Environmental Earth Sciences (2021) 80:787
https://doi.org/10.1007/s12665-021-10084-z

ORIGINAL ARTICLE

Spatial mapping of geotechnical soil properties at multiple depths in Sialkot region, Pakistan

Zain Ijaz[1] · Cheng Zhao[2] · Nauman Ijaz[1] · Zia ur Rehman[3,4] · Aashan Ijaz[5,6]

Received: 24 March 2021 / Accepted: 1 November 2021 / Published online: 21 November 2021

Abstract
This paper aims to create spatial maps (SMs) using a spatial interpolation technique based on extensive geotechnical subsoil data derived from comprehensive field and laboratory investigations. Sialkot, a rapidly developing industrial and agricultural district, is used as a case study. The subsoil information was assessed in terms of Standard Penetration Test N-values (SPT-N), shear wave velocity, soil type, soil consistency, and chemical analysis. Using ArcGIS, the SMs were created by treating each depth level as a surface and using the Inverse Distance Weighting (IDW) interpolation technique. Correlations were also developed using linear regression analyses for SPT-N values, and soil consistency in conjunction with depth, allowing quick and reliable assessment of soil strength and stiffness, and soil consistency during the preliminary planning and design process of any proposed project in the study area. The results show that at shallow depth (i.e., up to 3 m) the fine-grained soil is predominant with a plasticity index (PI) ranged between 7 and >17; SPT-N values between 2–8; and shear wave velocity between 138 and 195 m/s. Beyond, 3 m depth, the non-plastic coarse-grained soil is predominant exhibiting SPT-N values between 8 and >16; and shear wave velocity between 195 and >232 m/s. In addition, the correlation coefficient for SPT-N values exhibits good prediction accuracy, i.e., at shallow depth (up to 3 m) the correlation coefficient between actual and predicted value ranges between 82 and 90%; whereas beyond 3 m the correlation coefficient varies between 67 and 89%. Meanwhile, for PI value the correlation coefficient up to 9 m depth ranges between 82 and 94%. Moreover, the prediction accuracy for soil type using SMs is around 83%. This information enables engineers to construct a preliminary ground model for a new site using data derived from adjacent sites or sites with the same subsoils exposed to similar geological processes. Furthermore, having reliable information on the geometry and geotechnical properties of underground layers will make projects safer and more cost-effective.

Keywords Soil mapping · Standard penetration test · Spatial interpolation · Geographical information system · Soil exploration · Geotechnical properties

✉ Nauman Ijaz
nauman_ijaz99@hotmail.com; nauman_ijaz99@tongji.edu.cn

Zain Ijaz
zain@tongji.edu.cn

Cheng Zhao
zhaocheng@tongji.edu.cn

Zia ur Rehman
ziaur.rehman@uettaxila.edu.pk; lei-m16@tsinghua.org.cn; engr.zrehman@gmail.com

Aashan Ijaz
aashanijaz@gmail.com

1 Key Laboratory of Geotechnical and Underground Engineering of Ministry of Education, College of Civil Engineering, Tongji University, Shanghai 200092, China

2 Key Laboratory of Geotechnical and Underground Engineering of Ministry of Education, College of Civil Engineering, Tongji University, Shanghai 200092, China

3 Department of Civil Engineering, University of Engineering and Technology Taxila, Taxila 47080, Pakistan

4 State Key Laboratory of Hydroscience and Engineering, Tsinghua University, Beijing 100084, China

5 Department of Civil Engineering, University of Engineering and Technology Lahore, Lahore 54000, Pakistan

6 Highways, Communication and Works Department, Lahore, Punjab, Pakistan

Introduction

In any engineering project, the subsoil investigation and geotechnical testing of soil become necessary to acquire the data, essential to design the substructures. Because of the limited availability of time and the lack of data, large estimation errors occur in the design, and hence the risk factor for stability and cost of the project increases (Rwakarehe and Mfinanga 2014). Also, these investigations are usually performed under professional supervision and always require sophisticated instruments thus may prove to be a costly element in any project. On the other hand, the aftermath effects of construction with the improper exploration of the subsoil cause the structure to be ruinously settled (Muhwezi et al. 2014). Therefore, a proper but economical assessment of subsoil strata is always desirable in the construction industry all over the world.

Despite rapid technological progress in the construction industry, the urban underground has remained an enigmatic space (Angin 2016). Plenty of projects carried out in the past in both urban and developing areas, and their subsoil investigation reports (SIRs) based on lethargic laboratory and field tests, and decades of soil behavior observations, eventually has become only the part of the documentation, rather than providing guidelines for potential project designs. Furthermore, the initial feasibility reports for megaprojects are usually based on interrupted data from different SIRs rather than organized data (May et al. 2010; Yoo 2016). Therefore, there is a strong need to integrate such SIRs in the form of soil maps which not only play an important role for quick and economical assessment of subsoil properties during the preliminary stage of new projects but also provide a fair idea about the purpose for which land can be used (Aziz et al. 2017). These maps aid the designers in characterizing the soil strength, stiffness, and other critical engineering properties, which can be used to un-tediously estimate and evaluate the engineering design parameters of the soil (Zeraatpisheh et al. 2019; Tajik et al. 2020; Oda et al. 2013; Padarian et al. 2019). Furthermore, it can serve as a guide for local contractors in terms of foundation design parameters for a variety of infrastructure development projects where the project budget does not allow for an independent subsoil investigation.

There have been numerous studies around the world aimed at the development of the various type of soil maps using different techniques (Poppiel et al. 2021; Rasaei and Bogaert 2019; Pahlavan-Rad et al. 2018; Wang et al. 2016; Taghizadeh-Mehrjardi et al. 2020; Cracknell and Reading 2014; Kidd et al. 2020; Voltz et al. 2020). Among various techniques, Geographic Information System (GIS) proving to be a very effective tool for capturing, storing, retrieving at will, transforming, and displaying spatial data from the real world (Robinson and Metternicht 2006; Juárez-Camarena et al. 2016; Akumu et al. 2019). As per Hennig et al. 2013, the data can be displayed in three distinctive yet overlapping viewpoints: database, spatial analysis, and maps. Using spatial interpolation of subsoil data, some recent studies integrated the practical application of GIS in the field of engineering (Arrouays et al. 2017; Bargaoui et al. 2019; Arrouays et al. 2020). Some other researchers used GIS-based coding and analyzed the subsoil investigation data, and produced geophysical, geological, and subsoil maps (Gabàs et al. 2014; Aldefae et al. 2020; Coelho et al. 2021). Such maps are essential in providing design guidance, as well as the creation of construction and building rules and regulations, which can lead to cost savings in the soil exploration program due to the readily available organized data about sub-soil conditions for the site in question. Furthermore, such maps serve as a reference and solution for dealing with various engineering issues that may arise prior to the project's completion.

Different countries have developed their own soil maps, however, very few studies have been published in the literature for the South Asia region (Aziz et al. 2017; Zeraatpisheh et al. 2019; Tajik et al. 2020). Therefore, the authors place a great emphasis on the development of such maps for this region, in particular for rapidly growing cities or districts in terms of agricultural and commercial trade points of view, such as the district Sialkot. This district planned to connect the China Pakistan Economic Corridor (CPEC), through a trunk road network that will be extended throughout the region. The subject district falls under the flagship project of the "One Belt One Road initiative" that aims to establish a trade route for the region. In addition, the development of a special economic zone named, "Sialkot Export Processing Zone" has also significantly increased the importance of this region (Jahangir et al. 2020). Therefore, due to the rapid industrialization and infrastructure developments across the district, the authorities have recognized the significance of readily available subsoil information as an essential part of cost-effective construction planning and this study is a step forward.

Taking the aforementioned discussion into account the current study focuses on developing an organized database that can be visualized by employing spatial mapping based on different critical geotechnical properties such as strength, stiffness, soil type, soil consistency, seismic parameters, and chemical analysis at every location in the research region of district Sialkot, Pakistan.

