A SCALABLE MACHINE LEARNING MODELLING TOOL FOR MAPPING LANDSLIDE RUNOUT USING A CASE STUDY IN HAWKES BAY, NEW ZEALAND

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ABSTRACT

Understanding landslide runout is crucial for land use planning, utility networks, and assessing infrastructure resilience on slopes. Recent guidance recommends incorporating landslide runout models along with climate change implications when assessing land for development. The advancement of machine learning (ML) techniques can offer new insights and a tool to be used alongside current methods. A range of data inputs from land-use, remote observations, and field measurements can all be used for training models and as inputs to landslide runout predictions.

Modelling potential landslide runout scenarios requires extensive volumes of data. A ML trained model has been developed to map landslide runout direction and distance for a case study in Hawke Bay, New Zealand following rainstorm events in January 2023 and then cyclone Gabrielle February. A steepest path hydrological flow path model was developed alongside the ML approach for landslide direction. Ten thousand landslide runouts were used in the training along with features engineered from a 1 m resolution Digital Elevation Model (DEM).

The results show the model is capable of predicting expected runout distances with a reasonable degree of accuracy. To improve the results and create a probabilistic output for hazard mapping a stochastic parameter should be incorporated into the model along with additional disposing factors such as vegetation density, source size and topographic wetness. The hydrological flow path model performed better than the ML direction model in certain scenarios which is most likely due to the large amount of precipitation as the trigger causing high water content debris flows and debris floods. This highlights the inherent complexity of modelling landslide debris trails and why a probabilistic monte-carlo modelling approach will be best placed for quantifying the uncertainty into a hazard map.

1 INTRODUCTION

Landslides have killed more people in Aotearoa New Zealand than other geological hazards combined (De Vilder SJ et al, 2024) and New Zealand has been identified as one of the most vulnerable economies in the world to the impact of natural disaster as a percentage of GDP (NZGS, 2024). In the case of New Zealand, it is therefore important to understand landslide risk in the most cost-efficient way.

The analysis of landslides can broadly be broken down into two categories –

1. identification of terrain which is susceptible to landsliding,
2. *the source* and the direction and distance of the landslide path, *the runout*.

However, landslides are complex processes with many degrees of freedom influencing their triggering mechanism, source and runout. Traditionally landslides have been categorised into different types (Varnes, 1978) depending on host material which then has been linked, based on empirical data, to their typical runouts (Brideau et al, 2021). Debris flows type are particularly hazardous when considering runout given the potential for large travel distances, particularly when confined into channelised debris flows (Cascini et al., 2014).

There are many methods which are often combined to assess landslide runout out including geomorphological mapping (Parry, 2011), numerical modelling (Hungr and McDougall, 2009; Ceccato et al., 2024), topographic zoning (WSP, 2023), and back analysis (Sun et al., 2021). The appropriate method for assessing landslide runout is often case dependent – client requirements, potential risk, project budget, type of landslide, available expertise, data available, access and time constraints. A big data probabilistic model is most appropriate for insurance risk models, initial input into landslide risk analysis for land planning, utility networks and infrastructure resilience. For site specific landslide runout analysis, a more involved approach such as a Natural Terrain Hazard Survey (Ho and Roberts, 2016) would be more appropriate. This paper is a preliminary approach for probabilistic modelling of landslide *runout*. Our research has previously developed a probabilistic model of landslide susceptibility *source* for New Zealand (Stokes et al, in press) which this study uses.

All the above methods rely, to different degrees, on empirical historical data and the future being linked to the environments of the past (Lee, 2024). Current and future developing uncertainties such as climate and land use change inhibit our ability to predict both landslide source and runout to the absolute. We have shown that the general source model can be calibrated to different rainfall events and land-use allowing for the landslide susceptibility to be predicted for a rainfall event of a given magnitude or land use change (Stokes et al., in press). There is of course uncertainty over what magnitude rainfall triggering event is appropriate for predicting future events. Current guidance for climate-change scenarios that need to be considered in analysis is generally not provided definitively, which is not surprising given the dynamic uncertainty (De Vilder SJ et al, 2024). Therefore, a big data probabilistic approach can aid in decision making in such scenarios but cannot provide absolutes.

Probabilistic models rely on large datasets and appropriate statistical methods to develop return periods and correlations. Recent advances in statistics coupled with machine learning (ML) and availability of computing power allows for many more variables to be included in models enabling the prediction of much more complex non-linear processes to be developed. Obviously, this approach has limits, such as uncertain prediction outside of the limits of the training data, and to some extent model opaqueness, but the application of this method has already been successful in many fields. Within the field of ML, a Generative Adversarial Network (GAN) is a method which uses fake data to train a predictive model alongside real data. The use of GANs has been explored for landslide susceptibility assessments by (Al-Najjar and Pradhan, 2021) and (Stokes et al., in press) and debris avalanche footprints (Mead and Kereszturi, 2023). This paper presents a novel approach to modelling landslides which uses a GAN to predict landslide direction and runout distance from any start point. The model uses the output from a landslide susceptibility analysis (Stokes et al., in press) to model the runout from areas of high landslide susceptibility.

