

VALIDATING THE CURRENT STATE-OF-PRACTICE FOR SEISMIC RISK (AND RESILIENCE) ANALYSIS

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ABSTRACT: Regional risk analysis provides information for decisions made by communities, state and federal agencies, and the insurance industry. Model validation and updating are crucial since inaccurate predictions may lead to suboptimal decisions. Seismic risk (and resilience) analyses feature some of the most comprehensive prediction models. While several models and methods have been developed, validation of seismic risk analysis models has been limited due to limited data and computational challenges. Typical attempts at model validation focus on ground motion prediction equations and damage models for buildings and pipelines. In addition, most recent studies on seismic risk and resilience analysis have concentrated on more complex formulations for infrastructure functionality, interdependencies, or resilience optimization, while implicitly relying on tools like HAZUS and MAEViz to predict damage and recovery times. However, evaluating the credibility of sources that have become the standard of practice is essential. This paper assesses the state-of-the-art for analyzing the seismic risk (and resilience) analysis of physical infrastructures, such as buildings, roads, bridges, water, and wastewater systems. The paper uses data from the 2016 Kumamoto earthquake in Japan and compares the predicted and recorded impacts. The comparison demonstrates the actual predictive ability of the available models and drives future research toward essential enhancements.

Communities, utility companies, infrastructure managers, governing, regulatory, and policy bodies, and insurance and re-insurance companies have to make critical decisions concerning natural hazards. Risk (and resilience) analysis supports such decision-making by estimating the probabilities of various hazard scenarios and predicting their consequences. Seismic risk assessment has some of the most extensive suites of predictive models. Examples include seismic predictive models to simulate the earthquake intensity prediction (e.g., ground motion prediction equations, GMPEs) and the hazard impact on buildings and infrastructure (e.g., transportation, electrical power, potable water, wastewater).

Hazard impact models, particularly physical damage prediction models, are often building blocks in subsequent analysis for assessing infrastructure functionality, economic loss, and societal impact. Additionally, hazard impact models are the basis for developing (optimal) mitigation strategies and improving societal resilience. Two widely used resources for hazard impact analysis are HAZUS (FEMA 2014) and MAEViz (MAE Center 2011). They are used either as a whole package or by extracting selected models needed for the analysis of interest. They allow the convenient analysis of the physical structures and infrastructure damage with simple input data. Their conceptual simplicity, extensive coverage of impact metrics, computational efficiency, and significant work done to develop

them make HAZUS and MAEViz widely used in seismic risk analysis in academia and practice. However, due to the limited data available for the validation of rare events, the fundamental hazard impact models are often not carefully validated.

A handful of past studies have critically examined seismic impact assessment results. Ellingwood (1988) examined the seismic probabilistic risk assessment methods by comparing the factors (i.e., hazard characteristics and vulnerability) that significantly affect the risk outcomes. Bai et al. (2014) conducted a comparative study for concrete buildings using the fragility curves from the HAZUS and MAEViz. However, the case study only compared and highlighted the difference between the two predictions (HAZUS vs. MAEViz) but not with real-world data. Recently, Goda et al. (2016) conducted the validation of GMPEs with the recorded data from the 2016 Kumamoto Earthquake. While Crowley et al. (2008, 2020) and Riga et al. (2021) published a comparative analysis for seismic risk assessment considering both the GMPEs and building damage prediction obtained using the European Seismic Risk Model (ESRM20). However, these studies only focused on validating the GMPEs and the damage of a few building types. They did not check the models for other structures and infrastructure damage, and the structural damage for the few building types considered was based on models not widely used. Among the critical infrastructure, buried pipelines' fragilities have also been the subject of a few investigations using laboratory or real-world data (Liu et al. 2017; Bellagamba et al. 2019). However, there remains a consistent scarcity of literature that extensively validates the predictions.

This paper evaluates the current state of practice for seismic risk assessment. In particular, the focus is on the models for predicting hazard intensity measures and damage to buildings, and components of the transportation, electrical power, potable water, and wastewater infrastructure.

1. METHODOLOGY

We first compile data from past earthquake events for validation. We then select the prediction models from past research for predicting hazard intensity and physical damage. We compare the predictive results with the recorded data using error maps and confusion matrices.