Study area

Sialkot district is located in the east of Pakistan, between 32° 24′ N–32° 37′ N latitude and 73° 59′ E –75° 02′ E longitude, at an average height of approximately 256 m above sea level, between the rivers Ravi and Chenab, with a population density of 903 people per square kilometer (Malik et al. 2010). The climate is hot and wet in the

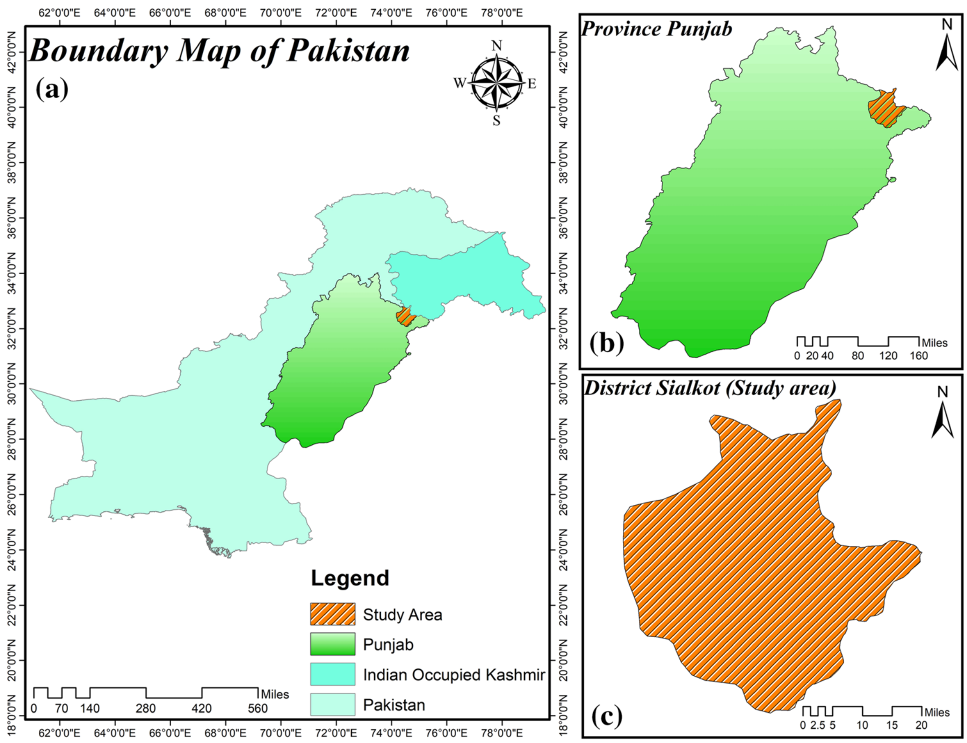

Fig. 1 Location of district Sialkot **a** District Sialkot location on the Pakistan map; **b** District Sialkot on the Punjab province map; **c** District Sialkot study area

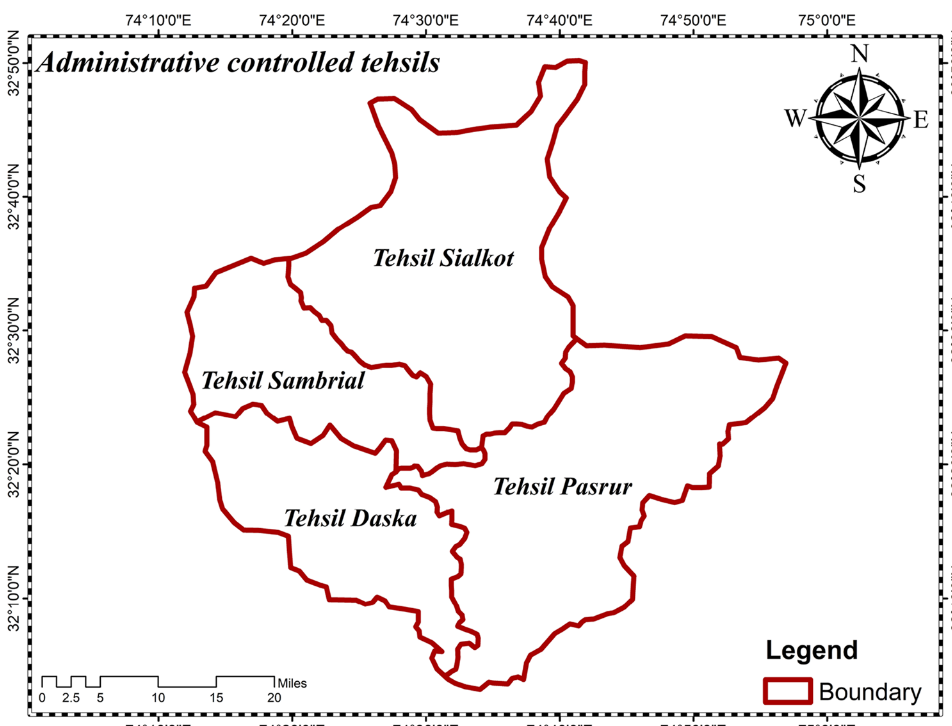

Fig. 2 Administratively controlled Tehsils of District Sialkot

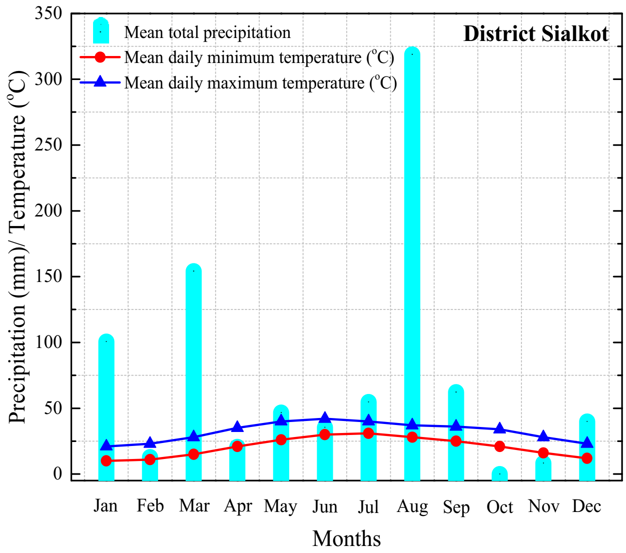

Fig. 3 Average climatic condition of the district Sialkot

summer and cold in the winter, with an average annual rainfall of about 1000 mm, with the peak rainfall season during the monsoon. Figures 1, 2, and 3 present the location, administrative controlled tehsils, and average climatic condition of the study area.

Fig. 4 presents the contour map of the Sialkot district. The data for elevations from mean sea level were collected using satellite data which is further transformed into visualization maps to get the idea of undulated landscape. The contour intervals are uniformly spaced which shows the study area lies in a plain landscape. The lowest point falls within the range of 222.03 m whereas the highest points lie in the range of 291.29 m above the mean sea level. The peak ground acceleration of the study area as per Pakistan's revised Building Code (BCP) (2007) ranges between 0.16 and 0.24 g (Quittmeyer and Jacob 1979).

Database description

A large number of subsoil information were gathered from extensive field and laboratory investigation reports carried out for various projects throughout the district. These pieces of information include numerical and alphanumerical data on geographical, geological, and engineering data (Sun 2012; Wadi et al. 2021). The detailed information gleaned from soil investigation reports (SIRs) is presented in Table 1.

Subsoil information data from 155 different construction project sites comprise of 282 boreholes executed in the study area were compiled. The borehole's average data were retrieved and recorded for further analyses. Figure 5 depicts the location of each borehole point. The thickness and location of each stratum, as well as the Standard Penetration Test N-values (SPT-N), soil consistency limits, shear wave velocity, and chemical analysis (i.e., sulphate content, and soluble salts) results at various depths, were also extracted against each borehole. Out of 155 sites, the average borehole data of 143 sites have