2 STUDY AREA

The sample dataset utilised the 10,000[1] debris trails from the New Zealand Landslide Database located in Hawkes Bay, New Zealand (Figure 1). The landslide type was predominantly rainfall induced shallow soil debris flows[2]. The dataset has been chosen given the large amount of landslide in a very local area, similar mechanism of occurrence, triggered by a single event and with the underlying geology being consistent over the study area comprising Paleogene to Neogene sandstone, mudstone and limestone (Figure 7 in the Appendix).

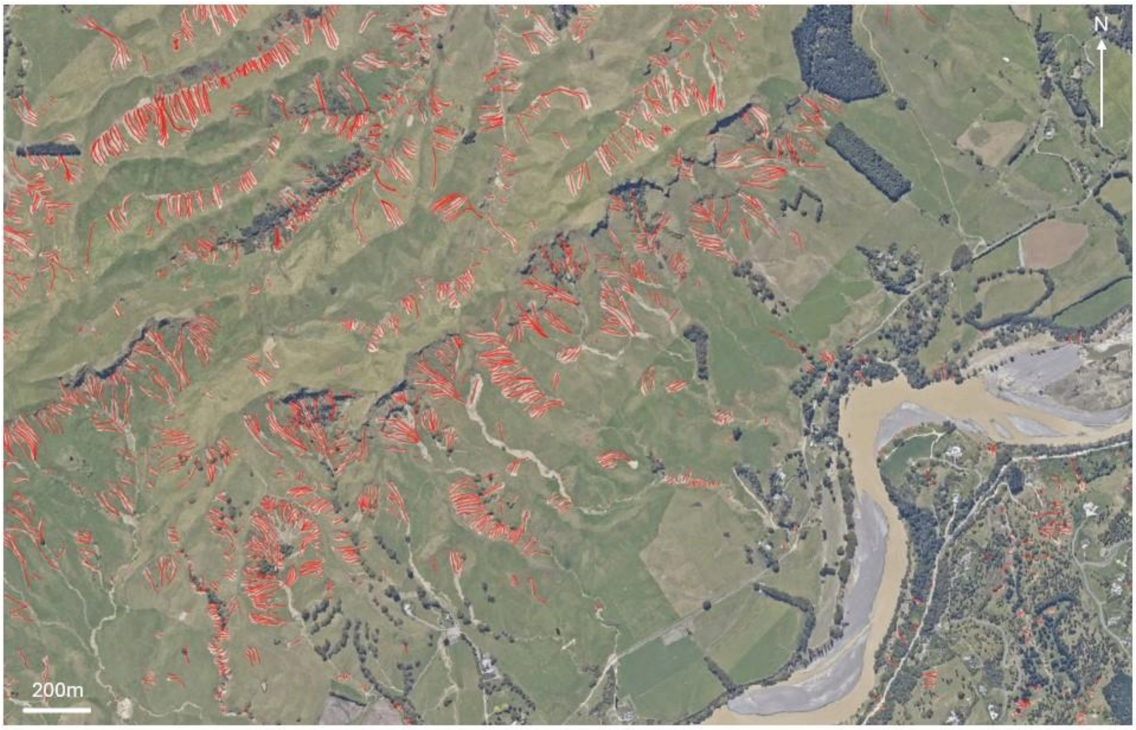

Figure 1: Extract of Landslide Runouts (red) in Study Area. Tukituki River, Hawkes Bay. Aerial Photograph downloaded from LINZ and captured between 19-21 February 2023.

[1] The dataset does not include exact information on the date of occurrence but based on an assessment using recent aerial imagery most if not all the landslides would have occurred following the Cyclone Gabrielle rainfall event in February 2023.

[2] although this isn't confirmed for all landslides

3 METHODOLOGY

There are many approaches of numerical modelling landslide runout. These range from a

- (Brideau et al., 2021) - purely empirical travel angle calculation,
- (Hungr and McDougall, 2009) - dynamic 'method of slices', and
- (Mikos and Bezak, 2021) - numerical physical finite volume models

These methods are limited as they can only be used modelling a single event at a time.

ML is the approach that has been employed in this paper and is considerable relevant through its successes across multiple disciplines (Scalia, 2022) and is being used more commonly in earth science (Dramsch, 2020) with many examples in the field of landslide susceptibility and runout by (Chen et al., 2024). ML differs from many of the traditional methods as it doesn't not rely on physical geometric process modelling but instead is rooted in the statistical and probabilistic branch of mathematics. There are many advantages to using this method:

1. It can utilise the large amounts of data which is now available.
2. The processing power requirements are lower than physical models which is particularly useful for large areas.
3. The flexible nature of the modelling method – physical models tend to be very set in stone with the data requirements for the model. An ML approach can be adapted to the available data and the model will quantify the predictive power of the output based on the data provided. For example, if the data does not include source volumes the model will still be able to produce a prediction, but the certainty of the model will be reduced.

3.1 Model Framework

The model utilises a variation of the GAN framework developed in the field of machine learning (Goodfellow et al., 2014) which has had considerable success in tasks such as realistic image generation and downscaling climate models (Rampal et al., 2024). The basic framework of a GAN is shown in Figure 2.

