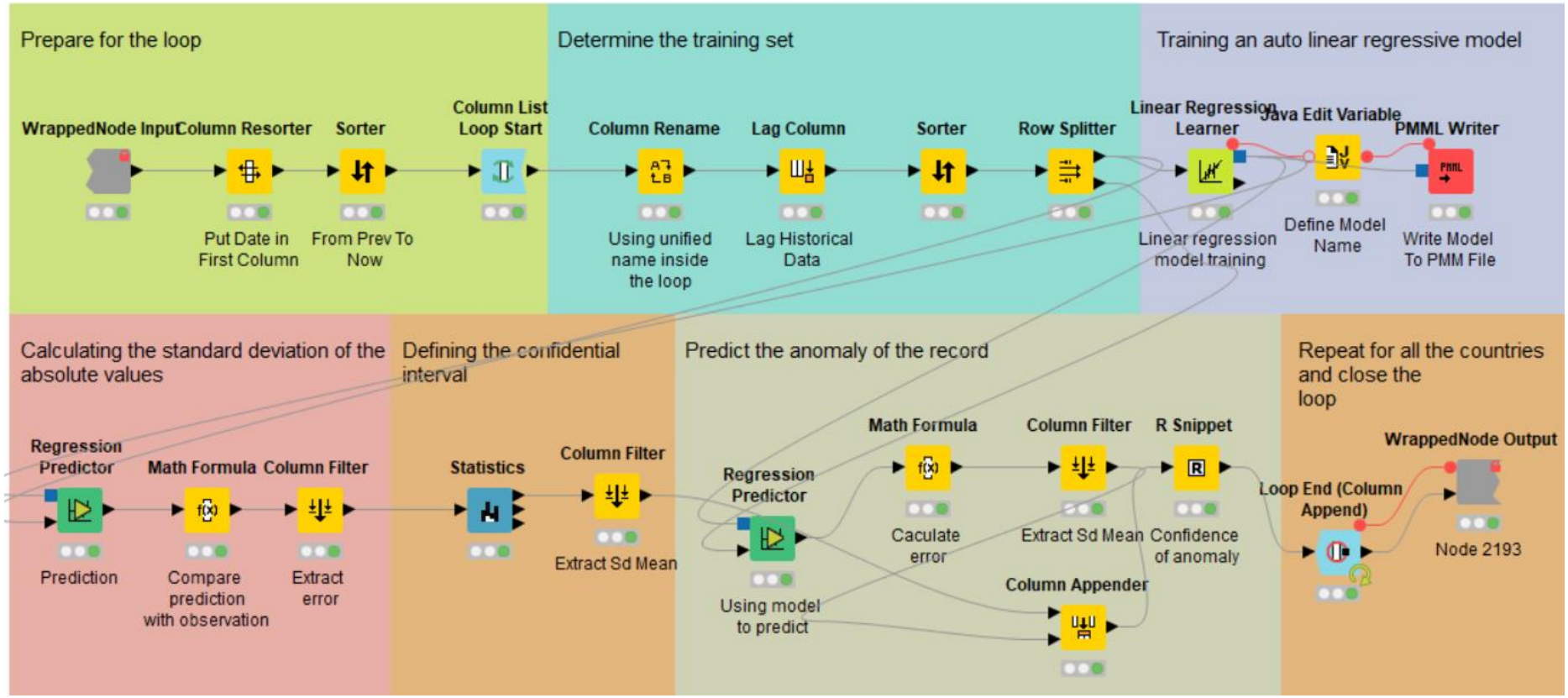


Figure 3. Workflow of anomaly detection.

Table 3 shows the detected significant anomalies (P<0.05) for each indicator and country together with their frequency (the ratio of anomalous records to all records). In Table 3, the ratios of anomalous records per indicator show different patterns among different countries. For instance, the ratios of anomalous records of milk price were similar among countries, while the ratios of anomalous records of feed maize price and number of patents differed. Extremely high or low anomaly ratios among some indicators, such as the anomaly ratios of 'average age of farmers' and 'farm income', were due to the limited number of available records. Elsayed (2012) suggested that a small data size would lead to inaccurate reliability prediction when applying multiple regression models. Since the DUAD models built in this study were based on linear regression, the limited observations of some indicators could be the reason for the extreme anomaly ratios.

Table 3. Anomalies detected per indicator per country for the period of 2008-01-01 to 2019-01-01.

Indicator	Country	Number of anomaly records (Total number of records)	Ratio of anomaly records
Milk price	DE	8(145)	6%
	FR	9(145)	6%
	IT	7(145)	5%
	NL	5(145)	3%
	PL	9(144)	4%
	UK	6(145)	4%
Feed barley price	DE	9(145)	6%
	FR	6(145)	4%
	IT	10(145)	7%
	NL	10(145)	7%
	PL	10(145)	7%
	UK	8(145)	6%
Feed maize price	DE	10(145)	7%
	FR	6(145)	4%
	IT	6(145)	4%
	NL	15(145)	15%
	PL	9(145)	9%
Feed wheat price	DE	10(145)	7%
	FR	7(145)	6%
	NL	11(145)	8%

	PL	8(145)	6%
	UK	7(145)	5%
Farm income	DE	0(2)	0%
	FR	0(2)	0%
	IT	0(2)	0%
	NL	0(2)	0%
	PL	0(2)	0%
	UK	0(2)	0%
Antibiotic usage	NL	0(4)	0%
	UK	4(6)	67%
Grassland share	DE	0(8)	0%
	FR	0(8)	0%
	IT	0(8)	0%
	NL	0(8)	0%
	PL	1(8)	13%
	UK	0(8)	0%
Monthly average precipitation	NL	14(145)	10%
Monthly average temperature	NL	13(145)	9%
Population	DE	0(12)	0%
	FR	0(12)	0%
	IT	0(12)	0%
	NL	0(12)	0%
	PL	1(11)	10%
	UK	0(12)	0%
Average age of dairy farmers	DE	1(1)	100%
	FR	1(1)	100%
	IT	1(1)	100%
	NL	1(1)	100%
	PL	1(1)	100%
	UK	1(1)	100%
Urban population	DE	0(12)	0%
	FR	0(12)	0%
	IT	0(12)	0%
	NL	0(12)	0%
	PL	0(12)	0%
	UK	0(12)	0%
Agriculture R&D investment	DE	0(8)	0%
	FR	1(5)	20%
	IT	2(7)	29%
	NL	0(5)	0%
	PL	1(4)	25%
	UK	0(8)	0%
Machinery installations in dairy farms	NL	3(18)	17%
	PL	3(18)	17%
	UK	2(18)	11%

Number of patents	DE	3(13)	23%
	FR	3(13)	23%
	IT	2(13)	15%
	NL	2(13)	15%
	UK	0(13)	0%

Anomalies and trends may differ among countries, and to illustrate this possibility, the milk price is shown in Figure 4. The milk prices in most countries showed a similar trend over the analysis period (2008-2020), showing upward trends from 2009 to 2014 and 2016 to 2020 and downward trends from 2008 to 2009 and 2015 to 2016. Several factors, including general demand, the energy market and various policies, could be responsible for the milk price trends. The considerable decline from 2015 to 2016 was mainly due to the lifting of the milk quota system in Europe, which had been effective since 1984 but was removed in 2015 (Kersting, et al., 2016).

