THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE FOR REAL TIME PIT MONITORING AT BATU HIJAU SITE, INDONESIA

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ABSTRAK

Program pemantauan lereng merupakan bagian dari sistem pengelolaan lereng untuk memitigasi risiko keruntuhan lereng. Kehadiran instrumentasi pemantauan tidak hanya membantu identifikasi bahaya dan mengontrol risiko tetapi juga mengurangi kecemasan tenaga kerja dengan memastikan kondisi lapangan yang dipantau oleh personel yang berpengalaman dan kompeten. Radar stabilitas lereng telah muncul sebagai instrumen utama dalam pemantauan berkelanjutan kondisi pit karena dirancang guna mendeteksi deformasi lereng hingga skala milimeter. Saat ini, dengan metode pemantauan radar yang ada, insinyur menetapkan nilai batas berdasarkan perpindahan atau kecepatan, yang biasanya bervariasi, tergantung pada karakteristik geoteknik daerah tersebut. Sementara itu, masalah muncul ketika nilai ambang yang terlalu konservatif diterapkan, menyebabkan banyak prediksi dan alarm yang salah. Penelitian ini mencoba mengatasi masalah ini dengan mengintegrasikan kecerdasan buatan untuk mendapatkan prediksi yang lebih akurat dan lebih cepat. Kecerdasan buatan dalam bentuk regresi terawasi dan pengelompokan tanpa pengawasan digunakan untuk mengevaluasi data radar secara langsung. Model regresi linier digunakan untuk mengukur hubungan antara waktu dan pergerakan. Berdasarkan teori pergerakan inversi kecepatan, gerakan linier secara bertahap akan berubah karakteristiknya ke arah gerakan progresif. Oleh karena itu, model linier dipilih sebagai model yang tepat untuk mengidentifikasi pergerakan selama masih dalam fase linier sedini mungkin. Hasil dari metode sebelumnya selanjutnya akan dikelompokkan menggunakan metode pengelompokan tanpa pengawasan. Ini adalah teknik pengelompokan fitur-ruang non-parametrik yang tidak memerlukan pengetahuan sebelumnya tentang jumlah klaster, dan tidak membatasi bentuk klaster. Kluster dengan jumlah piksel yang kurang dari jumlah ambang minimum piksel akan difilter sebagai prediksi palsu, dan sisanya tetap. Hasil uji coba menunjukkan bahwa metode ini mampu mengurangi prediksi palsu dan memiliki akurasi yang lebih baik dalam memprediksi pergerakan riil. Namun, pengalaman dan penilaian insinyur masih diperlukan untuk menentukan dengan benar parameter kecerdasan buatan serta memvalidasi hasil prediksi dengan kondisi riil. Peningkatan dengan mudah dapat dilakukan dengan meningkatkan frekuensi akuisisi data, sementara penelitian lebih lanjut diperlukan dengan melakukan analisis beberapa variasi kerangka waktu.

Kata kunci: Radar, Monitoring, *Machine Learning*, Geoteknik

ABSTRACT

Slope monitoring program is a part of slope management system to mitigate the risk of slope failure. The presence of monitoring instrumentation not only aids hazard and risk identification but also reduces any workforce anxiety by confirming ground condition that is monitored by experienced and competent personnels. Slope stability radar has emerged as the *go-to instrument for continuous pit monitoring tool as it is designed to detect slope deformation up to millimeters scales. Nowadays, with the current radar monitoring method, engineers assign a cut-off value based on displacement or velocity value depending on the geotechnical characteristic of the area. Meanwhile, the problem rises when a too conservative cut-off value is applied, causing many false predictions and alarms. This paper tries to overcome this problem by integrating artificial intelligence to get a more accurate and faster prediction. Artificial intelligence in the forms of supervised regression and unsupervised clustering are utilized to evaluate real-time radar data. Linear regression model is used to measure the correlation between time and movement. Based on inverse velocity movement theory, linear movement will gradually change its characteristic towards progressive movement. Therefore, the linear model is selected to be the correct model to identify real movement during the linear phase as early as possible. The result from the previous method will be further clustered using an unsupervised clustering method. It is a non-parametric feature-space clustering technique which requires no prior knowledge of the number of clusters, and does not constrain the shape of the clusters. Clusters with fewer pixels than the minimum cut-off number of pixels will be filtered out as false prediction, and the rest remains. Trial results show this method greatly reduces false prediction and gives better accuracy in predicting real movement. However, engineering experience and judgment are still needed to correctly determine the AI parameters and validate the prediction result to the real-life condition. Improvement is easily expected by increasing the acquisition rate, while further research is needed by incorporating multiple time-frames analysis.*

