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RESEARCH LETTER

Landslide susceptible areas identification using IDW and Ordinary Kriging interpolation techniques from hard soil depth at middle western Central Java, Indonesia

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Abstract
Initial assessment of landslide susceptible areas is important in designing landslide mitigation measures. This study, a part of our study on the developing a landslide spatial model, aims to identify landslide susceptible areas using hard soil depth. In here, hard soil depth, defined as the depth interpreted from cone penetration test where the tip resistance reaches up to 250 kg/cm^2, was used to identify landslide susceptible areas in a relatively small mountainous region in the middle western Central Java where landslides frequently occur. To this end, hard soil depth was interpolated using two different methods: inverse distance weighting and ordinary kriging (OK). The method producing the least errors and the most similar data distribution was selected. The result shows that OK is the best fitting model and exhibits clear pattern related to the recorded landslide sites. From interpolated hard soil depth in the landslide sites, it can be surmised that landslide susceptible areas are places possessing hard soil depth of 2.6–13.4 m. This finding is advantageous for policy makers in planning and designing efforts for landslide mitigation in middle western Central Java and should be applicable for other regions.

Keywords Translational landslide · Landslide susceptible area · Hard soil depth · Spatial interpolation

1 Introduction

Over the last decade, hundreds of landslides occurred in the middle western Central Java. Most of the landslides in this region are typical of rainfall-induced translational landslides (Hidayat 2018). In addition, it is predicted that Indonesia will experience about 2 percent to 3 percent more rainfall due to climate change (Sari et al. 2007). As a result, the number of landslide occurrences could be larger, and the impact could be worsening (Banholzer et al. 2014). Hence, appropriate mitigation measures in particular locations are critical. Accordingly,

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understanding landslide susceptible areas is helpful in designing policy for appropriate mitigation efforts.

Landslide occurs when the slope is unstable. Slope stability can be evaluated from the safety factor, defined as a ratio of the maximum load or stress that a soil can sustain (shear strength) to the actual load or stress that is applied (shear stress) (Das 1994). The higher of safety factor is the lower possibility of landslide to occur (Roslee and Talip 2012). Therefore, high slope stability exists when shear strength is high. However, soil shear strength unveils high spatial variability and is unsuitable to be directly measured due to difficulty of obtaining undisturbed sample (Apriyono et al. 2018). Nevertheless, the value can be estimated from its correlation with hard soil depth and other soil mechanical properties (Taharin et al. 2018). Moreover, translational landslides often arise in the areas where alternation between strong/weak layers exists (Zêzere et al. 2005; Šiljeg et al. 2015; Postance et al. 2018). Hence, hard soil depth can be deemed to be the location of this interchange, which is the central contribution of this study.

Hard soil depth is soil properties obtained from cone penetration test (CPT), the most widely used in situ tests for engineering applications to gain information on soil type and stratification, shear strength in clays, as well as relative density and friction angles in sand. In CPT, resistance at the tip and resistance in the sleeve due to skin friction is measured, and soil samples are taken at the full range of drilling depth. Clay soils have high skin friction, while sandy soils have high tip resistance. In our field measurement, hard soil depth is defined as the depth of cone where tip resistance reaches up to 250 kg/cm^2. Hard soil depth data is abundant as it is prerequisite for any civil structural planning and design. However, the data are usually scattered over a region. To estimate landslide susceptible areas using hard soil depth, understanding its spatial pattern is essential. To do this, an applicable spatial interpolation is required.

