EFFECT OF SOIL VARIABILITY ON THE BEARING CAPACITY OF FOOTINGS ON MULTI-LAYERED SOIL

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APPENDIX A

<u> </u>										
с ₁ /с ₂ Н/В	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	8.046	8.045	8.043	8.045	7.962	7.320	6.659	6.074	5.529	5.052
0.2	6.287	6.285	6.287	6.288	6.288	6.287	6.219	5.859	5.452	5.052
0.3	5.646	5.645	5.647	5.645	5.646	5.647	5.646	5.630	5.371	5.052
0.4	5.339	5.340	5.340	5.340	5.336	5.337	5.337	5.338	5.288	5.052
0.5	5.172	5.170	5.173	5.173	5.172	5.172	5.171	5.173	5.173	5.052
0.6	5.083	5.085	5.083	5.085	5.084	5.085	5.083	5.084	5.084	5.052
0.7	5.055	5.055	5.057	5.055	5.052	5.055	5.054	5.054	5.053	5.052
0.8	5.052	5.050	5.053	5.053	5.054	5.053	5.053	5.054	5.053	5.052
0.9	5.053	5.055	5.053	5.053	5.052	5.050	5.053	5.053	5.053	5.052
1.0	5.054	5.055	5.053	5.050	5.054	5.053	5.053	5.053	5.053	5.052
1.1	5.052	5.055	5.053	5.053	5.054	5.053	5.053	5.053	5.053	5.052
1.2	5.053	5.055	5.050	5.053	5.054	5.052	5.053	5.054	5.053	5.052
1.3	5.053	5.055	5.050	5.053	5.054	5.052	5.053	5.054	5.053	5.052
1.4	5.053	5.055	5.050	5.053	5.052	5.052	5.053	5.053	5.053	5.052
1.5	5.052	5.050	5.053	5.053	5.052	5.052	5.053	5.053	5.053	5.052
1.6	5.052	5.055	5.050	5.053	5.052	5.052	5.053	5.053	5.053	5.052
1.7	5.052	5.055	5.053	5.050	5.052	5.052	5.053	5.053	5.053	5.052
1.8	5.053	5.055	5.053	5.053	5.052	5.053	5.051	5.053	5.053	5.052
1.9	5.052	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
2.0	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.053	5.053	5.052
2.1	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
2.2	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.053	5.053	5.052
2.3	5.053	5.055	5.053	5.053	5.052	5.052	5.053	5.053	5.053	5.052
2.4	5.053	5.055	5.053	5.053	5.054	5.053	5.053	5.053	5.053	5.052
2.5	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.053	5.053	5.052
2.6	5.053	5.050	5.053	5.050	5.052	5.053	5.053	5.053	5.053	5.052
2.7	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
2.8	5.053	5.050	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
2.9	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
3.0	5.053	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052

Table A.1 Lower bound estimation for $c_{u1} / c_{u2} \le 1.0$.

$\sum c_1/c_2$										
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
H/B										
0.1	12.697	12.697	12.618	10.822	9.256	8.037	7.088	6.323	5.706	5.204
0.2	7.349	7.349	7.349	7.349	7.349	7.200	6.666	6.130	5.630	5.204
0.3	6.187	6.187	6.187	6.187	6.187	6.187	6.187	5.930	5.554	5.204
0.4	5.697	5.697	5.697	5.697	5.697	5.697	5.697	5.695	5.476	5.204
0.5	5.442	5.443	5.442	5.442	5.442	5.442	5.442	5.442	5.393	5.204
0.6	5.294	5.294	5.294	5.294	5.294	5.294	5.294	5.294	5.294	5.204
0.7	5.226	5.226	5.226	5.226	5.226	5.226	5.226	5.226	5.226	5.204
0.8	5.205	5.205	5.205	5.205	5.205	5.205	5.205	5.205	5.205	5.204
0.9	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.0	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.1	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.2	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.3	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.4	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.5	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.6	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.7	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.8	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
1.9	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.0	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.1	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.2	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.3	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.4	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.5	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.6	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.7	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.8	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
2.9	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204
3.0	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.204

Table A.2 Upper bound estimation for $c_{u1} / c_{u2} < 1.0$.

