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# A ONE-STEP NEWMARK MODEL FOR PROBABILISTIC ANALYSIS OF SEISMIC SLOPE DISPLACEMENTS

W. DU[1] and G. WANG[2]

**ABSTRACT**

Estimating the earthquake-induced sliding displacement is important to assess the stability of slopes during earthquakes. Current Newmark displacement models generally use ground motion intensity measures (IMs) as predicators, hence the uncertainties of the IM values should be accounted for in the displacement hazard analysis. This paper proposes a simple one-step predictive model for the Newmark displacement based on four seismological parameters (magnitude, rupture distance, fault categories and shear wave velocity) instead of IMs. Through benchmark examples, it is found that both the predicted median and the aleatory variability of the proposed model are comparable with other IM-based Newmark models. The one-step model demonstrates great advantage in saving the computational cost when applied in a fully probabilistic seismic displacement analysis of spatially distributed slope systems. Therefore, the new model can be used as an alternative for a more efficient probabilistic analysis of the earthquake-induced slope displacements especially in a regional scale.

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Estimating the earthquake-induced sliding displacement is important to assess the stability of slopes during earthquakes. Current Newmark displacement models generally use ground motion intensity measures (IMs) as predicators, hence the uncertainties of the IM values should be accounted for in the displacement hazard analysis. This paper proposes a simple one-step predictive model for the Newmark displacement based on four seismological parameters (magnitude, rupture distance, fault categories and shear wave velocity) instead of IMs. Through benchmark examples, it found that both the predicted median and the aleatory variability of the proposed model are comparable with other IM-based Newmark models. The one-step model demonstrates great advantage in saving the computational cost when applied in a fully probabilistic seismic displacement analysis of spatially distributed slope systems. Therefore, the new model can be used as an alternative for a more efficient probabilistic analysis of the earthquake-induced slope displacements especially in a regional scale.

## Introduction

Estimating the seismic displacement of natural slopes is particularly important for risk assessment of earthquake-induced landslides. Newmark firstly proposed a rigid sliding block model, which assumed that sliding is initialized when the shaking acceleration exceeds a critical acceleration, and the block deforms plastically along a shear surface. The critical acceleration ($a_c$) is determined by the properties of slopes (e.g., the strength of material and the geometric angle). The permanent displacement $D$ is calculated by double integrating the over exceeded parts with respect to time as shown in Fig. 1. Although this Newmark model ignores the internal deformation of sliding mass during shaking process, it is still applicable to natural slopes or landslides in stiff materials [1]. After Newmark's pioneering work, many researchers (e.g., [1], [2], [3]) have proposed their empirical equations using various ground motion database and function forms.

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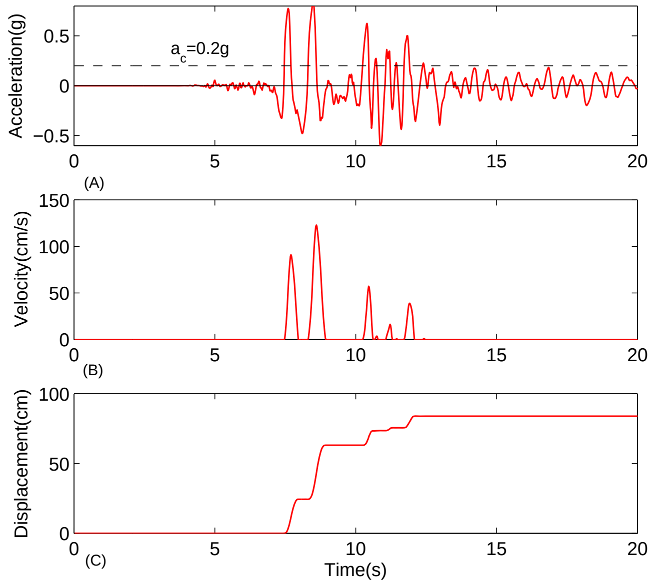


Figure 1. Illustration of Newmark displacement with critical acceleration ac=0.2g. (A) Earthquake acceleration-time history. (B) Velocity of sliding block versus time. (C) Displacement of sliding block versus time.

Currently all the Newmark displacement models are functions of critical acceleration $a_c$ and various ground motion intensity measures (IMs), such as the peak ground acceleration (PGA) and Arias intensity (Ia). Therefore, the typical procedure to estimate displacement is a two-step approach: firstly, ground motion prediction equations (GMPEs) are used to estimate the median and sigma values of IMs; secondly, sliding displacement values can be calculated using the predicted IMs as predicators. To estimate the variability of computed displacement, two levels of uncertainties, at the IM level as well as at the displacement level, should be well considered. More importantly, the uncertainty of GMPEs should be taken into account in the displacement hazard analysis. In other words, engineers should make a decision regarding which GMPE model should be used to predict IMs, and how to quantify the variability of IMs. Specific selection of GMPEs would have a significant impact on the computed displacement. Besides, this two-step approach would inevitably complicate the computational process: two levels of integration process should be conducted to derive the displacement hazard curves (see more details in [4]). These computational expenses will be much more remarkable if a large-scale landslide region is studied ([5]).

