Process Safety and Environmental Protection 206 (2026) 108123

Contents lists available at ScienceDirect

Process Safety and Environmental Protection

journal homepage: www.journals.elsevier.com/process-safety-and-environmental-protection

From data to decision. AI powered proactive safety of landslide Natech events

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ARTICLE INFO

Keywords:
Climate change
Dynamic risk assessment
LPG storage
LSTM networks
Machine learning
Natech events

ABSTRACT

The increasing intensity and frequency of extreme weather events underscore the growing risk of natural hazards impacting industrial facilities. Natech (Natural Hazard Triggering Technological) accidents can be triggered by both major and minor environmental phenomena, such as heavy rainfall and landslides. Building on the concept that in the AI era, data can be transformed into valuable knowledge for anticipating risk conditions by feature extraction, this study presents a dynamic risk assessment framework integrating natural hazards with process safety models. The approach dynamically updates failure probabilities of safety barriers depending on landslide probability over time, offering a real-time perspective on risk evolution. A case study on an LPG (Liquefied Petroleum Gas) storage facility in a landslide-prone region in Italy illustrates the application and effectiveness of this methodology. The model leverages Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs) to predict landslide occurrences and their cascading effects on industrial safety. Findings of this study provide new perspectives on proactive risk management based on AI applications in Natech scenarios.

1. Introduction

Climate change, digitalization, and evolving industrial infrastructures have reshaped traditional engineering paradigms, amplifying Natech risks. The frequency and intensity of landslides, floods, and extreme weather events have significantly increased over the past decade, posing heightened threats to critical infrastructures (European Environment Agency, 2010). The Seveso III Directive acknowledges the role of natural hazards in industrial risk assessment, emphasizing the need for robust predictive models and mitigation strategies (Laurent et al., 2021). In 2009, a near-miss was caused by the earthquake of moderate magnitudo in L'Aquila (Italy), when three steel silos of the Vibac factory collapsed or suffered extensive damage. Since these silos were full of solid polypropylene beads, no emergency occurred due to their release. Nevertheless, the silos collided with an adjacent precast warehouse, damaging the concrete and harming severely pipelines and electricity cables. Even without serious consequences, the factory business was completely interrupted (Grimaz and Maiolo, 2010). Conversely, in 2009, heavy rains induced slope movements, causing damage and fracture of a methane pipeline, resulting in the release, explosion, and jet fire of the natural gas, and damaging nearby buildings (Totani et al., 2017). Recently, a refinery in Livorno (Italy) experienced flooding, resulting in the release of hydrocarbons into a creek and reaching the sea (The European Commission, 2017), evidencing how extreme natural events can imply safety barriers degradation and hamper emergency response measures. These examples underscore the need to effectively integrate natural hazard prediction with dynamic risk assessment frameworks to anticipate and mitigate potential industrial disasters (Ricci et al., 2023), adopting a multi-risk approach to a quantitative risk assessment of Natech scenarios due to a variety of major hazard events, such as explosion or fire and domino escalation effects. The efforts are commonly devoted to evaluating local-specific Individual Risk contours of fatality of workers and members of the public at chemical and process plants and their vicinity, due to the likelihood of natural hazard occurrences, such as lightning, earthquakes, volcanic eruptions, extreme temperature waves, and flood phenomena. Additionally, as exemplified in Fig. 1, the academic community has been reacting with an increasing number of publications on Natural Hazard

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https://doi.org/10.1016/j.psep.2025.108123
Received 2 July 2025; Received in revised form 3 November 2025; Accepted 4 November 2025
Available online 5 December 2025

Triggering Technological disasters all over the world and especially in Europe, where many installations at major accident risk are located in areas exposed to hydrogeological and other natural hazards. Albeit Italy has historically been afflicted by natural calamities, statistical data on extreme weather phenomena depicted in Fig. 2 evidence a notable intensification of such events in the last 10 years, over the whole national territory, and this trend is expected to increase in the future due to an increase in extreme weather conditions attributed to climate change. Landslides represent a high-impact, low-predictability phenomenon affecting regions like Liguria, Italy.

This paper, for the first time, at least to our knowledge, focuses on AI-based applications to landslide occurrences, a potential triggering event with a wide territorial spread in Italy, as well as in the Liguria Region. Generally speaking, landslides are phenomena characterized by low predictability and high impact. Understanding where and when landslides are likely to occur can help the decision-making process and risk management strategies. Nevertheless, predicting landslides can be a complex task because there are many factors that can contribute to their occurrence, including geological conditions, weather patterns, and human activities, and complex mechanisms are involved in the evolution of the phenomenon. It is recognized that in case of slow-moving landslides, particularly, probabilistic analysis must consider both historical and ongoing movements to attain mapping techniques and models capable of pinpointing areas at potential landslide risk (Fell et al., 2008). In Italy, rainfall-induced shallow landslides are the most common. These are particularly dangerous because they can occur suddenly and can spread rapidly. They are triggered by intense or prolonged rainfall, which causes the soil to become saturated with water, leading to a loss of strength in the shallow layers that become unstable. A number of factors are considered relevant in contributing to the occurrence of these landslides, including rainfall intensity and duration, soil type, slope steepness, and the presence of vegetation (Park et al., 2013). Landslide consequences can be significant, including infrastructure or plant damage, loss of life, and erosion. Due to the sudden and rapid occurrence of a slide, often, measures like people's evacuation and protective interventions are challenging. Additionally, when shallow landslides interact with built structures like roads and buildings, they can cause extensive damage, disrupt transportation, and have socio-economic impacts on communities (Petley, 2012). Both in the case of the undersea layout of crude oil pipeline (Ji et al., 2023; Mcnutt and He, 2019) and underground design (Vairo et al., 2017), notable landslides, or ground destabilization are regarded as potential Natech accidents suitable to causing oil pipeline bursting and major ecological implications and environmental harm.

Understanding the contributing factors to shallow landslides is crucial for mitigating risks and reducing their impact. Predicting landslides can be complex due to various factors, including geological conditions, weather patterns, and human activities. Referring to the mining environment, it is reported that due to the influence of self-weight, excavation unloading, rainfall, and other factors, a large amount of rock and soil may collapse and slide in a short period in open-pit mines, posing serious hazards to mining workers' lives and assets. In this context, Jiang et al. (2022) studied major accident prevention by adopting the GBRT (Gradient Boosted Regression Trees) algorithm and an AI-based approach to event data. In this regard, an effective landslide risk prediction method can reduce the occurrence of safety accidents in the production process (Khan et al., 2015). Predictive efforts involve analyzing geological data about land characteristics (soil type, slope, faults), weather patterns, and triggering events (rainfall intensity and duration).

The prediction of risk of slope instability was faced in many studies according to the perspective of physical properties of slopes, without accounting for the spatial and temporal effects of rainfall on the instability generation, e.g., utilizing a data-driven model based on gradient boosting (Zhou et al., 2019), or artificial neural network (Chakraborty and Goswami, 2017). Different prediction methods of occurrence combine observational or simulation methods, resulting in data using statistical or mathematical models. Expert knowledge and experience are also utilized to identify high-risk areas and develop mitigation strategies (Baum and Godt, 2010). Physically based models are considered highly effective for landslide prediction, as they simulate landslide behavior under different conditions and provide insights into their evolution. However, these models require extensive data and computational resources, limiting their application in large or complex landscapes and real-time analysis. Simplified physically-based models have been proposed to address this challenge, providing useful analyses over large areas, but still demanding specific data. Gallage et al. (2021) performed artificial rainfall on the slope model and assessed the evolution law of slope failure at different slope angles with the rainfall effect, validating their findings by Geo-Studio numerical simulation. Calibration and validation of physically based models are additional difficulties (Gatto and Montrasio, 2023). An alternative approach involves using physically based models in conjunction with statistical or empirical models based on observed data, allowing better understanding and higher prediction accuracy. As commented by Alsulieman et al. (2024), Dynamic Risk Assessment models in the oil and gas industry are recently replacing time-static models like fault tree, event tree or bowtie to better capture the real-time-dependent risk behavior of safety barriers. For Natech events, AI and machine learning techniques are utilized to analyze historical data of various weather-induced events. Such an