1.1. Data compilation

We consider the damage from the mainshock of the 2016 Kumamoto earthquake in Japan. We compile and produce the necessary data in Mashiki, Kumamoto. We select the study area as Mashiki, Kumamoto, Japan, because this region has good data availability. Furthermore, this community was near the epicenter and experienced severe damage to buildings and critical infrastructure.

A considerable effort in conducting this study went into compiling validation data. We obtain the data for seismic intensity measures from USGS ShakeMap and select the measures for PGA , PGV , and S_a ($T = 0.3s$) based on the need for building damage prediction. We then produce the data for building inventory and components of the lifeline infrastructure. The infrastructure includes transportation (i.e., bridges), electrical power (i.e., transmission lines, substations, and power plants), potable water (i.e., pipeline and pumping stations), and wastewater (i.e., pipeline and wastewater treatment plant).

1.2. Prediction models

We select HAZUS and MAEViz as the two representative models for validation. They are widely used in academia and practice for risk and resilience analysis. Such models provide predictions for building and infrastructure damage and recovery. In this paper, we use the collected inventory data as inputs for HAZUS and MAEViz to obtain the predictions. We can validate other predictive models following the proposed methodology in future work.

1.3. Error map

Besides checking the prediction accuracy, we compare the recorded and predictive results by

measuring their difference (i.e., error). We use the relative error (δ_{IM}) for comparing hazard intensity predictive results. The relative error is defined as

$$\delta_{IM} = \frac{(IM - \widehat{IM})}{\widehat{IM}} \quad (1)$$

where IM denotes the recorded hazard intensity measurements, and \widehat{IM} represents the predicted hazard intensity we derive from the model. If $\delta_{IM} < 0$, the prediction is considered overestimated, and vice versa.

Most models predict building and infrastructure damage in the probability of damage states (e.g., Collapse, Extreme, Moderate, and Slight). Past studies usually use the most probable damage state (i.e., the damage state with the highest probability) to represent the predictive damage. In this paper, we use the most probable damage state to compare with the recorded damage state to check the models' accuracy. However, in some scenarios, the most and the second most probable damage state have a similar probability. Thus, we use the absolute error δ_{DS} in the models to measure the number of errors in the predictions. The absolute error δ_{DS} is defined as

$$\delta_{DS} = |DS - \widehat{DS}| \quad (2)$$

where DS denotes the recorded damage state, and \widehat{DS} is the most probable predictive damage state. For example, if we have a building in which DS is recorded as the moderate damage state ($DS = 2$), and \widehat{DS} is predicted as collapse ($\widehat{DS} = 4$), δ_{DS} is the error of two damage states.

2. COMPARATIVE ANALYSIS/VALIDATION OF THE PREDICTIVE MODELS

In this section, we compare the recorded hazard intensities and damage with the predictions by using the proposed methodology.

2.1. Hazard intensity map: recorded vs. predicted

We use the GMPEs developed by Boore et al. (2014) to predict hazard intensity measures. This GMPE is the most suitable for this case, given the geological site characteristic (Goda et al. 2016). Figure 1 compares the recorded and predicted values of PGA , PGV , and $S_a(T = 0.3s)$. We also show the 95% confidence intervals associated with each prediction. The shade of the dots indicates the variation in the distance from the fault plane projection on the ground surface, known as the Joyner Boore distance R_{jb} . As the distance from the fault plane increases, the predicted values go down. However, the accuracy of the prediction also seems to be highly dependent on R_{jb} . As the distance exceeds 250 km, the points seem to have high bias and depart from the 1:1 line. However, the plots are on the log scale; thus, looking at the confidence intervals, we can see that the prediction has a higher variance for low R_{jb} . Prediction confidence is lowest for the values where the hazard intensity is highest, which is undesirable because those would be locations expecting the most severe damage. We also provide graphical maps of the same analysis for Mashiki. Figures 2 (a)-(f) show the recorded and the median of the

