Nat. Hazards Earth Syst. Sci. Discuss., 2, 2443–2461, 2014
www.nat-hazards-earth-syst-sci-discuss.net/2/2443/2014/
doi:10.5194/nhessd-2-2443-2014

Natural Hazards and Earth System Sciences
Open Access
Discussions

Shear wave velocity by support vector machine based on geotechnical soil properties

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Received: 13 May 2013 – Accepted: 11 March 2014 – Published: 9 April 2014

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Shear wave velocity by support vector machine

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Abstract

Shear wave velocity (V_S) is a basic engineering property implemented in evaluating the soil shear modulus. In many instances it may be preferable to determine V_S indirectly by common in-situ tests, such as the Standard Penetration Test (SPT). In this paper, the relationship between V_S and geotechnical soil parameters such as standard penetration test blow counts (N_{160}), effective stress and fines content, as well as overburden stress ratio (σ_{vo}/σ'_{vo}), is investigated. A new mode based on support vector machine (SVM) approach is proposed to correlate geotechnical parameters and V_S, predicated on a total of 620 data sets, including field investigation records for the Kocaeli (Turkey, 1999) and Chi-Chi (Taiwan, 1999) earthquakes. This study addresses the question of whether Support Vector Machine (SVM) approach should be used to estimate V_S based on the specified geotechnical variables, and assessing the influence of each variable on V_S. Results revealed that SVM, in comparison to previous statistical relations, provides an effective means of efficiently recognizing the patterns in data and accurately predicting the V_S.

1 Introduction

Shear wave velocity (V_S) is a principal geotechnical soil property in earthquake site response analysis; at small shear strain levels, is directly related to V_S. Owing to difficulties in soil sampling, and high costs of representative undisturbed specimens, in-situ investigations (e.g. seismic measurements) in lieu of laboratory element testing, are preferred to determine V_S directly. Using surface wave velocity measuring techniques, a shear wave velocity profile can be established without boring and penetration (Kramer, 1996). These nondestructive, non-intrusive features make V_S-based approach a potentially attractive alternative for characterizing liquefaction susceptibility in sandy soils (Andrus et al., 2004).

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However, seismic in-situ tests are not always feasible; especially in urban areas, due to space constraints and noise level limits. Therefore, it is necessary to determine V_S indirectly through methods such as the Standard Penetration Test (SPT) and Cone Penetration Test (CPT), which are commonly used for conventional geotechnical site investigations.

In geotechnical engineering, different soil parameters are associated with the Standard Penetration Test blow counts (N_{SPT}). To the best of authors' knowledge, there is no established theoretical relationship between N_{SPT} and seismic soil properties (e.g. V_S). Hence, their association, and evaluation of geotechnical properties, requires empirical correlations, statistical analysis and system identification techniques.

The interdependency of factors involved in such problems prevents the use of regression analysis and demands a more extensive and sophisticated method. The Support Vector Machine approach (SVM) can be used to model complex systems, where unknown relationships exist between variables, without having specific knowledge of process. In recent years, the use of mention approach has led to successful application of the SVM in geotechnical sciences (e.g. Goh, 2007; Oommenet et al., 2010).

This treatment aims to develop a SVM for the prediction of V_S, based on various soil parameters, such as N_{160}, depth and etc. Following the aims of the study, first reviews previous attempts in correlating N_{SPT} and V_S, then a brief explanation of the case histories under consideration, and the phenomena of modeling with SVM are presented. Finally the developed SVM model is described and compared with previous studies.

2 Background to previously proposed correlations

The literature presents a portfolio of research regarding application of N_{SPT} for geotechnical characterization. Researchers have proposed correlations between N_{SPT} and V_S for different soil types, e.g. sand, silt and clay. Imai and Yoshimura (1975) studied 192 samples and proposed empirical relationships between seismic velocities and soil index properties. Sykora and Stokoe (1983) asserted that geological age and soil type have little influence in predicting V_S. Jafari et al. (2002) presented a detailed historical review on statistical correlations between N_{SPT} and V_S for fine grained soils. Hasancebi and Ulusay (2007) reported correlations for sand and clay soil type. Ulugergerli and Uyanık (2007) investigated statistical correlations using 327 specimens and defined empirically a range for V_S values. Dikmen (2009) investigated N_{SPT} and presented a correlation for all soil types.