$\langle c_1/c_2 \rangle$										
	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
H/B										
0.1	5.052	2.766	1.967	1.552	1.293	1.111	0.975	0.871	0.788	0.722
0.2	5.052	3.000	2.230	1.812	1.544	1.353	1.210	1.101	1.013	0.941
0.3	5.052	3.232	2.480	2.059	1.780	1.585	1.439	1.321	1.226	1.147
0.4	5.052	3.447	2.723	2.303	2.014	1.808	1.653	1.531	1.430	1.347
0.5	5.052	3.655	2.955	2.535	2.246	2.035	1.873	1.745	1.640	1.553
0.6	5.052	3.858	3.180	2.765	2.472	2.260	2.094	1.963	1.856	1.768
0.7	5.052	4.052	3.403	2.988	2.698	2.485	2.323	2.193	2.088	2.001
0.8	5.052	4.241	3.620	3.213	2.926	2.718	2.560	2.435	2.334	2.249
0.9	5.052	4.426	3.833	3.435	3.160	2.958	2.806	2.684	2.584	2.503
1.0	5.052	4.597	4.040	3.658	3.396	3.203	3.054	2.938	2.843	2.763
1.1	5.052	4.756	4.237	3.878	3.630	3.448	3.310	3.198	3.107	3.031
1.2	5.052	4.898	4.417	4.085	3.862	3.693	3.561	3.459	3.372	3.299
1.3	5.052	5.030	4.583	4.278	4.074	3.923	3.807	3.714	3.632	3.568
1.4	5.052	5.055	4.737	4.455	4.268	4.130	4.027	3.944	3.874	3.818
1.5	5.052	5.050	4.880	4.618	4.442	4.317	4.221	4.145	4.084	4.034
1.6	5.052	5.050	5.013	4.768	4.604	4.487	4.394	4.325	4.269	4.221
1.7	5.052	5.055	5.050	4.913	4.756	4.645	4.559	4.491	4.440	4.394
1.8	5.052	5.055	5.053	5.043	4.900	4.795	4.713	4.650	4.597	4.553
1.9	5.052	5.055	5.053	5.053	5.034	4.935	4.859	4.798	4.748	4.706
2.0	5.052	5.055	5.053	5.053	5.052	5.053	4.996	4.936	4.890	4.850
2.1	5.052	5.055	5.053	5.053	5.052	5.052	5.051	5.054	5.023	4.986
2.2	5.052	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.052	5.053
2.3	5.052	5.055	5.053	5.053	5.054	5.053	5.053	5.054	5.052	5.052
2.4	5.052	5.055	5.053	5.053	5.054	5.053	5.053	5.054	5.053	5.053
2.5	5.052	5.055	5.053	5.053	5.054	5.053	5.053	5.054	5.053	5.052
2.6	5.052	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.053
2.7	5.052	5.055	5.053	5.053	5.054	5.053	5.053	5.054	5.053	5.053
2.8	5.052	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.053	5.052
2.9	5.052	5.055	5.053	5.053	5.052	5.052	5.053	5.054	5.052	5.052
3.0	5.052	5.055	5.053	5.053	5.052	5.053	5.053	5.054	5.052	5.052

Table A.3 Lower bound estimation for $10.0 \ge c_{u1} / c_{u2} \ge 1.0$.