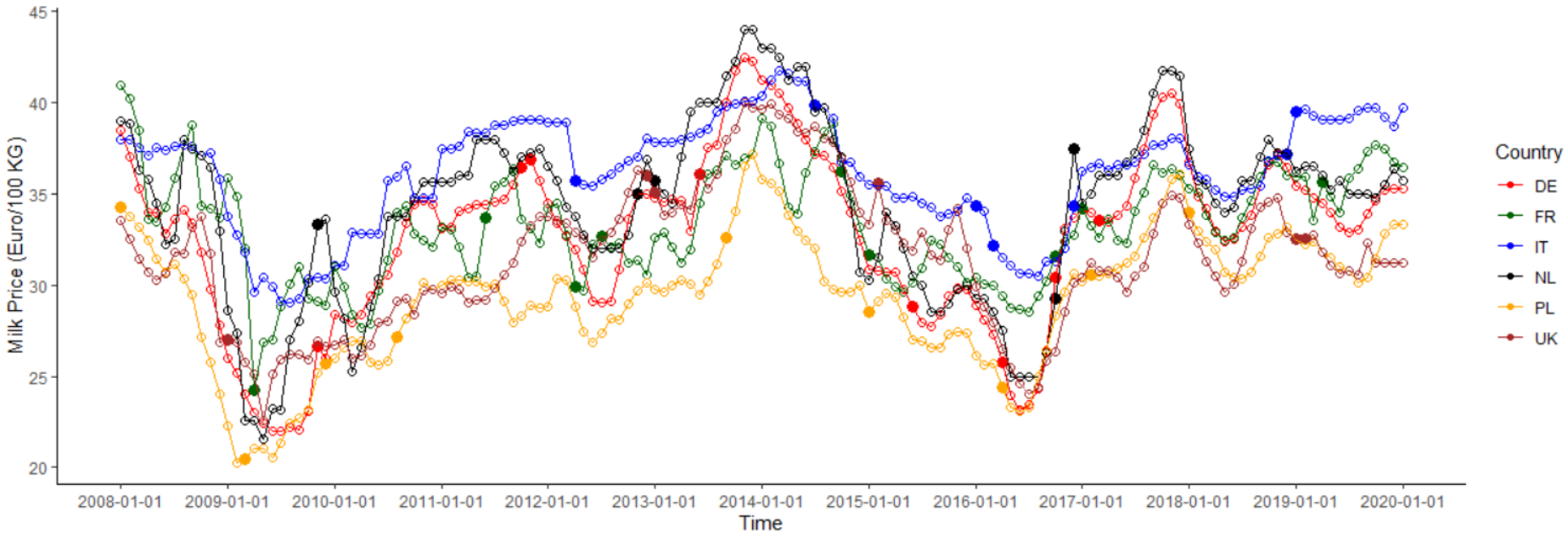


Figure 4. Milk price and detected anomalies in DE, FR, IT, NL, PL, UK from 2008 to 2019. The month when an anomaly is observed is indicated as a full circle.

3.5 Correlation between anomalous signals and food safety notification

The correlation coefficients (R) between the anomaly level of milk price and the number of reported RASFF notifications related to milk products in the related countries are presented in Figure 5. A threshold $R_{0\ (lag,\ window)}$ was calculated and presented in Figure 5 to indicate when the coefficients were significant. The figure shows that significant correlations between milk price anomaly levels and RASFF notification numbers occur in all six countries, with very weak correlations in Poland. Significant cross-correlation occurred under different time lags among the six countries. In the Netherlands and Germany, the highest peak appeared when the time lags were between 10 and 15 months, while in France and Italy, the corresponding time lags were between 20 and 23 months. The time lag with the most significant correlation in the United Kingdoms was five months, the shortest among the six countries.

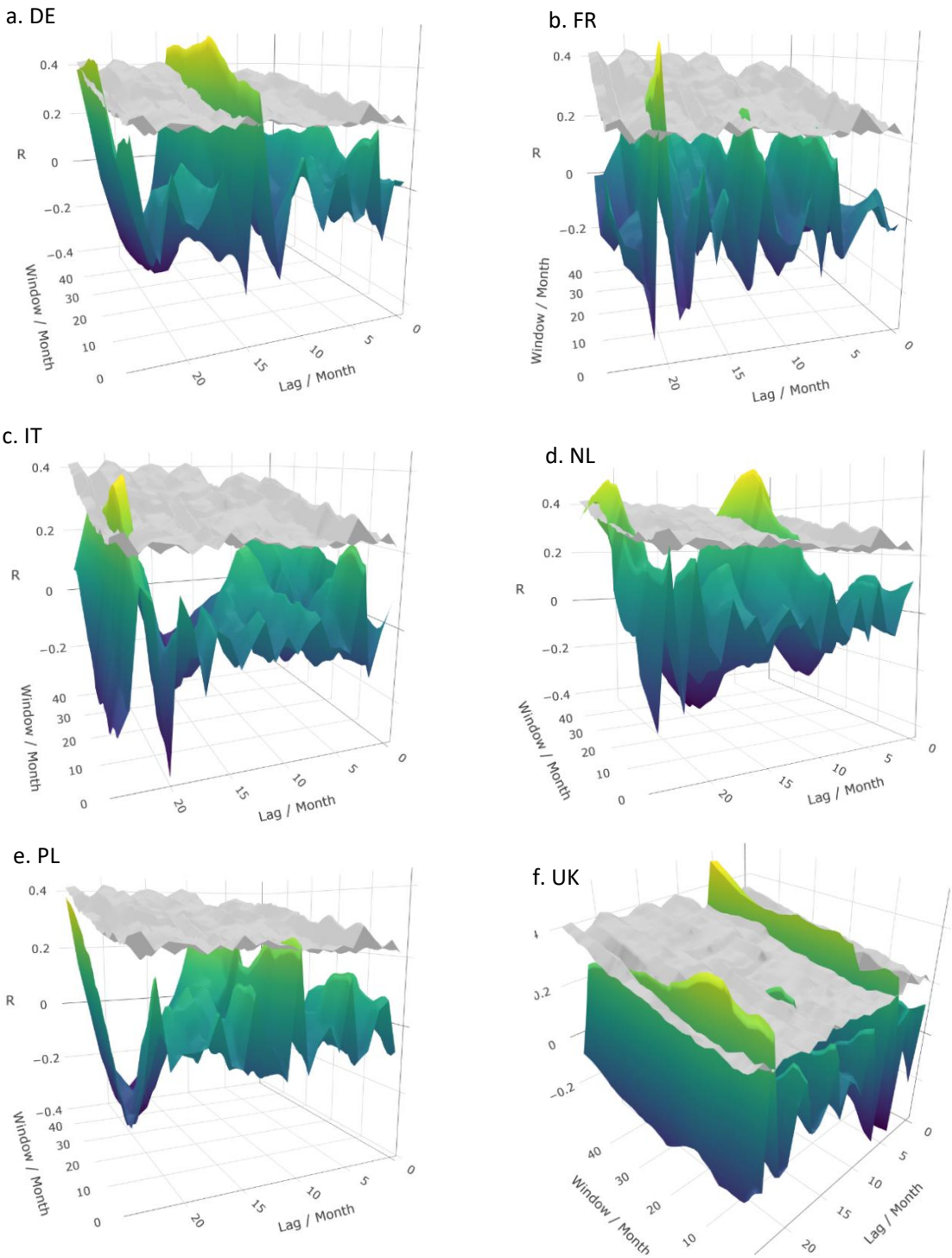


Figure 5. Cross correlation coefficient with different time lags and windows between RASFF notifications and anomaly levels of milk price in (a) Germany; (b) France; (c) Italy; (d) Netherlands; (e) Poland and (f) United Kingdom. The threshold surfaces are coloured in grey.

Since the overall trend inside the time window was removed by DCCA, the size of the time window impacted the correlation coefficient. A significant R with a larger time window indicates correlation in long-term time series, while a significant R with a smaller time window indicates correlation only in short-term time series. To eliminate the influence of the time window size and obtain an overall correlation, we averaged the significant correlation coefficient per time lag, recorded the maximum average correlation coefficient together with its corresponding time lag and applied the analysis to all the monthly updated indicators. The results are presented in Table 4. In all 6 countries, the anomalous milk prices show significant correlations with the number of reported notifications, followed by anomalous levels of feed maize price and feed barely price.

Table 4 Significant correlations between the number of reported milk safety notifications in RASFF/KAP and the level of anomaly per indicator per country

Indicator	RASFF												KAP	
	DE		FR		IT		NL		PL		UK		NL	
	Lag	Lag	Lag	R	Lag	R	Lag	R	Lag	R	Lag	R	Lag	R
milk price	10	10	21	0.37	22	0.35	10	0.41	11	0.27	5	0.38	10	0.38
feed maize price	7	7	20	0.42	-	-	4	0.32	7	0.35	-	-	7	0.48
feed wheat price	19	19	10	0.26	-	-	-	-	-	-	13	0.31	19	0.39
feed barley price	19	19	-	-	3	0.36	24	0.34	5	0.46	-	-	19	0.33
monthly average temperature	13	13	-	-	-	-	-	-	-	-	-	-	13	0.44
monthly average precipitation	9	9	-	-	-	-	24	0.28	-	-	-	-	9	0.4

A similar cross-correlation analysis was performed for the Netherlands with data from KAP, and the results were compared with those of RASFF. Figure 6 shows the cross-correlation results for all monthly updated indicators: all have significant correlations with the number of positive records in KAP (i.e., records with LOD>0). The areas of the R surfaces above the threshold in feed barley price (Figure 6b) and feed wheat price (Figure 6d) are relatively smaller than the areas for the other indicators, especially feed maize price. Such differences may be due to the different amounts of barley, maize and wheat in cows' diets. During lactating periods, barley and wheat are commonly applied as supplements in the form of pellets, while maize is used not only in supplements but also in silage, which is one of the most common types of

forage (Tóthi, 2003). Therefore, the significance levels of the cross-correlations between the anomalies in maize price and RASFF notifications were higher than the significance levels between the anomalies in wheat/barley price and RASFF notifications. Furthermore, the time lags where significant correlations were observed were longer for feed barley and feed wheat than for the other indicators. This observation suggests that anomalies in barley and wheat prices will not have an immediate impact on the safety of milk. Regarding window size, the highest correlation coefficients for each indicator appeared when the window size was approximately 36 months. However, for some indicators, such as milk price, barley price and wheat price, the significant correlations disappeared when the time window exceeded 36 months. These results indicate that the relationship between the anomalous levels of those indicators and milk safety was stable inside a certain time period (i.e., 36 months) but gradually changed over longer periods. By contrast, for indicators such as average monthly temperature and average monthly precipitation, the relationships with milk safety level were more consistent: they did not change even after a long period.