A GAN consists of two ML models a Generator and a Discriminator. In the context of realistic image generation, the generator creates fake images which could just be noise. The Discriminator is then trained to identify the difference between the fake images and real images. Repeated training of the models can lead to generated fake images which are authentic to human observers. This framework has been selected based on the information that is available – a database of real landslide debris trails. The general GAN inspired framework is shown in Figure 3. Instead of fake images the Generator creates fake (synthetic) landslide debris trails using an adapted random walk algorithm. Using a number of features extracted from the real and synthetic debris trails and a high-resolution DEM the Discriminator model is trained on a balanced dataset. The final step of the model is the 'Expert Discriminator' a landslide expert who assesses whether the landslide debris trails that have been generated are satisfactory.

The GAN model uses the combination of two gradient boosted decision tree machine learning architectures, an XGboost Classifier and an XGboost Regressor (Chen, 2016). Both architectures are highly reputable and have been successfully implemented across multiple disciplines and including recently to model landslide runout (Qui and Ghen, 2024). The classifier is used to predict the direction of landslide runout and the regressor is used to predict the termination point of the landslide.

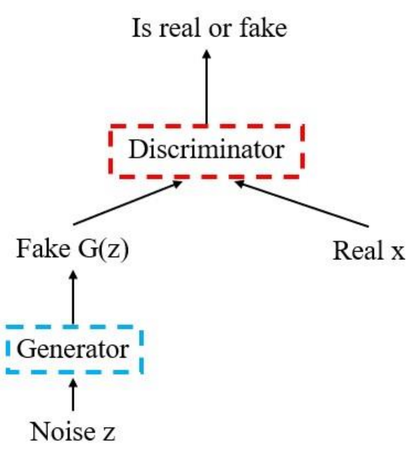

Figure 2: Generalised GAN Architecture after (Goodfellow et al., 2014)

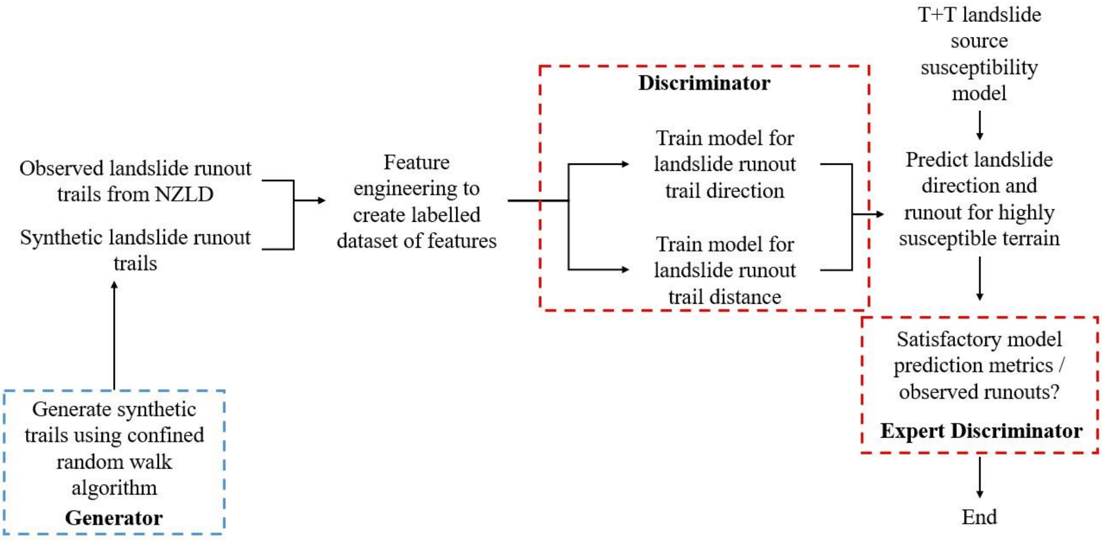

Figure 3: GAN inspired model architecture for landslide debris trail prediction

3.1 Selection of disposing factors

Factor or feature selection is critical for a good quality machine learning model (Qiu and Geng, 2024). Features must be engineered that provide the model with the most appropriate information for explaining how the system under study behaves. This is often and favourably derived from expert knowledge, but in its absence (or alongside) a brute force approach using statistical measures is possible. Features important for predicting landslide runout are well documented in the literature (McDougall, 2014; Reid et al., 2025) and include (but not limited to) height-to-length ratio (H/L), angle of reach, drop height between source area and endpoint, mean gradient of travelling path, mean curvature of travelling path, volume of failure mass, and normalised difference vegetation index, degree of channelisation. All these features can be calculated from a high-resolution DEM for any given runout footprint except for normalised difference vegetation index and volume of failure mass. As the model has been designed to predict runout length and direction different relevant disposing factors were included in each model.

3.2 Direction of landslide runout

The direction of landside runout is often modelled using hydrological flowlines which estimate the flow direction of water over a terrain using a simple algorithm which follows downward topographic movement. However, landslide processes differ from hydrologic processes so an ML model trained on actual landslide runout paths may provide more accurate predictions than one simply following the likely hydrologic flow path.