Fig. 4 Contour map of Sialkot District

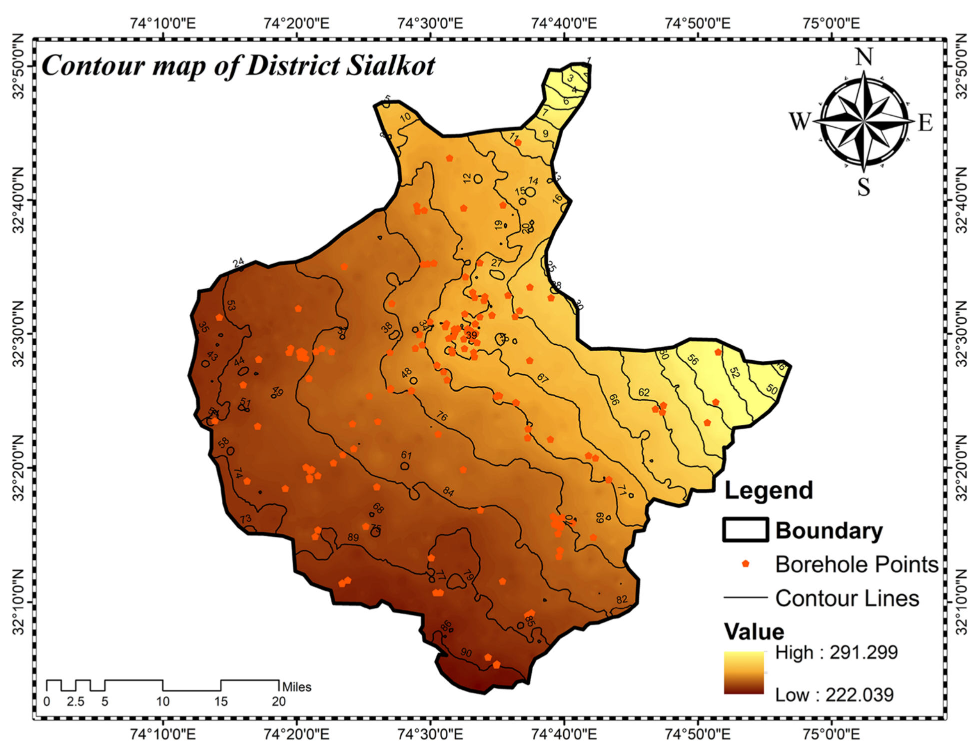

Table 1 Data retrieved from subsoil investigation reports

Borehole ID	The borehole's general information, such as the identification number, project, point, depth, location, contractor, and so on
Ground water-table	The depth of the water table and its variation throughout the monitoring period
Lithology	The thickness, consistency, color, characteristics of the soil along with composition and mineralogical details of layers encountered are described in detail. Additional information about rocks, such as aperture, roughness, discontinuities, weathering effect, and so on
In-situ tests	Provides information gleaned from various tests carried out inside the borehole. In general, in situ testing yields reliable results among which, standard penetration testing is found to be the most economical and widely used to evaluate the strength and stiffness of soil along with the bearing capacity evaluation. Furthermore, widely accepted correlations provide a thorough understanding of soil mechanical properties
Lab tests	Comprises laboratory test results for a variety of extracted rock and soil samples. Mainly, the retrieved geotechnical test data contained results of soil consistency, density, moisture content, soil and textural classification, strength characteristics, and various chemical test including suphate content and total soluble salts

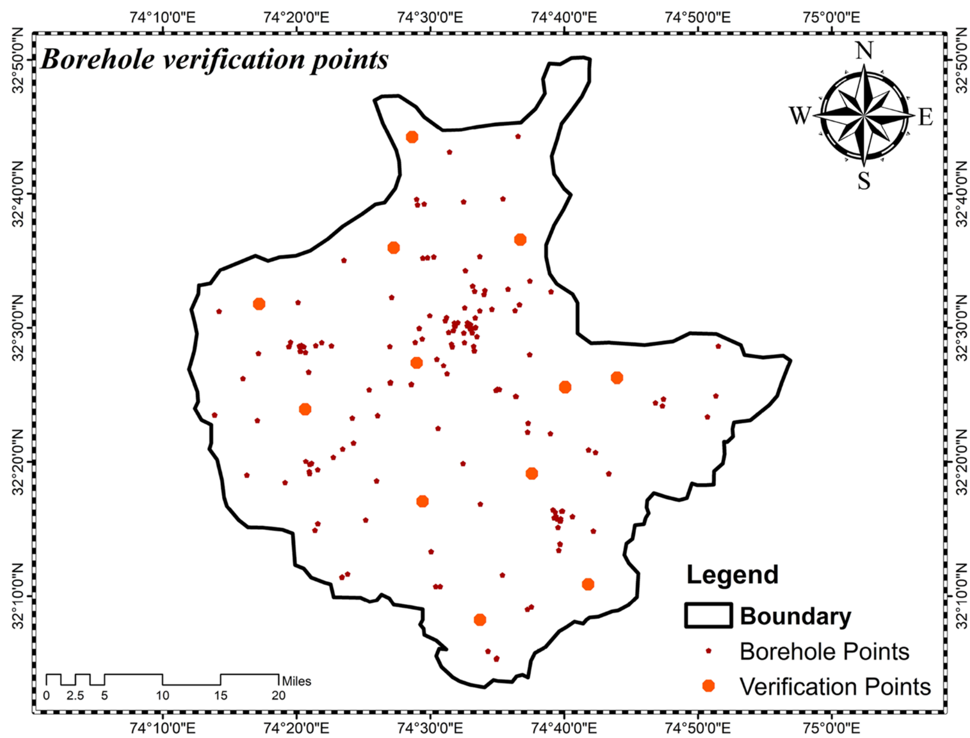

Fig. 5 Study area with locations of data points

been used to provide accurate lithological and stratigraphical information of each project site, while the remaining 12 SIRs evenly distributed throughout the district were used for validation purposes. It is pertinent to mention here, in terms of sources, the authors ensured that the SIRs selected for validation are from multiple sources and representative of the whole data set used in the development of the soil maps.

Results and discussion

Statistical evaluation of SPT-N data

To evaluate the homogeneity of the test data of the study region, various statistical techniques were incorporated. Table 2 presents the results of various statistical evaluations that illustrate the mean SPT-N values, their mode, variance, and standard deviation along with depth. In addition, skewness and kurtosis analyses were also incorporated to statistically measures the symmetry and tail-heaviness of the distribution of data. The results show that at 1.5m and 3m depth the data is slightly positively skewed, while with the increase in depth the data tends to be approximately symmetrical as can be seen in Fig 6 and Table 2. On the other hand, the value of kurtosis was found to be very low and negative along with depth showing the uniform distribution of data, i.e., platykurtic kurtosis. The statistical analyses of the database show that a wide range of data spectrum is considered in the development of spatial maps in the current study.

Table 2 Descriptive statistical analysis of database based on SPT-N value

Depth	1.5 m	3.0 m	4.5 m	6.0 m	7.5 m	9.0 m
Mean	6.599	7.472	8.695	9.972	11.702	13.567
Standard Error	0.204	0.202	0.223	0.242	0.268	0.267
Median	6	7	8	9	11	13
Mode	5	7	7	9	10	12
Standard Deviation	3.428	3.389	3.748	4.065	4.501	4.485
Sample Variance	11.750	11.489	14.049	16.526	20.260	20.118
Kurtosis	0.279	− 0.432	− 0.209	-0.590	− 0.573	− 0.291
Skewness	0.850	0.461	0.570	0.217	0.229	0.298
Range	15	14	17	18	22	21
Minimum	1	1	1	2	4	6
Maximum	16	15	18	19	21	23
Sum	1861	2107	2452	2812	3300	3826
Count	282	282	282	282	281	282

Figure 7a, b presents the variation of SPT-N and PI values with depth considering the maximum and minimum ranges and standard deviation. The SPT N-values tend to increase with an increase in depth while the PI value of the soil ranges from high plastic to non-plastic soil. Based on subsoil data, several linear regression models were developed and documented in Tables 3 and 4 to predict the SPT-N value and PI value using the depth factor. Furthermore, as developed regression models exhibit a strong relationship (i.e., R^2 value), thus they can be reliably used for quick and economical assessment of SPT-N values and soil consistency with reasonable accuracy during the initial, planning, and design phases of future projects in the study zone.

Development of SMs

Subsoil data were gathered from various locations from different reliable authorities throughout the district. All four administratively controlled tehsils have a uniform distribution of scattered points (Fig. 2). The coordinates of the site location, elevation from mean sea level, SPT-N values, soil type, soil consistency, and chemical composition at different depths were digitalized and used as input data in the Arc GIS 10.5 by integrating pertinent data from SIRs.

For the current study, ArcMap software (ArcGIS 10.5) (Booth and Mitchell, 2001) was used to create SMs using a spatial analyst and the Inverse Distance Weighting (IDW) interpolation technique. The IDW interpolation technique is based on the idea that the value at an unknown data point can be estimated as a weighted median of values at data points within a certain cut-off distance or from a set of nearby points (Masser and Crompvoets 2015). For GIS-interpolated SPT-N subsoil maps, this technique provides a better representation of data as demonstrated by various pertinent studies (Al-Ani et al. 2013; Aziz et al. 2017). It is pertinent to mention here, prior to the development of SMs using spatial analyst, IDW technique, various trials were made by incorporating different other methods such as Geostatistical analyst (i.e., diffusion, IDW, global polynomial, and Kernel), Spatial analyst (i.e., spline, IDW, universal and ordinary kriging). The interpolation results were then compared to the input value points for validation. The results show that among the different above-mentioned techniques, the IDW technique was found to be quite effective in precisely predicting the various geotechnical soil properties with real-time data. In addition, a number of supportive literature were also found on the efficacy of the IDW technique compared to other methods (Zhou and Michalak, 2009; Lu and Wong, 2008; Al-Ani et al. 2013; Gong et al. 2014).