***Keywords**: Radar, Monitoring, Machine Learning, Geotechnical*

A. BACKGROUND

Rock mass, intact rock with its inheritance of discontinuities, is one of the most complex/heterogeneous materials that humans have faced throughout history. Models that depict soil, rock, groundwater distributions and characteristics throughout the deposit are often based on incomplete information and subjective interpretations (Read & Stacey, 2009). Meanwhile, the scale of investigation and modeling techniques rely heavily on data availability. Thus, it would be impossible to explicitly model the behavior of a pit slope into the smallest detail as the number of available data is usually very scarce. These practical limitations and uncertainty leave some remaining hazards at the smallest detail that need to be understood through a comprehensive slope management system.

Slope monitoring program is integrated as part of the slope management system to mitigate the risk of slope failure. The presence of monitoring instrumentation not only aids hazard and risk identification but also reduces any workforce anxiety by confirming ground condition, which is monitored by experienced and competent personnels (Vaziri et al., 2010). Radar has emerged as the most leading-edge technologies among many ground surface monitoring instruments, due to its completeness in high precision, spatial coverage, and acquisition time (Carla et al., 2017). There have been many publications showing the successful implementation of radar in slope hazard early-warning systems. From all these examples, the most common time-dependent relationship of a slope failure is progressive displacement, where slope velocity tends to increase closer to the onset of failure, and can be analyzed with the inverse velocity method (Fukuzono, 1985).

With the current radar monitoring method, user or engineer assigns a cut-off value based on displacement or velocity value depending on the geotechnical characteristic of the area. The determination of the cut-off value itself is a subject to separate study. Meanwhile, the problem rises when a too conservative cut-off value is applied, causing many false predictions and alarms. These predictions/alarms are visualized in the computer and need to be checked and interpreted manually. This time-consuming and repetitive task is subject to error, as engineers are humans who are inconsistent and prone to procrastinate their tasks.

This paper proposes an additional method to the current normal radar monitoring standard, by implementing artificial intelligence that helps engineer identifying real movement. The AI, in the form of machine learning, will automatically analyze radar data's time relation and spatial correlation.

B. STUDY AREA

Batu Hijau Pit is one of the biggest copper porphyry open pits in Indonesia. It is currently operated by PT. Amman Mineral Nusa Tenggara. The mine is located in Sumbawa Island, West Nusa Tenggara Province. Since mining operation started in 2000, the mine has gone through a total of seven mining phases. Currently, the mine has a length of roughly 3 km, a width around 2.5 km, with a current maximum depth at -315 meters below sea level. In Batu Hijau Pit, each bench is 15 meters high, with bench face angle varies between 60 and 70 degrees, and the overall slope angle of the pit varies between 36 and 38 degrees.

From a geological point of view, The Batu Hijau deposit is situated within an East-west-trending Sunda Banda Arc (Hamilton, 1979). At the Batu Hijau, there are four different main lithology units (Figure 1). The oldest rock formation is volcanic rocks, which was intruded by diorite, and a latter intrusion of tonalite. The tonalite intrusion comprises multiple stages of intrusion which could be differentiated into intermediate tonalite and the latter young tonalite by the texture and mineralization. Clode et al. (1999) reported that the copper and gold mineralization is related to quartz veining and wall rock alteration, and centered inside the tonalite stocks. The tonalite porphyries were emplaced along the contact between andesitic volcanic rocks and equigranular quartz diorite. The time range of emplacement of the tonalite porphyry was relatively short, at 3.76 ± 0.12 to 3.67 ± 0.10 Ma (Garwin, 2002). Alteration-wise, there are four different alteration types in Batu Hijau: Secondary Biotite Alteration, Pale Green Mica (PGM), Chlorite-Epidote Alteration and Feldspar Destructive Alteration.