Two separate models have been used for the direction of landslide runout:

1. Hydrologic flow path model – This simply follows the direction of maximum H/L which is the steepest path.
2. XGboost classifier model – A ML boosted decision tree model which is trained on synthetic and real data using the following disposing factors: height-to-length ratio (H/L), angle of reach, drop height between source area and endpoint, mean gradient of travelling path, mean curvature of travelling path and degree of channelisation. The model predicts whether a trail is real or synthetic based on these factors.

3.3 Termination of landslide runout

To model the termination of a landslide the XGBoost regression architecture was employed. The model was trained using height-to-length ratio (H/L), angle of reach, drop height between source area and endpoint, mean gradient of travelling path, mean curvature of travelling path and degree of channelisation. The 'label' which is being predicted is the point along the debris trail, a value between 0 and 1. As it is a regression model, it can just be trained on the actual landslides trails and doesn't require any synthetic 'fake' runout out data.

3.2 Collinearity assessment of factors

Assessing the collinearity of factors or features is an important step when developing a machine learning model. Collinearity refers to the non-independence of predictor variables (Dormann et al., 2013). A 'folk lore' exists that a feature should not be included if its correlation coefficient is >0.7 with another feature as this can severely distort model estimation and prediction (Dormann et al., 2013).

3.3 Model Development

Prior to model development an appropriate study area was selected manually in the GIS environment QGIS. The relevant data was then cropped to reduce the memory requirements. The model was then developed in Python using the Integrated Development Environment (IDE) Visual Studio Code. The python modules used were geopandas, pandas, numpy, shapely, xgboost, sklearn, multiprocessing and rasterio. Each of the steps shown in the GAN inspired model architecture (Figure 3) required extensive functions to be written, a general step-by-step pseudo code of the method is provided in the Appendix at the end of the paper.

4 RESULTS

4.1 Determination of input variables

The collinearity of features input in the model has been calculated. The features associated with measuring the channel width and height have high collinearity and the features for related to measuring the angle of reach also have high collinearity. Given the current model architecture used will reduce the weight of features that are highly colinear, it is not necessary to remove them from the model.

4.2 Trained Model Validation Metrics

Both models were trained and tested using a 2/3 to 1/3 split ratio. The model metrics show the trained directional model can distinguish the difference between real and synthetic debris trails with a high level of accuracy, 91%. This is not surprising given the initial trails are generated from a random walk algorithm. The regression based trained runout trail distance model has a moderate performance with a relative Mean Absolute Error (MAE) of 31%.

4.3 Estimate of travel distance and direction

Over 6,000 debris trails were predicted using the model from the same start points as the original 11,000 real debris trails. Figure 4 shows a visual comparison between:

a) real debris trails from the event,
b) the initial random walk trails,
c) the predicted debris trails using the ML direction/runout model, and
d) the predicted debris trails using direction of max H/L with the ML runout model.

A preliminary set of results compares the real and predicted synthetic debris trails using the common metrics in Figure 5:

a) runout length,
b) total drop height, and
c) angle of reach.

A visual comparison between the three figures, Figure 4, Figure 5 and Figure 6, shows general correlation. The real trails frequency exhibits a behaviour more like a natural complex system with a power law relationship, a property of a system at self-organised criticality in Figure 5 (top) and (middle) (Bak et al., 1987) and a characteristic smooth gaussian distribution in Figure 5 (bottom) (Sornette, 2007). This is less pronounced in the synthetic debris flows frequency plots.