SMs based on SPT-N values

Figure 8 shows the SPT-N-based SMs at various depths, i.e., 1.5, 3 m, 4.5 m, 6 m, 7.5 m, and 9 m below the existing ground level (EGL). These SMs show the consistency and strength of the soil at various stratigraphic intervals. To evaluate the variation of SPT-N with depth, six maps were created. In general, there is an increasing trend in SPT-N values with an increase in depth highlighting the transformation of soil consistency from soft to hard (Terzaghi et al. 1996). The SMs show different ranges of SPT-N values, i.e., < 2, 2–4, 4–8, 8–16, and >16 of the study area at different depths highlighting soft, medium, and hard consistency of the soil. The results show that up to 3 m depth, the majority of the study area is predominant with SPT-N values falling in the range of 0–8, highlighting soft to medium-hard consistency of the soil as presented by pink, peach, and light brown color.

In addition, at 3 m depth, there are some yellow patches in the study area demonstrating hard consistency soil with SPT-N values ranges between 8 and 16. Further, with the increase in depth up to 9 m, the SPT-N values kept

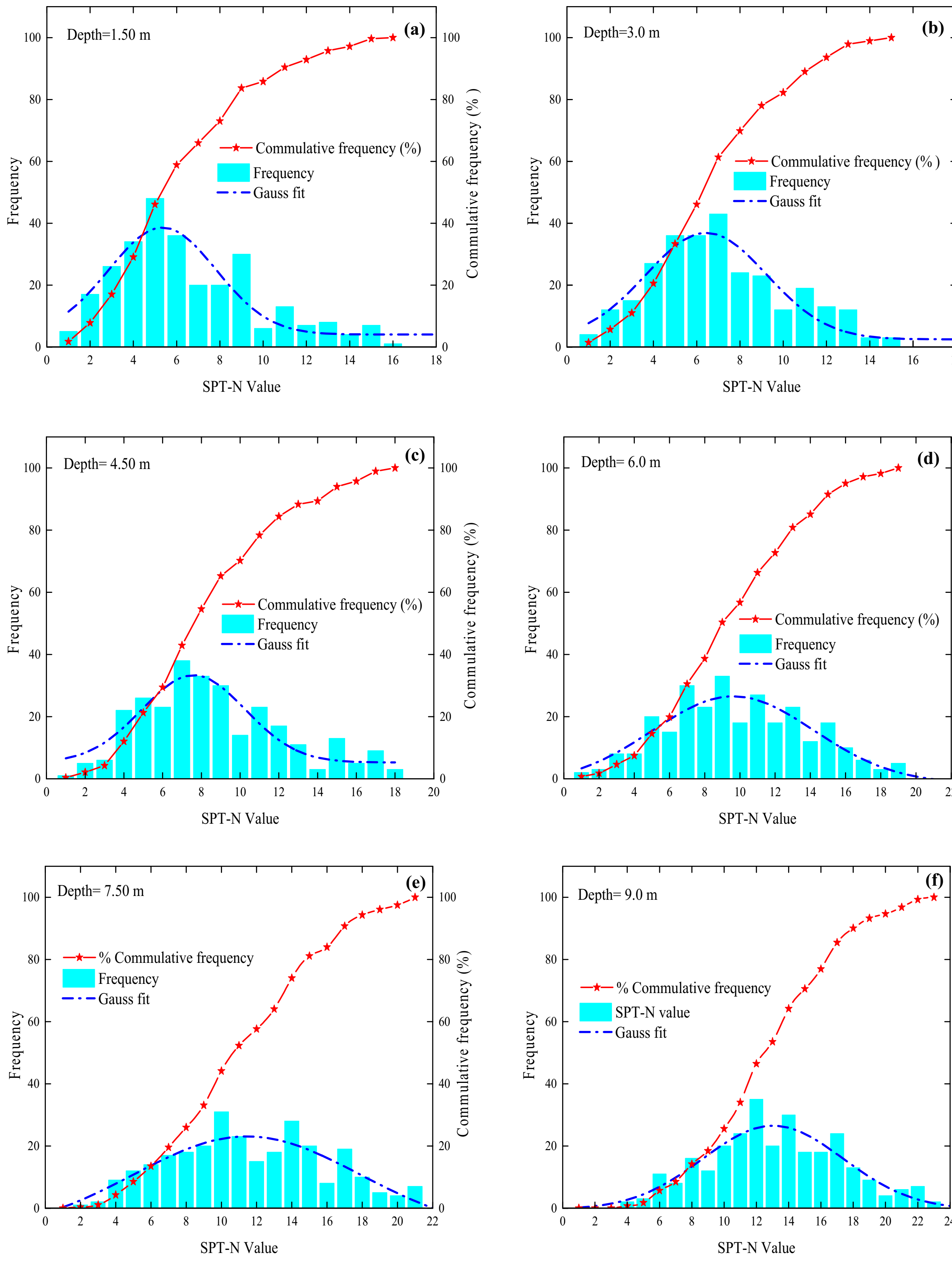

Fig. 6 SPT-N histogram at various depths

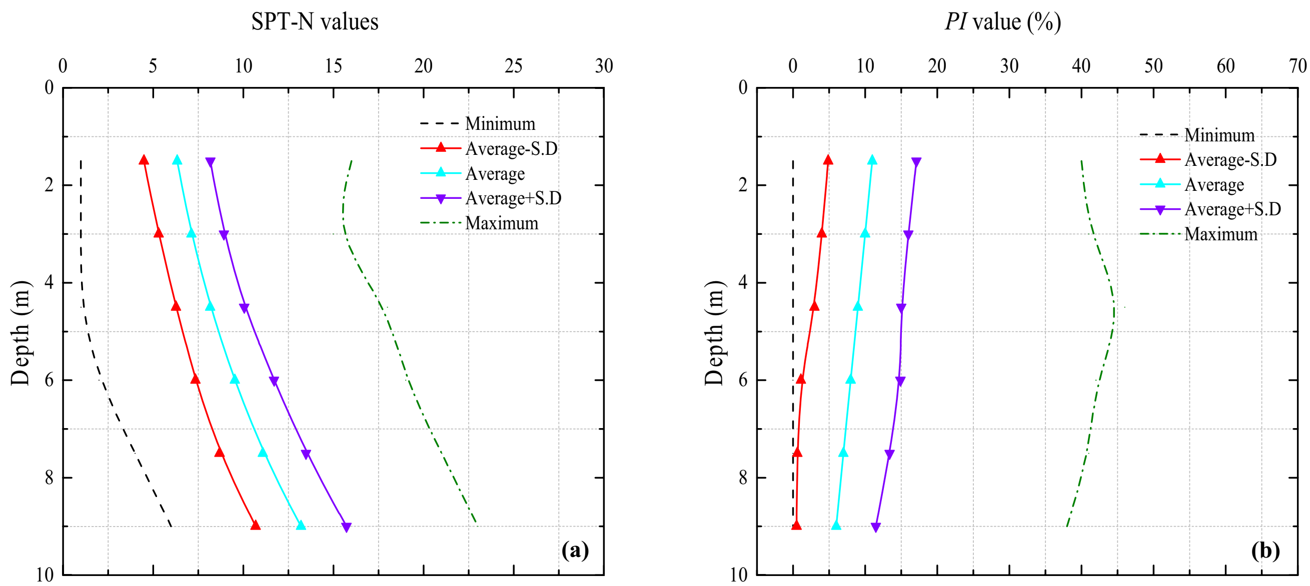

Fig. 7 Statistical variation of SPT-N and PI values with depth

Table 3 Linear Regression analysis of SPT-N with depth

Linear Regression of SPT-N values with depth		
Profile	Correlation	R^2
Average	$N=0.906\ (D)+4.476$	0.972
Average − SD	$N=0.802(D)+2.915$	0.972
Average + SD	$N=1.011(D)+6.038$	0.970

N SPT-N value, *D* depth

Table 4 Linear Regression analysis of PI with depth

Linear Regression of SPT-N values with depth		
Profile	Correlation	R^2
Average	$\mathrm{PI}=-0.666\ (D)+12.00$	0.999
Average − S.D	$N=0.684(D)+18.24$	0.944
Average + SD	$N=0.648\ (D)\ 5.75$	0.943

N SPT-N value, *D* depth

increasing and the study area is primarily displaying hard consistency soil with SPT-N values ranges between 8–16 and >16.

Further, shear wave velocity which is an important seismic design parameter is also taken into account in the current study. It is used to calculate various spectral acceleration under seismic loading which are regarded as a vital seismic design parameter in modern building codes, i.e., ASCE-07, IBC (2006) (Mahmood et al. 2016; Haider and ur Rehman 2021). Therefore, the authors have incorporated the shear wave velocity values corresponding to SPT-N values as shown in Fig. 8. In general, the shear wave velocity increases with an increase in depth corresponding to an increase in stiffness. The shear wave velocity for depths at depths 1.5 m, 3 m, 4.5 m, 6 m, 7.5 m, and 9 m ranges from 0 to > 23 2m/s, respectively.