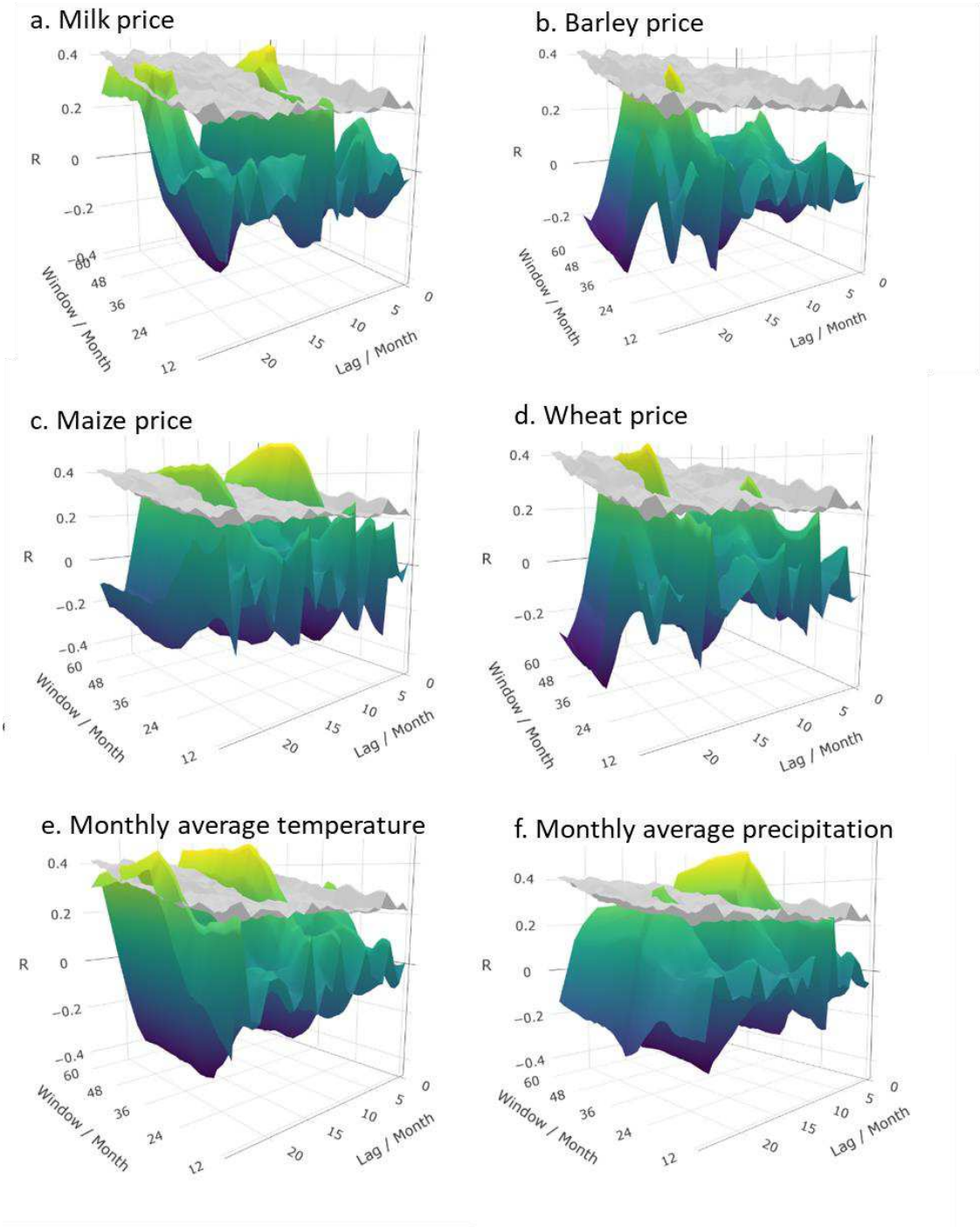


Figure 6. Cross correlation coefficient with different time lags and windows between KAP notifications and anomaly levels per indicator in the Netherlands. The threshold surfaces are coloured in grey.

The maximum correlation coefficient and related time lags of the anomaly level of each indicator against KAP-positive records are presented in Table 4. Compared with the results of

406 RASFF in the Netherlands, more significant correlations were observed when KAP was
407 employed as the reference, which may be due to the large number of cases in KAP. Hence, it
408 is expected that more significant correlations would be obtained if similar data were provided
409 for the other five countries.

410 *3.6 Bayesian network KNIME workflow*

411 To assess the potential risk of finding hazards in milk in circumstances of anomalies, a BN was
412 constructed for the Netherlands and integrated as a workflow in KNIME. The resulting workflow
413 is shown in Figure 7. This workflow was constructed in such a way that when an anomaly is
414 observed in any of the indicators, data are collected from all indicators. The prediction results
415 for the training set and validation set are presented in Table 5: the total accuracy and specificity
416 of the training set and validation set were good (>85%), while the sensitivity of both sets was
417 lower (74% and 54%). The lower sensitivity could be due to the limited number of positive
418 records in the training set (Lee, et al., 2015). An insufficient number of positive records ('>LOD')
419 causes the model to place excess emphasis on negative records ('<LOD'), resulting in lower
420 sensitivity. The sensitivity can be improved by using a more balanced dataset. In addition to
421 providing probabilities of finding contaminations, the BN is used to indicate the corresponding
422 hazard category. This information is sent by email to the registered user together with
423 information about the observed anomaly; thus, the user knows what to check for.

424

425 **Table 5**. Results of Naïve Bayes prediction model.

	Training set	**Validating set**
Sensitivity	74 %	54%
Specificity	88%	92%
Accuracy	87%	90%

426

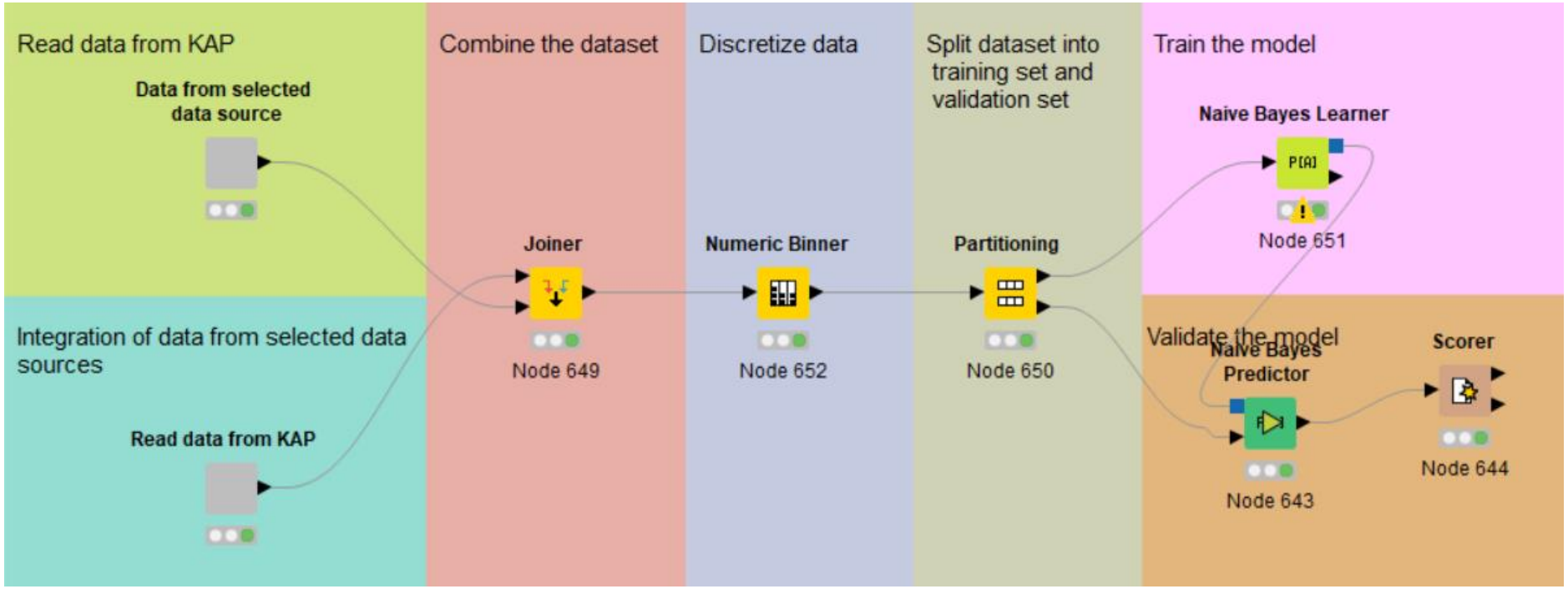


Figure 7. Workflow of Bayesian network model.