Various interpolation techniques commonly used in many literatures are: statistical methods such as linear regression (Lesch and Corwin 2008; Tabari Hossein and Sabziparvar 2011), geometric method such as inverse distance weighting (IDW) and local polynomial (Yanto et al. 2017; Apriyono et al. 2018; Santoso et al. 2018) and geostatistical methods such as ordinary kriging (OK), regression kriging (RK) and co-kriging (CK) (Baskan et al. 2009; Annelies and Vervoort 2010; Fritsch et al. 2011; Yao et al. 2013; Adhikary et al. 2017). Comparison of interpolation methods has been done in many literatures (Wong et al. 2004; Wang et al. 2014; Šiljeg et al. 2015). The performance of each method varies and highly depends on the case, location and model parameters (Šiljeg et al. 2015). Therefore, the main challenge lies on the determination of error characteristics and estimated values by testing and comparing various interpolation methods. This study is motivated by Santoso et al. (2018) and aimed to improve the skills of hard soil depth interpolation using various spatial interpolation techniques. In this study, OK was applied to enhance IDW performance. The performance of each interpolation technique is assessed using different error measures and the likeness of data dispersal. The most fitting interpolation method is then used to create a hard soil depth map. Landslide susceptible areas are inferred by superimposing landslide occurrences map with the hard soil depth map.

2 Study area and data

This study was performed in the middle western Central Java, Indonesia, covering three districts namely Banjarnegara, Purbalingga and Banyumas with total area of 3420 km^2 (Fig. 1). As can be seen from Fig. 1, the perimeter of the study area is dominated by hilly areas, while the middle part is relatively flat. The slope ranges from 1 degree in the middle to 37 degrees in the perimeter with the highest elevation is 3051 m above sea level.

The study area was chosen based on the quality and spatial density of hard soil depth and landslide record data. The hard soil depth was collected from CPT conducted in the period of 2005 – 2016 with some missing data in 2008 and 2009 (Fig. 2). Over this period, hard soil depth in 171 sampling sites was acquired. On the other hand, landslide record was obtained from the Regional Disaster Countermeasure Agency of those three districts. As many as 385 landslide events were recorded during the period of 2010–March 2020.

3 Methodology

3.1 Spatial interpolation

In this study, two different spatial interpolation techniques namely inverse distance weighting (IDW) and ordinary kriging (OK) were employed. In IDW model, interpolation is performed by assigning a weight to interpolating values—i.e. values of variable around targeted point. The weight in IDW is an inverse of interpolating variable distance obtained by dividing 1 with distance of each interpolating variable. Hence, the farther the distance, the smaller the weighted (Shepard 1968). Moreover, the influence of distance is governed by the value of power of distance. The higher of power, the smaller influence of distant variable. As the power of distance ranges from 1 to 6, it is useful to determine the power fittingly. Here cross-validation technique was applied using increased values of power from 1 to 6, and the root mean square error (RMSE)

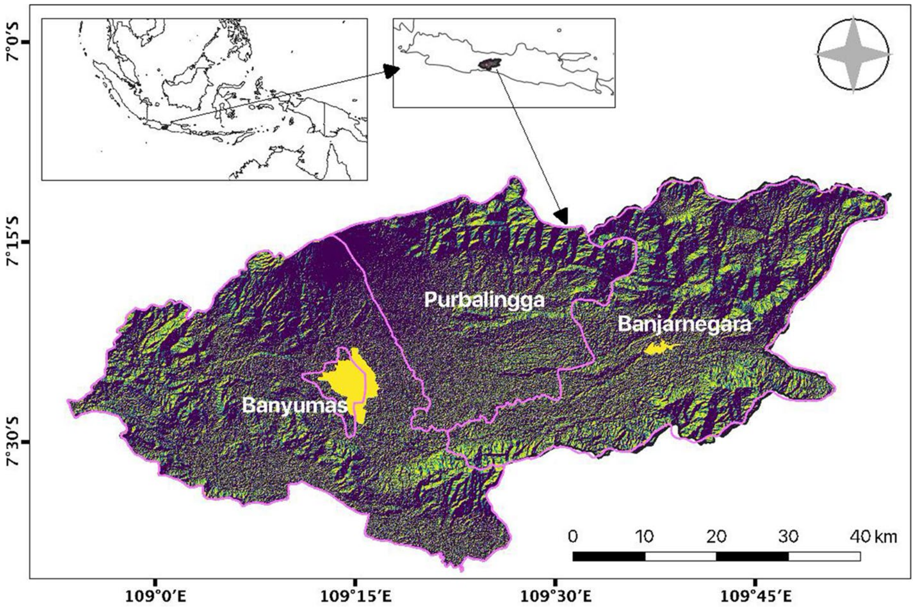


Fig. 1 Study area: the middle western Central Java covering the districts of Banjarnegara, Purbalingga and Banyumas