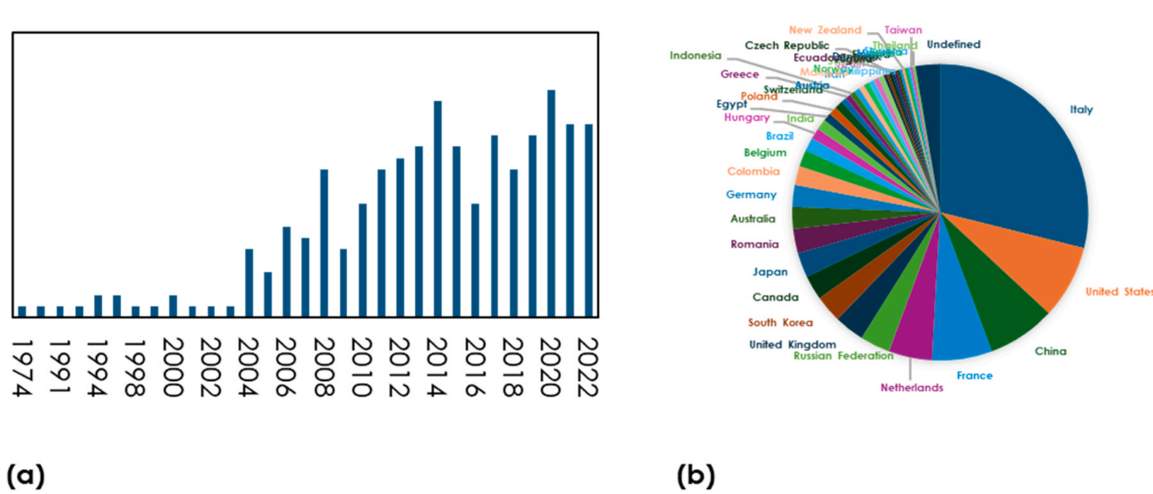

Fig. 1. (a) Number of published papers per year and (b) paper distribution over contributing countries. Scopus database. Query: Natech OR na-tech OR natural AND disaster OR natural AND hazard AND risk AND assessment OR analysis industrial AND accidents.

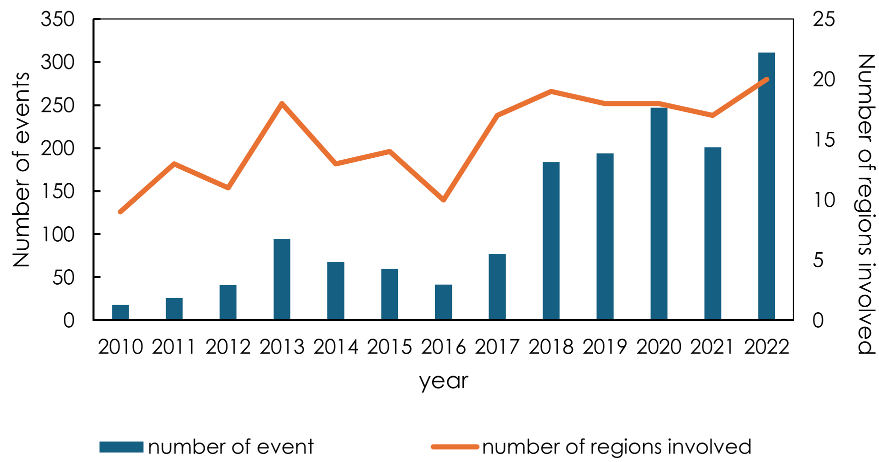

Fig. 2. Number of extreme events in Italy in the time span 2010–2022 and number of involved regions. Source: Osservatorio nazionale Città Clima (Osservatorio nazionale Città Clima, 2024).

analysis can also provide support in predicting future landslide occurrences, identifying high-risk areas, and understanding the impact areas for effective response and recovery efforts. Rainfall thresholds based on Bayesian probability and machine learning techniques have been proposed for landslide prediction (Berti et al., 2012; Dou et al., 2020; Huang, 2022). In a preliminary work (Vairo et al., 2023), applying a Gradient Boosting Decision Tree algorithm, a simplified model was proposed to predict shallow landslides. Due to limitations and underestimations found using the Gradient Boosting Decision Tree algorithm, the aim of this study is to develop an AI predictive model based on LSTM Recurrent Neural Networks (Hochreiter and Schmidhuber, 1997), as a novel, reliable approach to the early prediction of shallow landslides. LSTM avoids back-flow errors as in other AI methods. Applied to chemical process fault detection, Cen et al. (2023) developed a method reducing noise by principal component pursuit resulting in a low rank matrix to follow better trends in data, and then applied optimized LSTM extracting dynamic time series features of sensor data, while support vector data description is used to detect faults. Based on bowtie methodology Sarvestani et al. (2021) modeled the decrease of safety of storage installations over time, resulting in dynamic accident consequence risk prediction of LPG storage tanks.

Following the above approaches, in landslide-prone areas probability prediction results over time can form the basis of a dynamic risk assessment framework to provide early warnings for major accident hazards.

The novelty of this work lies in:

1. Direct coupling of an LSTM model with a probabilistic safety model, enabling scenario-specific risk updates.
2. Application to shallow landslides, which are underrepresented in Natech risk literature.
3. Real-time adaptability, moving beyond static QRA to support dynamic safety decision-making in industrial contexts.

2. Theoretical framework and methodology

2.1. Landslide prediction models

As mentioned, landslides result from complex interactions between geological, meteorological, and anthropogenic factors. Physically based models, such as those relying on the Richards equation for soil water movement, provide a fundamental understanding of slope instability but require extensive parameter calibration (Schilirò et al., 2023, Fredlund et al., 1978, Berardi et al., 2005). Empirical models, particularly those employing machine learning techniques, offer data-driven insights into landslide occurrences based on historical patterns. Bayesian probabilistic approaches (Berti et al., 2012) have been widely used for landslide risk quantification, yet their effectiveness depends on the quality of prior distributions and available datasets, while effective pre-processing serves as the bridge between physical insight and machine learning. Probabilistic Bayesian approaches are useful for predicting landslides and other events, even though it is essential to carefully consider the limitations of these approaches and employ them alongside other models and data to attain a comprehensive understanding of the phenomena under study.

One potential drawback of probabilistic Bayesian approaches for landslide prediction is their reliance on the assumption that the data used to build the statistical model is representative of the specific situation being investigated. If the data is biased or incomplete, the model results may be unreliable. Additionally, probabilistic Bayesian approaches can be sensitive to errors or uncertainties, hence noise, present in the data used for model construction. Noisy or erroneous data may result in less reliable model outcomes.

To enhance predictive capabilities, this study adopts LSTM networks, a class of RNNs designed for processing sequential data and capturing long-term dependencies. This facet makes them well-suited for capturing complex relationships in landslide prediction, where the temporal dynamics and interactions between variables play a crucial role.

The training process of an LSTM network involves optimizing the network's parameters to minimize the difference between its predictions and the actual landslide occurrences (Hochreiter and Schmidhuber, 1997). The optimization is not achieved through conventional backpropagation, as in other neural networks, where the error signals are propagated backward through time go astrayed, but in LSTM, allowing the network to update its internal state and adjust its predictions by an iterative gradient-based learning algorithm. By subsequent tracking from past occurrences and their corresponding variables, the LSTM network can discern patterns and relationships that aid in landslide prediction.

2.2. Dynamic Natech risk assessment

A comprehensive dynamic risk assessment integrates real-time environmental data into probabilistic safety models. This study employs a Bayesian network (BN) approach, updating probabilities dynamically as new evidence arises. By linking LSTM-based landslide predictions with a BN mapped from a bowtie risk model, we developed a real-time adaptive framework for industrial safety management.

The bowtie (BT) model is a well-established graphical tool in risk analysis that visually connects:

- Initiating events on the left side (fault tree structure).
- Top Events.
- Consequences on the right side (event tree structure).

In traditional QRA (quantitative risk assessment), probabilities within the bowtie are typically static, derived from historical frequencies or expert judgment (Vairo et al., 2022). Conversely, the increase or decrease of these probabilities produces real-time or predictive inputs, which here are the LSTM-derived landslide hazard forecasts. Event probabilities given a landslide down the bowtie are updated on the landslide forecast.

The LSTM model, as detailed in the following Section 2.4.1, outputs a landslide hazard class prediction (from Class 1–7). This prediction is not a binary result but a probability distribution across the seven classes (softmax output).

On these bases, LSTM outputs are used to:

- Update the prior probabilities of the bowtie events (e.g., probability of slope movement).
- Adjust the conditional probabilities of process equipment degradation or failure, barrier failure, or escalation nodes using Bayesian inference solved by applying Markov Chain Monte Carlo, as a function of the severity class predicted.
- Propagate these updates throughout the BN, leading to an updated posterior distribution of the Top Event and associated accident scenarios.

The workflow of the developed framework is schematized in Fig. 3.

2.3. An Italian Case Study: LPG Storage Facility in Liguria

The selected case study involves an LPG storage facility located in Imperia; Italy (Fig. 4), a region highly susceptible to rainfall-induced landslides. The site comprises pressurized storage tanks, pipeline connections, and automated safety systems. The primary Natech risks include:

- Structural failure due to landslide-induced mechanical stress
- Pipeline rupture and gas release leading to fire and explosion hazards
- Control system failures disrupting emergency shutdown procedures

By integrating real-time landslide forecasts into the risk model, the evolving probability of loss-of-containment scenarios are assessed, and dynamic risk mitigation strategies can be proposed.