In summary, the integrated workflow consisting of all the individual workflows developed in this study aims to monitor the developments in indicators assumed to influence the development of a food safety risk and to generate a warning when irregularities occur. In addition to warning about anomalies, the system also informs the user which associated hazard categories are most likely to be the cause of contamination; hence, the system indicates when to look for what factors. The system is fully automated and reflects the situation as it currently is in the market. Since we demonstrated a large time lag between anomaly detection and contamination in milk, this system provides the user time to implement preventive measures.

We demonstrated that anomalies can be used as an early warning for contamination in milk, and we believe the methodology may be applicable for any food supply chain in any part of the world.

4 Conclusion

The current research developed a workflow system for six EU countries to monitor data sources of indicators expected to impact food safety in milk. The automatically retrieved data were analysed for anomalies, and anomalies in several indicators were shown to be statistically linked to future contamination in milk. For the Netherlands, the workflow could also indicate which types of hazards were most likely to be present. The system was built on an open-source workflow platform, which will reduce the costs of implementation by stakeholders (authorities, industries, etc.). In the future, similar systems could be developed for other commodities and supply chains.

Acknowledgements

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Supplementary 1. Questionnaire.

Introduction

Thank you for taking the time to participate in this questionnaire.

Demeter is a collaborative project between six European food safety research institutes: RIKILT and Food and Biobased Research of Wageningen University and Research, the Department of Social Sciences of Wageningen University (all the Netherlands); University of Newcastle upon Tyne (United Kingdom); the Federal Institute for Risk Assessment (Germany); and the National Food Chain Safety Office (Hungary). The project is sponsored and partially funded by the European Food Safety Authority (EFSA).

The project objective is to support current (and future) EFSA procedures for emerging risk identification by providing a set of integrated, open-source solutions that will allow EFSA and EU Member State authorities to share data, knowledge and methods in a rapid and effective manner. The central component of this project is the development of an Emerging Risks Knowledge Exchange Platform for use by EFSA and EU Member State Authorities.

From this questionnaire, we would like to learn from your experience and insights to determine which indicators and data sources are considered most important in the future (3 to 5 years) of emerging and existing food safety risks in the cow milk supply chain. We have previously selected several indicators of four main drivers. We would like to kindly ask you to select the three most important indicators of each of the drivers and provide data sources for these indicators. A retrieval method for the data sources will be developed, and integration will be realized by machine learning such that a warning will be generated when a threshold is reached. The performance of the newly developed solution will be tested and validated for 12 months.

We estimate that you will need approximately 15-20 minutes to complete this questionnaire. Please note that you cannot save your answers in between.

Definitions

For the purposes of this survey, the following definitions are used:

Emerging risk: An emerging risk to human, animal and/or plant health is understood as a risk resulting from a newly identified hazard to which a significant exposure may occur or from an unexpected new or increased significant exposure and/or susceptibility to a known hazard. Emerging risks do not include risks characterized by a sudden appearance or risks associated with the inadvertent or accidental intake of food or feed that are not in compliance with recognized safety requirements.

Driver: Generally, the energy providing impetus to a development. In futures research, frequently used as internal/external factors influencing developments, decisions, policies, etc., helping to define possible future scenarios. Often used in parallel to or overlapping with the term “trends”. More specifically used in this report for describing the phenomena underlying trends and other developments that eventually lead to the emergence of risks.

Indicator: Measurement or observation (by some references referred to as “signals”): providing information on nature of the hazard and source of the risk; reliable, sensitive, & quantifiable; pointing to the risk directly or indirectly related to the food chain. Can be either qualitative or quantitative in nature.

Data source: A primary location from which data are obtained. The data source can be a database, a dataset, a spreadsheet or even hard-coded data.

Questions:

1. Contact information

- Email of respondent:
- Country:
- Type of institution:
  - ☐ Public authority
  - ☐ Academy
  - ☐ Public research institute
  - ☐ Industry
  - ☐ Other

2. Please read the following indicators and drivers of emerging and existing food safety risks in the milk supply chain, and answer the following questions

Driver 1: Economic

i. Select the three most important indicators and add indicators if missing;

- ☐ Energy prices (e.g., electricity and petrol) in your country
- ☐ Feed prices (e.g., hay, straw, grains, proteins, concentrate) in your country
- ☐ Fertiliser prices in your country
- ☐ Raw cow milk prices in your country
- ☐ Farm land prices in your country
- ☐ Dairy farm incomes in your country
- ☐ Labour costs on dairy farms in your country
- ☐ Market share of plant-based milk in your country
- ☐ Global demand for cow milk
- ☐ Cow milk consumption in your country
- ☐ Investments in R&D related to dairy supply chain
- ☐ Economic growth in your country
- ☐ Frequency of fraud in dairy sector in your country
- ☐ Transportation costs in your country
- ☐ Market share of the largest dairy company in your country
- ☐ Dairy farm size (number of cows per farm) in your country
- ☐ Production of industrial dairy compound feed in your country
- ☐ Others: _____

ii. Please explain how the selected indicators will have an effect on the emerging risk:

Indicator A:_____

Indicator B:_____

Indicator C:_____

iii. Can you define a threshold of concern of each of the selected indicators?

Indicator A:_____

Indicator B:_____

Indicator C:_____

iv. Please provide a data source for each of the selected indicators

Indicator A:_____

Indicator B:_____

Indicator C:_____

Driver 2: Environmental

i. Select the three most important indicators and add indicators if missing;

- ☐ Average temperature in your country
- ☐ Average precipitation in your country
- ☐ Share of land area used for pastures in your country
- ☐ Total renewable water resources in your country (km^3)
- ☐ Fertilizer consumption in your country
- ☐ Methane emission of dairy cattle in your country
- ☐ Manure production of dairy cattle in your country
- ☐ Contamination in feed driven by climate
- ☐ Nitrogen excretion by dairy cattle in your country
- ☐ Phosphorus excretion by dairy cattle in your country
- ☐ Usage of pesticides in dairy sector
- ☐ Usage of herbicides in dairy sector
- ☐ Usage of antibiotics in dairy sector
- ☐ Others: _____

ii. Please explain how the selected indicator will have an effect on the emerging risk:

Indicator A:_____

Indicator B:_____

Indicator C:_____

iii. Can you define a threshold of concern of each of the selected indicators?

Indicator A:_____

Indicator B:_____

Indicator C:_____

iv. Please provide a data source for each of the selected indicators

Indicator A:_____

Indicator B:_____

Indicator C:_____

Driver 3: Social

i. Select the three most important indicators and add indicators if missing;

- ☐ World population
- ☐ Inflow of foreign population into your country
- ☐ Agriculture share of GDP in your country
- ☐ Urban population in your country
- ☐ Average age of dairy farmers in your country
- ☐ Others: _____

ii. Please explain how the selected indicator will have an effect on the emerging risk:

Indicator A:_____

Indicator B:_____

Indicator C:_____

iii. Can you define a threshold of concern of each of the selected indicators?

Indicator A:_____

Indicator B:_____

Indicator C:_____

iv. Please provide a data source for each of the selected indicators

Indicator A:_____

Indicator B:_____

Indicator C:_____

Driver 4: Technological

i. Select the three most important indicators and add indicators if missing;

- ☐ Area cultivated with biotech/GM crops in your country
- ☐ Number of transferrable embryos used in dairy sector in your country
- ☐ Investments in R&D related to dairy sector in your country
- ☐ Number of patents related to dairy sector in your country
- ☐ Level of adoption of technology on dairy farms in your country
- ☐ Percentage of dairy farms using an automated milking system in your country
- ☐ Others: _____

ii. Please explain how the selected indicator will have an effect on the emerging risk:

Indicator A:_____

Indicator B:_____

Indicator C:_____

iii. Can you define a threshold of concern of each of the selected indicators?

Indicator A:_____

Indicator B:_____

Indicator C:_____

iv. Please provide a data source for each of the selected indicators

Indicator A:_____

Indicator B:_____

Indicator C:_____

Thank you very much for sharing your thoughts with us!