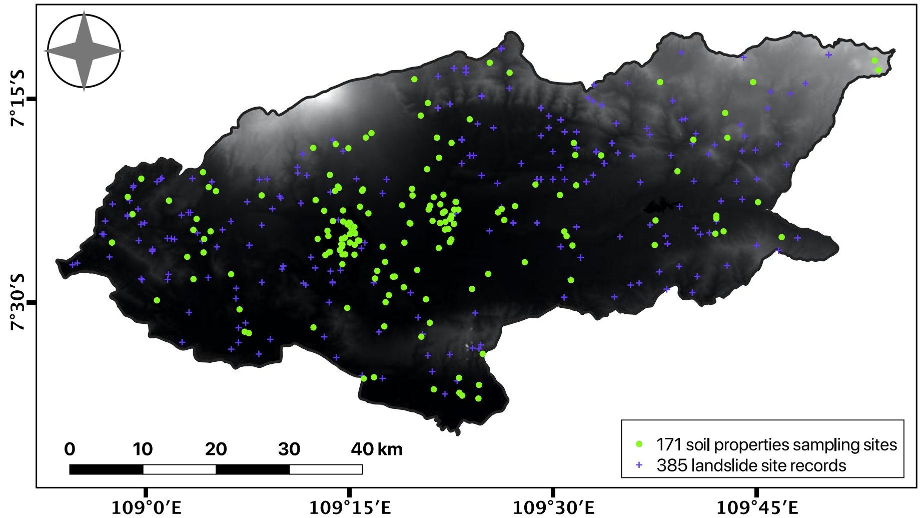


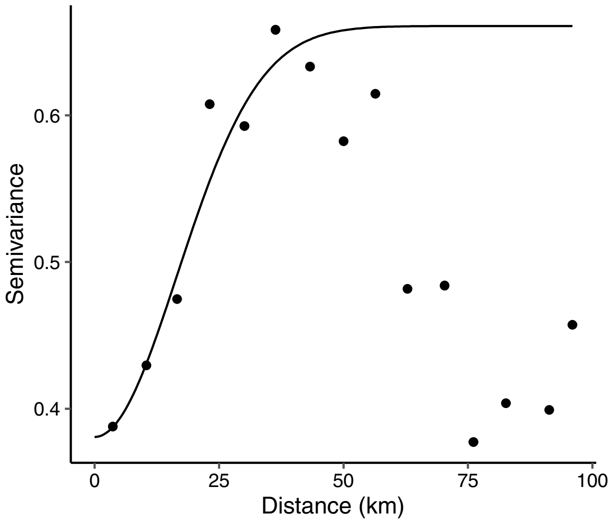
Fig. 2 Map of hard soil depth sampling (shown by circle) and landslide occurrence sites (marked by plus sign)

was computed for each value of power (Adhikary et al. 2017). The values of RMSE for the power of 1 to 6 are 5.29, 5.22, 5.35, 5.52, 5.56 and 5.75, respectively. It is found that the power of 2 yields the lowest RMSE, such that it is used in the IDW application in this study.

In anisotropic data, IDW is no longer relevant. On the other hand, OK model has an ability to take into account the effects of anisotropy on spatial data where point data falling into cluster is assigned a weight smaller than point data located outside of cluster (Boyle 2010). This occurs as the weighted is given based on a function constructed from data characteristics and presented as semivariogram model (Olea and Olea 1999). Many semivariogram models exist, where Gaussian, spherical and exponential functions are commonly used in numerous studies (Mälicke et al. 2018). A semivariogram should be selected in an OK model. Here, *gstat* R package was exploited to choose the best fitted semivariogram model. The *gstat* package has an ability to return a semivariogram model from a list of semivariogram models based on the value of RMSE (Pebesma and Gräler 2021). Four semivariogram models are available in *gstat* R package namely Gaussian, spherical, mattern and exponential (Gräler et al. 2016). For data used in this study, the Gaussian semivariogram model was returned. Figure 3 shows fitted semivariogram model of the hard soil depth in the study area built using Gaussian function with nugget that represents small-scale data variability of 0.38, sill that reflects the total variance contribution of 0.28 and range that separates correlated and uncorrelated distance of 23 km.