This paper proposes a one-step empirical model to predict the Newmark displacement, directly based on seismic information and geological conditions (e.g. moment magnitude $M_w$, rupture distance $R_{rup}$, shear wave velocity of the upper 30 m $V_{s30}$, *etc*) rather than intensity measures. The advantage of this proposed model is that it can greatly simplify this computational process in a fully probabilistic displacement hazard analysis, meanwhile, the results are generally in agreement with other existing two-step models. It is also to be noted that it is a pseudoprobabilistic approach just to compute the sliding displacement directly using IMs at a specific ground hazard level. Although it is simple, the probability of occurrence of the resulted sliding displacements is unknown. Compared with the fully probabilistic method, the pseudo-probabilistic analysis usually results in unconservative estimation in most cases ([6]). Therefore, the proposed one-step method is intended as a simplified approach for a fully probabilistic displacement analysis.

## One-step Newmark displacement prediction model

### The functional form

In this study, the subset of the PEER-NGA strong motion database is used to compute the sliding displacement. Only horizontal recordings from free-field conditions are used in the analysis, resulting in a total of 1560 pairs of ground motions of two horizontal directions ([7]). Regression analysis was performed to predict the sliding displacement as a function of seismological variables using mixed random effect algorithm proposed by Joyner and Boore ([8]). The displacement prediction model takes a form as follows:

$$\ln\left(D\right)_{ij} = \overline{\ln\left(D\right)_{ij}} + \eta_i + \varepsilon_{ij} \tag{1}$$

where $\ln\left(D\right)_{ij}$ and $\overline{\ln\left(D\right)_{ij}}$ represent the observed and the predicted logarithmic displacement value for the *j*-th recording and *i*-th event, respectively. $\eta_i$ refers to inter-event residual and $\varepsilon_{ij}$ denotes intra-event residual (within earthquake), respectively. This model assumes that displacement values ($D$) follow logarithmic normal distribution. The mixed random effect model is widely applied to predict ground motion IMs, such as the development of the NGA models (e.g. [7]).

Since currently there is no any Newmark displacement model available in literature using mixed random effect regression, some functional forms that have been used for GMPEs are first attempted. More specifically, PGA and Ia have been found to have a strong correlation with Newmark displacement. Therefore, the GMPE functional forms for PGA and Ia should be used as the preliminary functional forms. After several trials and comparisons, the final functional expression is adopted as:

$$\begin{aligned}\ln(D) = {} & c_1 + c_2 \cdot (8.5 - M_w)^2 + (c_3 + c_4 \cdot M_w)\ln(\sqrt{R_1^2 + h^2}) + c_5 \cdot Fr \\ & + (c_6 + c_7 \cdot M_w)\ln\left(\frac{R_{20}}{20}\right) + v_1 \cdot \ln\left(\frac{V_{s30}}{1100}\right)\end{aligned} \tag{2}$$

where $R_1 = \begin{cases} R_{rup} & if\ R_{rup} \le 20km \\ 20 & otherwise \end{cases}$ and $R_{20} = \begin{cases} 20 & if\ R_{rup} \le 20km \\ R_{rup} & otherwise \end{cases}$. $M_w$ refers to moment magnitude; $R_{rup}$ means rupture distance (km); $R_1$ and $R_{20}$ are two distance parameters derived from $R_{rup}$. $R_1$ is changing if $R_{rup}$ is smaller than 20 km, controlling the short-distance scaling. $R_{20}$ changes if $R_{rup}$ is greater than 20 km, controlling the long-distance scaling; $Fr$ is an indicator variable (1 for reverse and reverse-oblique types of faulting and 0 otherwise. Note an indicator variable representing the normal fault is not used since it is statistically insignificant to be included in the model); *h* is a fictitious hypocentral depth in km estimated during the regression, and $V_{s30}$ represents the averaged shear wave velocity of the upper 30 m (m/s). The influence of site effect is incorporated in Eq. 2 by using the $V_{s30}$ term.

It is to be noted that the Eq. 2 is regressed based on sliding displacements larger than 0.01 cm. Using probit regression analysis, the probability of "zero" displacement (displacement smaller than 0.01 cm) can be expressed as a function of seismological parameters as follows:

$$P(D=0)=1-\Phi(c_8-c_9\cdot M_w-c_{10}\cdot\ln(R_{rup})+c_{11}\ln(Vs30) \tag{3}$$

where $\Phi$ is the standard normal cumulative distribution function.