Figures

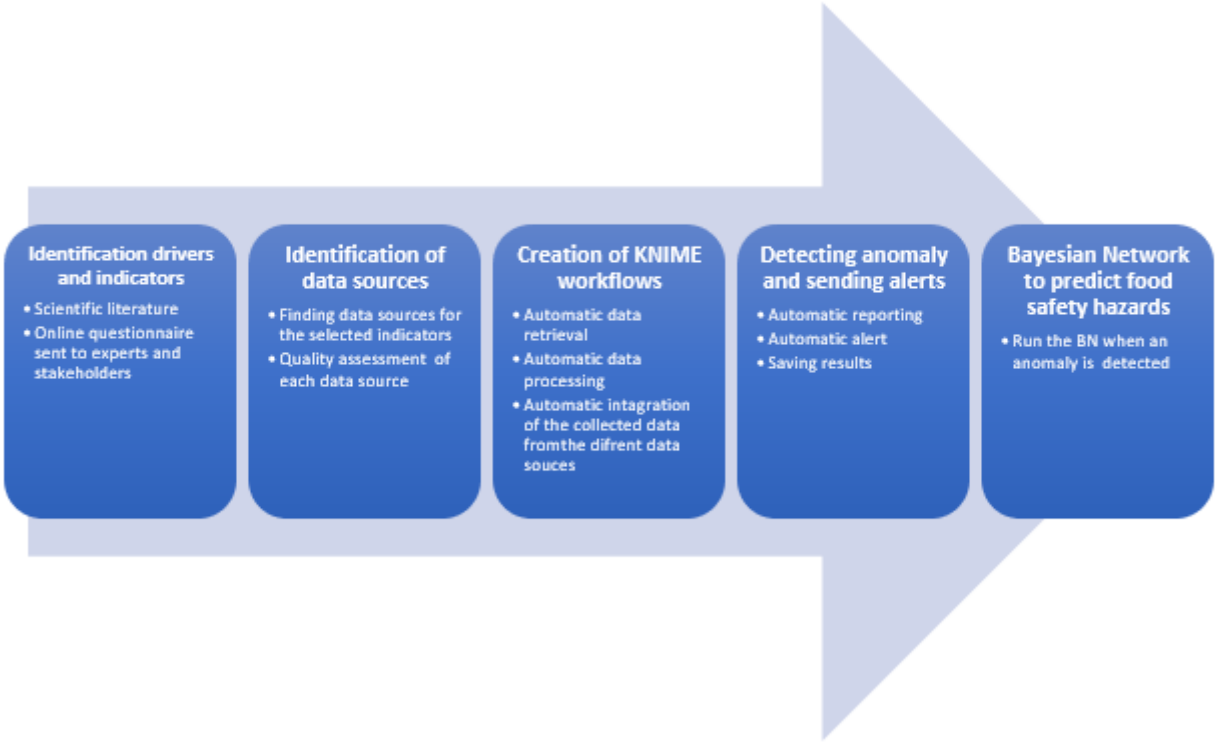


Figure 1

Districts steps in the automated food safety early warning system.

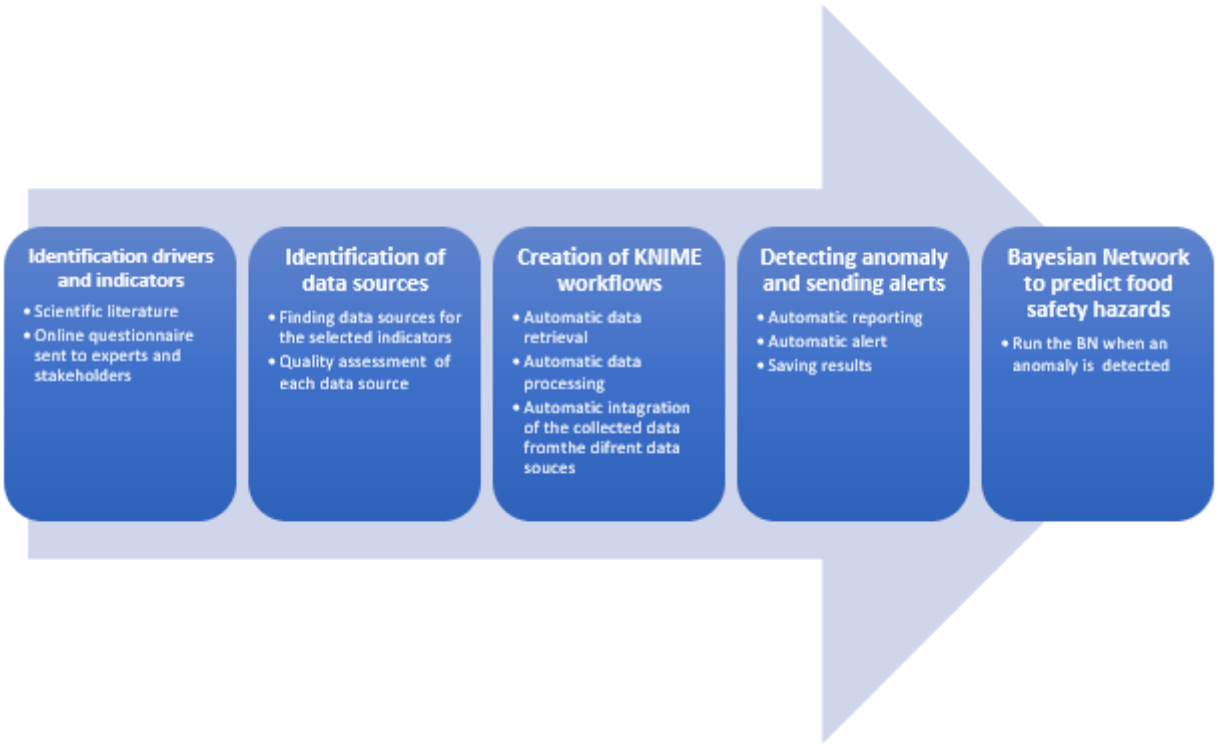
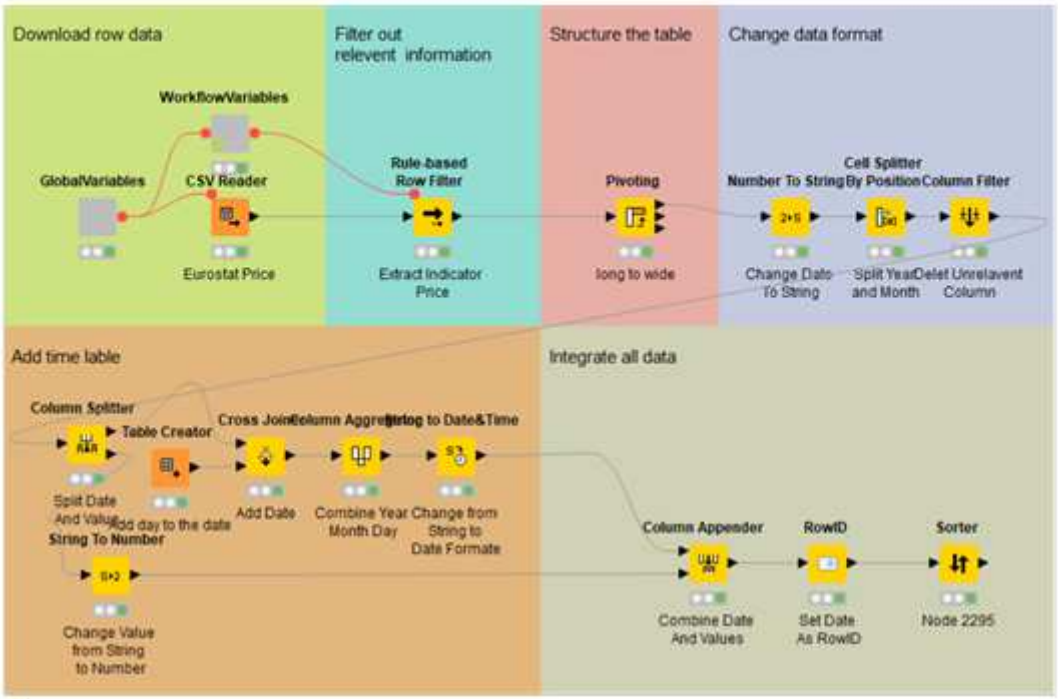


Figure 1

Districts steps in the automated food safety early warning system.

a.



b.