The interest in such kinds of facilities is evident, also considering a well-known comparative study on QRA approaches to determine third-party risks of an LPG plant used by the four European partners, and the spreading of obtained results to be used for land use planning and licensing (Gooijer et al., 2012). Natech risk assessment entails the examination of the probability and potential consequences of natural hazards and technological disasters, including earthquakes, landslides, and industrial accidents.

2.4. Methodology

The LSTM model was developed specifically for early prediction of landslide hazard levels, with the goal of providing actionable input for dynamic Natech risk assessment frameworks. Rather than using the model for generic landslide susceptibility mapping, it was applied to produce daily predictions of hazard severity levels, which were directly integrated into a Bayesian bowtie risk model. This strategy enables dynamic adjustment of the probability of technological failures at the LPG storage facility, based on environmental precursors as a function of time.

2.4.1. Long-short term memory networks (LSTM)

The LSTM-RNN computation sequence is described as mentioned before, applied to the landslide observations.

An LSTM unit consists of several components (Sherstinsky, 2020):

- The *Cell State (C)* acts as a memory component and carries information over time. It allows LSTM to capture and remember long-term dependencies in the input sequence.
- Three types of gates are considered in developing the model, namely:
- *Input Gate (i)*, which determines how much new information should be stored in the cell state and it is responsible for deciding which parts of the input are relevant and should be added to the cell state.

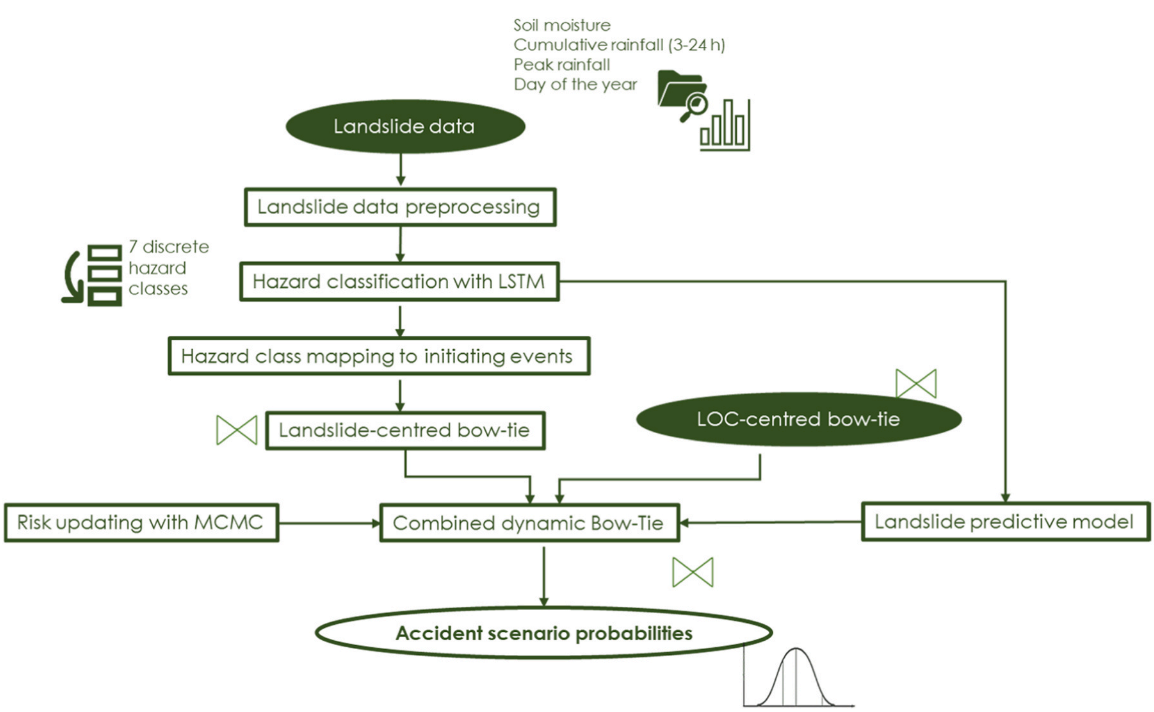

Fig. 3. Flowchart of the AI enforced methodology.

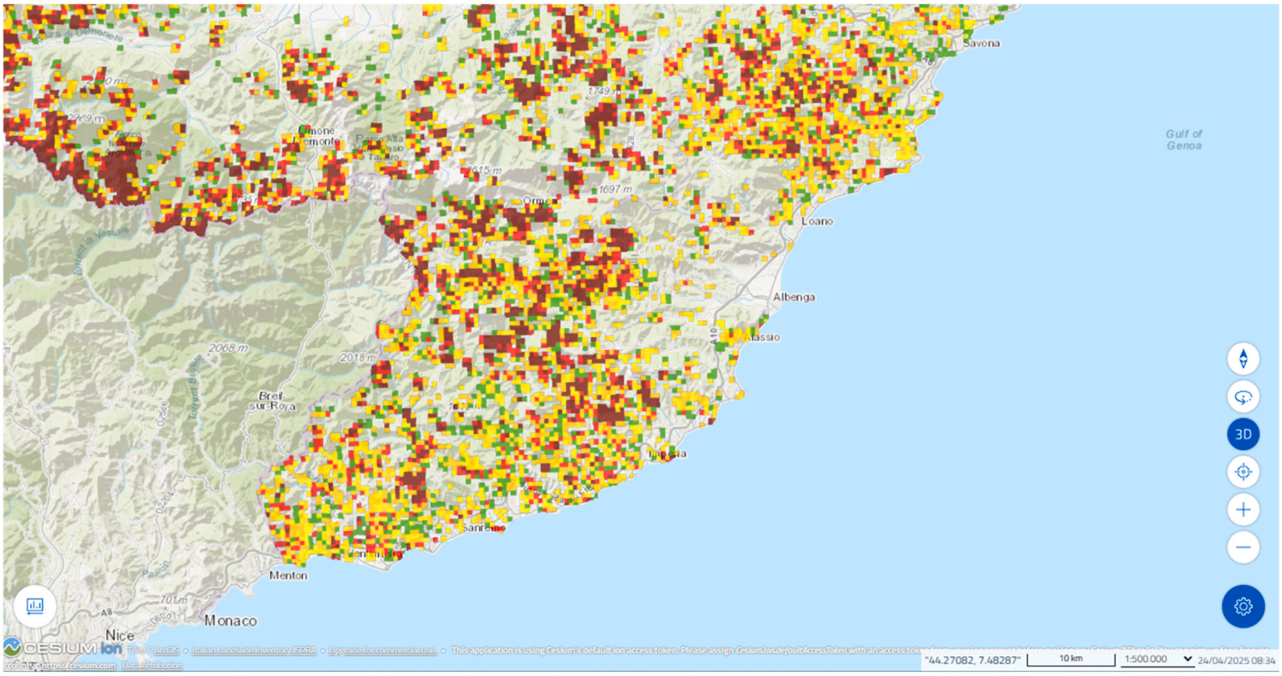

Fig. 4. Inventory of landslides in Italy (Project IFFI- Inventario dei Fenomeni Franosi), realized by ISPRA (Institute for environmental research and protection) and the Regions and Autonomous Provinces. Focus on the western region of Liguria (province of Imperia, Italy). In Fig. 4, the different pixel colors correspond to the spatial density of recorded landslides (dark red – higher density, to green – low density).

- *Forget Gate (f)*, determining how much information from the previous cell state should be discarded, thus allowing LSTM to forget irrelevant information from the past.
- *Output Gate (o)*, which determines how much information from the cell state should be exposed as the output. It regulates the output based on the current input and the cell state.
- The *Candidate Activation (g)* calculates a new candidate value that can be added to the cell state. It combines the current input with the previous hidden state and passes it through a non-linear activation function, usually the hyperbolic tangent (tanh) function.
- The logic procedure developed for the conceived LSTM unit can be summarized as follows:
- Calculation of the input gate (i) by applying a sigmoid activation function to a linear transformation of the input and previous hidden state.
- Calculation of the forget gate (f) by applying a sigmoid activation function to a linear transformation of the input and previous hidden state.
- Calculation of the output gate (o) by applying a sigmoid activation function to a linear transformation of the input and previous hidden state.
- Calculation of the candidate activation (g) by applying a tanh activation function to a linear transformation of the input and previous hidden state.
- Updating the cell state (C) by combining the previous cell state with the new candidate activation and input/forget gates.
- Computing the hidden state (h) by applying the output gate to the cell state passed through a tanh activation function.

A schematic logic diagram for the designed LSTM approach is depicted in Fig. 5.