Geotechnically, the pit is divided into 9 geotechnical domains, characterized by rock type, alteration and structural sets (Figure 1). The UCS of the rock in Batu Hijau varies from 42 to 100 MPa, with the diorite being significantly weaker than the other rock types. The RMR value of the pit varies between 20 and 70, with a mean value between 30 and 40. In a more general perspective, the pit can be divided into two regions, East and West. The East Region is characterized by weak rock mass properties, whereas the West Region has a strong, blocky, structurally controlled type of rock mass. A typical failure in Batu Hijau is commonly caused by poor rock mass properties, resulting from complex intensive structural geology distribution (Aprilia et al., 2010).

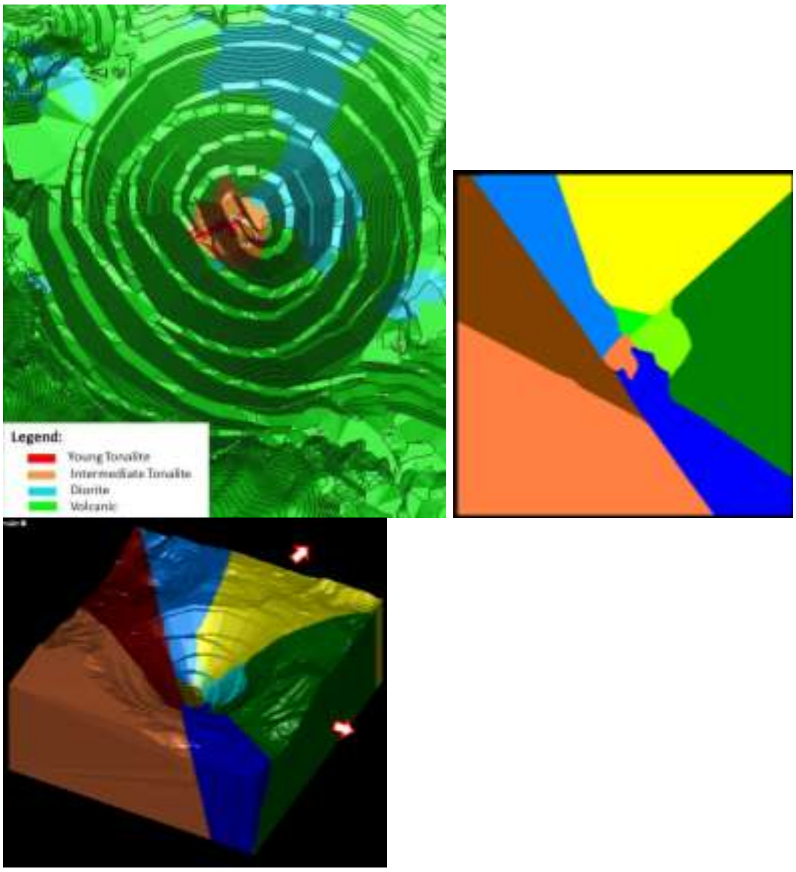

Figure 1. Lithology and geotechnical domain model in Batu Hijau Pit.

C. DATA AND INSTRUMENTATION

The use of ground-based radar in open-pit mines has become a standard practice for early warning slope hazard monitoring equipment. All types of radar work by measuring phase difference of a continuous transmitted microwave signal which is back-scattered by slope surface. The difference of measured phase waves is then back calculated to get the relative displacement or deformation of the surface. Radar possesses some advantages over other instruments such as high precision, long-range capability and high frequency acquisition rate (Farina et al., 2013).

Batu Hijau Mine is currently operating a real-time radar monitoring system which is considered as the most advanced technology in this field today. Among the radar monitoring technologies, IDS GeoRadar's IBIS-FM, which relies on the interferometric signal, is currently deployed in Batu Hijau site. Several radars are placed radially in the outer edge of the pit limit, covering every area of Batu Hijau Pit. The average distance from radar to pit wall of each radar is approximately 1.5 to 2 km. Each radar has roughly 2 minutes of acquisition time, which means 30 sets of data are collected every hour.

In the example, the machine learning method collects real-time radar data within the last constant time interval, usually 1 or 2 hours. In this paper, we provide real sample data from Radar 2 (Figure 2), facing the north Pit area, as an example to show how the prediction generation process works.