Row ID	S Date	D DE	D FR	D IT	D NL	D PL	D UK
2018-12-01	2018-12-01	36.47	36	37.2	37.25	33.2	32.9
2018-11-01	2018-11-01	37.16	36.73	37.08	37.25	32.85	34.8
2018-10-01	2018-10-01	36.63	36.71	36.81	38	32.57	34.6
2018-09-01	2018-09-01	35.43	35.98	35.44	37	31.6	34.3
2018-08-01	2018-08-01	33.83	34.63	35.26	35.75	30.72	33.09
2018-07-01	2018-07-01	33.19	33.7	35.25	35.75	30.38	31.26
2018-06-01	2018-06-01	32.56	32.63	34.86	34.25	30.4	30.06
2018-05-01	2018-05-01	32.38	32.43	34.89	34	30.69	29.63
2018-04-01	2018-04-01	32.99	32.9	35.24	34.5	31.96	30.51
2018-03-01	2018-03-01	34.21	33.85	35.81	35.5	32.41	31.32
2018-02-01	2018-02-01	34.88	35.04	35.98	35.75	32.95	32.31
2018-01-01	2018-01-01	36.76	35.27	36.57	37.5	34.02	33.35
2017-12-01	2017-12-01	39.96	36.01	38.08	41.5	36.07	34.79
2017-11-01	2017-11-01	40.52	36.4	38.02	41.75	35.8	34.92
2017-10-01	2017-10-01	40.34	36.17	37.68	41.75	34.46	34.52
2017-09-01	2017-09-01	39.39	36.6	37.7	40.5	33.71	32.82
2017-08-01	2017-08-01	37.44	35.11	37.15	38.5	32.57	30.97
2017-07-01	2017-07-01	35.89	34.04	36.78	37.25	31.61	30.53
2017-06-01	2017-06-01	34.38	32.32	36.62	36.75	31.25	29.64

Figure 2

An example workflow of data extraction and processing from the EU commodity price dashboard (a) and the dataset obtained after the integration (b).

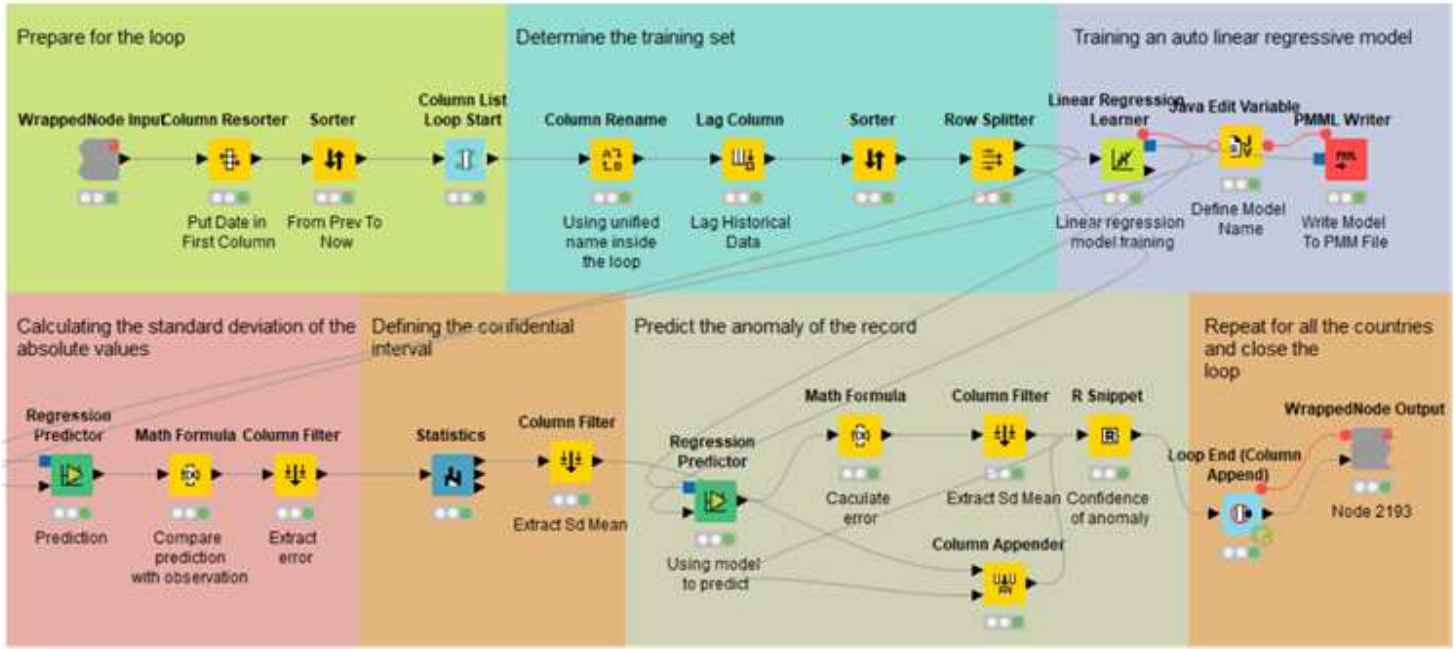


Figure 4

Workflow of anomaly detection.

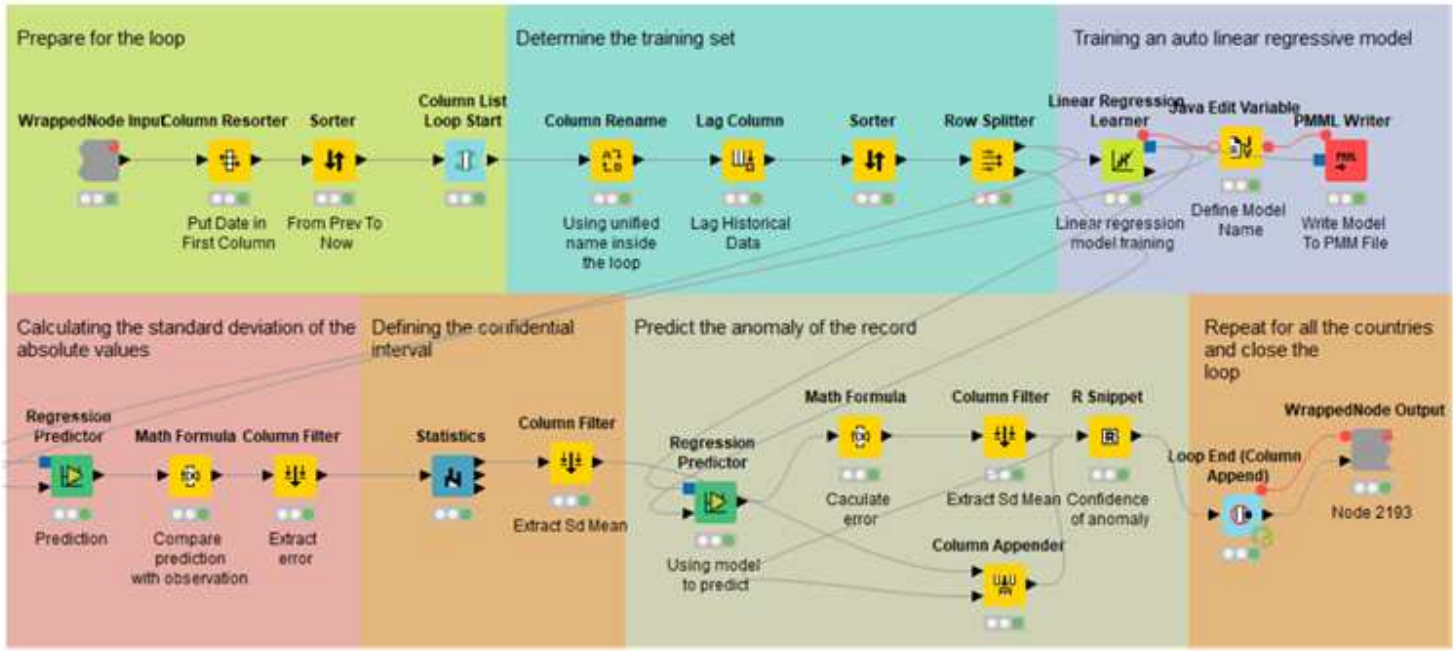


Figure 4

Workflow of anomaly detection.