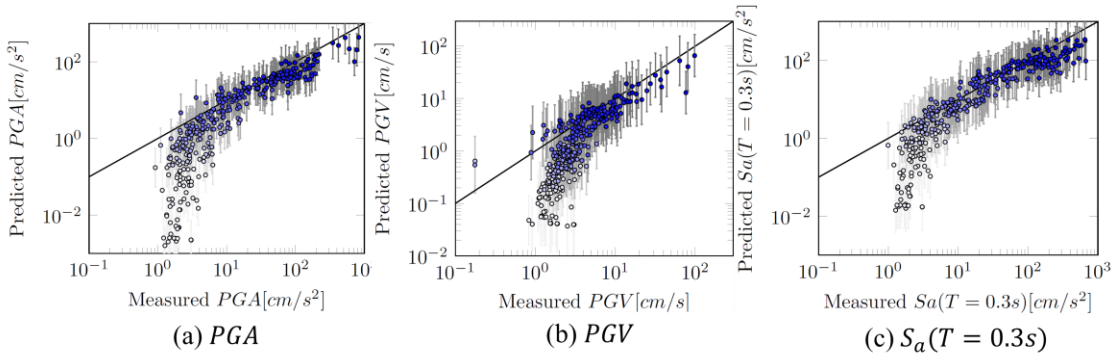


Figure 1. Comparison between recorded and predicted intensity measures

predicted hazard intensities, while Figures 2 (g)-(i) show the error plots in terms of the percentage difference between the median predicted and the recorded values. We observe that the predicted intensity measures are up to 100% lower than the recorded.

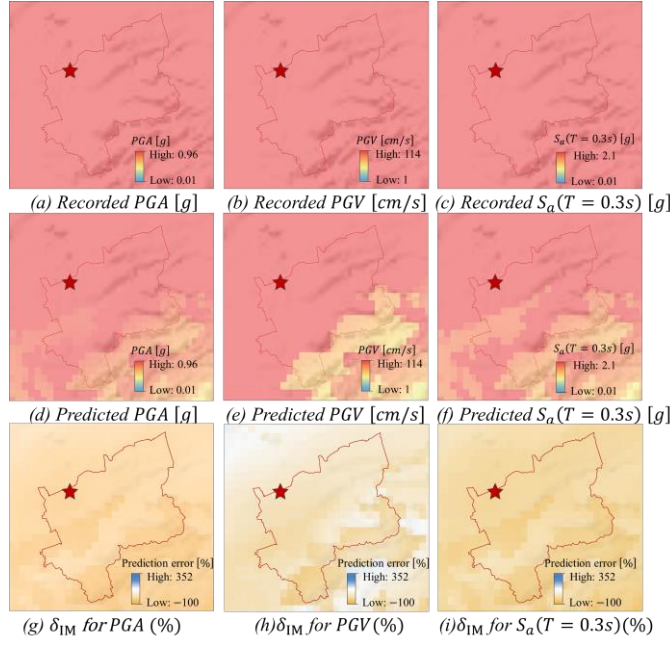


Figure 2. Spatial comparisons of intensity maps for Mashiki

2.2. Building damage: recorded vs. predicted

We show the recorded and the predictive results in Figure 3 (a)-(c) using the predicted hazard intensity measures (PGA for HAZUS and both PGA and Sa for MAEViz). The damage states for the buildings include insignificant, moderate, heavy, and complete,

heavy, and complete; the definitions of these damage states are available in Bai et al. (2014). Figures 3 (d) and (e) show the absolute error associated with the most probable damage state. Figures 4 (a) and (b) show the confusion matrices for both models. The blue dots represent the predicted value and the recorded value of each building. Overall, HAZUS and MAEViz do not provide accurate predictions in this case. HAZUS tends to underestimate the complete damage state, and MAEViz tends to overestimate the damage. However, HAZUS has a more accurate prediction for the low- and medium-damage states (i.e., Slight and Moderate). MAEViz provides a more