Sensitivity analysis was done to the semivariogram model by changing the values of nugget, sill and range to be 50% below and 50% above the fitted values. The interpolated hard soil depth from those changing semivariogram model parameters was then compared with that of the fitted model (Fig. 4). It can be inferred that the model is insensitive the parameter changes implying that the model is trustable.

Fig. 3 Variogram of the ordinary kriging model



3.2 Measurement of interpolation error and performance

Error measurement is important in the selection of the best fitting interpolation model. To do this, cross-validation procedure was applied. To compare the performance of each interpolation technique, the similarity of spatial variability of interpolated and observed values were examined.

Cross-validation is a very useful technique in model selection. This technique can be exploited for detecting autocorrelation to prevent model overfitting due to systematic spatial similarity between predictor and response. In addition, cross-validation can be used to select model parameters which give the least error. In here, leave-one-out cross-validation—i.e. take one value out and estimate value at the leaving points—was executed. Interpolation technique producing the lowest value of mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) was chosen (Willmott and Matsuura 2005; Buchwalder et al. 2006; Yao et al. 2013; Chai and Draxler 2014).

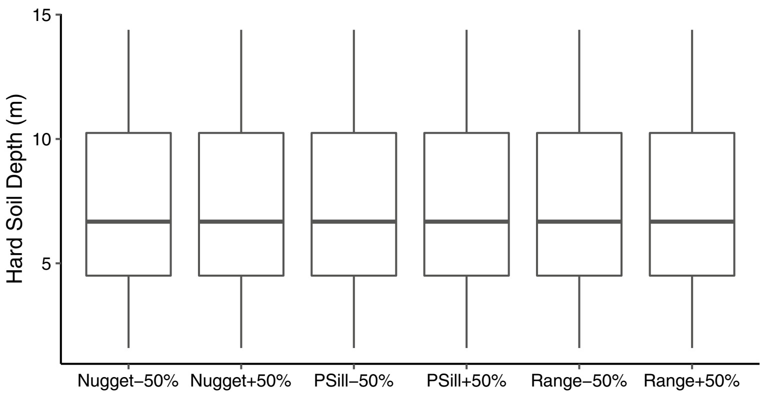


Fig. 4 Sensitivity analysis of the semivariogram model achieved by changing the parameter 50% below and 50% above the fitted values

A good interpolation technique should exhibit similar hard soil depth variability of the interpolation and the observation. Boxplot is an efficient way to inform the dispersion of data by displaying five statistical summaries namely minimum, first quartile, median, third quartile and maximum with less space. The best fitting model is one with the most comparable shape of boxplot between interpolation and observation.

3.3 Spatial correlation of landslide occurrences and hard soil depth

Landslide susceptible areas in the study is detected from the spatial correlation of landslide occurrence sites and their hard soil depth. This is done by visual examination and numerical review. The first assessment was carried out by superimposing interpolated hard soil depth map and landslide event sites, and the second was performed by extracting hard soil depth where landslide occurs and computing several goodness of fit indices such as success index (SI), average index (AI), accuracy (ACC), recall, balanced accuracy (BA) and distance to perfect classification (D2PC) (Formetta et al. 2016).