Others have developed correlating equations accounting for stress-corrected V_S, energy-corrected N_{SPT} (e.g. Pitilakiset et al., 1999; Kikuet et al., 2001), energy- and stress-corrected N_{SPT}, depth (e.g. Tamura and Yamazaki, 2002) and fines content (e.g., Ohta and Goto, 1978). V_S can also provide estimation of effective stress (σ'_v) for clayey soils as suggested by Mayne and Martin (1998). Mayne (2001) presented a relationship for the total unit weight (γ) of saturated soils in terms of V_S and depth (Z). However, almost all the foregoing studies have focused on relationships between uncorrected N_{SPT} and V_S. Table 1 summarizes an inventory of prior researches and their proposed empirical correlations.

3 Overview of database and case histories

The destructive Kocaeli (Turkey) earthquake ($M_W = 7.4$) occurred in 1999. The epicenter was located near the city of Izmit, and fault rupture was physically visible through most of the seismically impacted area; from Karamürsel to Akyazı. In the vicinity of Adapazari, with peak ground accelerations recorded at approximately 0.4 g, as much as 70 % of buildings were subjected to large ground settlements, liquefaction or subsidence. Sea water inundation occurred at Değirmendere and Gölçük districts (Hanna et al., 2007). As illustrated in Fig. 1, the southern shores of Izmit Bay are covered by Holocene deposits, these are principally fine-grained sandy sediments which become finer (more silty and clayey) northwards into the depths of Izmit Bay (Cetin et al., 2004). A total of 135 CPT profiles (19 were seismic CPTs) and 46 soil borings with multiple

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SPTs were completed in the city of Adapazari. Figure 2 shows soil profiles at the police station site, in the town of Gölçük located on the east shore of Izmit Bay. Accordingly, the soil liquefaction susceptibility is significant (Hanna et al., 2007).

The 1999 Chi-Chi (Taiwan) earthquake ($M_W = 7.6$), triggered numerous major liquefaction incidents in several coastal hydraulic fills and inland alluvial areas. The significant extent of ground failure, that is liquefaction, ground softening, and lateral spreading, were documented by researchers in several affected areas (Risk Management Solutions Inc, 2000). Further complementary information regarding the geotechnical and geological conditions of the sites are available in (Cetin et al., 2004; Chua et al., 2004).

Later site investigation programs were undertaken by National Center for Research on Earthquake Engineering (NCREE) (Scawthorn, 2000), resulting in a total of 92 CPT soundings (63 were seismic CPTs) and 98 soil borings with SPTs. Moreover, results of seismic CPTs and Spectral Analysis of Surface Waves (SASW) tests were used to interpret shear wave velocity data (Hanna et al., 2007).

Hanna et al, 2007 synthesized the results of both site investigation programs. Interpretations were predicated on SPT borings; 38 for the Kocaeli, and 25 for the Chi-Chi earthquake regions.

4 Descriptive variables for the proposed models

The field test results of the two mentioned earthquakes, i.e Chi-Chi and Kocaeli, are used in this investigation to develop a SVM model. The dataset, explained in Hanna et al. (2007), consists of 620 case records; 330 for Kocaeli and 290 for Chi-Chi. The database – a sample given in Table 2 – covers a wide range of soils and seismic parameters, including soil layer depth (Z), corrected SPT blow number (N_{160}), FC, Fines Content (% $\leq 75\,\mu$m), ground water table depth (D_w), total and effective overburden stresses (σ_{vo}, σ'_{vo}), stress ratio (σ_{vo}/σ'_{vo}) and V_S. Further details regarding the measurement and interpretation of the foregoing parameters are available in Hanna

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et al. (2007). Figure 3 illustrates the distribution of descriptive variable characteristics for all case histories.

5 Principles of modeling using SVM

The SVM has recently emerged as an elegant pattern recognition tool and a better alternative to Artificial Neural Network (ANN) methods. The method has been advanced by Vapnik (1995) and is gaining popularity due to many attractive features. The formulation is based on Structural Risk Minimization (SRM) which has been shown to be superior to the Empirical Risk Minimization (ERM) used in conventional neural networks (Vapnik, 1995). This section of the paper serves an introduction to this relatively new procedure. Details of this method can be found in Boser et al. (1992), Cortes and Vapnik (1995), Gualtieri et al. (1999) and Vapnik (1998).