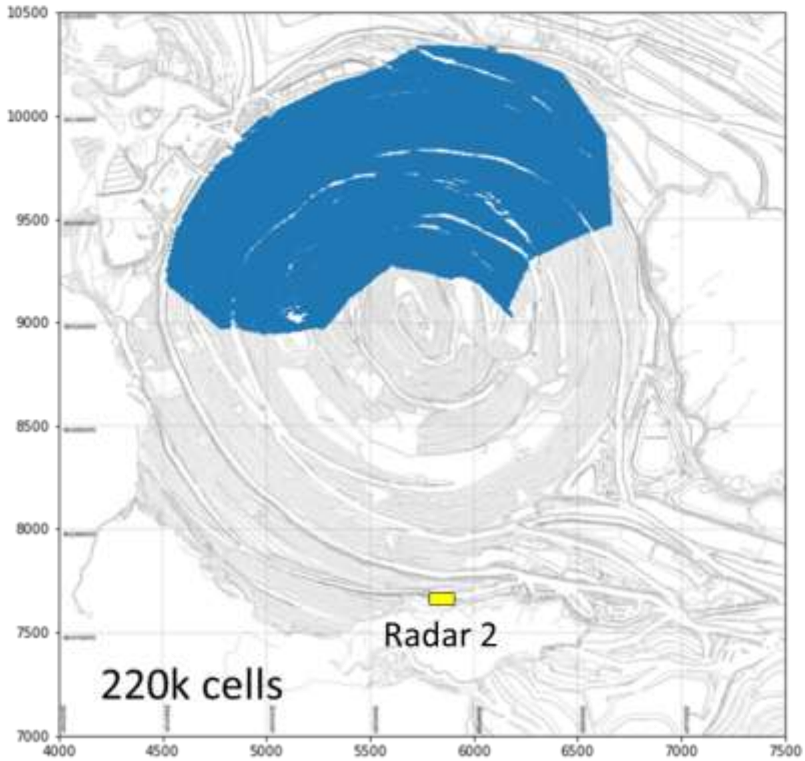

Figure 2. Radar 2 covering area.

D. PREDICTION MODEL

The three predicting methods used to generate prediction are radar's velocity threshold filtering, regression, and unsupervised clustering (Figure 3).

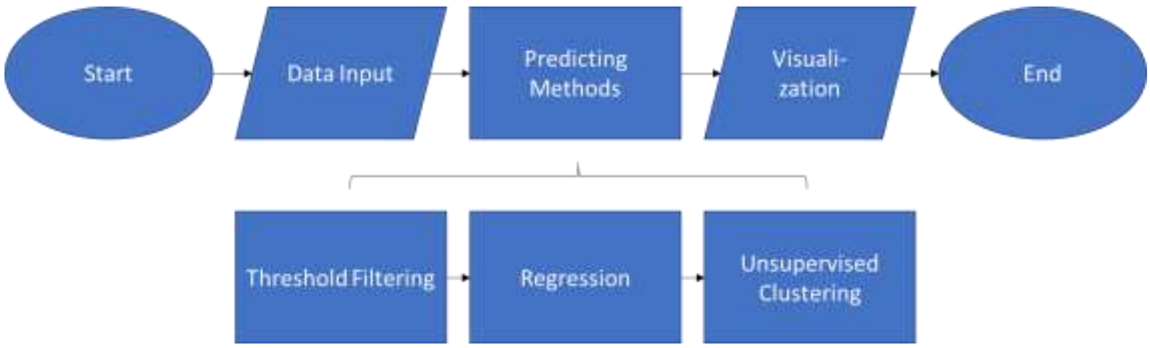

Figure 3. Flowchart model prediction.

D.1. VELOCITY CUT-OFF

The long process to determine Trigger Action Response Plan (TARP) threshold value involves multiple back analysis studies. Therefore, this paper will not be discussing the statistical study of TARP threshold in Batu Hijau site. The most recent TARP study in Batu Hijau, conducted in 2020, incorporates a 1.5 mm/hour cut-off velocity value as an early warning indicator.

Traditional velocity cut-off method is still the most effective and efficient way to classify real movement (Figure 4). It runs first to greatly reduce the number of cells that will be processed by the AI model next. This saves a significant amount of computational power and processing time. However, when computational power is no longer an issue, machine learning models can be run alternatively first.