In Fig. 5, input data are denoted as X, where X has dimensions $(batch\_size, sequence\_length, input\_features)$. Since in the developed model X_train and X_test were reshaped to have dimensions ($batch\_size$, 1, 8), the sequence length is 1 and the number of input features is 8.

The LSTM layer performs computations on the input sequence and captures long-term dependencies. It consists of LSTM units, and each unit has multiple components, including a cell state and three gates (input, forget, and output gate). The designed LSTM layer performs the described computations for each input timestep, according to the sequence provided by Eqs. (1–6):

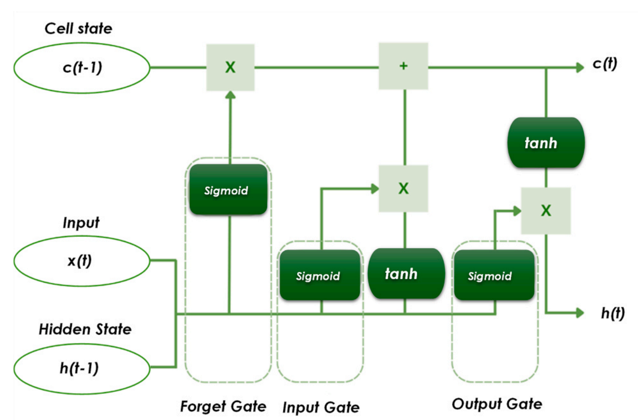

Fig. 5. LSTM architecture. Adapted from Shailendra et al. (2023).

Computation of the input gate (i_t):

$$i\_t \quad = sigmoid(W\_i{\cdot}X \quad + \quad U\_i{\cdot}h\_\{t-1\} \quad + \quad b\_i) \tag{1}$$

Where: W_i and U_i are weight matrices, X is the input, $h\_\{t\text{-}1\}$ is the previous hidden state (initially set to 0), and b_i is the bias vector.

Computation of the forget gate (f_t):

$$f\_t \quad = sigmoid(W\_f{\cdot}X \quad + \quad U\_f{\cdot}h\_\{t-1\} \quad + \quad b\_f) \tag{2}$$

Computation of the output gate (o_t):

$$o\_t \quad = sigmoid(W\_o{\cdot}X \quad + \quad U\_o{\cdot}h\_\{t-1\} \quad + \quad b\_o) \tag{3}$$

Computation of the candidate cell state (g_t):

$$g\_t \quad = \tanh(W\_g{\cdot}X \quad + \quad U\_g{\cdot}h\_\{t-1\} \quad + \quad b\_g) \tag{4}$$

Updating the cell state (C_t) :

$$C\_t \quad = \quad f\_t \quad \odot \quad C\_\{t-1\} \quad + \quad i\_t \quad \odot \quad g\_t \tag{5}$$

where $\odot$ denotes element-wise multiplication.

Finally, computation of the hidden state (h_t) is performed, according to Eq. (6):

$$h\_t \quad = \quad o\_t \quad \odot \tanh(C\_t) \tag{6}$$

After the LSTM layer, a Dropout layer is applied to prevent overfitting. Dropout randomly sets a fraction of the LSTM units to 0 during training. The next layer is a Dense layer with 500 units and ReLU (Rectified Linear Unit) activation function. The ReLU activation function is a non-linear activation function used in neural networks, including the LSTM model.

ReLU is defined by Eq. (7).

$$f(x) \quad = \max(0, \quad x) \tag{7}$$

For any input value x, ReLU returns 0 if x is less than or equal to 0, and it returns x itself if x is greater than 0.

At last, the output Dense layer with softmax activation function produces the final predictions. The number of units in this layer is equal to the number of classes in the output.

The softmax function is a commonly used activation function in neural networks, particularly in multi-class classification problems, which allows ensuring that the predicted probabilities sum up to 1. It is often applied to the output layer of a neural network to convert the raw output values into a probability distribution over multiple classes. The softmax function takes a vector of real numbers as input and transforms it into a probability distribution, for each element in the input vector, according to Eq. (8).

$$softmax(x[i]) \quad = \quad e^{\quad x[i]} / sum(e^{\quad x[i]})) \mathrm{for} j \mathrm{in} range(num\_classes) \tag{8}$$

where $x[i]$ is i-th element of the input vector and $num\_classes$ is the total number of classes.

The softmax function exponentiates each element of the input vector and then normalizes the resulting values by dividing them by the sum of all exponentiated values. As anticipated, the normalization ensures that the output probabilities sum up to 1, making them suitable for representing the relative likelihoods of different classes.

During the training step, the model uses the categorical cross-entropy loss function to compare the predicted probabilities with the true labels and optimize the model's parameters using the Adaptive Moment Estimation (Adam) optimizer (Kingma and Ba, 2017). In order to test the predictive ability, the accuracy of the model is evaluated by means of the categorical cross-entropy, a loss function commonly used in multi-class classification problems that accounts for the dissimilarity between the predicted probability distribution and the true probability distribution of the target classes.

In neural networks and deep learning, categorical cross-entropy is used to optimize the model's parameters during training (Hochreiter and Schmidhuber, 1997). The goal is to minimize the cross-entropy loss, which indicates how well the predicted probabilities align with the true class labels, according to Eq. (9).

$$crossentropy = \quad -\sum y_{true} * \log(y_{pred}) \tag{9}$$

where y_{true} is true probability distribution of the classes (one-hot encoded vector) and y_{pred} is predicted probability distribution of the classes.

The loss value is calculated for each sample in the training data, and the overall loss is computed as the average or sum of these individual losses.

By minimizing the categorical cross-entropy loss, the model learns to improve its predictions and assigns higher probabilities to the correct classes, while reducing the probabilities for incorrect classes. In the developed model, the categorical cross-entropy loss function is used in the model compilation step. The model is optimized to minimize the categorical cross-entropy loss using the specified Adam optimizer in the proposed model during the training process. The Adam algorithm, selected for its fast convergence, robustness to noisy gradients, and efficient memory usage, maintains a learning rate for each parameter in the model, which is adapted based on the estimate of both the first-order moment (the average of gradients) and the second-order moment (the average of squared gradients) and combines the benefits of two other popular optimization algorithms, AdaGrad and RMSprop.

The accuracy of a model is typically evaluated by comparing its predicted outputs to the true labels or values in the dataset. In classification problems, accuracy represents the proportion of correct predictions made by the model out of the total number of predictions, allowing for determination of its overall predictive capability:

$$Accuracy = \quad \frac{number\ of\ correct\ predictions}{total\ number\ of\ predictions} \tag{10}$$

2.4.2. Sample collection and dataset description

The training samples were derived from a dataset provided by ARPAL (the regional agency for Liguria environmental protection) covering daily meteorological and landslide reports for the entire Imperia province (Liguria, Italy) between 2014 and 2019. Daily entries include:

- Soil moisture (from in situ sensors).
- Accumulated rainfall over 3, 6, 12, and 24 h.
- Peak rainfall over 3 and 24 h.
- Calendar day of the year (to account for seasonal variability).

The dataset used in this study mainly contains rainfall and soil moisture data, which represent the most significant triggering and predisposing factors for shallow rainfall-induced landslides in Liguria. It must be evidenced that other variables (e.g., slope angle, soil type, vegetation, land use) are not systematically recorded across the whole region, so that to the purpose of this study, the proposed methodology focused on meteorological triggers.

Landslide occurrence data (target labels) were extracted from recorded shallow landslide events, georeferenced, and categorized by severity. Out of 2191 total days, only 365 days included landslide events, confirming class imbalance. As summarized in Table 1, to obtain more homogeneous classes, a seven-class hazard scale was adopted, ranging from small (0–1 events) to very high hazard (14 + events). Soil moisture serves as the predisposing factor, while the cumulated and peak rainfalls serve as the triggering factors. It is important to note that due to the lack of precise knowledge regarding the exact time of landslide occurrence, the cumulated and peak rainfall data are calculated from 00 UTC and cover the entire day.

The classification into seven hazard levels (Table 1) is directly based on observed daily frequency of events in the dataset. The classification is adapted from Berti et al. (2012) and Park et al. (2013).

The data were randomly partitioned into training (70 %), validation (15 %), and testing (15 %) subsets. This prevents overfitting and ensures that accuracy values are not inflated by reusing data across groups.

The adopted methodology can be summarized in the following

Table 1
Classification of landslide events.