6 Modeling shear wave velocity using SVM

By means of a SVM fitting, a model can be represented as a set of inputs in which different pairs of them are connected. In order to develop the evolved SVM, the database is divided into two different sets, namely, training and testing. The training set consists of 500 inputs–output data pairs. The testing set, which consists of 120 inputs–output data unforeseen during the training process, is merely used for testing the trained SVM models. It should be noted that the training and testing sets are randomly selected from the data sets with approximately the same statistical properties. In order to illustrate the model's predictive performance in comparison with observed data, 100 (from 50) data lines (inputs-output) are randomly selected from the training set. As it is shown in Fig. 4, predicted and measured values are properly close.

As presented in Table 3, the statistically assessed accuracy of the model is determined by R^2 (absolute fraction of variance), RMSE (root mean squared error), MSE (mean squared error), and MAD (mean absolute deviation) which are defined as follow:

$$R^2 = 1 - \left[\frac{\sum_{i=0}^{M} \left(Y_{i(\text{Model})} - Y_{i(\text{Actual})}\right)^2}{\sum_{i=1}^{M} \left(Y_{i(\text{Actual})}\right)^2} \right] \tag{1}$$

$$\text{RMSE} = \left[\frac{\sum_{i=0}^{M} \left(Y_{i(\text{Model})} - Y_{i(\text{Actual})}\right)^2}{M} \right]^{1/2} \tag{2}$$

$$\text{MSE} = \frac{\sum_{i=0}^{M} \left(Y_{i(\text{Model})} - Y_{i(\text{Actual})}\right)^2}{M} \tag{3}$$

$$\text{MAD} = \frac{\sum_{i=1}^{M} \left| Y_{i(\text{Model})} - Y_{i(\text{Actual})} \right|}{M} \tag{4}$$

The ability of the SVM model in predicting unforeseen data is tested for the testing dataset. As it is illustrated in Fig. 5 results from the model agree well with measured values. Moreover, for V_S in the range of 100 to 200 m s^{-1}, the developed model is more accurate.

7 Validation of predictive methods

The accuracy of the proposed model in predicting V_S, is compared to correlations presented by Kiku et al. (2001), Hasancebi and Ulusay (2007) and Dikmen (2009) (cf.

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Table 1). A statistical comparison is performed for all the 620 cases which are initially used for the model development. Figure 6 illustrates the scattering of predicted (calculated by different methods) vs. observed V_S.

It can be noted from the above diagrams that, the correlations of Kiku et al. (2001), Hasancebi and Ulusay (2007) and Dikmen (2009), overestimate measured values, for observed $V_S < 100$ (m s^{-1}). For $V_S > 238$ (m s^{-1}), measured values of V_S are higher than the predictions. Apparently, the disparity of V_S prediction by the SVM approach is the least.

8 Conclusions

In this study, it has been attempted to deploy a system identification technique to develop the V_S correlation with geotechnical soil properties, and assess their influence on V_S. The evolved Support Vector Machine (SVM) have been used to obtain a model for the prediction of V_S.

A SVM model was developed for V_S based on the depth of sampling, N_{SPT}, total and effective stress, fine content, and stress ratio (σ_{vo}/σ'_{vo}).

The validation and performance of the new model was assessed, and contrasted with previous statistical correlations. For all 620 case records, including V_S and geotechnical soil properties, predicted and measured V_S values were compared. The results manifested that predictions by the correlations of Kiku et al. (2001), Hasancebi and Ulusay (2007) and Dikmen (2009) over estimateV_S up to $V_S = 100$ (m s^{-1}) and give lower V_S values over $V_S = 238$ (m s^{-1}). However, the proposed approach predicts V_S with high accuracy and low variance.

In the field, a change in the soil layer may alter the V_S values and this can be a source of error. Hence, predictive correlations are best suited for homogenous sites. Results obtained from this study and previous researches reveal that empirical correlations derived from a local dataset should not be implemented for different sites with significantly varying features. Therefore, these proposed relationships should be used with caution in geotechnical engineering and should be checked against measured V_S.