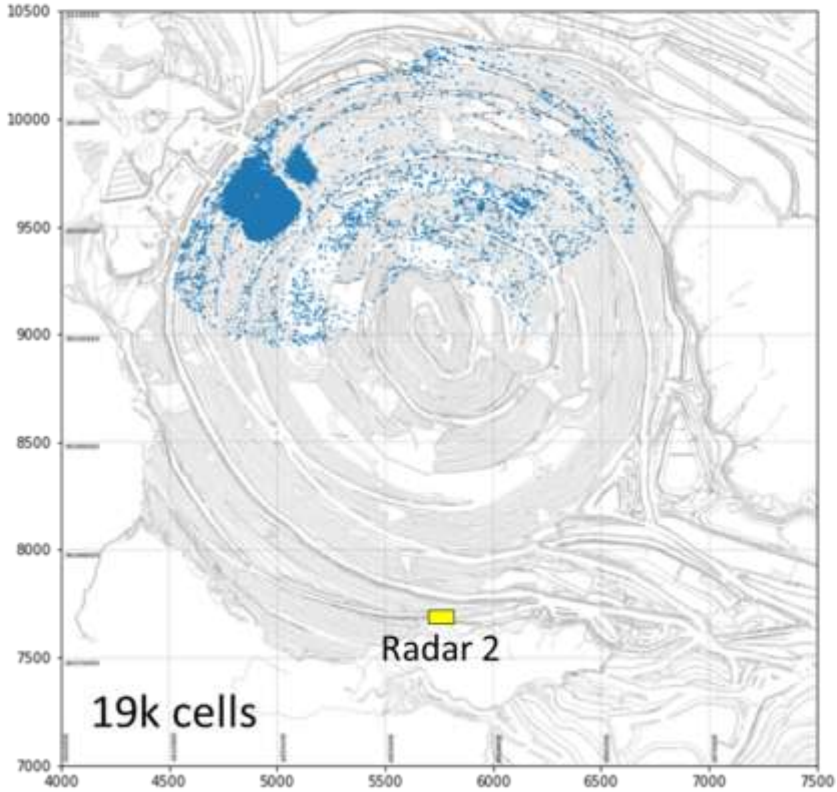

Figure 4. Real time prediction example after applying traditional cut-off threshold.

D.2. LINEAR REGRESSION MODEL

Regression is the easiest way to determine correlation between variables. There are many forms of regression model: linear, polynomial, exponential and others. However, linear regression, which is the simplest regression model, is used. Based on linear/progressive movement theory, real movement is assumed to be highly correlated with time when compared to noise or no movement. As stated in Fukuzuno (1985), linear movement will gradually change its characteristic towards progressive movement. Therefore, the linear model is selected to be the correct model to identify real movement during the linear phase as early as possible. Other reasons for using linear models are its simplicity and more computational friendly than other models.

The main premise that needs to be understood when applying this step is “every real movement has a high correlation with time, however not everything correlated with time is real movement”. This model uses the above assumption to distinguish and classify real movement from non-real movement. Linear regression is run on every radar pixel which contains a set of displacement data within the last time interval (Figure 5). It evaluates the correlation between displacement and time with the value of coefficient of determination, more commonly known as R-squared (R^2). A cut-off coefficient of determination was previously determined based on the context of site characteristic justified by multiple trial-error results. Figure 6 shows the effect of regression filtering when applied to the previous dataset (Figure 4).