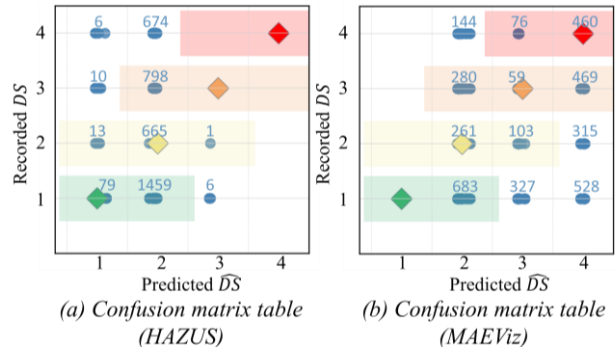


Figure 4. Confusion matrices between recorded and predicted building damage

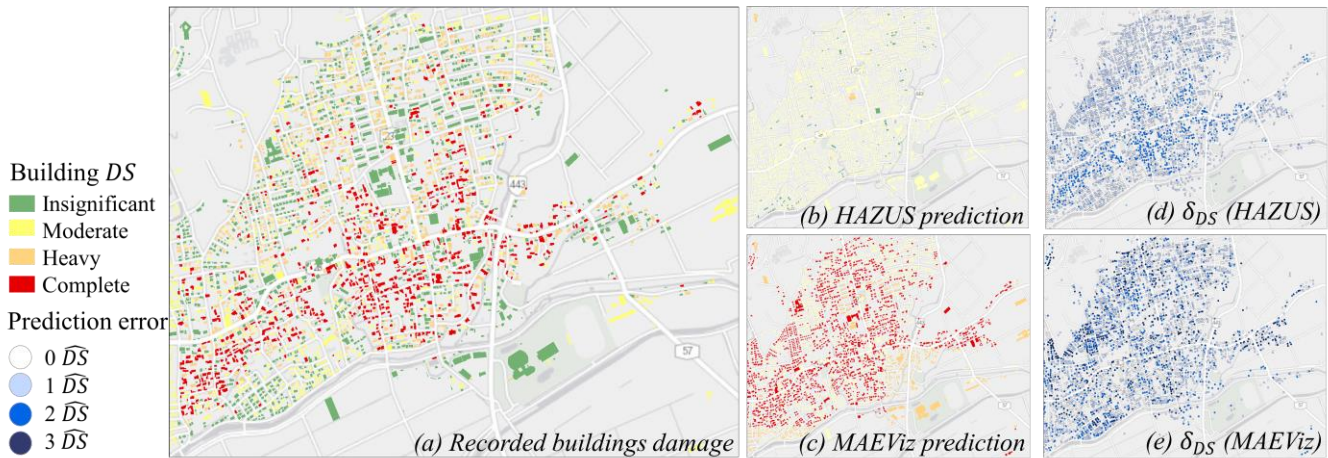


Figure 3. Comparison between recorded and predicted building damage

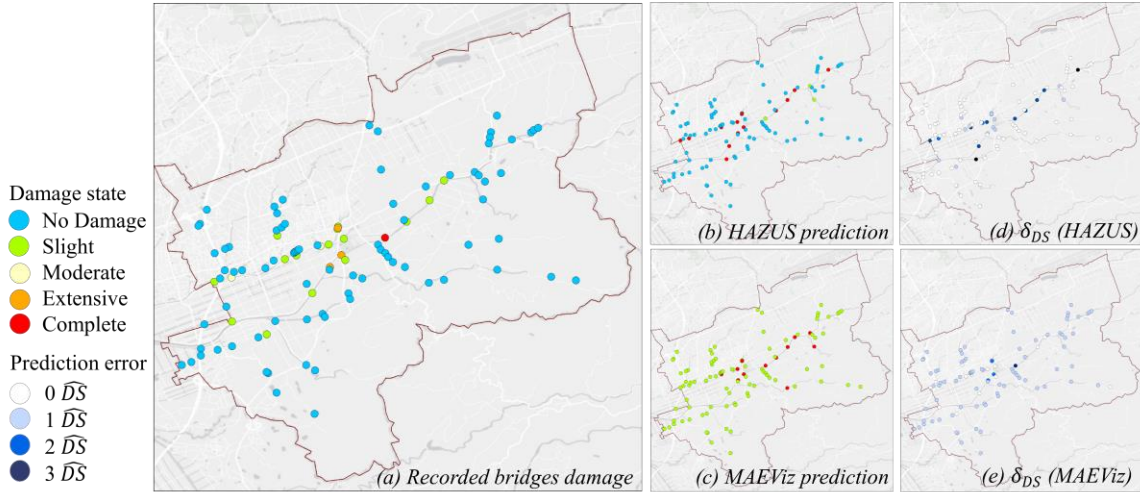


Figure 5. Comparison between recorded and predicted bridge damage

accurate prediction of the higher damage state (i.e., Extreme and Collapse). HAZUS generally has larger prediction errors than MAEViz.