SMs based on soil type

SMs were developed based on the soil types found below the study area. A Unified Soil Classification System (USCS) was used to classify subsoil types. Various soil types were assigned numerical codes: (1) CH, fat clay; (2) CL, lean clay; (3) CL-ML, silty clay; (4) ML, Silt; (5) SM, silty sand; (6) poorly graded silty sand; (5). Six maps were created based on the observed trend of soil variation with depth, as shown in Fig. 9. SMs were established at depth intervals of 1.5 m, 3 m, 4.5 m, 6 m, 7.5 m, and 9 m, respectively. The maps show that CL and CL-ML were generally dominant at shallower depths (up to 3m), whereas the northern side of the district (Tehsil Sialkot) was dominated by SP-SM type of soil. Beyond the 3m stratum, the SP-SM soil type occupied the majority of the district. Further exploration of the depths reveals the dominance of the SP-SM/SM soil type. Such distribution pattern of soil types conforms with the geology of the study area, i.e., alluvium plain.

SMs based on soil consistency

Soil consistency, i.e., plasticity index (plasticity index (PI)= liquid limit (LL) – plastic limit (PL)) is an important soil property that defines the moisture-volume relatioship which is critical for the stability of any civil engineering structure built on it. In addition, there are various correlations

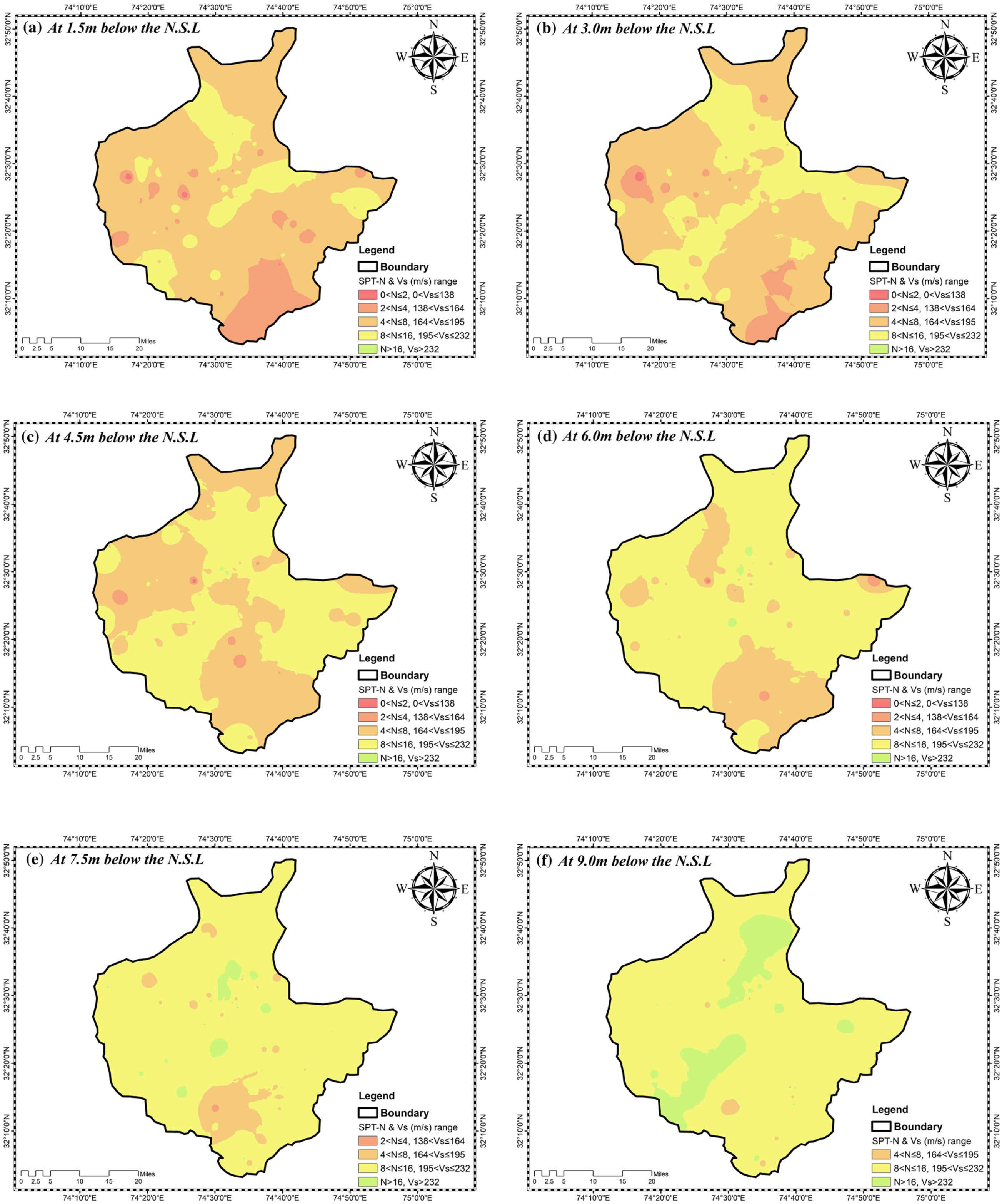

Fig. 8 SMs based on SPT-N values

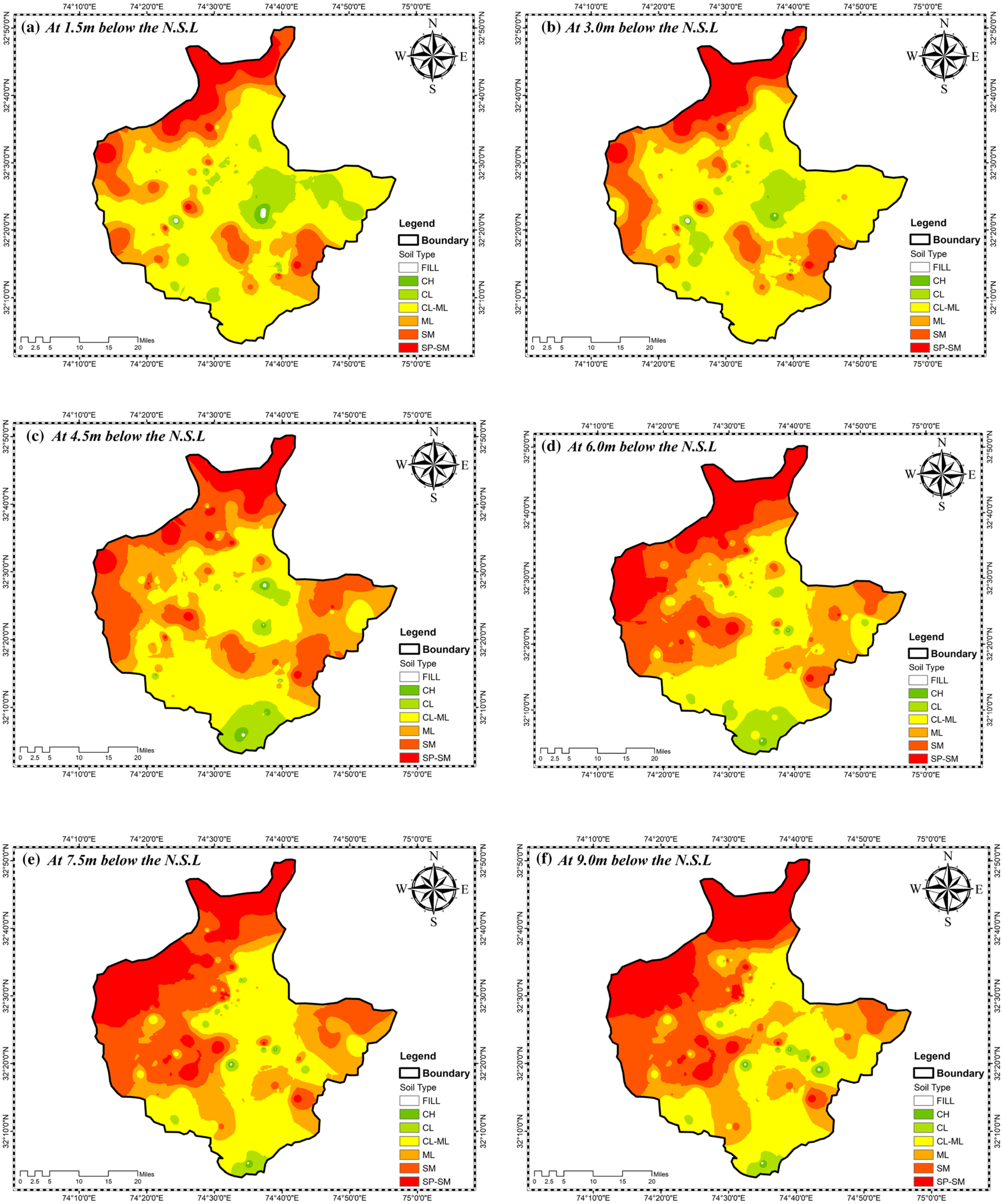

Fig. 9 SMs of district Sialkot based on soil type

developed in the literature that use soil consistency as a predicting tool to envisage various geotechnical properties, i.e., soil activity, swelling and shrinkage, compressibility, hydraulic conductivity, strength, etc. These correlations are of significant importance for quick and preliminary assessment of different aforementioned geotechnical properties (Rehman et al. 2017; Ijaz et al. 2020a). Therefore, in the current study, the authors established the SMs based on soil consistency (i.e., PI) for subsoil strata for quick assessment of engineering behavior as shown in Fig 10. The SMs show four ranges of PI; (1) non-plastic soil (PI = 0); (2) low plastic soil (0 > PI ≤7); (3) medium plastic (7> PI ≤ 17); and (4) high plastic soil (PI > 17). In general, the soil consistency (i.e., PI) decreases or tends to exhibit non-plastic behavior with an increase in depth of the soil, and these results are inconsistent with the soil type maps shown in Fig 10. Up to 3 m depth, the PI of the major portion of the study area falls under the medium to high plastic soil range. Beyond 3 m, the high values of PI tend to diminish and gradually reduce and fall in the range of low to the non-plastic range. For example, at 9 m depth, the study area is predominant with non-plastic soil (i.e., PI = 0). This trend is attributed to change in soil type as can be seen in Fig. 9, i.e., with an increase in depth, the study area is predominant with SP-SM type of soil which exhibits non-plastic behavior (i.e., PI = 0) which validates the soil consistency behavior.

SMs based on chemical analysis

Chemical analysis is of crucial importance in terms of the presence of specific chemicals, i.e., sulphate, soluble salts which may play a critical role and affect the foundations if its concentration is beyond the permissible limits, i.e., > 0.5 (sulphate content). Such chemical analyses are important for engineers to understand the soil behavior based on the presence of hazardous material in the soil. To analyze the distribution of the percentage of total soluble salts and sulphate content at shallow depth, interpolated SMs were developed using the available data at 1.5m depth. The soil contains traces of sulphate contents and total soluble salts, and the majority of the district area falls under the permissible limits, i.e., 0.24% and 0.50%, respectively, as shown in Fig. 11.