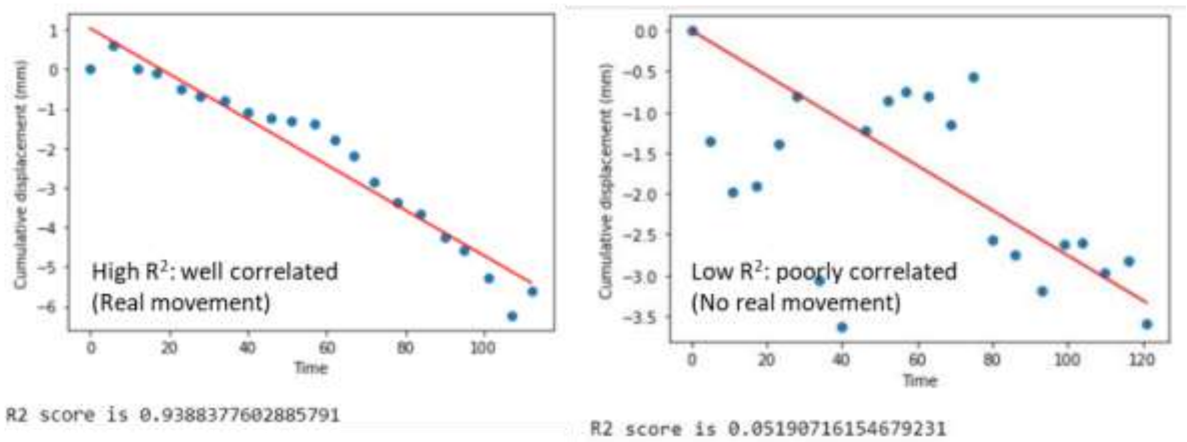

Figure 5. Pixels examples of linear regression model measure the correlation between time and movement.

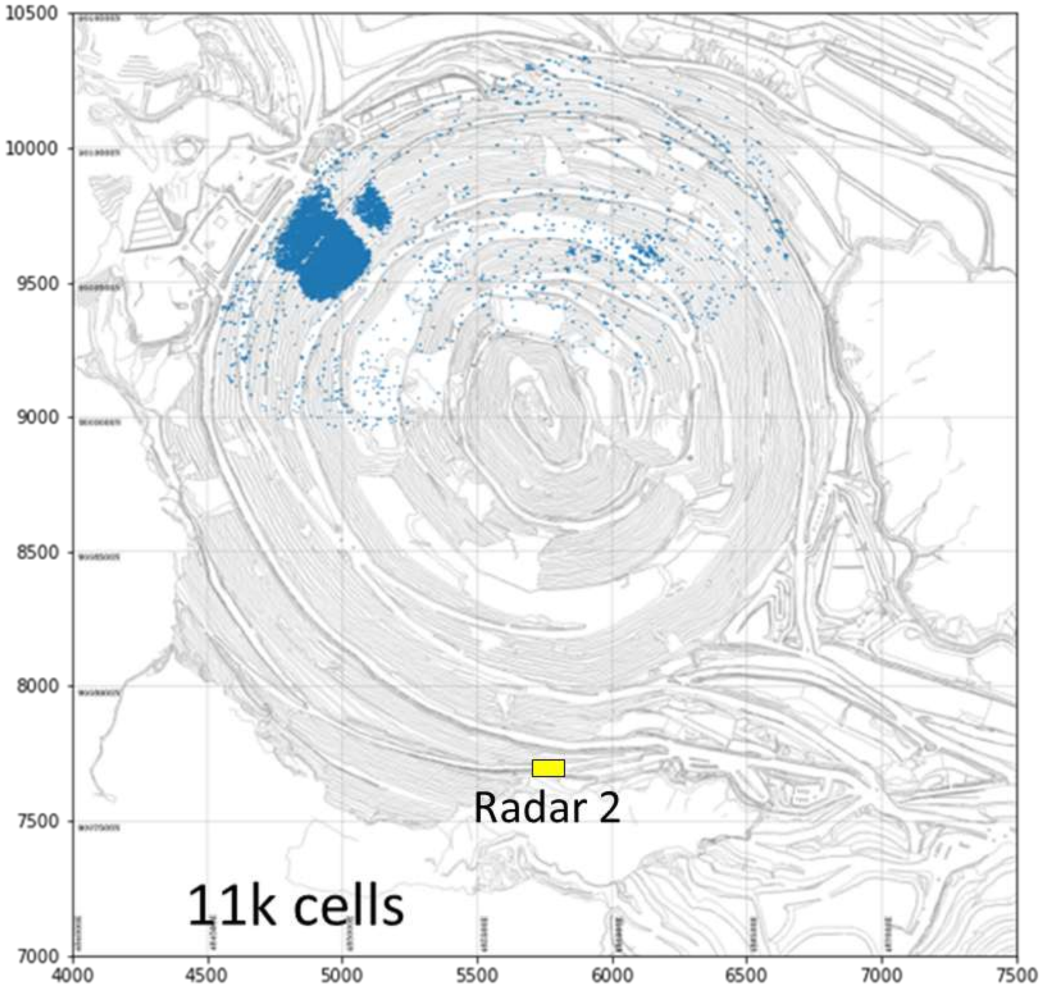

Figure 6. Real time prediction example after applying linear regression filter.