The non-zero displacement values are estimated by Eq. 2, and Eq. 3 is used to specify the the probability of zero displacement $P(D=0)$. During this regression, the displacement data larger than 0.01cm are collected to derive Eq. 3. Consequently, the predicted displacement according to a specified percentile *p* (in decimal form, i.e. *p*=0.5 for the 50$^{th}$ percentile) can be determined as:

$$\ln D_p=\ln D+\sigma\cdot\Phi^{-1}\left(\frac{p-P(D=0)}{1-P(D=0)}\right) \tag{4}$$

The proposed model is termed as DW13 model. A total of thirteen coefficients are included in the model. The regression process can be implemented in statistical programming software like R, especially the 'nlme' function ([9]). The regression coefficients for six $a_c$ values: 0.05g, 0.075 g, 0.1 g, 0.15 g, 0.2 g and 0.25 g, are tabulated in Table 1. All coefficients yield small p-values, therefore they are statistically significant. For the case of $a_c$=0.15 g, $c_4$ and $c_7$ are statistically insignificant, and hence they are removed in the final functional form. The reported inter- and intra-event standard deviations (in natural logarithmic scale) are also listed. It is clear that the total standard deviation value increases as $a_c$ increases. This implies that the uncertainty of the predicted sliding displacements is smaller if $a_c$ is smaller.

**Inter-event and intra-event residuals**

The distributions of inter- and intra-event residuals against indicators (e.g., earthquake magnitudes and rupture distances) for $a_c$=0.1g are shown in Fig. 2. The trend lines obtained by simple linear regression are also plotted in these figures. From these plots, no obvious biases between residuals and variables used in the regression equation can be found. The slightly biased trend in the intra-residuals versus moment magnitude plot is possibly caused by a paucity of data at small magnitudes ($M_w$<5). The distributions of residuals imply that the proposed model can yield unbiased predicted displacement over a large magnitude and distance range.

Table 1. Coefficients for the proposed DW13 displacement model

| Parameter | $a_c$=0.05 g | $a_c$=0.075 g | $a_c$=0.1 g | $a_c$=0.15 g | $a_c$=0.2 g | $a_c$=0.25 g |
|---|---|---|---|---|---|---|
| $c_1$ | 8.23 | 7.11 | 7.29 | 7.13 | 6.12 | 15.21 |
| $c_2$ | -0.18 | -0.08 | -0.14 | -0.21 | -0.25 | -0.27 |
| $c_3$ | -4.57 | -5.17 | -4.10 | -2.77 | -2.42 | -5.33 |
| $c_4$ | 0.31 | 0.40 | 0.22 | -- | -- | -- |
| $c_5$ | 0.64 | 0.75 | 0.72 | 0.80 | 0.74 | 1.04 |
| $c_6$ | -4.84 | -3.21 | -4.67 | -1.35 | -1.65 | -0.72 |
| $c_7$ | 0.31 | 0.09 | 0.38 | -- | -- | -- |
| $h$ | 5.72 | 4.19 | 4.23 | 4.55 | 5.53 | 14.3 |
| $\nu_1$ | -1.26 | -0.92 | -0.86 | -0.55 | -0.57 | -0.43 |
| $\tau$ | 0.39 | 0.50 | 0.54 | 0.45 | 0.42 | 0.29 |
| $\sigma$ | 1.55 | 1.56 | 1.60 | 1.78 | 1.78 | 1.76 |
| $\sigma_t$ | 1.59 | 1.63 | 1.70 | 1.84 | 1.82 | 1.78 |
| $c_8$ | 4.25 | 2.44 | 3.05 | 2.70 | 1.23 | -0.95 |
| $c_9$ | 0.99 | 0.79 | 0.63 | 0.39 | 0.33 | 0.27 |
| $c_{10}$ | -1.92 | -1.58 | -1.55 | -1.32 | -1.07 | -0.87 |
| $c_{11}$ | -0.81 | -0.46 | -0.46 | -0.37 | -0.25 | 0.04 |

Note: $\tau$: standard deviation of inter-event residuals; $\sigma$: standard deviation of intra-event residuals; $\sigma_t$: standard deviation of total residuals ( $\sigma_t = \sqrt{\sigma^2 + \tau^2}$ ).