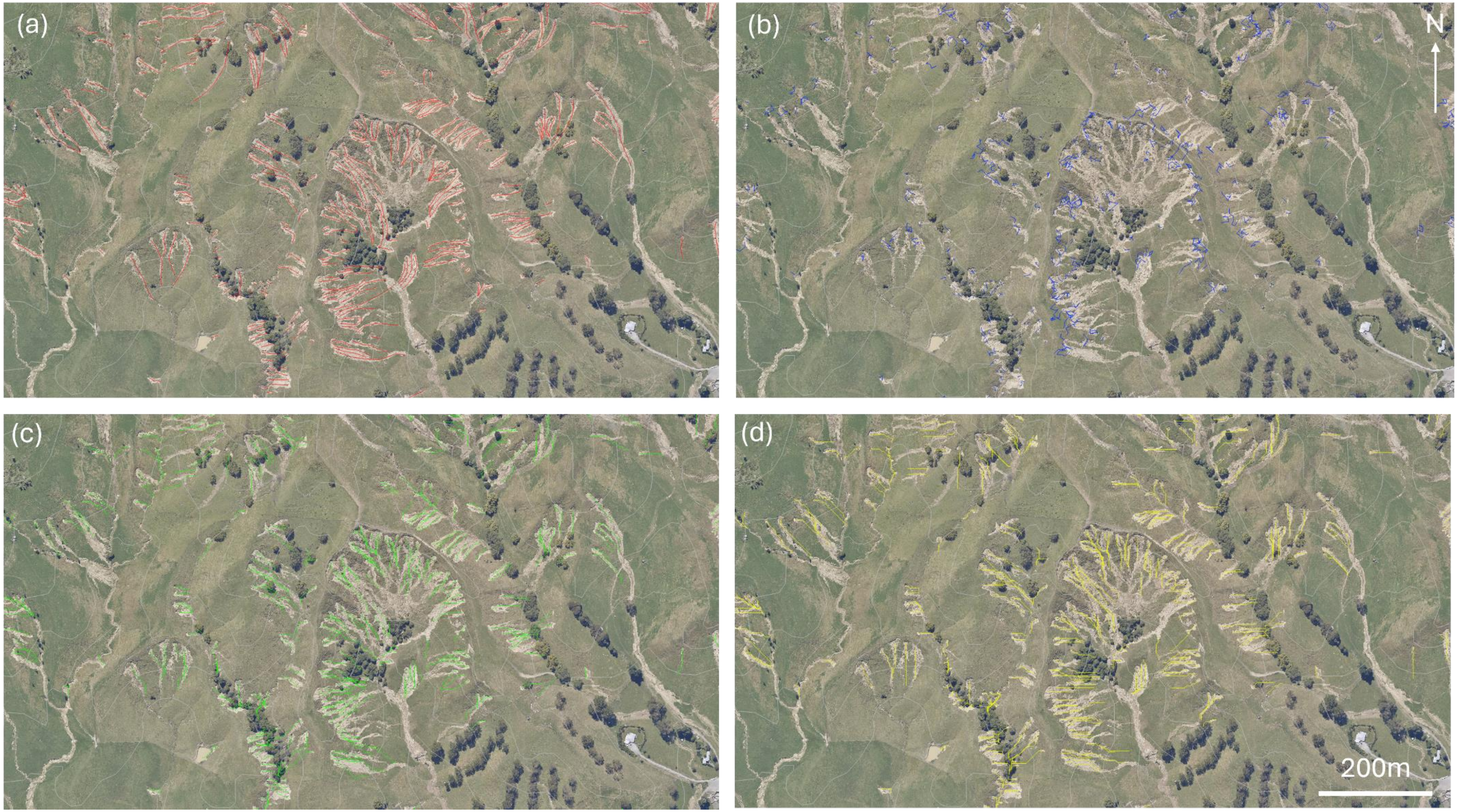

Figure 4: Example model output for a specific location in the study area. (a) The real debris trails. (b) The initial generated random walk debris trails. (c) The predicted debris trails from the ML Direction and ML runout models. (d) The predicted debris trails from the hydrologic flow path direction and ML runout model.