<u> </u>										
c ₁ /c ₂	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
H/B										
0.1	5.204	2.877	2.060	1.636	1.372	1.189	1.053	0.950	0.868	0.799
0.2	5.204	3.112	2.328	1.903	1.627	1.433	1.288	1.174	1.082	1.005
0.3	5.204	3.342	2.581	2.151	1.866	1.664	1.512	1.391	1.293	1.211
0.4	5.204	3.558	2.820	2.390	2.101	1.893	1.732	1.603	1.497	1.409
0.5	5.204	3.767	3.052	2.624	2.329	2.115	1.950	1.816	1.706	1.614
0.6	5.204	3.967	3.278	2.851	2.555	2.337	2.170	2.038	1.929	1.837
0.7	5.204	4.162	3.498	3.076	2.780	2.566	2.402	2.271	2.164	2.075
0.8	5.204	4.352	3.714	3.300	3.013	2.803	2.644	2.517	2.412	2.325
0.9	5.204	4.535	3.925	3.524	3.248	3.047	2.892	2.770	2.671	2.587
1.0	5.204	4.707	4.132	3.748	3.485	3.292	3.145	3.027	2.932	2.853
1.1	5.204	4.866	4.329	3.969	3.722	3.539	3.398	3.287	3.197	3.122
1.2	5.204	5.012	4.516	4.183	3.954	3.784	3.653	3.547	3.461	3.391
1.3	5.204	5.145	4.688	4.384	4.175	4.021	3.900	3.803	3.724	3.657
1.4	5.204	5.204	4.847	4.568	4.379	4.240	4.132	4.045	3.974	3.913
1.5	5.204	5.204	4.995	4.736	4.562	4.435	4.338	4.261	4.197	4.144
1.6	5.204	5.204	5.133	4.893	4.730	4.611	4.521	4.449	4.390	4.342
1.7	5.204	5.204	5.204	5.039	4.886	4.774	4.688	4.620	4.565	4.518
1.8	5.204	5.204	5.204	5.175	5.032	4.927	4.845	4.780	4.727	4.683
1.9	5.204	5.204	5.204	5.204	5.170	5.070	4.993	4.931	4.880	4.838
2.0	5.204	5.204	5.204	5.204	5.204	5.199	5.132	5.073	5.024	4.984
2.1	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.161	5.122
2.2	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.3	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.4	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.5	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.6	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.7	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.8	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
2.9	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204
3.0	5.204	5.204	5.204	5.204	5.204	5.204	5.204	5.200	5.204	5.204

Table A.4 Upper bound estimation for $10.0 \ge c_{u1} / c_{u2} \ge 1.0$.



Figure A.1 Displacement vectors at near failure (two-layered spatially variable purely cohesive material).



Figure A.1 Displacement vectors at near failure (two-layered spatially variable purely cohesive material). *(Continued)*



Figure A.1 Displacement vectors at near failure (two-layered spatially variable purely cohesive material). *(Continued)*



Figure A.2 Displacement vectors at near failure (single-layered spatially variable cohesive-frictional material).



Figure A.2 Displacement vectors at near failure (single-layered spatially variable cohesive-frictional material). *(Continued)*



Figure A.2 Displacement vectors at near failure (single-layered spatially variable cohesive-frictional material). (*Continued*)

APPENDIX B










































 $c_{\rm u1}/c_{u2} = 40.0, H/B = 0.5).$



Figure B.44 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.025_0.25 case (where $\mu_{c1} / \mu_{c2} = 0.025$ and H/B = 0.25).



Figure B.45 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.025_0.5 case (where $\mu_{c1} / \mu_{c2} = 0.025$ and H/B = 0.5).



Figure B.46 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.025_1.0 case (where $\mu_{c1} / \mu_{c2} = 0.025$ and H/B = 1.0).



Figure B.47 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.05_0.25 case (where $\mu_{c1} / \mu_{c2} = 0.05$ and H/B = 0.25).



Figure B.48 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.05_0.5 case (where $\mu_{c1} / \mu_{c2} = 0.05$ and H/B = 0.5).



Figure B.49 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.05_1.0 case (where $\mu_{c1} / \mu_{c2} = 0.05$ and H/B = 1.0).



Figure B.50 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.1_0.25 case (where $\mu_{c1} / \mu_{c2} = 0.1$ and H/B = 0.25).



Figure B.51 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.1_0.5 case (where $\mu_{c1} / \mu_{c2} = 0.1$ and H/B = 0.5).



Figure B.52 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.1_1.0 case (where $\mu_{c1} / \mu_{c2} = 0.1$ and H/B = 1.0).



Figure B.53 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_0.333_0.25 case (where $c_{u1}/c_{u2} = 0.333$ and H/B = 0.25).



Figure B.54 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.333_0.5 case (where $c_{u1}/c_{u2} = 0.333$ and H/B = 0.5).



Figure B.55 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.333_1.0 case (where $c_{u1}/c_{u2} = 0.333$ and H/B = 1.0).



Figure B.56 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.50_0.25 case (where $c_{u1}/c_{u2} = 0.50$ and H/B = 0.25).



Figure B.57 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.50_0.5 case (where $c_{u1}/c_{u2} = 0.50$ and H/B = 0.5).