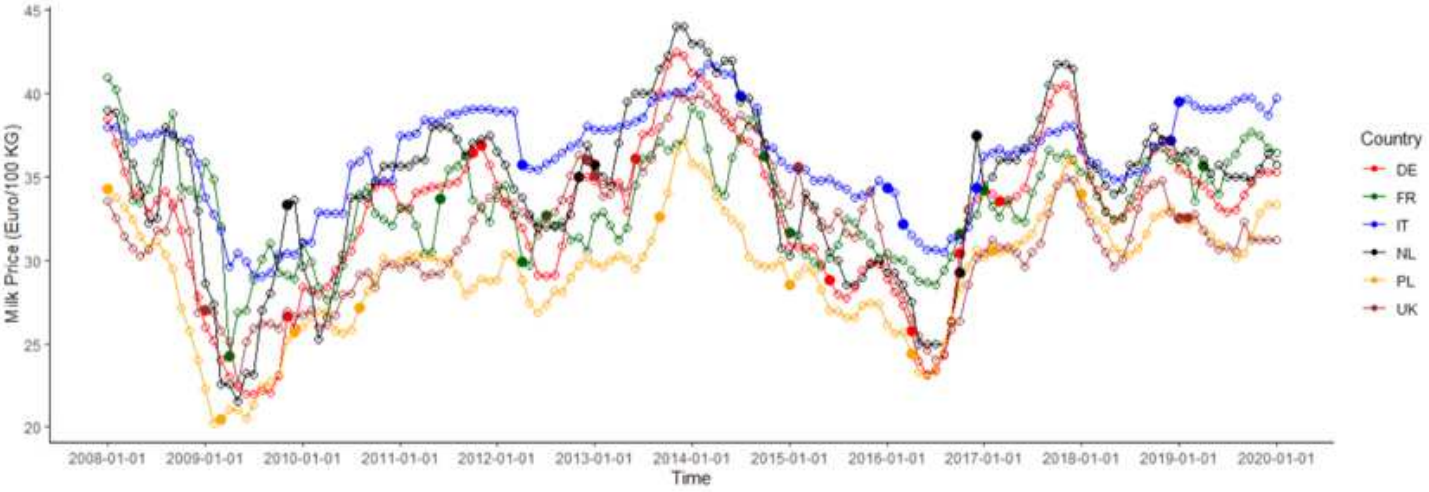


Figure 5

Milk price and detected anomalies in DE, FR, IT, NL, PL, UK from 2008 to 2019. The month when an anomaly is observed is indicated as a full circle.

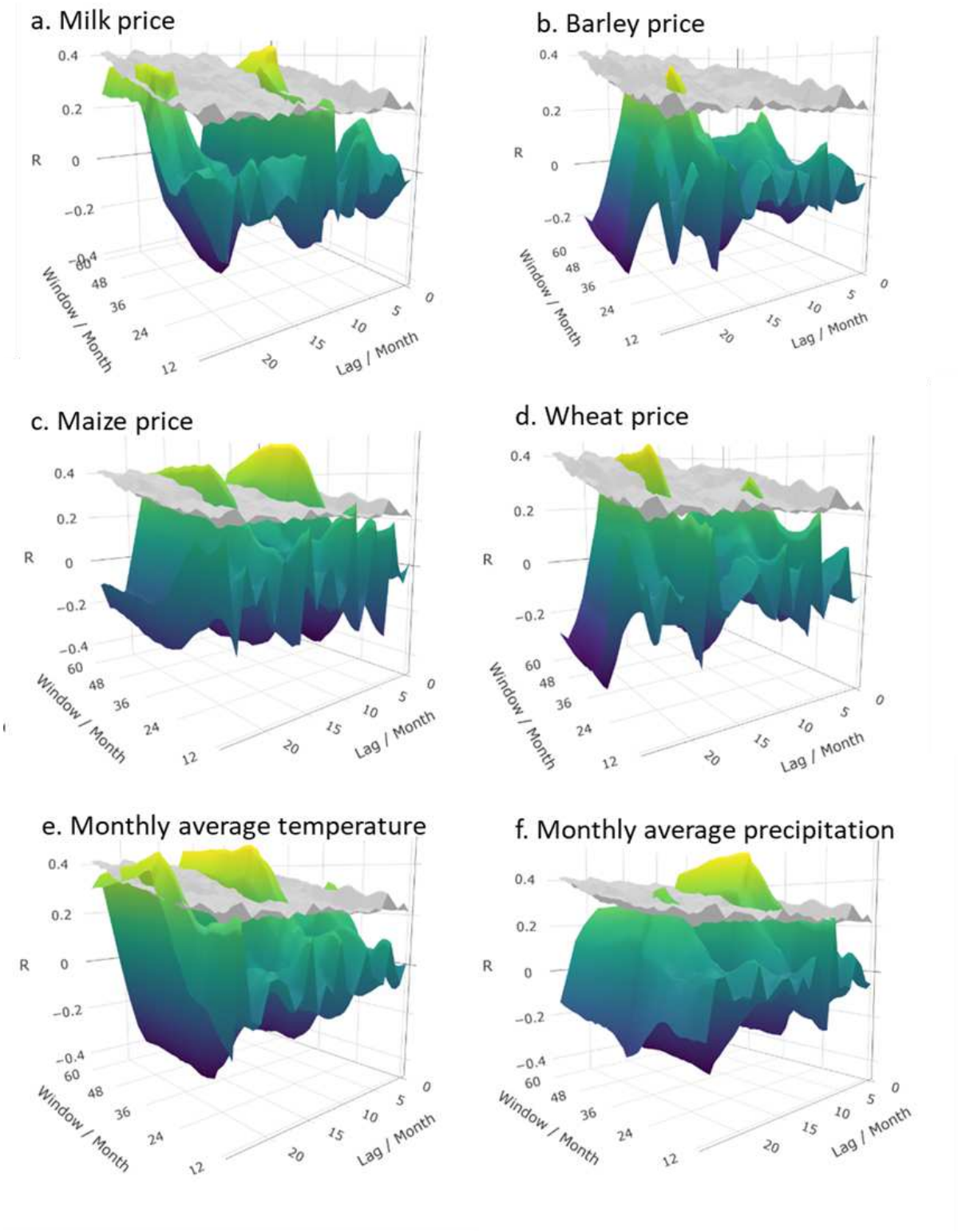
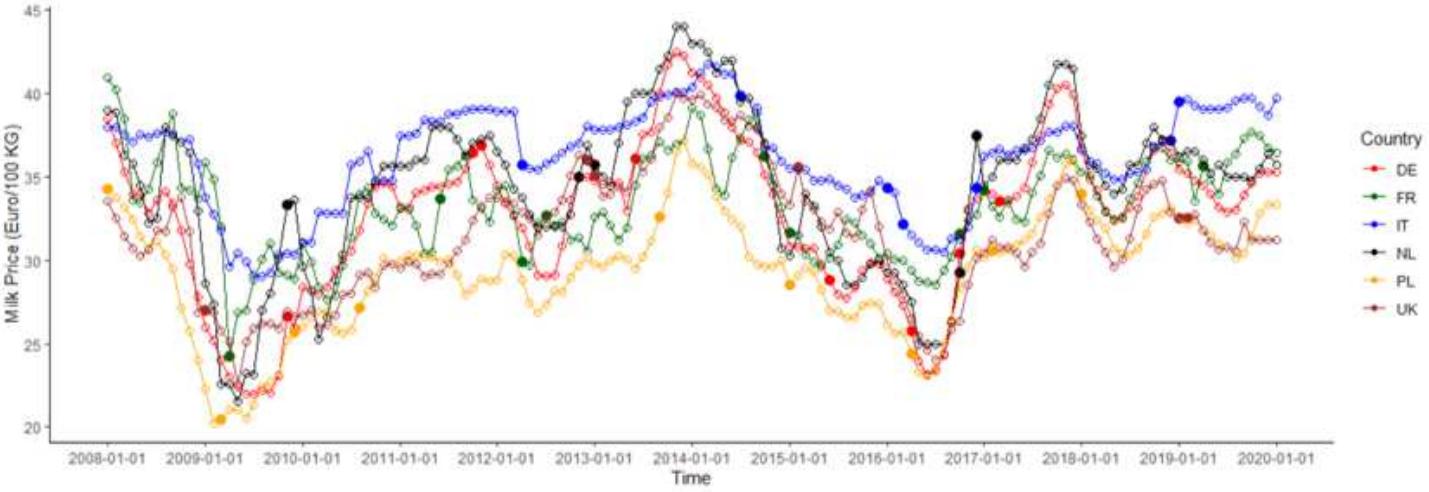


Figure 6

Cross correlation coefficient with different time lags and windows between KAP notifications and anomaly levels per indicator in the Netherlands. The threshold surfaces are coloured in grey.



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Milk price and detected anomalies in DE, FR, IT, NL, PL, UK from 2008 to 2019. The month when an anomaly is observed is indicated as a full circle.