The distribution of intra-event residuals against rupture distance shows a strong trend: the scatter of residuals generally increases with increasing rupture distance. Hence, it is tempting to get the standard deviation of intra-event residuals within varying rupture distance bins, as shown in Fig. 3. The distance bins are partitioned into overlapping intervals in logarithmic scale from 0.1km to 200 km, where the horizontal bar indicates the range of the interval in each bin. A simple trilinear model is used to represent the empirical data:

$$\sigma = \begin{cases} a & if \quad R_{rup} \leq 1\,km \\ a + b \cdot \ln R_{rup} & if \quad 1\,km < R_{rup} < 100\,km \\ a + 4.6 \cdot b & if \quad R_{rup} \leq 200\,km \end{cases} \tag{5}$$

where a=0.76, b=0.23 for $a_c$=0.05 g; a=0.89, b=0.237 for $a_c$=0.075 g and a=1.05, b=0.22 for $a_c$=0.1 g. For the case of $a_c \geq 0.15$ g, the rupture distance has little influence on the sigma value, so the reported constant values in Table 1 (e.g., $\sigma = 1.78$ can be used for the case of $a_c$=0.15 g) are recommended. For the standard deviation of inter-event residuals, no obvious trend is observed for various scenarios, and then the constant values reported by regression analysis can be used.

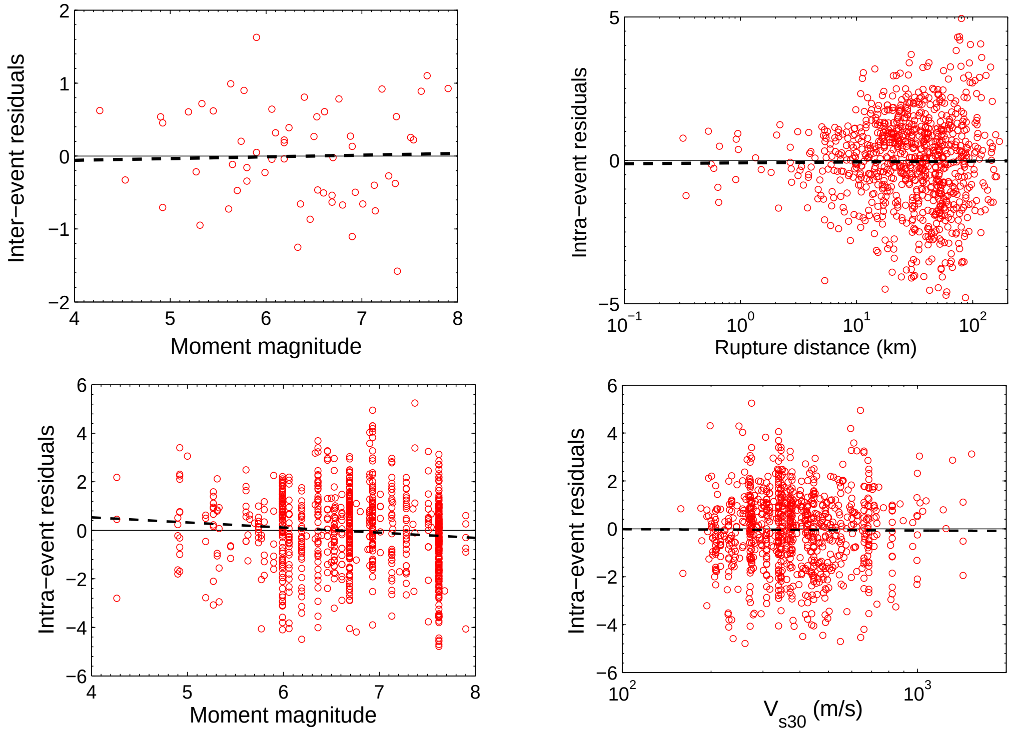


Figure 2. Distributions of inter-event and intra-event residuals for $a_c$=0.1g with respect to moment magnitude, rupture distance and shear wave velocity, respectively.

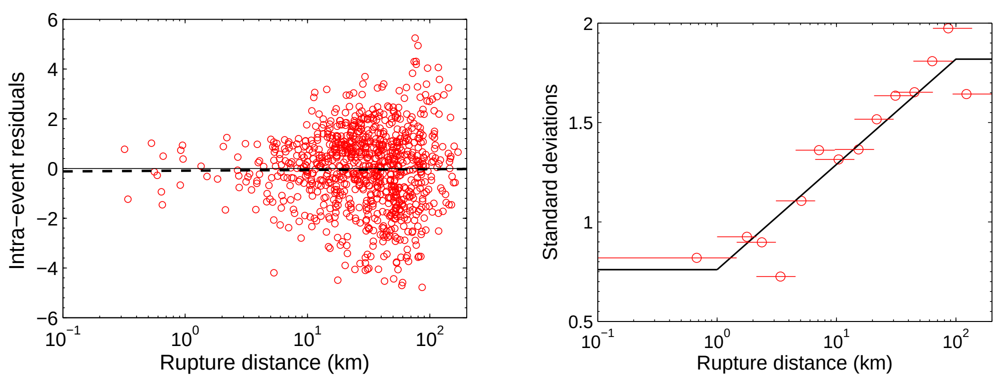


Figure 3. (a) Distribution of intra-event residuals for $a_c$=0.05g with respect to rupture distance; (b) Trilinear relationship of intra-event standard deviations, where the point denotes the median value of each bin, and the horizontal bar indicates the range of the interval, respectively.