D.3. MEAN SHIFT CLUSTERING

From many clustering methods that are available out there, no method is more suitable than the mean shift unsupervised clustering method. Mean shift is a non-parametric feature-space clustering technique which does not require prior knowledge of the number of clusters and does not constrain the shape of the clusters. It uses an iterative mode search, which initializes with random seed, then calculates the mean of the cluster, shifts the search window to the mean, and repeats until converge. It will generate several clusters that are potentially detected as real movement. Because the mean shift clustering method uses a radial basis function (RBF) kernel, the location or coordinate of each pixel will be referenced and fixed first from the cartesian coordinate.

The main premise that needs to be understood when applying this step is “every real movement has high spatial correlation, however not every highly spatial correlated signal is real movement”. For example, pixels that lie next to each other will have higher spatial correlation than those pixels that lie 100 meters apart. It means that a potential real movement must consist of a minimum number of pixels, known as minimum area extent. The cluster of several close-proximity pixels is an indicator of real movement that triggers the alarm.

There are two main parameters that affect the clustering result, which are bandwidth, equivalent to distance and minimum bin frequency, equivalent to minimum area extent. Bandwidth determines the maximum distance of the kernel function; in other words, it dictates the maximum distance of two pixels that is required to be recognized as a group. The second parameter is the minimum bin or cluster frequency, which determines the minimum number of pixels required for a single cluster.

There is no value that works well straight away for all purposes and instances of the data. Instead, the right value should be carefully adjusted, depending on the targeted movement size. The most suitable value must be justified based on real time observation from several trials. Figure 7 shows the final prediction after applying mean shift clustering.

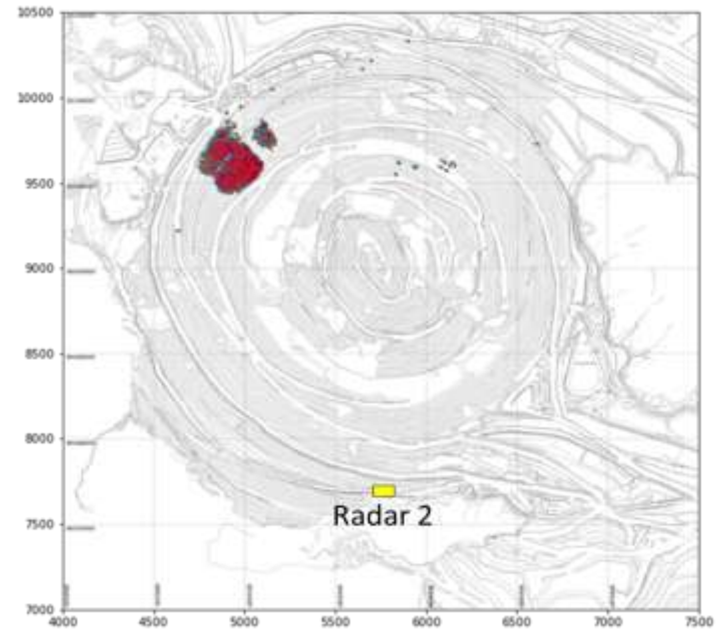

Figure 7. Final prediction after applying mean shift clustering method.

E. CONCLUSION

The conclusions from this research are:

1. In addition to the current normal cut-off TARP response, two supplementary machine learning models are used to analyze real-time radar. The first model is a regression model, which tries to measure the correlation of movement/deformation with time. The second method is an unsupervised clustering technique to understand the data's spatial correlation.
2. These supplementary methods are created to assist engineers, not to replicate or substitute them. Engineering experience and judgement are still needed to correctly determine the AI parameters and validate the prediction result to the real-life condition.
3. Multiple field tests were done to adjust the correct cut-off value for each machine learning parameter. The machine learning parameters that are vital to the classification result are the coefficient of determination, the bandwidth (distance) and the minimum requirement pixel number of a cluster (minimum area extent).
4. Trial result shows a significant reduction of false predictions/alarms, thus giving better accuracy in predicting real movement. However, false predictions are still encountered. This is because the radar data quality is greatly affected by physical weather conditions.
5. Improvement and further research will be conducted by applying multiple timeframes analysis to generate better prediction.

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