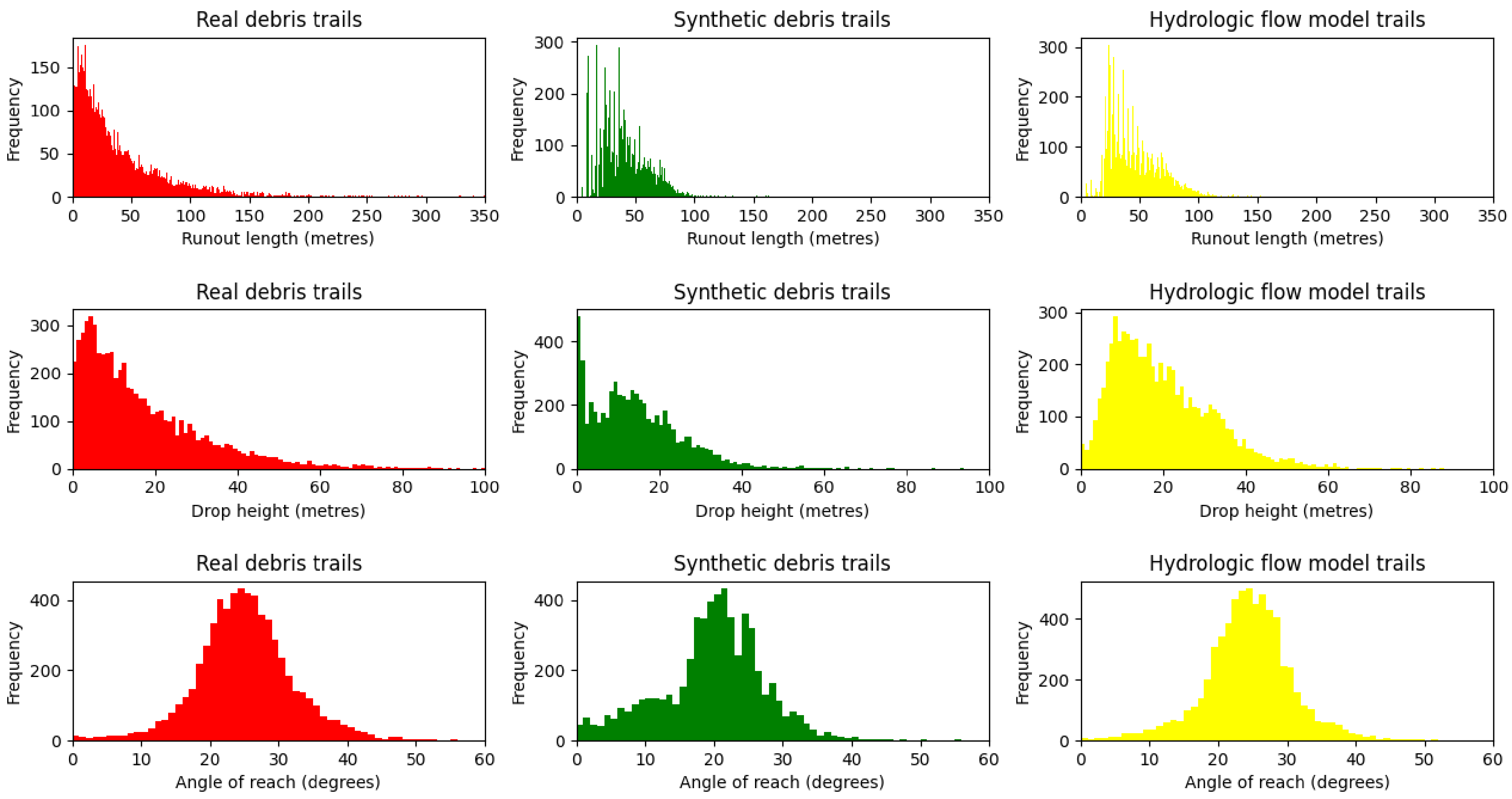

Figure 5: Comparison between real and predicted synthetic debris trails using the ML Direction model and hydrologic flow model. Common metrics (top) runout length, (middle) total drop height and (bottom) angle of reach.

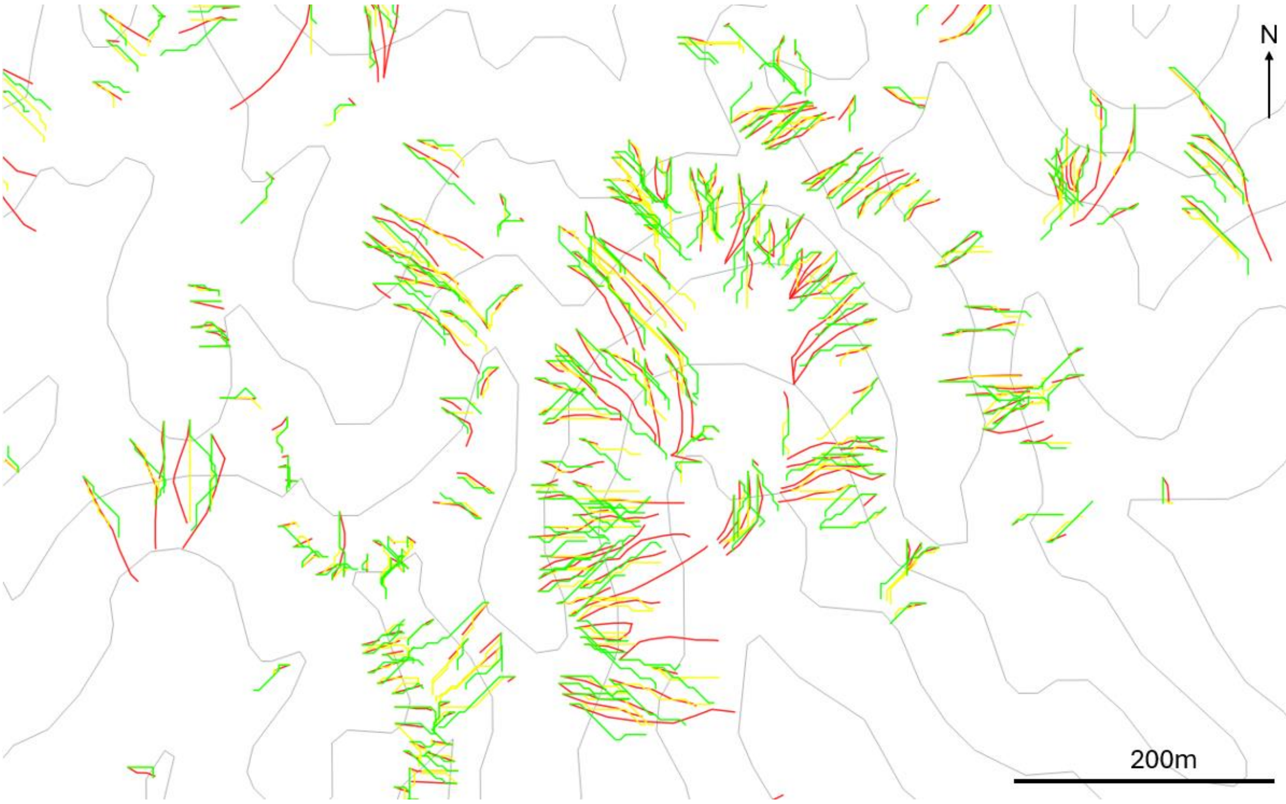

Figure 6: Landslide debris runout overlay of trails in Figure 4. Red – The real debris trails (Figure 4a). Green – The predicted debris trails from ML direction and ML runout models (figure 4c). Yellow – The predicted debris trails from the hydrologic flow path direction and ML runout model (Figure 4d).