## Comparison with other two-step displacement models

Fig. 4 shows the predicted displacement with respect to rupture distance for various earthquake scenarios. The estimated displacement values from Newmark displacement models are also shown in these plots. For simplicity purpose, one predictive model from each group of scholars is selected. These predicted equations are listed as follows:

1. [PGA, $M_w$] BT07 model [10]:

$$\ln(D) = -0.22 - 2.83\ln(a_c) - 0.333(\ln(a_c))^2 + 0.566\ln(a_c)\ln(PGA) + 3.04\ln(PGA) - 0.244(\ln(PGA))^2 + 0.278(M_w - 7)$$
$$\sigma_{\ln D} = 0.66 \tag{6}$$

2. [PGA, Ia] J07 model [1]:

$$\log_{10}(D) = 0.561\log_{10}(Ia) - 3.833\log_{10}\left(\frac{a_c}{PGA}\right) - 1.474, \qquad \sigma_{\log_{10} D} = 0.616 \tag{7}$$

3. [PGA, Ia] RS08 model [2]:

$$\ln(D) = 2.39 - 5.24\left(\frac{a_c}{PGA}\right) - 18.78\left(\frac{a_c}{PGA}\right)^2 + 42.01\left(\frac{a_c}{PGA}\right)^3 - 29.15\left(\frac{a_c}{PGA}\right)^4 - 1.56\ln(PGA) + 1.38\ln(Ia)$$
$$\sigma_{\ln D} = 0.46 + 0.56\left(a_c / PGA\right) \tag{8}$$

4. [Ia] HL11 model [3]:

$$\log_{10}(D) = 0.847\log_{10}(Ia) - 10.62a_c + 6.587a_c\log_{10}(Ia) + 1.84, \qquad \sigma_{\log_{10} D} = 0.295 \tag{9}$$

All the selected equations have been proposed in recent years. The averaged PGA values from four NGA GMPE models ([7], [11], [12], [13]) and the averaged Ia values from three predictive models ([14], [15], [16]) are used to reduce epistemic uncertainties of IMs. Four earthquake scenarios (generally large magnitude combined with small critical accelerations) are shown in Fig. 4. The figure also shows the computed Newmark displacements using strong motion time histories from the NGA database within a magnitude bin [$M_w$-0.25, $M_w$+0.25] and shear wave velocity bin [$V_{s30}$-200 m/s, $V_{s30}$+200 m/s]. For example, the Fig. 4(a) displays the computed Newmark displacement data using strong motions of $5.75 < M_w < 6.25$, $200 < V_{s30} < 600$, strike-slip faulting, and $a_c$ =0.05g.

Two observations can be made. First, empirical data are almost evenly distributed around the predicted median curves, implying that the proposed model can get unbiased predictions for these earthquake scenarios. Second, the curves obtained from different models are generally comparable. Remind that DW13 model is a one-step method. Despite the difference in the functional forms and indictors that these equations are based on, quite consistent predictive values (especially for short and median rupture distance) can be seen from these plots. Much larger scatters can be observed in the far distance range, where the predicted displacements are very small and hence have little engineering significance. Besides, although there are some discrepancies among these models, the DW13 predictive curves are generally located in the middle of these curves. Hence, the new model can reasonably predict the displacement values based directly on seismological variables.