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Table 1. Inventory of proposed correlations between uncorrected N_{SPT} and V_S by previous researchers.

Ref.	Proposed relation for all soils
Imai and Yoshimura (1975)	$V_S = 89.9N^{0.341}$
Ohta and Goto (1978)	$V_S = 85.35N^{0.348}$
Sykora and Stokoe (1983)	$V_S = 100.5N^{0.29}$
Jafari et al. (1997)	$V_S = 22N^{0.85}$
Kiku et al. (2001)	$V_S = 68.3N^{0.292}$
Jafari et al. (2002)	$V_S = 27N^{0.73}$ (Clay type)
Hasancebi and Ulusay (2007)	$V_S = 90N^{0.309}$
Ulugergerli and Uyanık (2007)	$a - V_S = 23.29\ln(N) + 405.61$
	$b - V_S = 52.9e^{-0.011N}$
Dikmen (2009)	$V_S = 58N^{0.39}$

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Table 2. A sample of the database used in this paper extracted from Hanna et al. (2007).

Z (m)	N_{160}	FC (%)	D_w (m)	σ_{vo} (kPa)	σ'_{vo} (kPa)	σ_{vo}/σ'_{vo}	V_S (m s^{-1})
3.3	6	83	0.74	59	33.4	1.77	170
17.8	31	80	5	342.5	217	1.58	294
2	6	56	0.4	36.1	20.1	1.80	110
2.7	12	53	0.84	47.5	28.9	1.64	110
18.2	18	5	0.5	378	204.4	1.85	262
1.4	4	99	0.44	23.9	14.3	1.67	100
9	6	98	1.7	168	96.4	1.74	200
16.2	13	74	2.5	300.2	165.8	1.81	172
6.8	23	14	1.03	136.7	80.1	1.71	151
2.6	6	92	1.64	45.6	36	1.27	253
7.9	40	11	1.5	138.8	74.8	1.86	150
14.8	5	98	2.5	273.4	152.8	1.79	172
13.2	30	20	3.2	263.2	165.1	1.59	179
2.5	13	65	0.45	42.4	21.9	1.94	105
2.8	4	99	0.71	48.8	27.9	1.75	121
6.5	8	99	1.72	118.6	70.8	1.68	95
9	48	5	0.77	167.3	85	1.97	250
2.6	4	99	1.5	43.2	32.2	1.34	85
7.7	39	11	2.6	133	82	1.62	150
17.8	16	12	0.85	328.7	162.4	2.02	243
4.1	25	71	1.9	70	48	1.46	306
3.4	4	78	1.5	56.8	38.3	1.48	150
4	7	83	0.5	69.7	34.7	2.01	150
14.8	36	35	1.9	302.7	176.2	1.72	363
5.5	24	97	1.3	99.7	57.7	1.73	155

Table 3. Statistical information for the SVM model for predicting V_S.

Statistic	R^2	MSE	MAD	RMSE
Neural training	0.95	1870	31	43
Neural testing	0.96	1718	25	41

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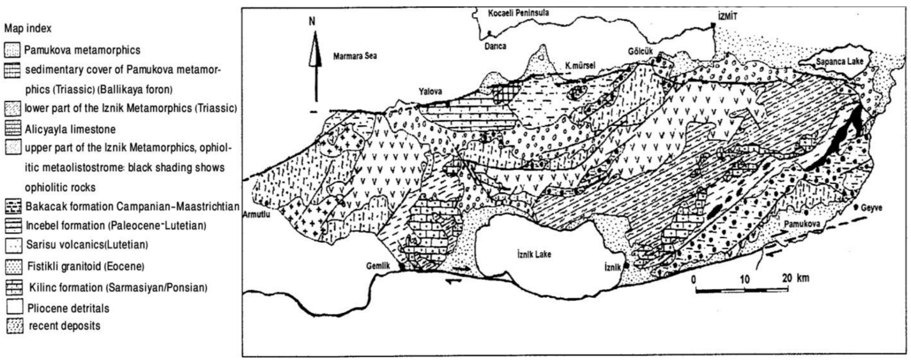

Fig. 1. Simplified geological map of Armutlu peninsula (Cetin et al., 2004).