Class (Label)	Hazard level	Nr events
1	Small	0–1
2	Moderate	2–3
3	Moderate-medium	4–5
4	Medium	6–7
5	Medium-high	8–11
6	High	12–14
7	Very high	14 +

phases:

1. Landslide Prediction Using LSTM-RNNs
   - *Input features*: Soil moisture, cumulative rainfall (3–24 h), peak rainfall, day of the year.
   - *Training data*: 6-year dataset from ARPAL (2014–2019).
   - *Classifications*: Landslide events categorized into seven hazard levels.
   - *Evaluation*: Categorical cross-entropy loss and accuracy metrics.
2. Dynamic bowtie risk assessment
   - *Integration* of LSTM predictions with Bayesian network-based risk analysis.
   - *Failure probabilities* updated based on Bayesian inference by means of Markov Chain Monte Carlo sampling, resulting in dynamical landslide occurrence probability in a selected region and for the various hazard classes.
   - *Sensitivity analysis* conducted to assess the impact of different hazard levels on accident scenarios.

3. Results and discussion

To test the actual capability of the outlined framework, the assessment of Natech risk for an LPG storage facility in a landslide-sensitive zone was performed. For predicting the Natech accidental scenarios and taking the corresponding risk reduction measures, the relevant point is understanding the interaction between natural forces and the technological sites by evaluating:

- how the Adversity (i.e., the landslide) affects the System;
- how the System (i.e., the LPG storage facility) when subjected to the Adversity, delivers the Capability of interest;
- what is the quality of the Delivered Capability compared to the Required Capability (i.e., the system safety).

The Natech hazard identification was conducted by means of a What-if analysis and the preliminary findings of Vairo et al. (2023), obtaining the results summarized in Table 2.

Being the bow–tie modelling approach an emerging area already in use in the majority of chemical process industries and recently extended with reliable results to other fields of investigation (e.g. Turner et al., 2022; Ferrari et al., 2024), in this work the above-mentioned information was applied to design a novel landslide bowtie structure, allowing for dynamic risk assessment informed by LSTM-predicted hazard levels, account for both preventive and mitigative intervention strategies. The landslide initiating events (hazard classes, in Table 1) were used to determine the landslide triggered events, by means of a bowtie. The landslide triggered events are then used as initiating events in the Natech bowtie schematized in Figs. 5,6. It should be noted that landslide can induce Natech scenario, either by direct damage of the storage system or by a degradation mechanism acting on the safety system or on safety barriers in place. In this regard, the importance of correct integration of barrier management and QRA was recently demonstrated in peculiar application, evidencing the attained risk reduction in terms of specific accident scenarios by effective barrier maintenance (Yuan et al., 2023). In the proposed dynamic framework, Natech precursors are derived from a combination of real-time environmental measurements and weather forecast data. These inputs—primarily rainfall intensity, soil moisture, and seasonal factors—are processed by the LSTM model to predict the likelihood and severity class of a landslide event. The output is a probabilistic precursor signal that informs the dynamic updating of initiating event probabilities in the Bayesian bowtie model. This integration ensures the system is responsive to evolving environmental conditions, supporting timely decision-making.

The proposed bowtie is conceived as a combination of two bowtie models.

Specifically, the left side integrates not only initiating causes (e.g., equipment or barrier failures), but also the environmental trigger of those causes, namely the landslide occurrence predicted by the LSTM model.

The selected structure allows developing a chained bowtie, where the first bowtie represents the natural hazard, it is centered in the landslide event and links the landslides precursors to the failure / degradation in the system leading to the initiating events. The outcomes from the first part are directly integrated into the second bowtie representing the technological system (LPG facility failures and consequences), as shown in Fig. 6.

The landslide hazard classes serve as precursor events, dynamically updating the initiating event probabilities of the Natech bowtie. This combined representation goes beyond a standard fault/event tree representation, i.e., it can provide a comprehensive risk model that explicitly captures the linkage between natural hazard precursors and process safety initiating events, thus updating the overall risk profile.

The causes of, e.g., an LPG loss of containment, identified by the hazard analysis, are:

- Rupture of a pipe on a pressurized storage system
- Sudden catastrophic failure of vessels
- Failure of an excess flow control valve on demand
- Failure of an automatic shutoff valve to close
- Failure of a level/flow sensor.

Table 2
Landslide triggered events on an LPG storage facility. Adapted from Vairo et al. (2023).

Off-site event	Operator error	Abnormal load	Failure	Management	Loss of service	Triggered initiating event	Consequences
Landslide	• Containment degraded. • Failure to respond correctly to an alarm.	• Internal temperature or pressure outside design limit. • Pressurization / under pressure	• Safety system degraded. • Control system degraded. • Containment system degraded.	• Inadequate materials or specifications. • Hidden defects in containment system. • Failure to detect dangerous situations. • Failure of process controls.	• Loss of cooling water / nitrogen. • Loss of compressed air	• Rupture of pipe on a pressurized storage system • Sudden catastrophic failure of vessels • Failure of an excess flow control valve on demand • Failure of an automatic shutoff valve to close • Failure of a level / flow sensor	• Catastrophic failure - fireball and flash fire or pool fire. • Localised failure of a pressure vessel – jet flame and flash fire and possible explosion. • Pipe failures • BLEVE of vessels • Vaporiser leak jet fire, flash fire, and explosion. • Leak inside cylinder filling plant - confined explosion.

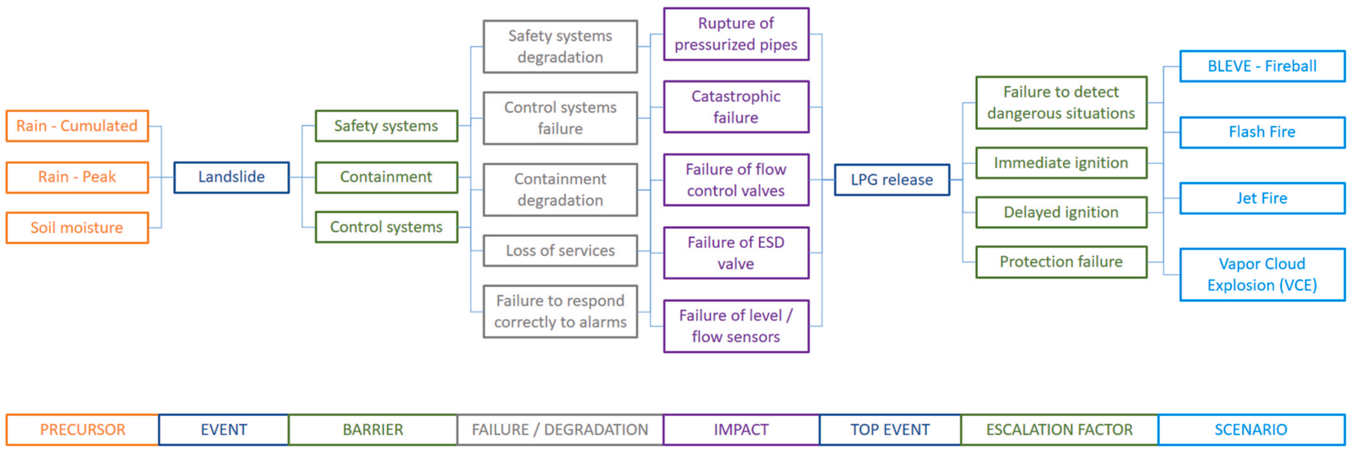

Fig. 6. Combined bowtie from initiating precursor events producing a landslide, which causes failures of alarm/control systems, as well as functional degradation of safety systems and assets. This can lead to equipment failure events, and to a loss of containment top event resulting through escalation events in major hazards, covering different Natech scenarios.

3.1. Landslides prediction

The model prediction accuracy is evaluated using the confusion matrix approach, which provides detailed information about the model's performance in terms of true positive, true negative, false positive, and false negative predictions. From the confusion matrix, the true positive rate (TPR) and false positive rate (FPR) can be calculated to assess the model's performance. The TPR, also referred to as sensitivity or recall, is computed on the one hand by dividing the number of correctly predicted positive cases by the total number of positive cases in the dataset. On the other hand, the FPR is obtained by dividing the number of incorrectly predicted positive cases by the total number of negative cases in the dataset. These metrics help to gain insights into the model ability to correctly identify positive cases, while minimizing false negatives, which would have a noticeably higher impact than false positives. Fig. 7 presents the confusion matrix, providing an immediate visualization of the LSTM model predictive performance on landslides occurrence. As previously mentioned, the predictive model was optimized to reduce false negatives, i.e., missed predictions of landslides, or underestimated impact. From the already mentioned Fig. 7, it can be argued that that there are no false negatives (the upper right-hand side of the matrix is all zeros), while there are a few overestimates; in particular, two class 1 events were predicted as class 3 and 4 events, and one class 4 event was predicted as class 6.

The LSTM model shows high predictive accuracy, globally attaining a loss of 0.098 and an accuracy equal to 98.67 %.