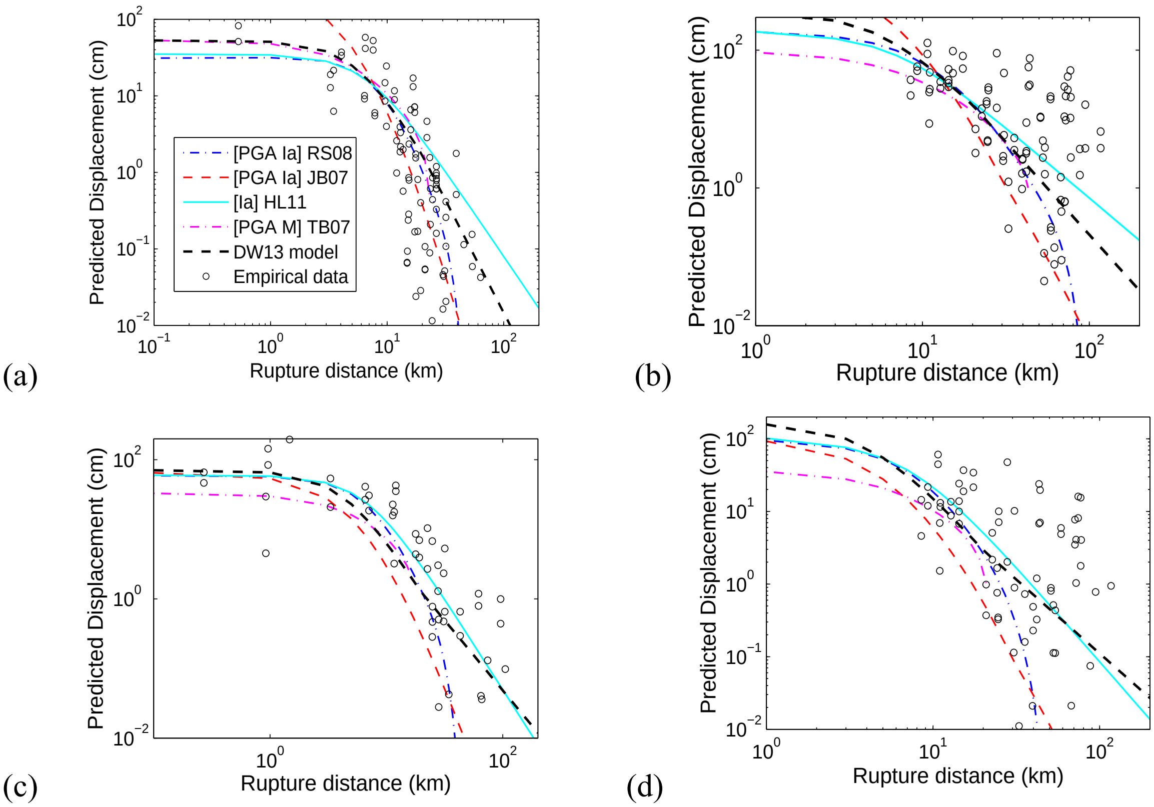


Figure 4. Comparison of the median predictions of the DW13 model with other models. The computed empirical displacement data are also shown for each scenario: (a) $M_w$=6, Strike-slip fault, $V_{s30}$=400 m/s and critical accelerations $a_c$=0.05g; (b) $M_w$=7, reverse fault, $V_{s30}$=400 m/s and $a_c$=0.05g; (c) $M_w$=7, Strike-slip fault, $V_{s30}$=400 m/s and $a_c$=0.1g and (d) $M_w$=7, reverse fault, $V_{s30}$=400 m/s and $a_c$=0.1g.

The total standard deviations of this model are about 1-1.8 in the natural log scale for different $a_c$ values with different rupture distance. Albeit it is larger than any other reported sigma values (range from 0.7 to 1.5 for different models) of the Newmark displacement prediction models based on IMs, it is indeed similar if the variabilities of the predictors, i.e., IMs, are also considered in the Newmark displacement models. Monte-Carlo simulation is used to compute the total aleatory variability of the one-step and two-step displacement models for given earthquake scenarios. For the two-step models, 100 sets of correlated vector IMs are generated firstly. For the vector models, the joint occurrence of multiple IMs is specified by using the empirical correlations. The correlation coefficient between PGA and Ia is specified as ρ(PGA, Ia)=0.88 ([14]). Secondly, for each set of vector IMs, 100 displacement residuals are simulated following a lognormal distribution. The standard deviation of the resulted 10000 displacement values is then calculated to estimate the total aleatory variability for each two-step Newmark displacement model. For the one-step model, only 100 displacement residuals need to be generated for each scenario. Fig. 5 shows the standard deviations versus rupture distances for different magnitude scenarios. For the IM-based models, the total sigma values considering both the aleatory variabilities of GMPEs and Newmark displacement models are about 1.5-2.5 for $a_c$=0.1g. It is noted that small displacement values have to be excluded in the calculation, since they are of little engineering importance but appear to be highly scattered in log scale. By comparison, the sigma of one-step displacement model reveals a generally consistent trend compared with other models. Since aleatory variability represents the inherent uncertainty that cannot be significantly reduced, the new DW13 model is not intended to reduce the aleatory variability but indeed simplify the computational procedures, as well as eliminates the epistemic uncertainties in using different GMPEs to obtain IMs.