Figure B.59 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_0.75_0.25 case (where $c_{u1}/c_{u2} = 0.75$ and H/B = 0.25).







Figure B.61 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_0.75_1.0 case (where $c_{u1}/c_{u2} = 0.75$ and H/B = 1.0).



Figure B.62 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_1.333_0.25 case (where $c_{u1}/c_{u2} = 1.333$ and H/B = 0.25).



Figure B.63 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_1.333_0.5 case (where $c_{u1}/c_{u2} = 1.333$ and H/B = 0.5).



Figure B.64 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_1.333_1.0 case (where $c_{u1}/c_{u2} = 1.333$ and H/B = 1.0).



Figure B.65 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_2.0_0.25 case (where $c_{u1}/c_{u2} = 2.00$ and H/B = 0.25).



Figure B.66 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_2.0_0.5 case (where $c_{u1}/c_{u2} = 2.00$ and H/B = 0.5).



Figure B.67 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_2.0_1.0 case (where $c_{u1}/c_{u2} = 2.00$ and H/B = 1.0).



for COHESIVE_3.0_0.25 case (where $c_{u1}/c_{u2} = 3.00$ and H/B = 0.25).



Figure B.69 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_3.0_0.5 case (where $c_{u1}/c_{u2} = 3.00$ and H/B = 0.5).



Figure B.70 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_3.0_1.0 case (where $c_{u1}/c_{u2} = 3.00$ and H/B = 1.0).



Figure B.71 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_10.0_0.25 case (where $c_{u1}/c_{u2} = 10.0$ and H/B = 0.25).



for COHESIVE_10.0_0.5 case (where $c_{u1}/c_{u2} = 10.0$ and H/B = 0.5).


Figure B.73 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_10.0_1.0 case (where $c_{u1}/c_{u2} = 10.0$ and H/B = 1.0).



for COHESIVE_20.0_0.25 case (where $c_{u1}/c_{u2} = 20.0$ and H/B = 0.25).



Figure B.75 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_20.0_0.5 case (where $c_{u1}/c_{u2} = 20.0$ and H/B = 0.5).



Figure B.76 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_20.0_1.0 case (where $c_{u1}/c_{u2} = 20.0$ and H/B = 1.0).



Figure B.77 The variation of $\mu_{N^*c \text{ AV}}$ and $COV_{N^*c \text{ AV}}$ with respect to COV_c and θ_c/B for COHESIVE_40.0_0.25 case (where $c_{u1}/c_{u2} = 40.0$ and H/B = 0.25).



Figure B.78 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_40.0_0.5 case (where $c_{u1}/c_{u2} = 40.0$ and H/B = 0.5).



Figure B.79 The variation of $\mu_{N^*c AV}$ and $COV_{N^*c AV}$ with respect to COV_c and θ_c/B for COHESIVE_40.0_1.0 case (where $c_{u1}/c_{u2} = 40.0$ and H/B = 1.0).

APPENDIX C

Model Variable and Data Sets	Mean	Standard Deviation	Maximum	Minimum	Range			
Soil cohesion of layer 1 (c ₁)								
Training set	Training set 5.47		10.00	1.00	9.00			
Testing set	5.29	2.43	9.99	1.12	8.87			
Validation set	5.46	2.63	9.99	1.01	8.98			
Soil cohesion of lay	er 2 (<i>c</i> ₂)							
Training set	5.42	2.54	10.00	1.00	9.00			
Testing set	5.53	2.59	9.99	1.02	8.97			
Validation set	5.29	2.63	9.97	1.01	8.96			
Soil cohesion of lay	er 3 (c ₃)							
Training set	5.48	2.63	10.00	1.00	9.00			
Testing set	5.51	2.64	9.99	1.02	8.97			
Validation set	5.74	2.57	9.98	1.01	8.97			
Soil cohesion of lay	er 4 (c ₄)							
Training set	5.54	2.63	10.00	1.00	9.00			
Testing set	5.27	2.59	9.99	1.01	8.98			
Validation set	5.38	2.62	9.99	1.01	8.98			
Soil cohesion of lay	er 5 (<i>c</i> ₅)							
Training set	5.51	2.55	10.00	1.00	9.00			
Testing set	5.38	2.58	9.97	1.01	8.96			
Validation set	5.42	2.59	10.00	1.00	9.00			
Soil cohesion of lay	er 6 (<i>c</i> ₆)							
Training set	5.70	2.58	9.99	1.01	8.98			
Testing set	5.52	2.52	9.99	1.02	8.97			
Validation set	5.42	2.70	9.99	1.02	8.97			
Soil cohesion of lay	er 7 (<i>c</i> ₇)							
Training set	5.35	2.53	10.00	1.00	9.00			
Testing set	5.64	2.66	9.96	1.01	8.95			
Validation set	5.41	2.59	10.00	1.02	9.98			
Soil cohesion of lay	er 8 (c ₈)							
Training set	5.67	2.62	10.00	1.00	9.00			
Testing set	5.31	2.49	9.99	1.03	8.96			
Validation set	5.47	2.59	9.99	1.02	8.97			
Soil cohesion of lay	er 9 (c ₉)							
Training set	5.58	2.60	10.00	1.00	9.00			
Testing set	5.41	2.54	9.97	1.02	8.95			
Validation set	5.52	2.63	9.99	1.00	8.99			