Validation of SMs

The borehole logs from 143 of the 155 investigation reports in the study area were used to prepare SMs, while the remaining 12 reports were used for validation. The actual SPT-N values, PI values, and soil type for a given depth and location were compared and validated with the predicted interpolated points using ArcGIS. In general, the validation points were evenly distributed throughout the district, resulting in a negligible difference between actual and predicted values.

A comparison of actual and predicted values based on SPT-N and PI values are shown in Fig. 12a, b. While Table 5 shows a comparison of actual and predicted values based on soil type. The analyses show that the developed SMs exhibit a very good accuracy between actual and predicted values of soil type exhibiting accuracy of more than 83%. Besides, Table 6. presents the strength of predicted SPT-N and PI value using the correlation coefficient approach. The results show relatively good strength between actual and predicted values of SPT-N and PI, which authenticate the practicality of the developed maps.

Civil engineering applications

The SMs developed in this study are critical for construction in the Sialkot region and could help in making preliminary decisions for future projects. For instance, the SMs based on SPT-N value gives an idea about the ground condition for footing placement. At 1.5 m depth, many weak spots (i.e., SPT-N= 0–2) are identified in the Sialkot district which is not suitable for construction and required ground improvement or engineering fill (Fig. 8). However, these weak spots tend to diminish beyond 3 m depth which means that foundation at/below 3 m depth could be constructed without prior heavy mechanical ground improvement. Similarly, a clear idea of the engineering properties of ground could also be taken using the SMs based on soil type (Fig. 9). For instance, CH is considered to be disastrous soil in terms of its volumetric change behavior for Civil Engineering structures. It is identified that for the Sialkot region at various depths, few spots bear the problematic soil. Thus, prior care must be taken to deal with this soil in the highlighted region in the SMs (Fig. 9). These soils can be dealt with by the replacement with suitable engineering fill or by stabilization using different additives (Rehman et al. 2018; Ijaz et al. 2020a, b, c). The selection of these methods depends on the availability of the additive/filler materials at the site. Moreover, the idea about the soil-moisture volume behavior could be taken using SMs based on soil consistency (Khalid et al. 2015, 2019). For instance, different spots have been identified in the Sialkot region for which soil consistency could be regarded as highly plastic. Furthermore, the chemical analysis results exhibit that total soluble salts and sulphate content within the study area falls within the permissible range with few exceptions (Fig. 11). Therefore, care should be taken while carrying out construction in those spots for which sulphate content is not within the permissible limits, i.e., use of sulphate resistant cement which enhances the durability of the foundation in high sulphate zone.

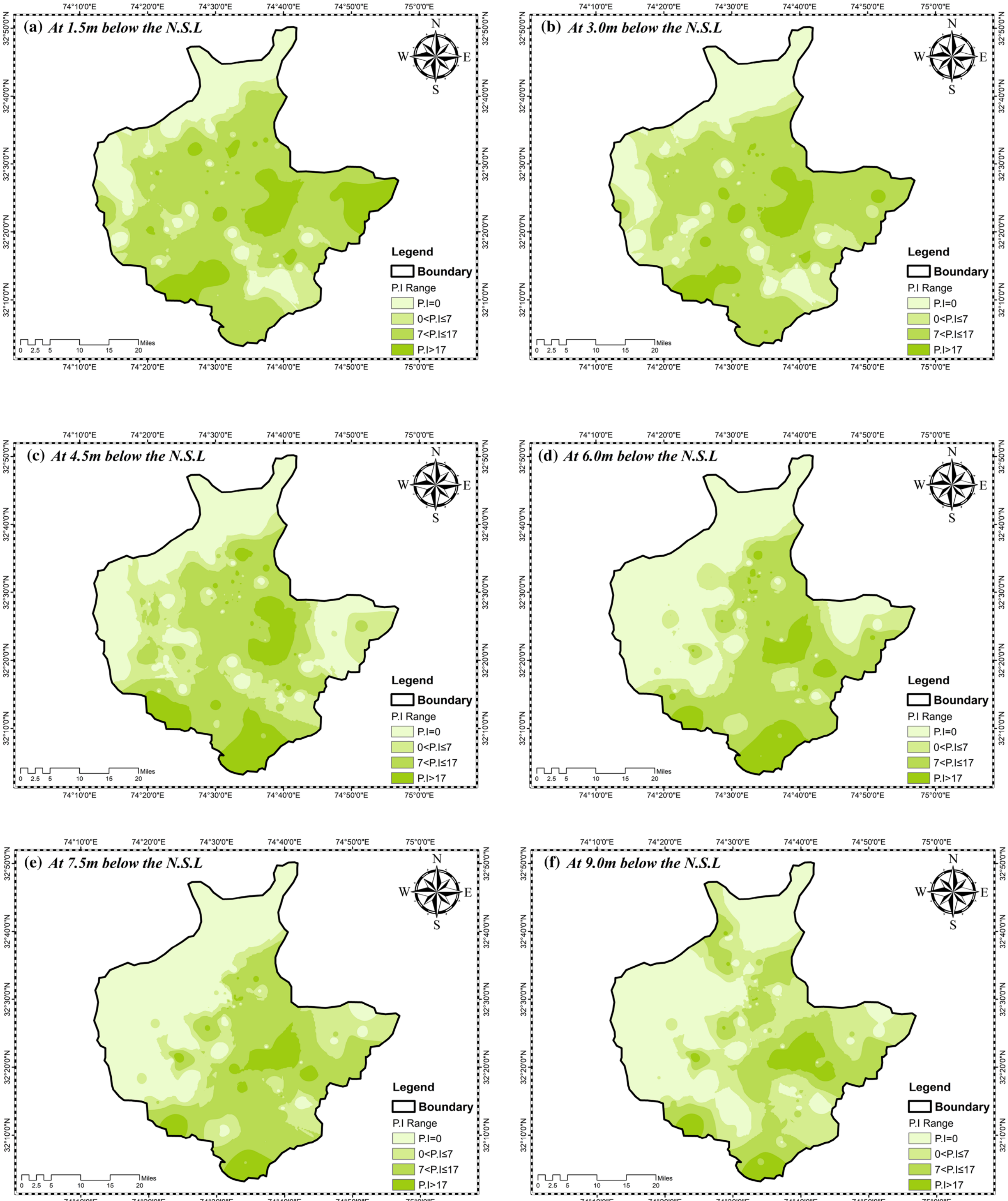

Fig. 10 SMs based on soil consistency (i.e., PI)