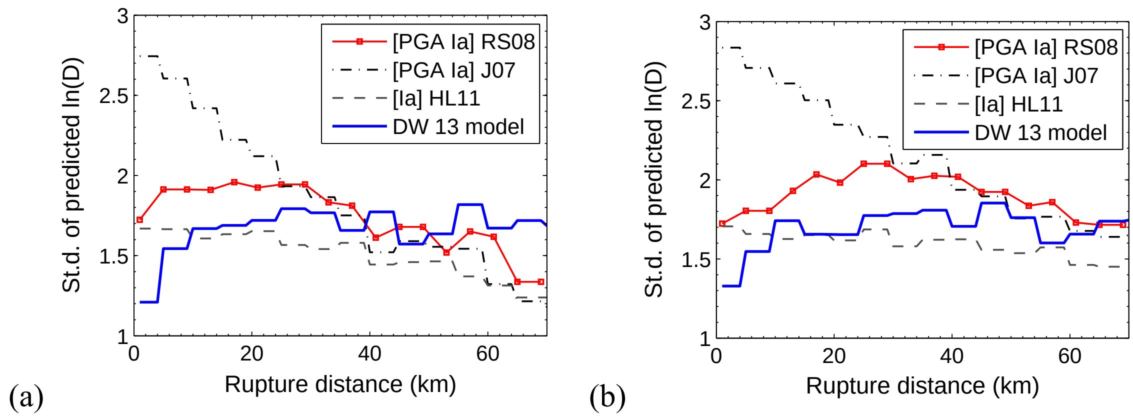


Figure 5. Standard deviations considering aleatory variability of GMPEs and Newmark displacement models, for $a_c$=0.1g and (a) $M_w$ 7.5 (b) $M_w$ 6.5 strike-slip earthquakes. Cut-off displacement value is 0.01 cm.

Finally, a hypothetical area is investigated to compare different displacement models in estimating the spatial distribution of Newmark displacements in a regional scale. The 30 km × 30 km area is divided into 900 sites separated by 1 km × 1 km in distance. The following Gutenberg-Richter relationship is assumed to describe the seismicity of the source:

$$\log_{10} \lambda_m = 4.4 - 1.0 M_w \tag{10}$$

where $\lambda_m$ is the mean annual rate of exceedance of the moment magnitude $M_w$. A 30 km-long linear fault is located close to this area, shown in Fig. 6(a).

To perform a two-step analysis using the IM-based models, a computational efficient method proposed by the authors [5] is used to derive the displacement hazard curves over the region. The computational algorithm employs a Monte Carlo simulation with data reduction techniques. The spatial correlation model [5] for PGA and Ia is also used to account for their spatial distribution over the region. A total of 90 earthquake scenarios, 5,400 IM-maps and

324,000 displacement maps are generated to obtain statistically reliable results.