5 DISCUSSION AND LIMITATIONS

5.2 Discussions

The results show a model can be trained to predict landslide runout and direction from real and random data. However, the direction and distance of the predicted runout are not always consistent with the real data. The ML approach for both direction and distance of the debris trail (Figure 4c) has an accuracy of greater than 90% when considering the spatial overlap between the real and synthetic debris trails (Figure 6). The hydrological flow path direction model (figure 4d) and ML distance model has an accuracy of 97% (Figure 6). There are some notable exceptions in the output where the ML direction debris trails appear to not follow exactly the same path as the real debris trails. The lowest correlation is where the landslide occurs close or on a spurline. In these situations, it is likely there are a few alternative paths the debris trail could take at the beginning of the trail leading to much larger differences further along. The hydrological flow path model performed better in such situations (Figure 4d). Given the trigger event was an unprecedented very high-volume short duration rainfall event, some of the trails might include secondary sedimentation of the landslide deposit which could be classified as a colluvial deposit or debris flood deposit (Jakob and Hungr, 2005; Church and Jakob, 2020). These deposits are more water dominated so are more likely to follow a hydrologic flow path and also typically have a longer runout than the landslide debris alone.

The differences observed between the three datasets – real debris trails (Figure 4a), ML-direction/ML-distance debris trails (Figure 4c) and H/L max direction/ML-distance debris trails (Figure 4d) can be accounted for by the complexity of landslide runouts. Landslide debris trails are influenced by many factors which are difficult or impossible to account for in a model. There is potential for improving the model by adding factors including calibration to rainfall (von Ruette et al., 2016), storm direction / slope aspect, topographic wetness index, vegetation density and subsurface information. But this reductionist approach has limits and may not be able to account for the inherent chaos and complexity in the system (Lee, 2024). In the context of landslide debris trails, no two events or locations are the same. Nevertheless, the likeness of the synthetic trails to the natural system (the real trails) (Figure 5) could be increased through model refinement.

The end goal of this approach was not to directly replicate the real debris trails but to produce landslide hazard zonation maps which consider multiple possibility trail routes and runouts. This goal on the whole was achieved by this method.

5.2 Refinement of the model

A way of countering the unpredictable nature of debris trails is to use a stochastic approach, such as a monte-carlo simulations, notably used in climate change models (Randall et al., 2004). This can be added easily into the ML modelling approach and after multiple landslide debris runouts, it is then possible to synthesise the output into a coherent probabilistic map. A probabilistic runout map based on many landslide runouts will have a much more explaining power and provide the end user with a practical output which depicts the hazard opposed to a map based on single debris trails.

5.3 Limitations

It is important to acknowledge the limitations of this ML modelling approach (Baynes and Parry, 2024). In its current form, it cannot replace physical models of debris trails, which provide velocity, energy, and inundation estimates for detailed hazard assessments at specific locations. However, the relatively low computational demands of this method enable the analysis of larger datasets and the prediction of many more debris trails across a broader scale—something not feasible with conventional physical models. For detailed design in a specific use case, a physical model combined with expert judgement remains essential.

The methodology introduces an *expert discriminator* – a human landslide expert to determine whether the final landslide debris trails generated by the model are plausible. It would defeat the whole object of this method, and likely not possible, for every single trail to be inspected. It is likely that a sample would be inspected; the size of which has not been determined at this stage.

There are also limitations to the real debris trails used for training the ML models. These have been collected by aerial photograph interpretation following the event without ground truthing. Some of the debris trails may have been obscured by vegetation and there could be human error involved in interpretation.

Finally, the study area selected consisted of 10,000 debris trails from a single event in a single geology material type which can be considered a large sample. The predictive power of the model in other geology types in other events will likely be limited given the confinements of the modelling process.

6 CONCLUSION

The modelling approach and framework have been selected based on the high level of success achieved in other fields of study and the availability of large datasets. The results have yielded promising predictions based on visual comparison and metrics (Figure 6). However, the results are not yet satisfactory for use in hazard prediction. Introducing a monte-carlo simulation approach into the modelling framework will increase the predictability and confidence in the output which can be synthesised into a probabilistic landslide runout map. Adding additional disposing factors such as vegetation and topographic wetness may also increase the predictability. The scaling up of the method should be possible through code parallelism and optimisation without the need of costly high-performance computing.

7 APPENDIX

A summary of the pseudocode followed for the methodology is provided below:

Generate synthetic trails using confined random walk algorithm:

1. *Start points of sampled debris trails selected.*
2. *Random points added sequentially within a maximum specified distance of previous point.*
3. *Next point selected within a certain distance of the previous point*
4. *Algorithm is stopped with the same number of points as the original sampled debris trail.*

There are many ways to develop this algorithm. GAN models tend to start with random noise implying a large amount of flexibility (Goodfellow et al., 2014).