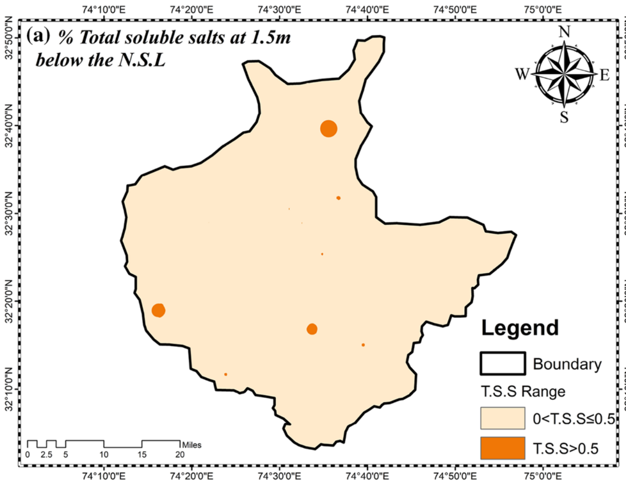

Fig. 11 SMs based on chemical analysis

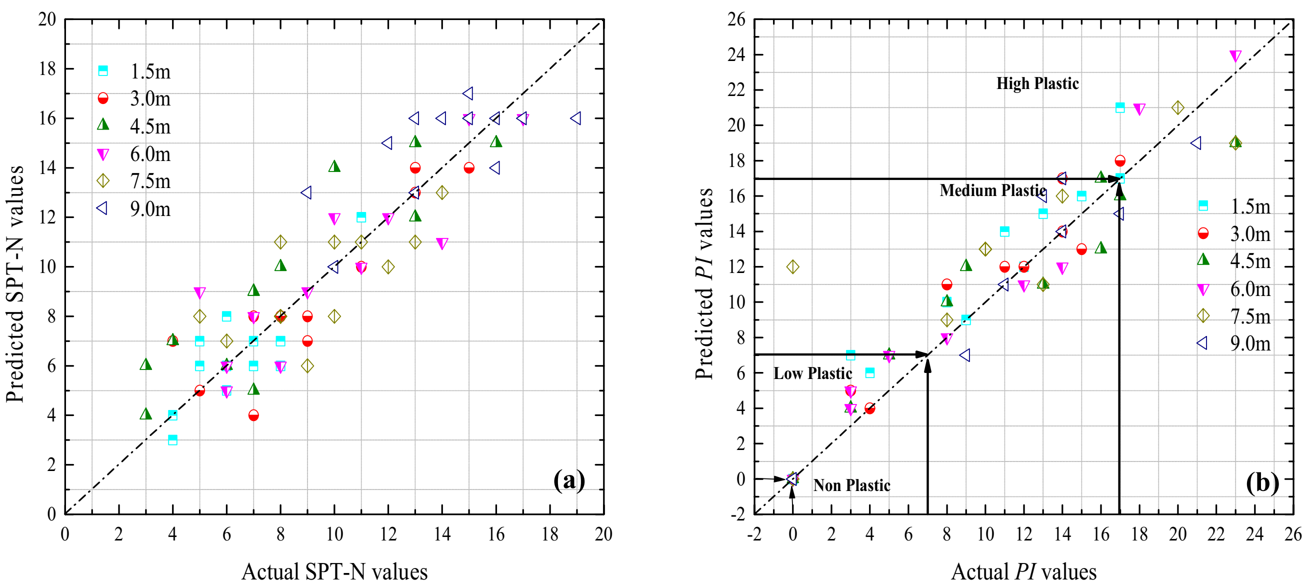

Fig. 12 Comparison of actual and predicted values; **a** SPT-N values; **b** PI values

Summary

The current study presents the spatial maps of district Sialkot by integrating a large database of SIRs. SMs show that CL and CL-ML were generally dominant at shallower depths (up to 3 m) with average SPT-N values ranges between 2-8 and shear wave velocity between 138-195 m/s. While the soil consistency up to 3m exhibits higher values of plasticity index (PI) falls in the range of 7 ≥ PI > 17. Whereas beyond 3m, the soil stratum was enriched with SP-SM soil type having SPT N-value ranges between 9 AND >16 with average shear wave velocity through 195->232 m/s. While the soil consistency beyond 3 m depth tends to exhibit low plastic and non-plastic behavior. Furthermore, at shallow footing depth (i.e., 1.5m) the sulphate contents and soluble salt presents non-hazardous nature of the soil. In addition, the statistical analyses of the database show that a wide range of uniformly distributed data spectrums is considered in the current study to develop spatial maps.

Table 5 Comparison of actual and predicted soil type

Comparison of Actual and Predicted Soil types												
Depth	BH-24		BH-47		BH-76		BH-92		BH-127		BH-144	
(m)	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*
1.5	CL	CL	CL	CL	**SP**	**ML**	CL	CL-ML	CL	CL-ML	CL-ML	ML
3	CL-ML	CL	CH	CL	CL-ML	ML	CL-ML	CL-ML	CL-ML	CL	**ML**	**CL**
4.5	CL-ML	CL	CL-ML	CL-ML	CL	CL-ML	CL-ML	ML	CL-ML	CL	**CL-ML**	**SP-SM**
6	CL	CL	CL	CL-ML	CL-ML	CL-ML	CL-ML	ML	**SP-SM**	**ML**	CL-ML	CL-ML
7.5	CL-ML	CL-ML	CL-ML	CL-ML	CL	CL-ML	**SP**	**ML**	CL	CL-ML	SP-SM	SP-SM
9	CL-ML	CL-ML	CL-ML	CL-ML	ML	CL-ML	**SP**	**CL**	**CL-ML**	**SP-SM**	ML	ML
Depth	BH-177		BH-199		BH-211		BH-225		BH-237		BH-239	
(m)	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*	*A*	*P*
1.5	SP	SP-SM	SP-SM	ML	CL	CL-ML	CL-ML	CL-ML	SP-SM	SM	CL-ML	CL
3	CL-ML	CL	**SP**	**CL**	SP-SM	SP	ML	ML	CL-ML	CL-ML	SP-SM	SP-SM
4.5	ML	ML	CL	CL-ML	SP	SP-SM	SP-SM	SP-SM	SP	SP-SM	SM	SP-SM
6	CL	CL-ML	SP	SP-SM	SM	SP-SM	SP	SP-SM	SP-SM	SM	SP-SM	SP-SM
7.5	SM	SP-SM	SP	SP-SM	**ML**	**SP-SM**	SP-SM	SM	SP	SP-SM	SP-SM	SM
9	SP	SP-SM	SP	SM	SM	SP-SM	SP-SM	SP-SM	**CL**	**SP-SM**	SP-SM	SP-SM

P: Predicted Soil type from zonation maps; *A*: Actual soil type from the borehole log

Bold text shows that the actual and predicted soil types do not match

Table 6 Correlation coefficient approach for strength prediction SPT-N and PI value

Depth	Correlation coefficient	
m	SPT-N	PI
1.5	0.82	0.93
3	0.90	0.94
4.5	0.89	0.95
6	0.88	0.98
7.5	0.70	0.82
9	0.67	0.93

Acknowledgements The authors are thankful for the technical support of Tongji University, Shanghai, China, and the University of Engineering and Technology, Taxila. Special thanks to Building Research Station, Communication and Works Department, and NESPAK PVT. LIMITED for collaboration regarding sharing of data.

Author contributions ZI: conceptualization, methodology, software, writing—original draft. CZ: supervision, project, administration, review, and editing. NI: validation, formal analysis, investigation, software, writing—original draft. ZuR: methodology, software, review and editing. AI: visualization, formal analysis, review, and editing.

Funding No funding available for the current study.

Code availability Open source commercially available computer program ArcGIS 10.5 is used in the titled study. Therefore, Code availability on author's account is not applicable.

Declarations

Conflict of interest No conflict of interest exists in the submission of this manuscript.