 Table C.1
 The results of the ANN input and output statistics.

Model Variable and Data Sets	Mean	Standard Deviation	Maximum	Minimum	Range
Soil cohesion of laye	er 10 (c ₁₀)				
Training set	5.41	2.64	9.98	1.01	8.97
Testing set	5.60	2.74	9.97	1.05	8.92
Validation set	5.49	2.62	9.97	1.01	8.96
Friction angle of lay	yer 1 (ø ₁)				
Training set	12.57	4.32	20.00	5.01	14.99
Testing set	12.68	4.24	19.99	5.02	14.97
Validation set	12.62	4.29	19.99	5.01	14.98
Friction angle of lay	yer 2 (ø ₂)				
Training set	12.48	4.34	20.00	5.01	14.99
Testing set	12.45	4.33	19.99	5.03	14.96
Validation set	12.23	4.36	19.91	5.04	14.87
Friction angle of lay	yer 3 (ø 3)				
Training set	12.40	4.35	19.98	5.00	14.98
Testing set	12.25	4.32	19.93	5.09	14.84
Validation set	12.29	4.46	19.98	5.01	14.97
Friction angle of lay	ver 4 (<i>ø</i> 4)				
Training set	12.70	4.41	19.99	5.01	14.98
Testing set	12.56	4.36	19.99	5.15	14.84
Validation set	12.19	4.29	19.98	5.01	14.97
Friction angle of lay	ver 5 (ϕ_5)	1.00	• • • • •		1 = 0.0
Training set	12.39	4.39	20.00	5.00	15.00
Testing set	12.33	4.25	19.98	5.01	14.97
Validation set	12.50	4.41	19.97	5.02	14.95
Friction angle of lay	ver 6 (ϕ_6)				
Training set	12.83	4.27	19.99	5.00	14.99
Testing set	12.60	4.19	19.99	5.10	14.89
Validation set	12.39	4.33	19.96	5.01	14.95
Friction angle of lay	ver 7 (ϕ_7)				
Training set	12.39	4.38	19.99	5.00	14.99
Testing set	12.45	4.25	19.99	5.09	14.90
Validation set	12.34	4.35	19.97	5.01	14.96
Friction angle of lay	ver 8 (ϕ_8)				
Training set	12.37	4.39	19.99	5.00	14.99
Testing set	12.28	4.33	19.86	5.01	14.85
Validation set	12.48	4.33	19.98	5.04	14.94

 Table C.1
 The results of the ANN input and output statistics. (Continued)