2.3. Transportation damage: recorded vs. predicted

Figure 5 (a)-(c) shows the recorded and the predicted results in HAZUS and MAEViz using the predicted hazard intensity measures (PGA and Sa for both HAZUS and MAEViz). Figures 4 (d) and (e) show the absolute error associated with the most probable damage state. Figures 6 (a) and (b) show the confusion matrices for both models. HAZUS and MAEViz perform relatively better than when predicting building damage. It is possible partly because the bridge construction is more standardized than the general building stock. Overall, HAZUS predicts better in the case of no damage, and MAEViz tends to overestimate the damage. However, HAZUS has larger absolute

errors compared with MAEViz. MAEViz’s predictions are more consistent and have fewer errors. It would likely be easier to recalibrate the model.

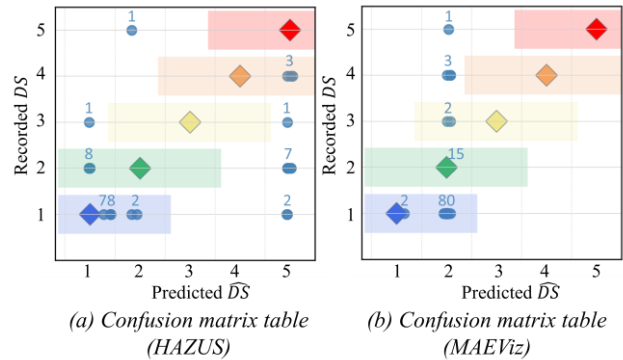


Figure 6. Confusion matrices between recorded and predicted bridge damage

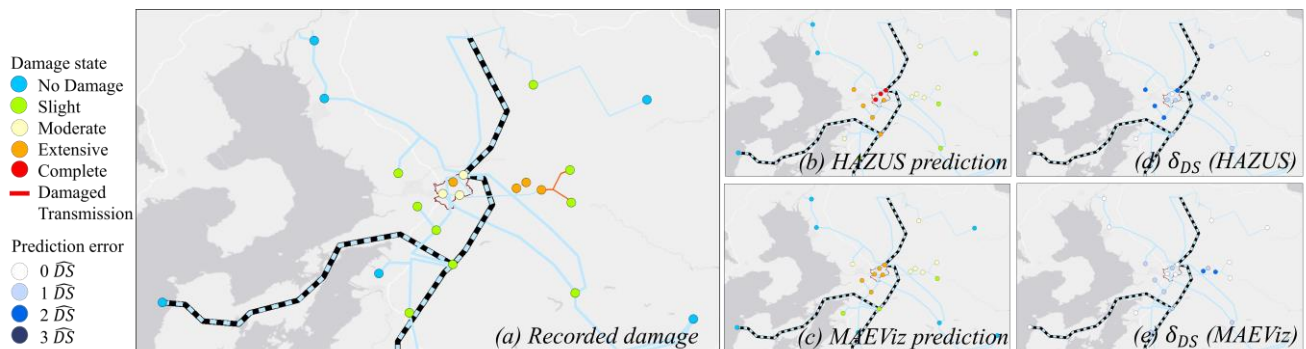
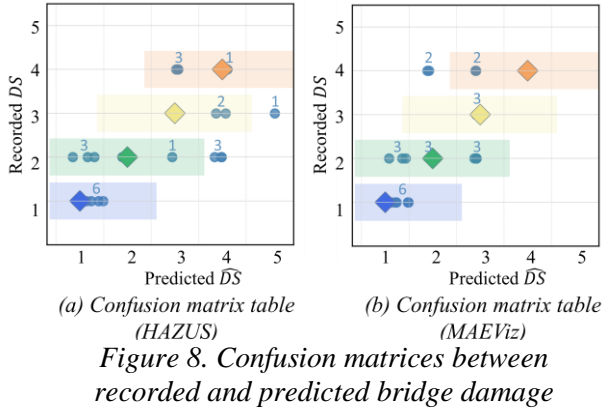


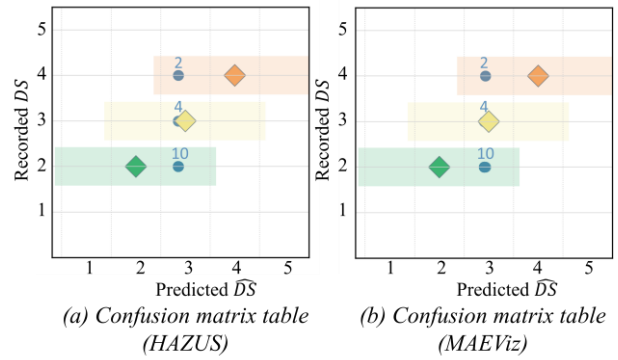
Figure 7. Comparison between recorded and predicted in the electrical power infrastructure