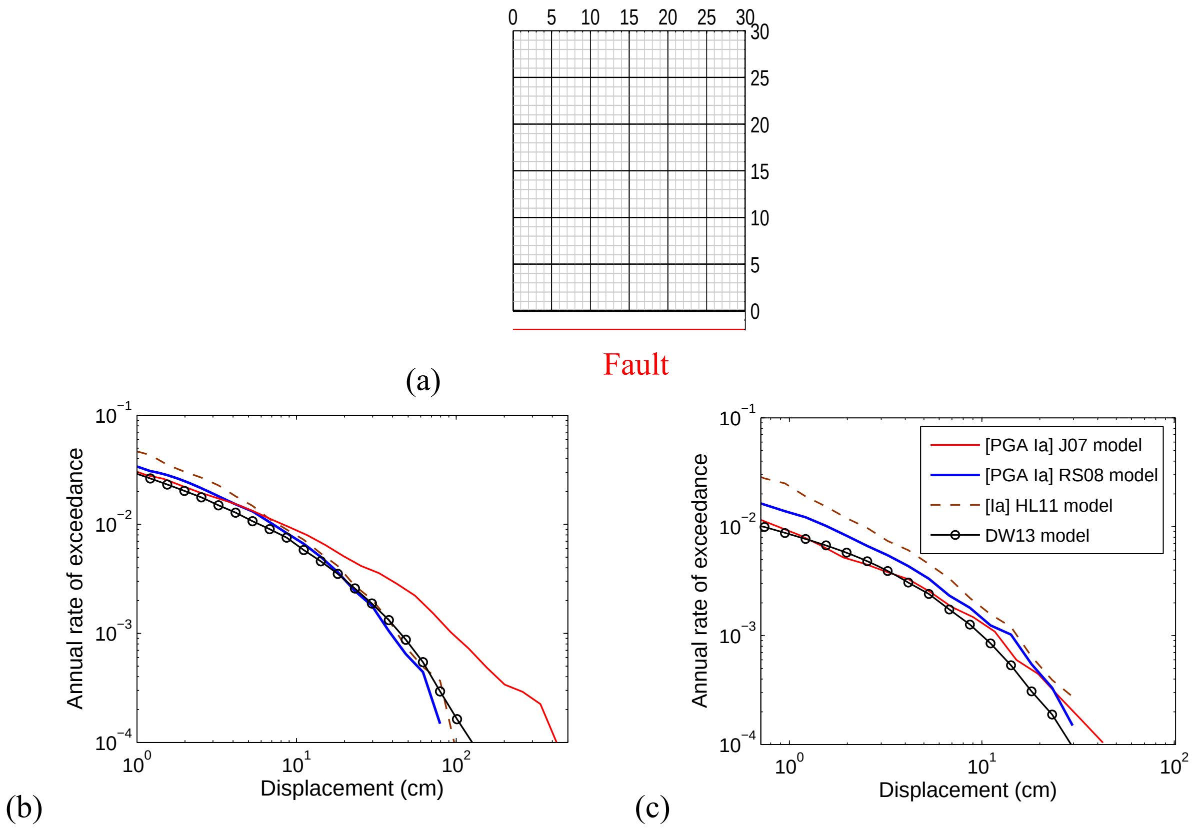


Figure 6. (a) A 30 km×30 km area divided into 1 km×1km grids and the location of the fault trace. Displacement hazard curves using different displacement prediction models for (a) exceedance area ratio AR* as 10%, and (b) AR* as 20%. Four models are considered here: [PGA, Ia] J07 model (Eq. 7), [PGA, Ia] RS08 model (Eq. 8), [Ia] HL11 model (Eq. 9), and the proposed DW13 model. Given a specified value of $D$ (denoted as $D^*$), its exceedance area ratio $AR^*$ is defined as the ratio of the areas where displacements exceed the specified $D^*$ value against the total area of the region.

For the one-step displacement model, the spatial correlation of the Newmark displacement residuals is also needed. Our study (reported elsewhere) shows that a correlation range of 15 km is a reasonable estimation for displacement residuals in Eq. 4, if an exponential model is used to characterize the spatial correlation:

$$\rho(h) = \exp(-3h/b) \tag{11}$$

where $h$ refers to separation distance (km), $b$ is the range of spatial correlation, and $\rho(h)$ is used to quantify the correlation coefficient of displacement residuals at the separation distance of $h$. Clearly this correlation $\rho$ equals 1 at zero separation distance and decreases to zero if $h$ increases to infinity.

Fig. 6 shows the comparison of the displacement hazard curves using the one-step model and other aforementioned IM-based models. It is to be noted that the averaged values of seven GMPEs (four NGA models for PGA prediction and three models for Ia prediction) are adopted in these two-stage displacement models. The proposed DW13 model can yield generally consistent curves comparing with other models in Fig. 6. Generally, similar trends in Fig. 6 can be observed among these hazard curves at the range of return periods 100-2500 years. The performance of the DW13 model is consistent with other IM-based models for various hazard levels. It is not our intention to judge which model is superior to the others, but to provide an illustrative comparison between the one-step versus the two-step approaches. Since the one-step approach eliminates the necessity to predict the IMs, the computational process is much more efficient compared with these two-step models. Only a total of 5,400 displacement maps are used in the one-step model, which is only 1.6% of the number of displacement maps needed in the two-step models.

## Conclusions

This paper provides a new Newmark displacement predictive model. Unlike most existing Newmark displacement models using IMs as predicators, the proposed model can give an estimation of the Newmark displacement directly based on seismological information and site conditions (e.g. $M_w$, $R_{rup}$, $V_{s30}$, *etc*). Compared to the IM-based displacement models, the new model can result in reasonably consistent estimation of displacement hazard curves for various cases.

The reported total standard deviations are in the range of 1.6-1.84 in natural log scale for $a_c$=0.05g-0.25g, respectively. Although it appears to be much larger than any IM-based Newmark displacement model, this sigma value of the one-step method is actually comparable to these two-step models if the aleatory variability of both the Newmark displacement predictions and IMs are incorporated. All these results imply that the proposed displacement model is applicable for the probabilistic displacement analysis, and it can be used as an alternative model to estimate the Newmark displacement.

The performance of this model over a large region is also comprehensively studied. It is observed that the one-step model can result in comparable results with other two-step models. In contrast to other two-step IM-based methods, the great benefit of using this new proposed model is that it can significantly reduce the computational cost. Based on the example presented in this paper, the computational effort of the one-step method is only one tenth of that of the two-step approaches for generating statistically stable results in the regional scale analysis.

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