4 Result and discussion

4.1 Interpolated hard soil depth

Figure 5 shows the map of interpolated hard soil depth using IDW and OK. While the overview of those two maps is equivalent, the detail is distinctive. The IDW hard soil depth map is characterized by circular pattern surrounding high or low values as it is controlled by the squared distance among the points. On the other hand, the area of a unique hard soil depth in the OK map is arbitrary depending on the data structure within the range. The power of 2 in the IDW formula produces more localized interpolated values as the farther the distance the lower the influence. In contrast, the range of 23 km in the OK semivariogram model creates smoothed interpolated surface. As a result, IDW interpolation is able to capture higher and lower numbers compared to the OK. This can be seen from the range of IDW and OK interpolated hard soil depth. Hard soil depth of IDW and OK spans from 1.1 to 19.8 and 1.4 to 14.6, respectively.

4.2 Measurement of interpolation error and performance

To provide insight on the comparison among interpolation approaches at point scale, quantitative error measures of MSE, RMSE and MAE were calculated and are shown in Table 1. These are error measures commonly used in many literatures (Willmott and Matsuura 2005; Buchwalder et al. 2006; Yao et al. 2013; Chai and Draxler 2014). For all error measures, the lower the value, the better the interpolation performance. In Table 1, the lowest value is denoted with bold marker. As shown in Table 1, the value of MSE, RMSE and MAE from OK is 20.93, 4.58 and 3.39, respectively. On the other hand, the value of MSE, RMSE and MAE from OK is 0.46, 0.68 and 0.54, respectively, indicating the best fitting model. As expected, the result improves the performance of hard soil depth interpolation in the overlapping region by Santoso et al. (2018).

To strengthen the analysis at regional scale, hard soil depth distribution of both hard soil depth interpolated and observed values were compared and presented in Fig. 6. It can be observed that the median of IDW is closer than that of OK. However, the minimum,

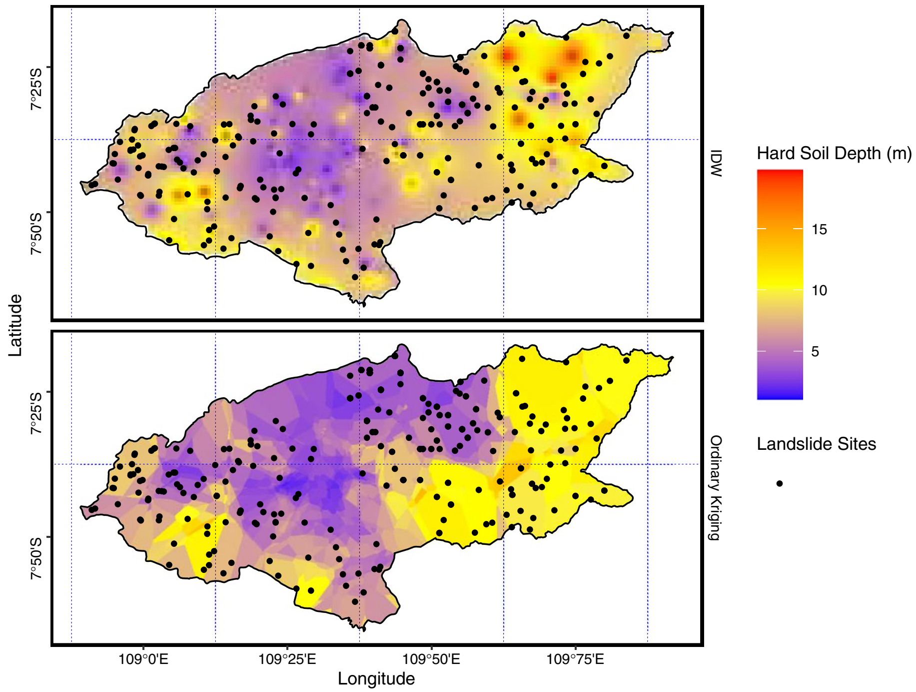


Fig. 5 Interpolated hard soil depth using IDW (top) and ordinary kriging (bottom) along with the location of landslide events (black dot)

Table 1 Error measures of cross-validation using different interpolation methods

Error Measures	IDW	OK
MSE	20.93	**0.46**
RMSE	4.58	**0.68**
MAE	3.39	**0.54**

The bold values are significantly lower than the unbold values indicating better performance

maximum, 1st quartile and 3rd quartile of OK are better approaching the observation. Hence, it can be deduced that OK interpolation performs better than IDW. Based on the investigation of error and data distribution above, it is suggested that OK performs better than IDW in estimating spatial distribution of hard soil depth in the middle western Central Java (Fig. 7).