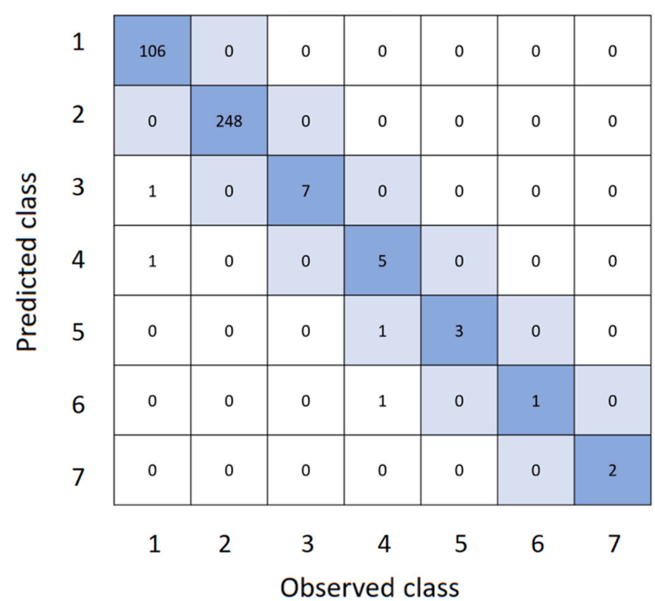

Fig. 7. Confusion matrix.

3.2. Dynamic risk model

In the following, the results of dynamic risk assessment in the explored context are provided, firstly without accounting for Natech precursors.

The dynamic risk assessment procedure, which follows the framework depicted in sub-Section 2.2, is as follows.

1. **LSTM Forecast**. Predicts the likelihood of landslide severity class (e.g., Class 4: Medium hazard).
2. **Trigger Event Update**. The predicted landslide class is mapped to initiating events. Each class adjusts the likelihood of these initiating events.
3. **Barrier Performance Update**. Higher hazard classes may also increase the chance of safety system functional degradation (e.g., instrumentation malfunction, power loss, and other utilities).
4. **Bayesian Inference** using Markov Chain Monte Carlo derives a posterior failure distribution from a prior one and a landslide likelihood. Substituting posterior probabilities in the respective BN nodes (mapping the bowtie structure) updates its joint probability distribution. Resulting probabilities are computed for:
   - Top Event (LPG release)
   - Escalation events
   - End scenarios
5. **Decision Support Output**. If the posterior probability of a high-severity accident and major hazard (e.g., BLEVE) exceeds a credibility threshold (10^{-6}), alerts or emergency responses shall be initiated.

The risk quantification used Markov Chain Monte Carlo sampling to propagate uncertainty in barrier failures and escalation factors, as indicated in the causal structure of the Bayesian bowtie (Fig. 6).

All probabilities, including those associated with causes, barrier failures, escalation factors, and the top event, are expressed as annual values, in line with standard practices in Quantitative Risk Assessment (QRA). The threshold value of 1×10^{-6}/year, referenced in the discussion, corresponds to the commonly accepted individual risk acceptability criterion in many regulatory frameworks (e.g., Seveso III

Directive and international QRA guidelines).

The landslide hazard classification (Table 1) is based on the number of landslide events per day within the six-year dataset covering the province of Imperia (2014–2019). Each day was labeled according to the number of reported landslide occurrences in the region, leading to seven discrete hazard classes. The model, therefore, performs a daily hazard classification.

To integrate it with the annualized risk framework of the dynamic Bow-Tie, the following methodology was adopted:

1. Hazard Prediction Basis: The LSTM model outputs a predicted hazard class for each day, effectively classifying the expected severity of landslide occurrence on a daily basis.
2. Initiating Event Linkage: These hazard classes are mapped to initiating events in the dynamic Bow-Tie. For example, a predicted class 2 event may correspond to a moderate slope movement with potential to degrade containment systems.
3. Annualization Process: To convert these discrete daily hazard class predictions into annual initiating event probabilities:
   a. The annual frequency of each hazard class is estimated from the historical dataset. For instance, if hazard class 2 occurred on 30 days across six years, this implies an observed frequency of 5 events/year.
   b. For each class, we define a class-specific initiating event probability, which reflects both the annual frequency and the conditional likelihood that such an event triggers a technological impact (e.g., barrier degradation or containment failure).
   c. This initiating event probability is used in the Bow-Tie structure as the input to the fault tree for the Natech scenario.
4. Dynamic Updating: When the LSTM model predicts a specific class on a given day, the model dynamically updates the prior (baseline annual) initiating event probability with a posterior probability that incorporates the forecast. This approach is aligned with Bayesian updating principles, where the predicted hazard class serves as evidence to revise the risk profile.

Table 3 summarizes the expected values of the annual frequencies for each event in the accident chain, which are considered, in the Bayesian Network of the Dynamic bowtie, as random variables with associated Probability Density Functions (PDFs).

These frequencies, typically expressed as failures per year in conventional Quantitative Risk Assessment (QRA), are converted into probabilities over a defined time horizon and embedded as prior distributions in the network. When a landslide prediction is produced by the LSTM model, indicating a certain hazard class, this new evidence serves as a **precursor** that updates the initiating event probabilities and propagates throughout the network using Bayesian inference. Here, the prior annual frequencies (e.g., 2.01E-07 for pipe rupture) are updated using Bayes theorem, with the likelihood of a class 2 hazard prediction, yielding posterior expectations (e.g., 1.55E-07).

This mechanism dynamically adjusts the likelihood of barrier failures, top events, and consequences, reflecting the changing risk profile under forecasted conditions.

The shift in probabilities expected values reflects how forecasted environmental threats (from LSTM) dynamically reweigh scenario likelihoods, yielding an updated risk profile. This is all under the condition that indeed a landslide ruptures the pipe, causes a catastrophic failure, etc.

The posterior probability distribution reflects the updated belief about the likelihood of specific events after incorporating new evidence, specifically the predicted landslide hazard class. It is calculated using Bayesian inference, which using Markov Chain Monte Carlo method combines the prior probability distribution with the likelihood of the new evidence obtained from the LSTM model. This process involves applying Bayes' theorem to re-evaluate the full joint probability distribution of the network, ensuring that each node's probability accurately represents the most current and relevant information about the system's risk state.

Table 3
Bowtie elements.

Elements	Expected pdf value before landslide prediction (occ/y)	Expected pdf value after landslide (class 2) prediction
Cause		
Rupture of pressurized pipe	2.01E-07	1.55E-07
Catastrophic failure	1.08E-10	6.63E-07
Failure of flow control valve	2.10E-06	1E-5
Failure of ESD valve	1.30E-07	1E-6
Failure of level / flow sensors	3.00E-04	1E-3
Barrier failure		
Safety systems	1.20E-07	1E-6
Containment	4.20E-07	1E-7
Process control systems	1.04E-07	1E-6
Escalation Factor occurrence		
Protection failure	2.20E-09	1E-8
Immediate ignition	1.40E-2	1E-2
Delayed ignition	1.10E-3	1E-3

The resulting posterior predictive distribution is shown in Fig. 8, where the probability characterized by highest density represents the most likely probability for the Top Event, which was estimated equal to 3E-7.

The dynamic bowtie is then updated with the landslide precursors, associated with the predictions of the above-described model. In case of landslide (class 2) prediction, the Posterior Predictive Probability is correspondingly modified as represented in Fig. 9.

The Top Event most likely probability moves in connection with the prediction of a landslide associated with a class 2 hazard. It should be noted that the inclusion of dynamic landslides prediction causes the shift of the top event probability from 3E-7–1E-6, whereas static inference keeps the baseline unchanged. This evidence underlines the added value of dynamic landslides precursors integration.

The increase in the probability of the Top Event, following a landslide forecast, results in an increase in the probability of accident scenarios. Each hazard class corresponds to an initiating event severity (from minor slope movement to high regional instability). These classes modulate initiating event probabilities (pipe rupture, valve failure, containment degradation) in the dynamic bowtie.

In order to provide a representation of predicting different landslide phenomena, the second part of the combined bowtie is divided into a fault tree and an event tree. The approach is particularly useful in understanding how the probabilities of various events or scenarios change based on preceding events or conditions, as the prediction of different

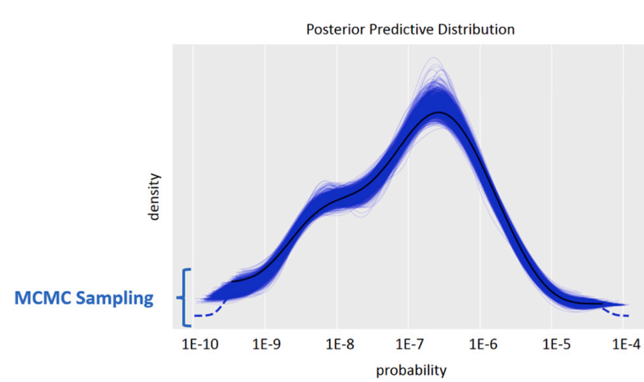

Fig. 8. Posterior Predictive distribution w/out landslide precursors.