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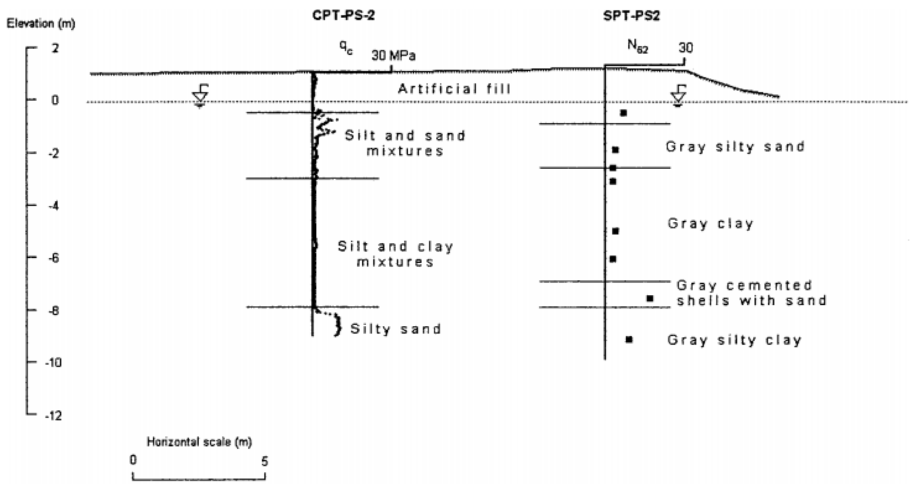

Fig. 2. Soil profile at the police station site located on the east shore of Izmit Bay, in the town of Gölçük (Cetin et al., 2004).

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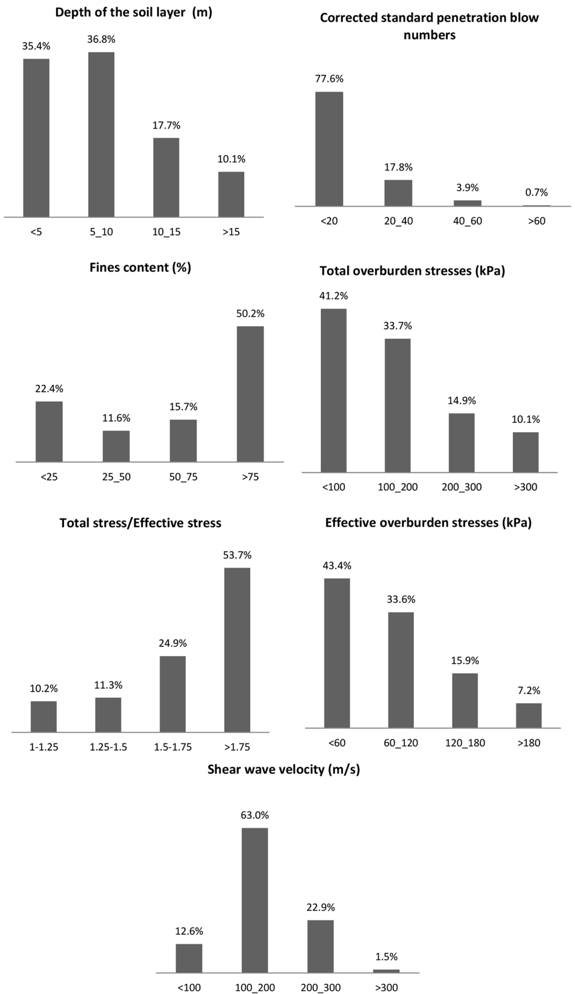

Fig. 3. Distribution of descriptive variable characteristics for all case histories.

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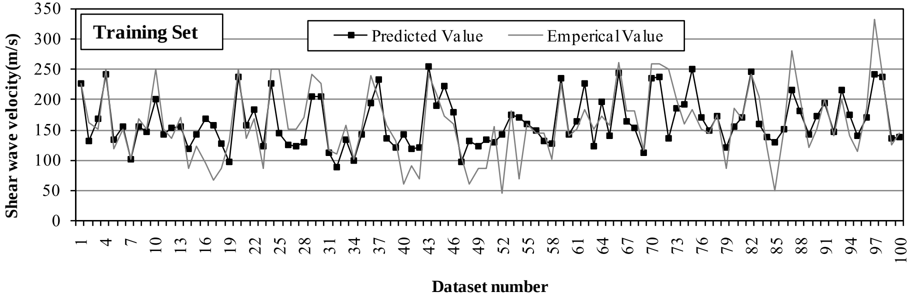

Fig. 4. SVM model predicted performance in comparison with observed data for the training set (100 inputs-output data).