4.3 Spatial correlation of landslide occurrences and hard soil depth

In the previous section, it was clearly shown that OK approach produces the most fitting model. Hence, it is used in this section to assess spatial correlation of hard soil depth and landslide occurrences. First, visual assessment of the relationship is done based on the map, as shown in Fig. 3 (bottom). It can be seen that landslide events are separated by

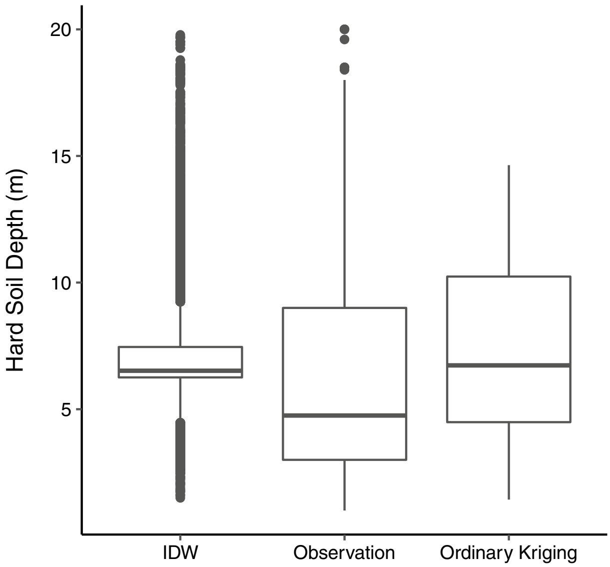


Fig. 6 Boxplot of hard soil depth from IDW and ordinary kriging interpolation compared to the observation

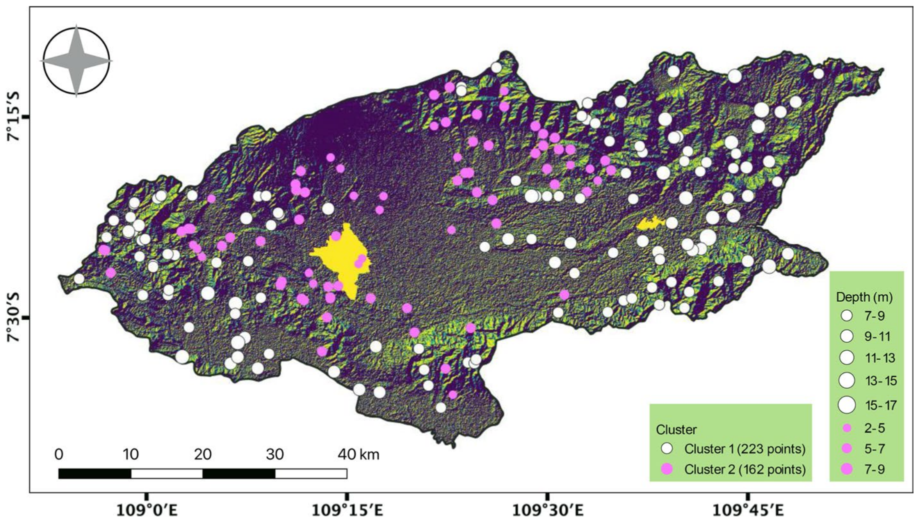


Fig. 7 Landslide event clusters and its related hard soil depth. Average depth of cluster 1 and cluster 2 is 9.6 and 4.4 m, respectively

shallow hard soil depth in the middle part indicating that landslide is unlikely to occur when the hard soil is too shallow. With the help of IDW interpolation illustrated in Fig. 3 (top), the landslide is undetected in the deep hard soil location (red circles). Hence, it can be inferred that landslide will not likely occur when the hard soil setting is too shallow and too deep.