2.4. Electrical power damage: recorded vs. predicted

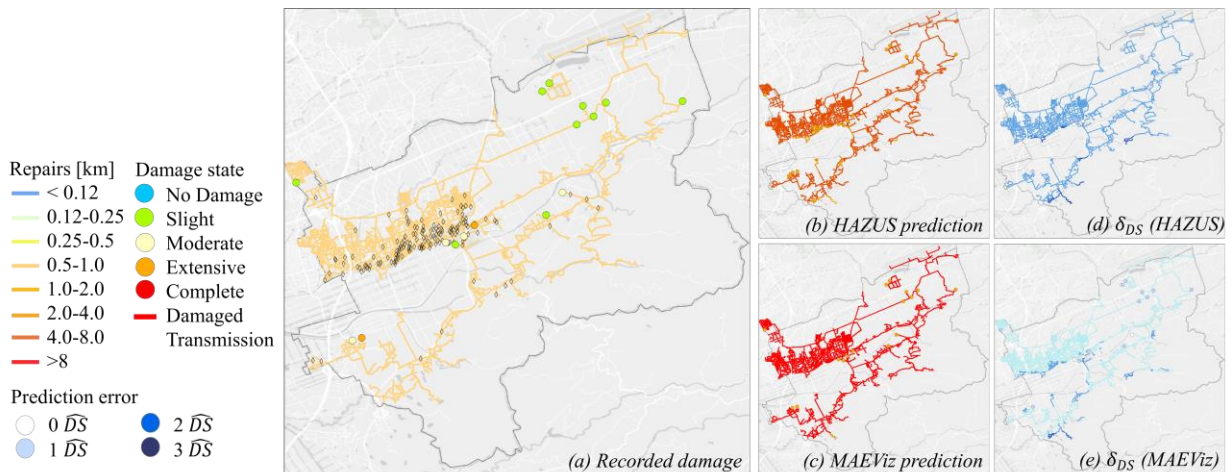
Figure 7 (a)-(c) shows the recorded and the predicted results in HAZUS and MAEViz using the predicted hazard intensity measures (PGA for HAZUS and MAEViz). Figures 7 (d) and (e) show the absolute error associated with the most probable damage state. Figures 8 (a) and (b) show the confusion matrices for both models. HAZUS and MAEViz do not have models for predicting damage to transmission lines. Most transmission lines are presumed to be not vulnerable to ground shaking. We thus predicted the electrical substations' damage for the electrical power infrastructure. HAZUS and MAEViz predict the damage of the electrical substations relatively well. They have a similar prediction in the None and Slight damage state. However, HAZUS has a larger prediction error than MAEViz.

2.5. Potable water network damage: recorded



vs. predicted

Figure 9 (a)-(c) shows the recorded and the predicted results in HAZUS and MAEViz using the predicted hazard intensity measures (PGA for pumping stations and PGV for the pipeline for both HAZUS and MAEViz). Figures 9 (d) and (e) show the absolute error associated with the most probable damage state. Figures 10 (a) and (b) show the confusion matrices for both models. The damage to the pumping station was available in the Mashiki water pipeline damage report (The Kumamoto Prefecture environmental and living office 2018). We present the damage states for the pumping stations and repair rates for the pipes. The recorded repair rate is ~0.86 repairs per km.



Overall, HAZUS and MAEViz tend to overestimate the damage to the potable water pipelines. MAEViz performs significantly better in predicting the repair rates for pipes. For the potable water facility, both models are not accurate, but the prediction error is only one damage state off.

2.6. Wastewater network damage: recorded vs. predicted

Figure 11 (a) – (c) shows the recorded and the predicted results in HAZUS and MAEViz using the predicted hazard intensity measures (PGA (for the treatment plant) and PGV (for the pipeline) for both HAZUS and MAEViz). Figures 11 (d) and (e) show the absolute error associated with the most-likely damage state. Figures 12 (a) and (b) show the confusion matrices for both models. We present the damage states for the wastewater treatment plant and the repair rates for the wastewater pipes. The recorded repair rate for the wastewater pipelines is below 0.5 per km. The repair rate prediction models for wastewater pipelines are identical to the ones for potable water pipelines at the same location because HAZUS and MAEViz do not differentiate between potable water and wastewater pipes. Hence, the trends in the results are similar, with a slight overestimation of damages. We only have one wastewater facility, and both models predict moderate damage, whereas the actual damage state is extensive, with only one damage stage off.