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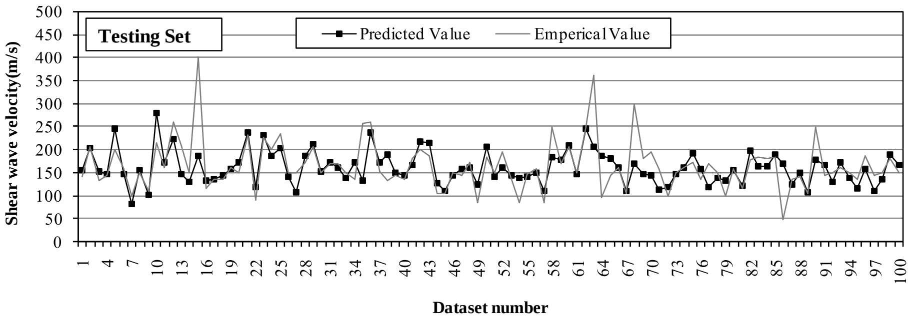

Fig. 5. SVM model predicted performance in comparison with observed data for the testing set.

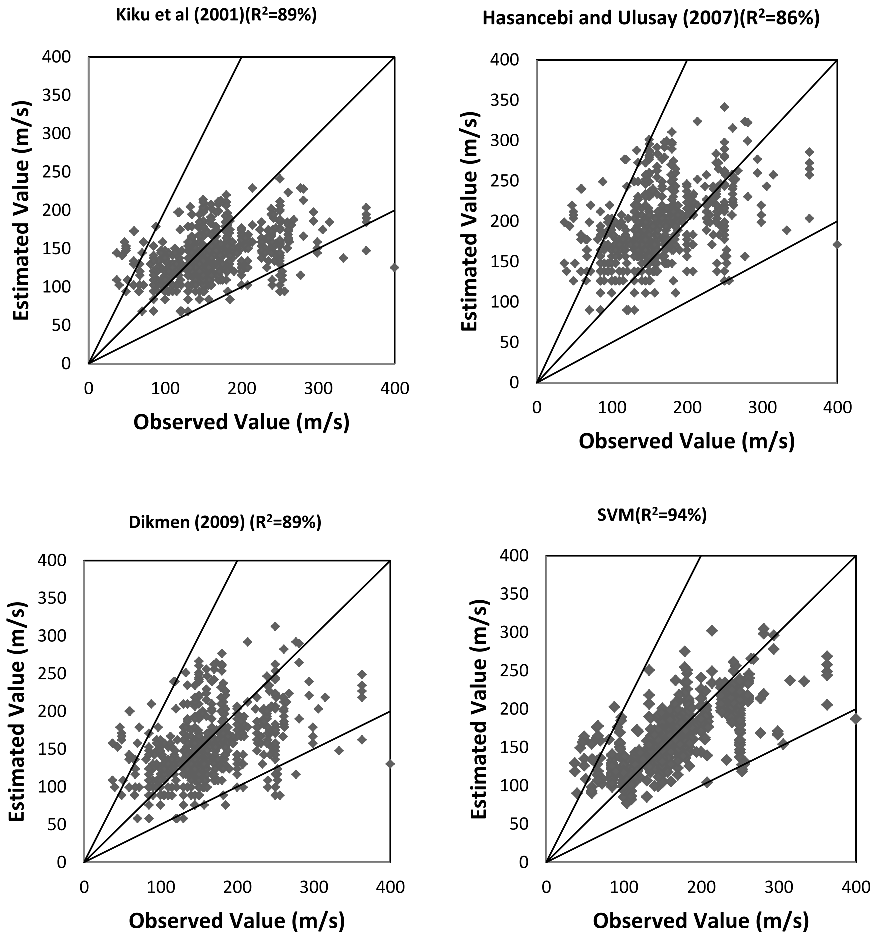

Fig. 6. Estimated vs. measured Shear wave velocity ($m\,s^{-1}$) by different researchers correlations.