Feature engineering to create labelled dataset of feature:

1. *Create data dictionary for each debris trail*
2. *Iterate through each point of the debris trail and:*
    a. *Extract height from DEM*
    b. *Calculate angle of debris trail (iterative and total)*
    c. *Calculate drop height (iterative and total)*
    d. *Calculate plan length*
    e. *Calculate full length*
    f. *Calculate sinuosity of trail*
    g. *Calculate DEM height at 5m, 10m, and 15m perpendicular to trail direction to measure confinement*
    h. *Calculate how far along the debris trail the point is*
3. *Concatenate all data dictionaries into a pandas dataframe.*

Train model for landslide runout trail direction:

1. *Select relevant features for landslide runout trail direction*
2. *Create balanced dataset of real and synthetic data*
3. *Train XGBoost model on real and synthetic data to identify the correct landslide direction*

Train model for landslide runout trail distance:

1. *Select relevant features for landslide runout trail distance*
2. *Create balanced dataset of real and synthetic data*
3. *Train XGBoost regression model on real and synthetic data to identify the correct landslide runout distance*

T+T landslide source susceptibility model:

1. *Extract data from T+T landslide susceptibility model within study area.*
2. *Select 10,000 locations which are highly susceptible to landslides (Relative Probability >0.7).*
3. *Use these points as start points for landslide prediction.*

Predict landslide direction and runout for highly susceptible terrain:

1. *Select each start point*
2. *Create features for all possible directions in the Von Neumann neighbourhood for the point.*
3. *Use trained direction model to predict most likely landslide direction.*
4. *Use trained distance model to predict if the current point is the end of the landslide runout trail.*
5. *Iterate back through steps 2 to 5 until the model predicts it has reached the end of the landslide trail.*
6. *Then select a new start point – step 1.*
7. *If the generated landslide trails are as expected by an expert discriminator, then end the model otherwise use generated landslide trails to retrain the direction model to improve model parameters.*

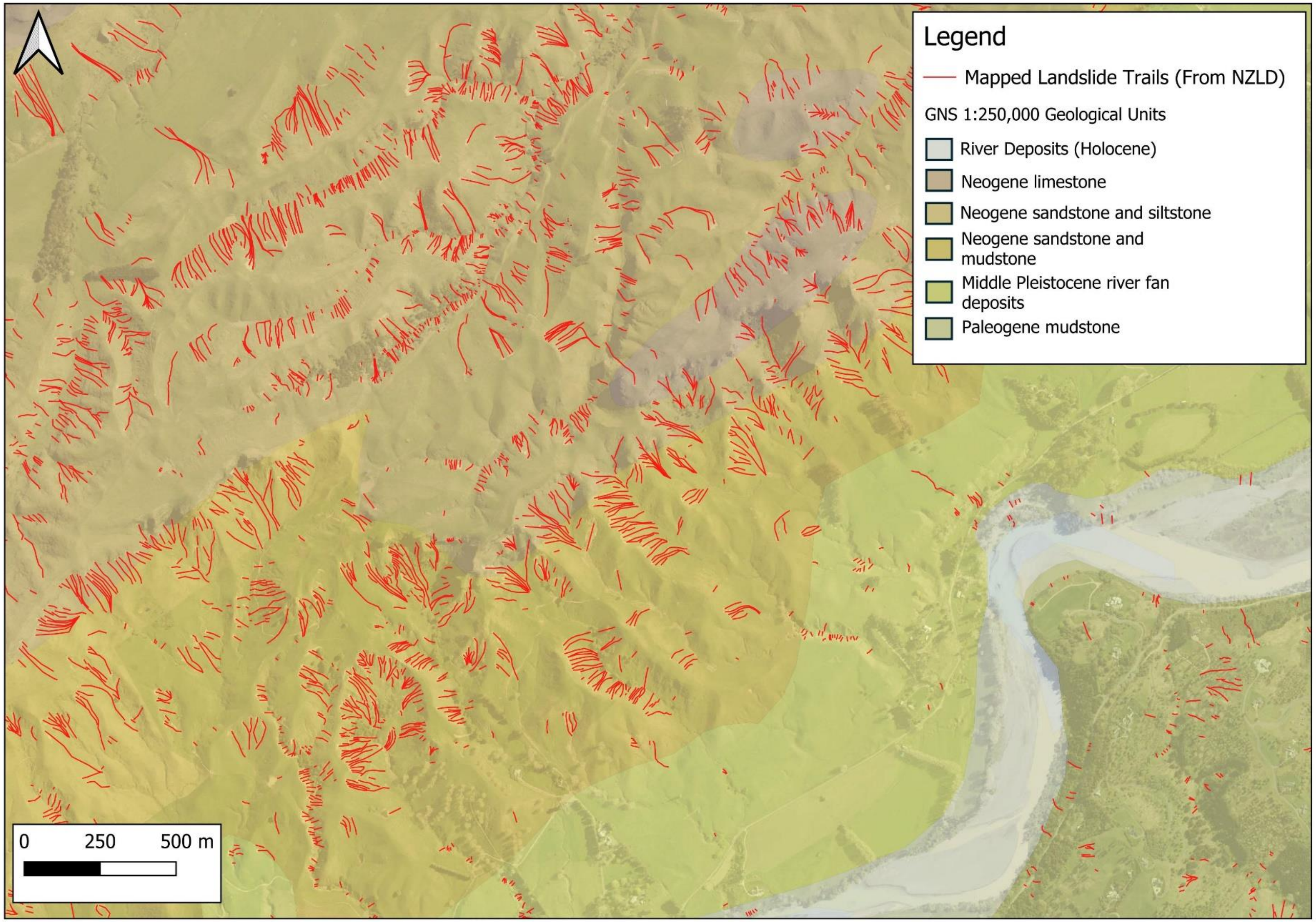

Figure 7: Typical Geological units in the study area comprising Paleogene to Neogene Mudstone, Sandstone and Limestone.

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