References

Akumu CE, Baldwin K, Dennis S (2019) GIS-based modeling of forest soil moisture regime classes: Using Rinker Lake in northwestern Ontario, Canada as a case study. Geoderma 351:25–35

Al-Ani H, Eslami-Andargoli L, Oh E, Chai G (2013) Categorising geotechnical properties of surfers paradise soil using geographic information system (GIS). Int J Geomate 5(2):690–695

Aldefae AH, Mohammed J, Saleem HD (2020) Digital maps of mechanical geotechnical parameters using GIS. Cogent Eng 7(1):1779563

Angin Z (2016) Geotechnical field investigation on giresun hazelnut licenced warehause and spot exchange. Geomech Eng 10(4):547–563

Arrouays D, Savin I, Leenaars J, McBratney AB (eds) (2017) GlobalSoilMap-Digital Soil mapping from country to globe: proceedings of the Global Soil Map 2017 Conference, July 4–6, 2017, Moscow, Russia. CRC Press

Arrouays D, McBratney A, Bouma J, Libohova Z, Richer-de-Forges AC, Morgan CL, Mulder VL (2020) Impressions of spatial maps: The good, the not so good, and making them ever better. Geoderma Reg 20:e00255

Aziz M, Khan TA, Ahmed T (2017) Spatial interpolation of geotechnical data: a case study for Multan City, Pakistan. Geomech Eng 13(3):475–488

Bargaoui YE, Walter C, Michot D, Saby NP, Vincent S, Lemercier B (2019) Validation of digital maps derived from spatial disaggregation of legacy soil maps. Geoderma 356:113907

Booth B, Mitchell A (2001) Getting started with ArcGIS, GIS by ESRI

Coelho FF, Giasson E, Campos AR, Tiecher T, Costa JJF, Coblinski JA (2021) Digital soil class mapping in Brazil: a systematic review. Sci Agricola 78(5):e20190227. https://doi.org/10.1590/1678-992X-2019-0227

Cracknell MJ, Reading AM (2014) Geological mapping using remote sensing data: A comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. Comput Geosci 63:22–33

El May M, Dlala M, Chenini I (2010) Urban geological mapping: geotechnical data analysis for rational development planning. Eng Geol 116(1–2):129–138

Gabàs A, Macau A, Benjumea B, Bellmunt F, Figueras S, Vilà M (2014) Combination of geophysical methods to support urban geological mapping. Surv Geophys 35(4):983–1002

Gong G, Mattevada S, O'Bryant SE (2014) Comparison of the accuracy of kriging and IDW interpolations in estimating groundwater arsenic concentrations in Texas. Environ Res 130:59–69

Haider A, ur Rehman Z (2021) Evaluation of seismicity of Karachi city in the context of modern building codes. Arab J Geosci 14(2):1–12

Hennig S, Gryl I, Vogler R (2013) Spatial data infrastructures, spatially enabled society and the need for society's education to leverage spatial data. Int J Spatial Data Infrastruct Res 8:98–127

Ijaz N, Dai F, Meng L, Ur Rehman Z, Zhang H (2020a) Integrating lignosulphonate and hydrated lime for the amelioration of expansive soil: A sustainable waste solution. J Clean Prod 254:119985

Ijaz N, Dai F, ur Rehman Z (2020b) Paper and wood industry waste as a sustainable solution for environmental vulnerabilities of expansive soil: a novel approach. J Environ Manag 262:110285

Ijaz N, Dai F, ur Rehman Z, Ijaz Z, Zahid M (2020c) Laboratory evaluation of curing period for stabilized expansive soil by a new paper/timber industry waste based cementing material. In: IOP Conference Series: Earth and Environmental Science (Vol. 442, No. 1, p. 012008). IOP Publishing

Jahangir A, Haroon O, Mirza AM (2020) Special Economic Zones under the CPEC and the belt and road initiative: parameters, challenges and prospects. In: Syed J, Ying YH (eds) China's belt and road initiative in a global context. Palgrave Macmillan Asian Business Series, Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-030-18959-4_12

Juárez-Camarena M, Auvinet-Guichard G, Méndez-Sánchez E (2016) Geotechnical zoning of Mexico Valley subsoil. Ingeniería Investig Tecnol 17(3):297–308

Khalid U, Rehman Z, Farooq K, Mujtaba H (2015) Prediction of unconfined compressive strength from index properties of soils. Sci Int (lahore) 27(5):4071–4075

Khalid U, ur Rehman Z, Liao C, Farooq K, Mujtaba H (2019) Compressibility of compacted clays mixed with a wide range of bentonite for engineered barriers. Arab J Sci Eng 44(5):5027–5042

Kidd D, Searle R, Grundy M, McBratney A, Robinson N, O'Brien L, Triantafilis J (2020) Operationalising digital soil mapping–Lessons from Australia. Geoderma Reg 23:e00335

Lu GY, Wong DW (2008) An adaptive inverse-distance weighting spatial interpolation technique. Comput Geosci 34(9):1044–1055

Mahmood K, Farooq K, Memon SA (2016) One dimensional equivalent linear ground response analysis—a case study of collapsed Margalla Tower in Islamabad during 2005 Muzaffarabad Earthquake. J Appl Geophys 130:110–117

Malik RN, Jadoon WA, Husain SZ (2010) Metal contamination of surface soils of industrial city Sialkot, Pakistan: a multivariate and GIS approach. Environ Geochem Health 32(3):179–191

Masser I, Crompvoets J (2015) Building european spatial data infrastructures, 3rd edn. ESRI Press, Redlands

Muhwezi L, Acai J, Otim G (2014) An assessment of the factors causing delays on building construction projects in Uganda. Int J Constr Eng Manag 3(1):13–23

Oda K, Lee MS, Kitamura S (2013) Spatial Interpolation of consolidation properties of Holocene clays at Kobe Airport using an artificial neural network. Int J Geotech Constr Mater Environ 4(1):423–428

Padarian J, Minasny B, McBratney AB (2019) Using deep learning to predict soil properties from regional spectral data. Geoderma Reg 16:e00198

Pahlavan-Rad MR, Dahmardeh K, Brungard C (2018) Predicting soil organic carbon concentrations in a low relief landscape, eastern Iran. Geoderma Reg 15:e00195

Poppiel RR, Demattê JAM, Rosin NA, Campos LR, Tayebi M, Bonfatti BR, Rahmati M (2021) High resolution middle eastern soil attributes mapping via open data and cloud computing. Geoderma 385:114890

Quittmeyer RC, Jacob KH (1979) Historical and modern seismicity of Pakistan, Afghanistan, northwestern India, and southeastern Iran. Bull Seismol Soc Am 69(3):773–823

Rasaei Z, Bogaert P (2019) Spatial filtering and Bayesian data fusion for mapping soil properties: A case study combining legacy and remotely sensed data in Iran. Geoderma 344:50–62

Rehman ZU, Khalid U, Farooq K, Mujtaba H (2017) Prediction of CBR value from index properties of different soils. Tech J 22(2):17–26

Rehman Z, Khalid U, Farooq K, Mujtaba H (2018) On yield stress of compacted clays. Int J Geo-Eng 9(1):1–16

Robinson TP, Metternicht G (2006) Testing the performance of spatial interpolation techniques for mapping soil properties. Comput Electron Agric 50(2):97–108

Rwakarehe EE, Mfinanga DA (2014) Effect of inadequate design on cost and time overrun of road construction projects in Tanzania. J Constr Eng Project Manag 4(1):15–28

Sun CG (2012) Applications of a GIS-based geotechnical tool to assess spatial earthquake hazards in an urban area. Environ Earth Sci 65(7):1987–2001

Taghizadeh-Mehrjardi R, Schmidt K, Amirian-Chakan A, Rentschler T, Zeraatpisheh M, Sarmadian F, Scholten T (2020) Improving the spatial prediction of soil organic carbon content in two contrasting climatic regions by stacking machine learning models and rescanning covariate space. Remote Sens 12(7):1095

Tajik S, Ayoubi S, Zeraatpisheh M (2020) Digital mapping of soil organic carbon using ensemble learning model in Mollisols of Hyrcanian forests, northern Iran. Geoderma Reg 20:e00256

Terzaghi K, Peck RB, Mesri G (1996) Soil mechanics. Wiley, New York

Voltz M, Arrouays D, Bispo A, Lagacherie P, Laroche B, Lemercier B, Schnebelen N (2020) Possible futures of soil-mapping in France. Geoderma Rég 23:e00334

Wadi D, Wu W, Malik I, Ahmed HA, Makki A (2021) Assessment of liquefaction potential of soil based on standard penetration test for the upper Benue region in Nigeria. Environ Earth Sci 80(7):1–11

Wang S, Wang Q, Adhikari K, Jia S, Jin X, Liu H (2016) Spatial-temporal changes of soil organic carbon content in Wafangdian, China. Sustainability 8(11):1154

Yoo C (2016) Effect of spatial characteristics of a weak zone on tunnel deformation behavior. Geomech Eng 11(1):41–58

Zeraatpisheh M, Ayoubi S, Jafari A, Tajik S, Finke P (2019) Digital mapping of soil properties using multiple machine learning in a semi-arid region, central Iran. Geoderma 338:445–452

Zhou Y, Michalak AM (2009) Characterizing attribute distributions in water sediments by geostatistical downscaling. Environ Sci Technol 43(24):9267–9273