To verify aforementioned visual assessment, the values of hard soil depth in the landslide sites (or nearest locations) are extracted and clustered using K-Means clustering algorithm based on silhouette score to get the optimum cluster (Aytaç 2020). Silhouette score is a metric used to evaluate the goodness of fit in clustering technique calculated using the mean intra-cluster distance and the mean nearest-cluster distance (Al-Zoubi and al Rawi 2008). The value of silhouette score ranges from − 1 to 1. A score of 1 denotes the best meaning as the mean clusters are well apart from each other and clearly differentiated, a score of 0 indicates overlapping clusters and a score of − 1 is the worse as it infers that the clusters are assigned mistakenly.

The result shows that the hard soil depth in the landslide locations of the study area ranges from 2.6 to 13.4 m. Therefore, these depths can be used as the initial sign of landslide susceptible areas. Using K-Means clustering algorithm, these depths fall into 2 clusters with silhouette score of 0.75, indicating good separated cluster with 25% of overlapping data between the clusters. The first cluster (white circle) is characterized with medium to high altitude and steep hill with average hard soil depth of 9.6 m. The second cluster (blue circle) lies in the medium to low elevation and gentle slope with average hard soil depth of 4.4 m. Accordingly, it can be inferred that Cluster 1 is related to large massive landslides, while Cluster 2 corresponds to slightly small landslides such as streambank or roadside landslides.

Using the proposed criteria, the values of success index, average index, accuracy, balance accuracy, recall and distance to perfect calculation were computed as the goodness of fit (GOF) indices. The result is presented in Table 2. As shown in Table 2, the values of GOF range from low to medium. However, for initial detection of landslide susceptible areas, it is acceptable.

This finding is consistent with landslide mechanisms commonly occurring in Indonesia: translational and rotational landslide (Cepeda et al. 2010). In this type of landslide, it requires acting force and rupture surface to make landslide happens. Acting force presents in the form of gravitational force from soil mass and soil water content. Between the surface and hard soil depth, the water content of sampling sites ranges from 22 to 98% denoting the presence of groundwater in the soil layer. Moreover, soil type in the soil layer above the hard soil depth is dominated by clay, peat and silt with the portion of 44%, 22% and 19%, respectively. While initial water content suspends landslide triggering, these types of soil stimulate landslide initiation (Fan et al. 2016).

Rupture surface needs more stable underlying material (Muller and Martel 2000; Jesus et al. 2017). This can be either hard rock or hard soil. Hence, the hard soil depth can be viewed as the location of rupture surface. When the rupture surface is too shallow, acting gravitational force is smaller due to low volume of soil mass and soil water content. This condition lessens the probability of landslides to occur. On the other hand, deep rupture surface is associated with sedimentary lithology class and low slope of

Table 2 Summary of goodness of fit (GOF) indices

GOF Indices	Value	Optimum
Accuracy (ACC)	0.28	1
Average Index (AI)	0.50	1
Success Index (SI)	0.50	1
Balanced Accuracy (BA)	0.50	1
Recall	1	1
Distance to Perfect Classification (D2PC)	0	0

land. As a result, landslides are unlikely to happen in the area with a very deep rupture surface.

5 Conclusion

Two interpolation methods namely IDW and OK were employed to simulate spatial distribution of hard soil depth useful for initially assessing landslide susceptible areas in the middle western Central Java, Indonesia. To select the best fitting model, the model was tested based on various error measures and data distribution similarities. While the MSE, RMSE and MAE values from OK are significantly lower than that of IDW, the boxplot of interpolated hard soil depth from OK is also more analogue to the observation. It can be concluded that OK performs better than IDW. Based on this, hard soil depth resulted from OK interpolation procedure was superimposed with landslide sites. It is clearly shown that landslide occurs in the areas where hard soil depth ranges from 2.6 to 13.4 m indicating the landslide susceptible areas. This finding is useful for policy makers in designing mitigation efforts to landslide susceptible areas and subsequently to save more lives.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11069-021-04982-5.

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