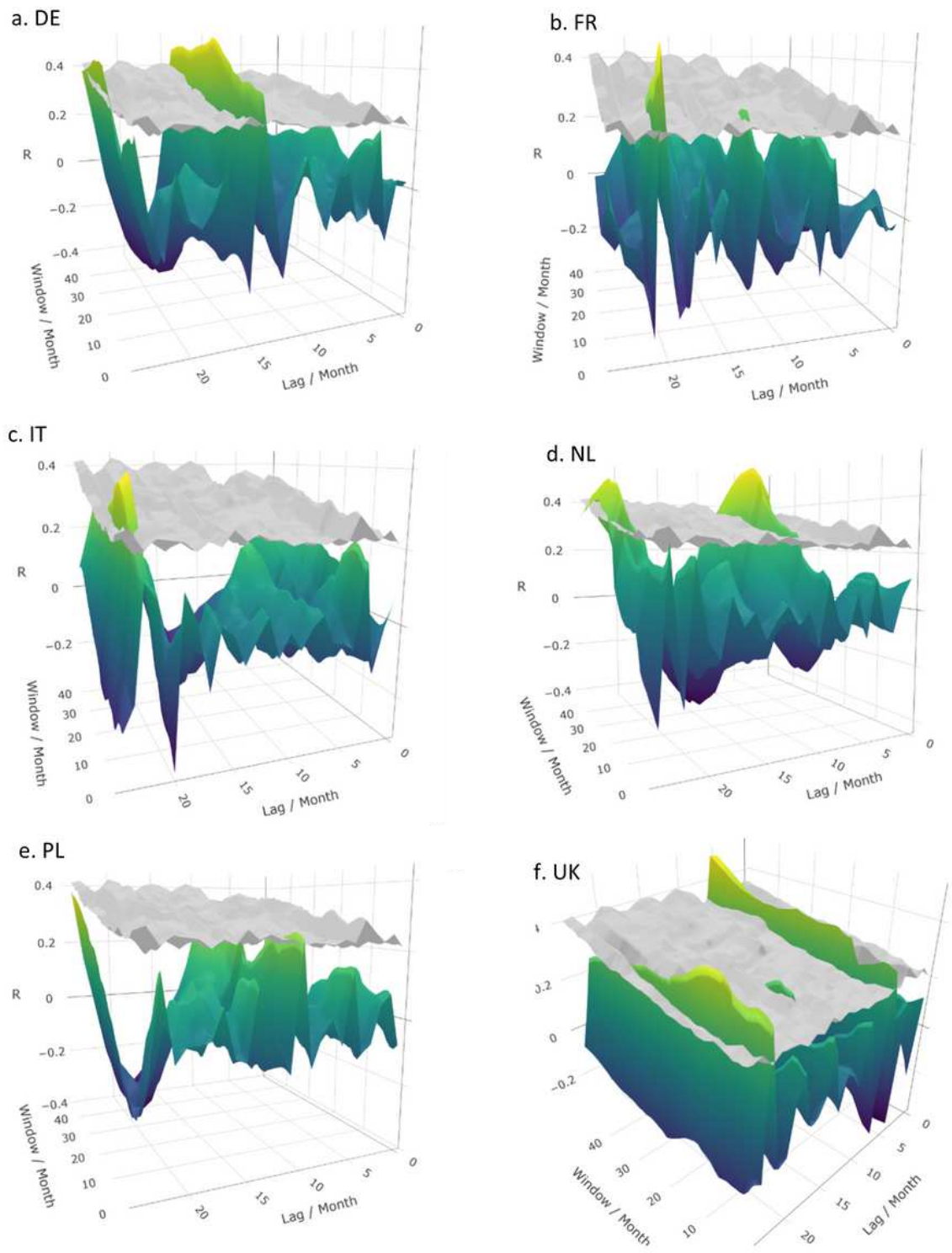

Figure 7

Cross correlation coefficient with different time lags and windows between RASFF notifications and anomaly levels of milk price in (a) Germany; (b) France; (c) Italy; (d) Netherlands; (e) Poland and (f) United Kingdom. The threshold surfaces are coloured in grey.

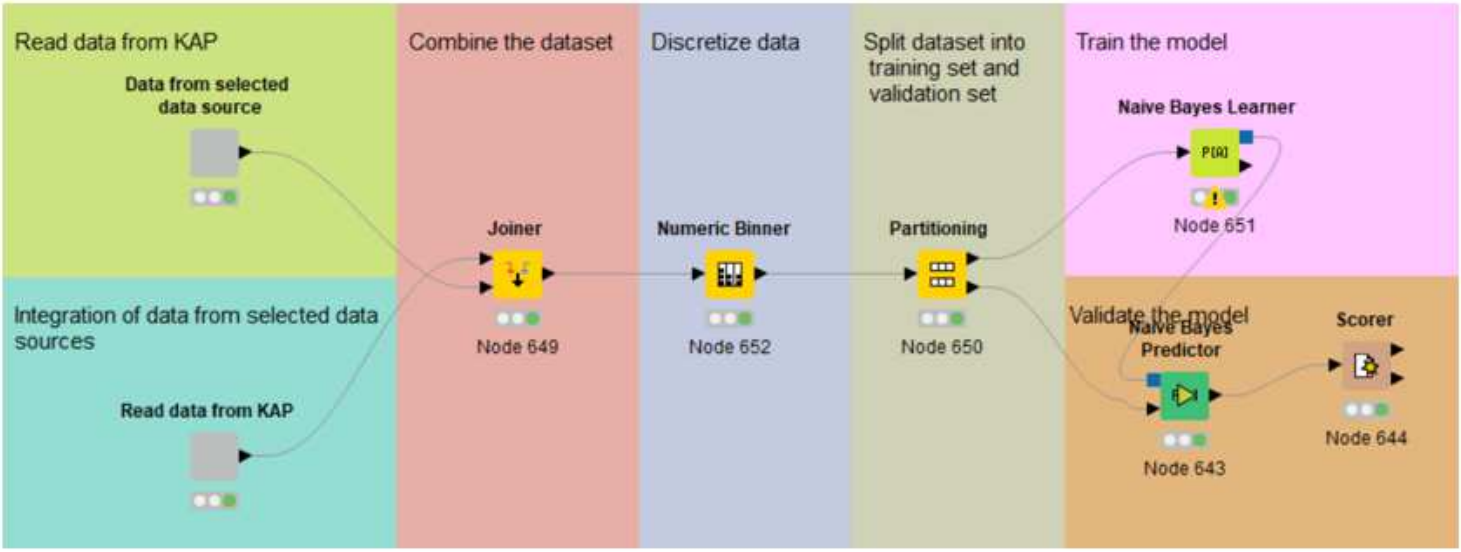

Figure 7

Workflow of Bayesian network model.

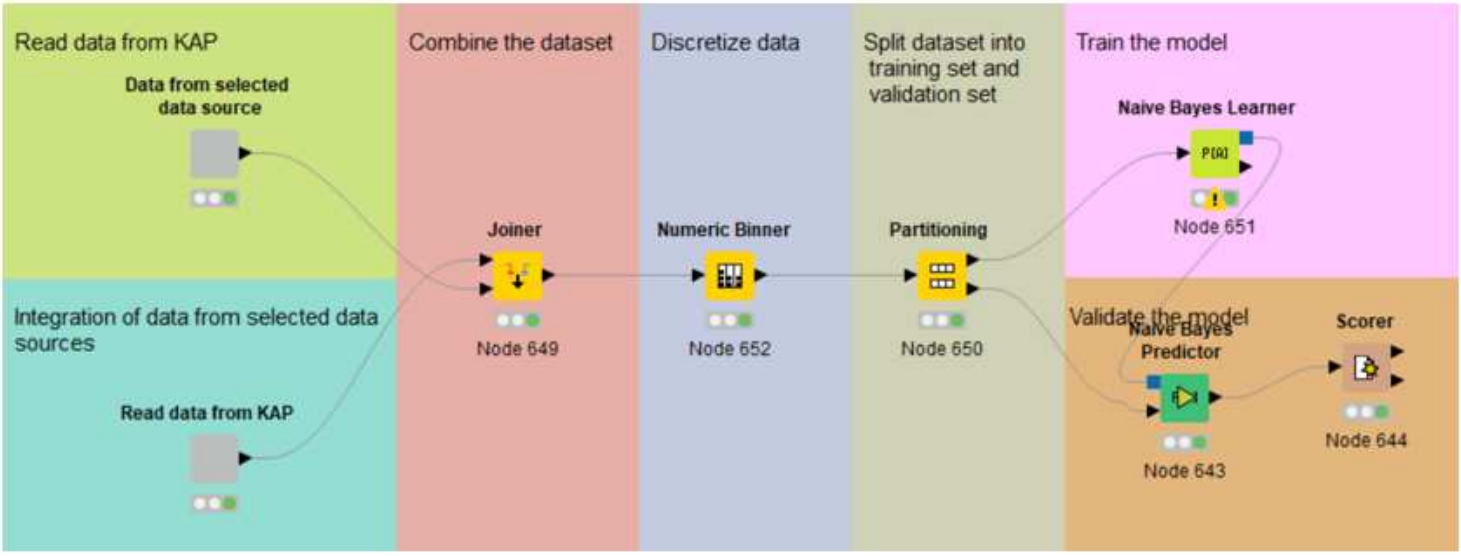

Figure 9

Workflow of Bayesian network model.