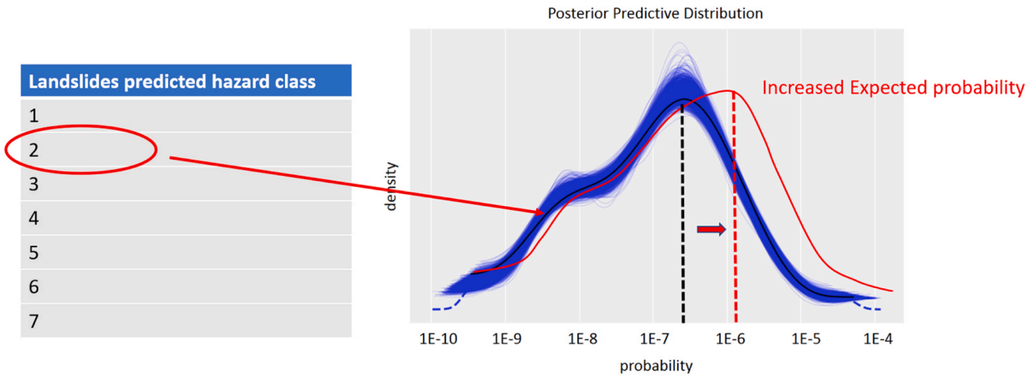

Fig. 9. Posterior Predictive Distribution after a landslide prediction.

classes of landslides. Accidental scenario probabilities, increasing as the top event probability increases, can, thus, be illustrated through fault and event tree analysis. It should be noted that the probabilities given in the trees represent the expected value of the relevant probability distributions, according to the designed dynamic analysis.

Figs. 10, 11 and 12 show the expected values of the probabilities of the occurrence of a containment failure before and after the prediction of a class 2 and class 5 landslide, while Figs. 13, 14 and 15 show the relative expected values of the probabilities of the accident scenarios.

The evolution of the probability of occurrence of the different scenarios following predictions of different landslide classes is depicted in Fig. 16, where the scenario credibility limit is set at the threshold value of 10^{-6} adopted in many European Countries for establishment falling under the Seveso legislation framework (Laurent et al., 2021).

In this work, the prediction of landslides was integrated into the QRA of an LPG Storage Facility. From Fig. 16, it can be argued that, as a result of different forecasts, some scenarios originally ranked as not credible (expected probability lower than 1E-06) become credible (i.e., an expected probability greater than 1E-06). The awareness that any kind of natural hazard can trigger technological disasters is increasing; nevertheless the most of QRA models recently published mainly focus on major natural disasters while minor phenomena as landslides, are poorly explored (Mesa-Gómez et al., 2021). In this context, to provide a decision-making basis for an emergency response to natural hazards, a methodology for landslide Natech was proposed by Hao et al. (2023), even though the landslide was considered as a secondary event due to other natural hazards. Moriguchi et al. (2023) performed the risk assessment of chemical release due to landslide induced by rainfall estimating the probability of landslides was estimated only based on historical data. The novelty of the present study is represented by the evidence that even a minor phenomenon could potentially lead to severe consequences on the storage site. Early prediction based on the analysis of precursors and the assessment of the cascade effects probabilities by means of the interlinked bowties can provide dynamic pictures of the near future state of the system, allowing operators to adopt the most appropriate countermeasures promptly. Summarizing the proposed framework relying on the LSTM Model, demonstrating robust predictive capabilities with a 98.67 % accuracy, successfully distinguished between minor and high-impact landslide events. The dynamic updates provide an effective enhancement of actual risk, possibly supporting

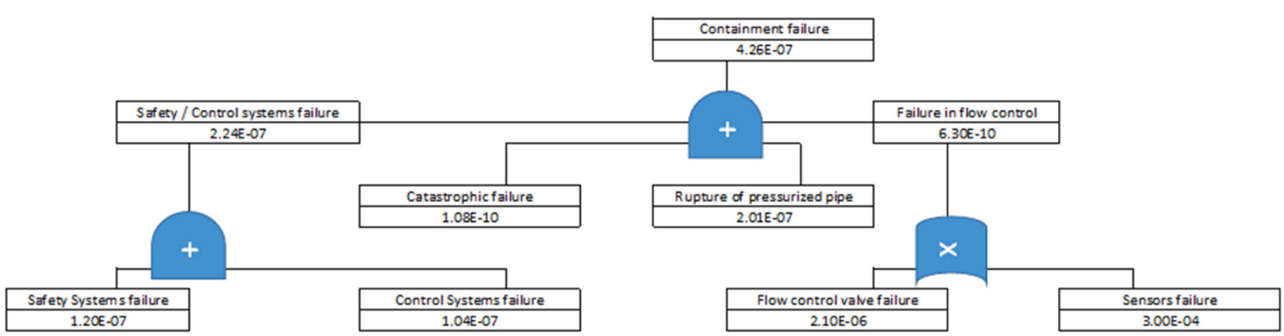

Fig. 10. FTA based on the expected value of the probability distributions, before landslide prediction.

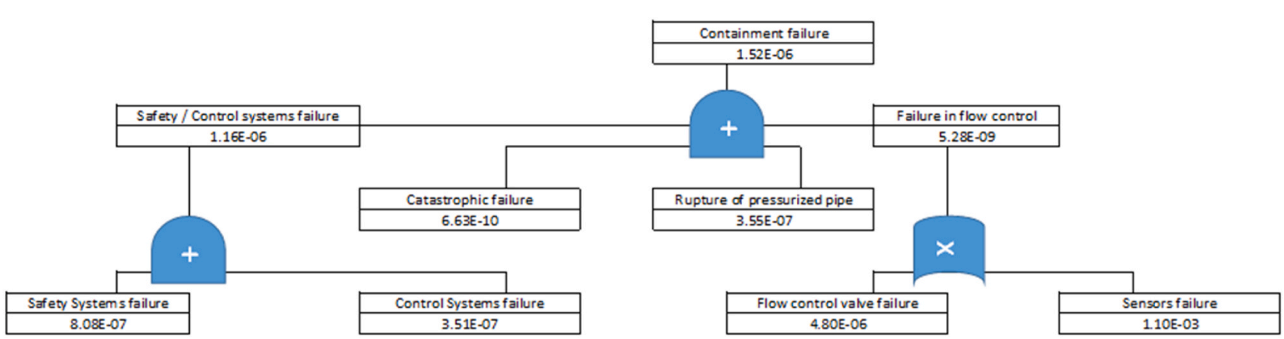

Fig. 11. FTA based on the expected value of the probability distributions, after landslide class 2 prediction.

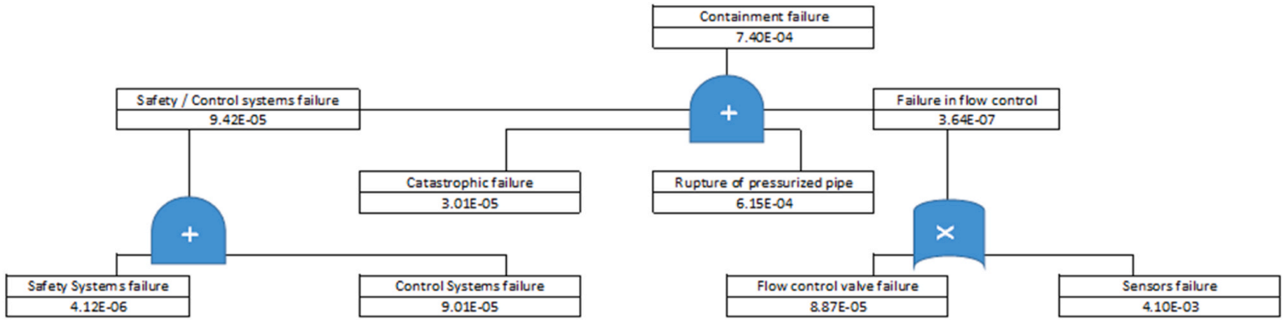

Fig. 12. FTA based on the expected value of the probability distributions, after landslide class 5 prediction.