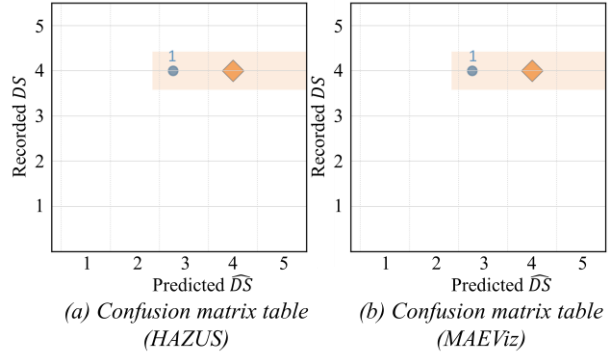


Figure 12. Confusion matrices between recorded and predicted bridge damage

3. CONCLUSIONS

This paper validated the state of practice for predicting the hazard intensity measures and damage to buildings, components of the transportation infrastructure (i.e., bridges), components of the electrical power infrastructure (i.e., transmission lines, substations, and power plants), components of the potable water infrastructure (i.e., pipeline and pumping stations), and components of the wastewater infrastructure (i.e., pipeline and wastewater treatment plant). The paper compared the recorded values with those predicted by suitable GMPEs, HAZUS, and MAEViz, for Mashiki, Kumamoto, Japan, due to the 2016 Kumamoto earthquake. We then present the model accuracy by using the relative and absolute errors. This paper is the first to validate GMPEs and damage models comprehensively. Most analyses show that the predictive models do not accurately

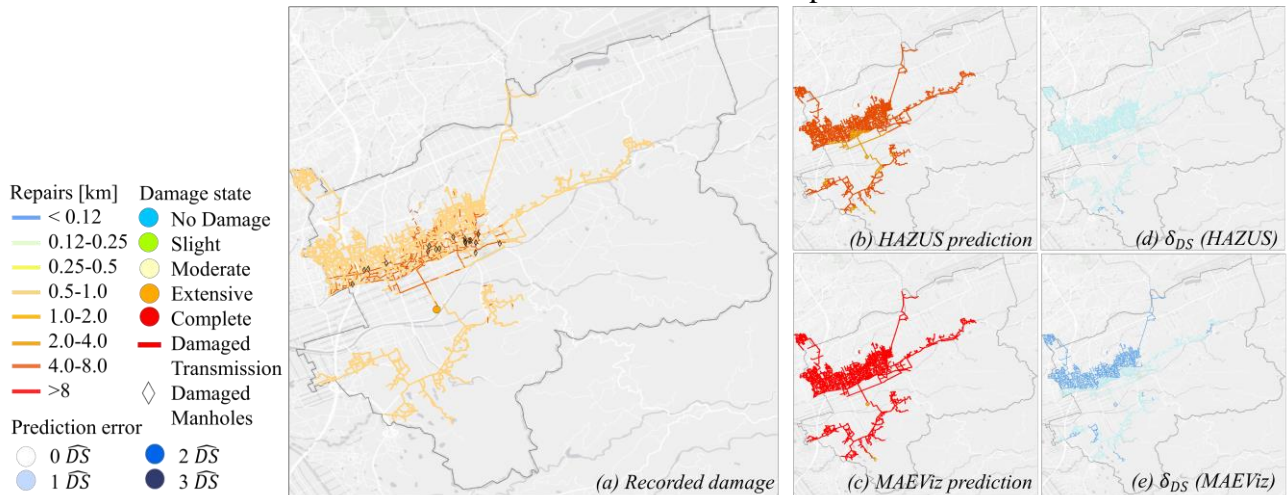


Figure 11. Comparison between recorded and predicted in the potable water infrastructure

predict the recorded values. Instead, the models tend to underestimate the hazard intensity and overestimate the damages. The performance is better for infrastructure components than buildings, which we attribute to higher standardization uniformity in infrastructure components than buildings. The current paper focused on the validation of the damage prediction models. Ongoing work is extending the validation to other damage prediction models, and predictive models for building and infrastructure recovery, economic losses, resilience, interdependencies, and network functionality. Beyond the validation, ongoing work is also developing a Bayesian approach for updating the model parameters as data becomes available.

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