A NEW APPROACH TO LIQUEFACTION POTENTIAL MAPPING USING SATELLITE
REMOTE SENSING AND SUPPORT VECTOR MACHINE ALGORITHM

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1. ABSTRACT

In order to help communities better plan and mitigate the effects of seismic hazards, it is important to use innovations in
science and technology to improve our techniques for mapping the spatial extents of seismic hazards. Earthquake induced
ground shaking in areas with saturated sandy soils pose a major threat to communities as a result of the soil liquefaction.
Liquefaction is the process of changing a saturated cohesionless soil from a solid to liquid state due to increased pore
pressure. Many major earthquakes, especially those in coastal regions, result in liquefaction related ground failures that can
lead to infrastructure damage or slope stability issues. Traditionally liquefaction potential is assessed on two scales:
regionally based on surficial geologic unit or locally based on geotechnical sample data. Regional liquefaction potential maps
fail to capture the variability of liquefaction potential on the local scale. On the other hand, collection of geotechnical data on
the local scale is costly and only done for specific engineering projects and therefore not generally available for regional
mapping.

Today, the advent of advanced remote sensing products from air and space borne sensors allow us to explore the land surface
parameters (geology, moisture content, temperature) at different spatial scales (remote sensor footprint). In this study, we
explore the use of satellite based remote sensing data (Landsat 7 ETM+), together with digital elevation model, ground water
table, land cover classification, geology, water index and normalized difference vegetation index (NDVI) to characterize the
liquefaction potential of northern Monterey and southern Santa Cruz counties in California. The earthquake hazard for the
study area has been classified as extremely high by the California geological survey. We classified the data using a
supervised approach into seven classes based on the liquefaction potential map developed by Dupre and Tinsley (1980).
Dupre and Tinsley (1980) developed this map by crossing the borders of the traditional approaches and by combining both
local and regional scale information using interpretation and judgment. They used the standard penetration test, ground water
table, historical evidence of the liquefaction induced ground failure caused by the San Francisco earthquake of 1906 and the
geologic maps of Quaternary deposits (Dupre and Tinsley, 1980). The supervised classification of the data was achieved
using Support Vector Machine (SVM). SVM is a machine learning/artificial intelligence algorithm that has the ability to
simulate the learning capabilities of a human brain and make appropriate predictions that involve intuitive judgments and a
high degree of nonlinearity. Researchers have verified the superior capability of SVM to classify remote sensing data over
the conventional methods. (Foody and Mathur, 2004; Oommen et al., 2008).

The accuracy of the developed liquefaction map was analyzed both qualitatively and quantitatively. Considering the large
size of the dataset a single set validation approach was used to quantify the accuracy of the developed liquefaction map. In
the single split validation approach a random selection of 80% (42473 pixels) of the data was used for training and the
remaining 20% (10618 pixels) was used for testing. The confusion matrix for the testing dataset showing the producers
accuracy, users accuracy and the overall accuracy is presented in Table 1. The producers accuracy represent how well the
class is produced and the users accuracy represent how much confidence should the user have in the produced class. It is
noted from Table 1 that except for high all the other classes have both the producers and users accuracy greater than 75% and
the overall classification accuracy is 84%. Figure 1 shows a qualitative comparison of the developed liquefaction potential
map using SVM to the map of Dupre and Tinsley 1980. It is observed that the spatial variability in liquefaction potential is
well captured by the developed map. Both the qualitative and quantitative analysis suggest that the combination of remote
sensing data and other relevant spatial data together with machine learning can be a promising approach for liquefaction
potential mapping. Further, machine learning can be used to help understand the relative importance of the various
parameters in identifying liquefaction hazard and to optimize future data collection efforts.
Table 1: Confusion matrix showing the supervised classification accuracy of the developed map using an independent testing dataset

<table>
<thead>
<tr>
<th></th>
<th>Very Low</th>
<th>Low</th>
<th>Moderate-Low</th>
<th>Moderate</th>
<th>Moderate-High</th>
<th>High</th>
<th>Very High</th>
<th>Producers Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>2290</td>
<td>166</td>
<td>34</td>
<td>15</td>
<td>22</td>
<td>10</td>
<td>0</td>
<td>90.3</td>
</tr>
<tr>
<td>Low</td>
<td>92</td>
<td>1631</td>
<td>19</td>
<td>37</td>
<td>126</td>
<td>56</td>
<td>19</td>
<td>82.4</td>
</tr>
<tr>
<td>Moderate-Low</td>
<td>10</td>
<td>42</td>
<td>1144</td>
<td>115</td>
<td>8</td>
<td>9</td>
<td>1</td>
<td>86.1</td>
</tr>
<tr>
<td>Moderate</td>
<td>4</td>
<td>31</td>
<td>52</td>
<td>2000</td>
<td>3</td>
<td>113</td>
<td>275</td>
<td>80.7</td>
</tr>
<tr>
<td>Moderate-High</td>
<td>11</td>
<td>89</td>
<td>10</td>
<td>25</td>
<td>574</td>
<td>20</td>
<td>0</td>
<td>78.7</td>
</tr>
<tr>
<td>High</td>
<td>0</td>
<td>21</td>
<td>5</td>
<td>20</td>
<td>9</td>
<td>196</td>
<td>5</td>
<td>76.6</td>
</tr>
<tr>
<td>Very High</td>
<td>0</td>
<td>5</td>
<td>2</td>
<td>229</td>
<td>0</td>
<td>6</td>
<td>1067</td>
<td>81.5</td>
</tr>
<tr>
<td>Users Accuracy (%)</td>
<td>95.1</td>
<td>82.2</td>
<td>90.4</td>
<td>81.9</td>
<td>77.4</td>
<td>47.8</td>
<td>78.1</td>
<td>84%</td>
</tr>
</tbody>
</table>

Figure 1: Comparison of the liquefaction potential map developed using remote sensing and machine learning to the map of Dupre and Tinsley (1980). It is observed that the spatial variability in liquefaction potential is well captured by the developed map.

2. REFERENCES