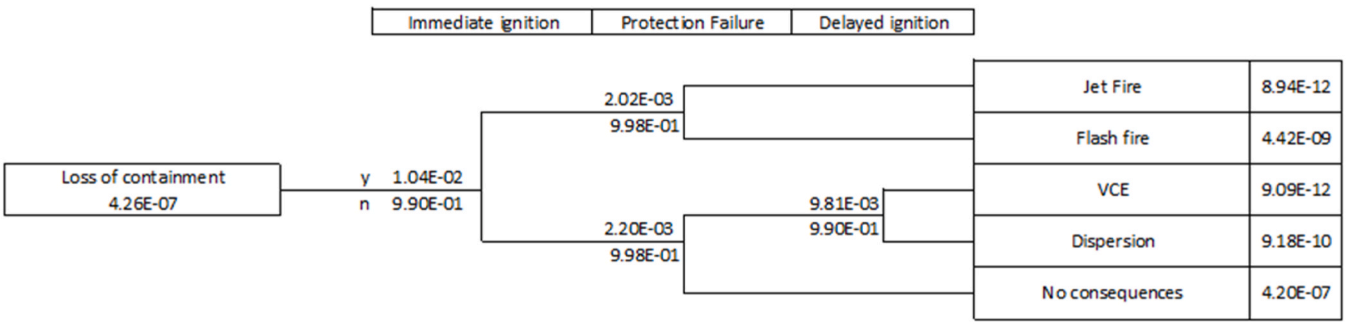

Fig. 13. ETA based on the expected value of the probability distributions, before landslide prediction.

real-time safety decisions and emergency action planning.

4. Conclusions

This study demonstrates that natural hazards, when predicted and quantified dynamically, can significantly alter the industrial risk landscapes. The LSTM-based model achieved 98.67 % accuracy in classifying hazard levels with very few misclassifications (which, moreover, are few overestimates, while there are no underestimates). Its ability to predict daily landslide hazard classes is instrumental in dynamically updating the annualized initiating event probabilities. These updates, in turn, significantly influence the posterior probability of top events within the dynamic Bow-Tie framework.

The method provides:

- A scalable tool for AI-enhanced Natech risk management.

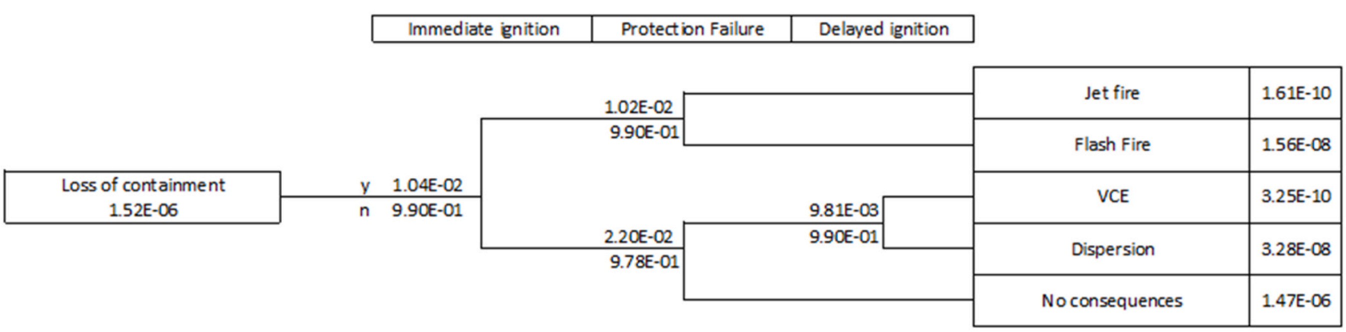

Fig. 14. ETA based on the expected value of the probability distributions, after landslide class 2 prediction.

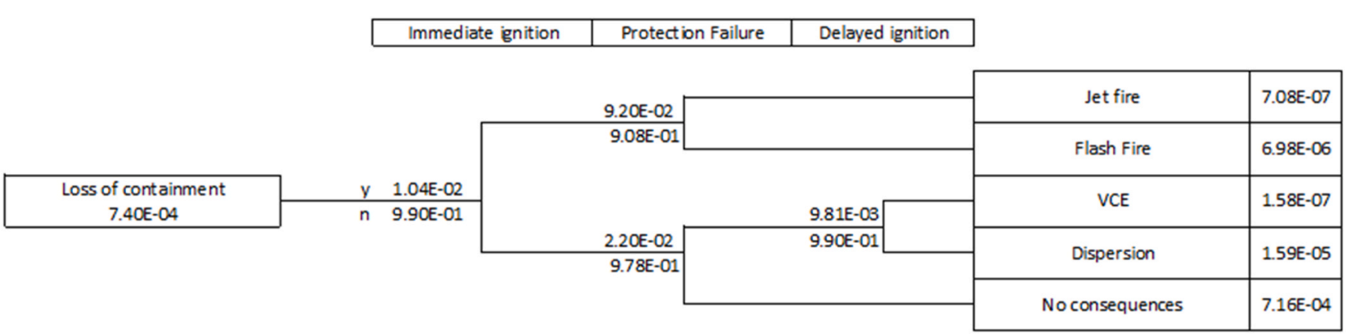

Fig. 15. ETA based on the expected value of the probability distributions, after landslide class 5 prediction.

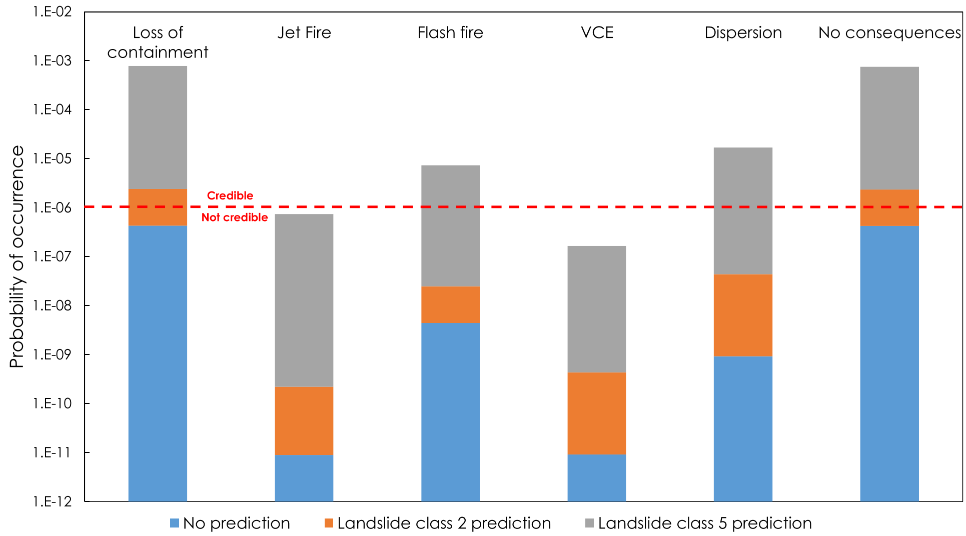

Fig. 16. Evolution of the probability of occurrence of different scenarios following predictions of different landslide classes.

- A practical case showing that even low-severity landslides can elevate accident scenarios above credibility thresholds.
- A framework adaptable to other natural hazards (e.g., floods, heat-waves), effectively supporting traditional risk management approaches.

Ongoing work based on the developed approach focuses on expanding datasets, incorporating multi-hazard precursors, and refining real-time risk dashboard implementations for emergency preparedness by evaluating the effectiveness and prioritization of countermeasures.

Key findings include:

- LPG storage facilities in landslide-prone regions require enhanced safety protocols, considering the heightened risk posed by natural hazards.
- Machine learning and AI driven approaches can significantly improve landslide risk prediction, supporting proactive hazard mitigation and a decision support system.
- Dynamic Bayesian risk assessment provides a real-time risk evolution model, adapting to changing environmental conditions and for underrepresented hazard levels.
- It was demonstrated that the probability of catastrophic events increased from 3E-7–1E-6 after landslide forecasts, so that some accident scenarios, previously deemed improbable, became credible risks.

As a main limitation of the study, it is worth mentioning the uncertainty associated with the assumptions made in calculating the probability of the accident, being the quality of the results obtained by applying the proposed approach, connected to the reliability of available observations. In this regard, it must be evidenced that the need for additional expansion of the dataset mainly for underrepresented hazard levels, will improve model interpretability and integrate additional natural hazard predictors to refine Natech risk assessments. Further challenges may include the use of real-time monitoring data to update risk profiles by accounting for multi-state interactions and probability updates, thus facilitating dynamic safety barrier management.

CRediT authorship contribution statement

Hans J. Pasman: Writing – review & editing, Validation, Methodology, Conceptualization. **Tomaso Vairo:** Writing – review & editing, Writing – original draft, Validation, Software, Investigation. **Margherita Pettinato:** Writing – original draft, Visualization, Investigation, Formal analysis. **Stefania Magrì:** Visualization, Validation, Investigation, Data curation. **Bruno Fabiano:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The corresponding author, Bruno Fabiano is an editor for the journal Process Safety and Environmental Protection, but has had no access to, or involvement in, the peer review process for this paper or its handling by the journal at any point.

Acknowledgements

Authors are grateful to the staff of SATURN department of ARPAL (Genoa, Italy), for data pre-processing.

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