Model Variable and Data Sets	Mean	Standard Deviation	Maximum	Minimum	Range			
Friction angle of layer 9 (ϕ_9)								
Training set	Training set 12.62		20.00	5.00	15.00			
Testing set	12.42	4.37	19.98	5.00	14.98			
Validation set	12.37	4.32	19.94	5.04	14.90			
Friction angle of lay	ver 10 (\$\$ _{10})							
Training set	12.50	4.36	19.99	5.00	14.99			
Testing set	12.88	4.37	20.00	5.03	14.97			
Validation set	12.07	4.38	19.94	5.10	14.84			
Soil thickness of lay	ver 1 (<i>h</i> ₁)							
Training set	0.61	0.29	1.00	0.20	0.80			
Testing set	0.58	0.28	1.00	0.20	0.80			
Validation set	0.61	0.28	1.00	0.20	0.80			
Soil thickness of lay	ver 2 (<i>h</i> ₂)							
Training set	0.62	0.28	1.00	0.20	0.80			
Testing set	0.60	0.29	0.29 1.00		0.80			
Validation set	0.58	0.27	1.00	0.20	0.80			
Soil thickness of lay	ver 3 (h ₃)							
Training set	0.60	0.29	1.00	0.20	0.80			
Testing set	0.61	0.29	1.00	0.20	0.80			
Validation set	0.62	0.29	1.00	0.20	0.80			
Soil thickness of lay	ver 4 (h ₄)							
Training set	0.60	0.28	1.00	0.20	0.80			
Testing set	0.61	0.28	1.00	0.20	0.80			
Validation set	0.60	0.29	1.00	0.20	0.80			
Soil thickness of lay	ver 5 (h ₅)							
Training set	0.59	0.28	1.00	0.20	0.80			
Testing set	0.58	0.28	1.00	0.20	0.80			
Validation set	0.61	0.29	1.00	0.20	0.80			
Soil thickness of lay	ver 6 (h ₆)							
Training set	0.60	0.28	1.00	0.20	0.80			
Testing set	0.61	0.27	1.00	0.20	0.80			
Validation set	0.60	0.29	1.00	0.20	0.80			
Soil thickness of lay	ver 7 (h_7)							
Training set	0.61	0.28	1.00	0.20	0.80			
Testing set	0.57	0.28	1.00	0.20	0.80			
Validation set	0.61	0.28	1.00	0.20	0.80			

 Table C.1
 The results of the ANN input and output statistics. (Continued)

Model Variable and Data Sets	Mean	Standard Deviation	Maximum	Minimum	Range
Soil thickness of lay	rer 8 (h ₈)				
Training set	0.59	0.28	1.00	0.20	0.80
Testing set	0.59	0.28	1.00	0.20	0.80
Validation set	0.59	0.29	1.00	0.20	0.80
Soil thickness of lay	er 9 (h ₉)				
Training set	0.60	0.29	1.00	0.20	0.80
Testing set	0.61	0.28	1.00	0.20	0.80
Validation set	0.60	0.29	1.00	0.20	0.80
Footing width (<i>B</i>)					
Training set	2.50	0.93	4.00	1.00	3.00
Testing set	2.51	0.93	4.00	1.00	3.00
Validation set	2.51	0.92	4.00	1.00	3.00
Bearing capacity of	strip footii	ng (q_u) for $c - \phi$	case		
Training set	39.77	14.49	93.31	7.26	86.05
Testing set	39.60	14.19	14.19 87.94 11.67		76.27
Validation set	39.28	14.51	80.19	9.04	71.15
\widetilde{N}_c					
Training set	0.858	0.313	2.260	0.174	2.085
Testing set	0.868	0.304	2.106	0.216	1.890
Validation set	0.862	0.321	2.175	0.255	1.920
${\widetilde N}_{c-\phi}$					
Training set	1.043	0.255	3.035	0.524	2.511
Testing set	1.038	0.243	1.951	0.578	1.373
Validation set	1.018	0.224	1.830	0.561	1.269

Table C.1 The results of the ANN input and output statistics. (Continued)

 Table C.2
 The results of null hypothesis tests inputs and outputs.

Model Variable and Data Sets	<i>t</i> -value	Lower Critical value	Upper Critical value	t-test	<i>F</i> -value	Lower Critical value	Upper Critical value	F-test		
Soil cohesio	Soil cohesion of layer 1 (c ₁)									
Training	1.042	-1.961	1.961	Accept	0.996	-0.937	0.937	Accept		
Testing	-1.607	-1.961	1.961	Accept	1.024	-0.916	0.916	Accept		
Validation	-0.218	-1.961	1.961	Accept	0.973	-0.869	0.869	Accept		

Model Variable and Data Sets	<i>t</i> -value	Lower Critical value	Upper Critical value	t-test	<i>F</i> -value	Lower Critical value	Upper Critical value	F-test
Soil cohesio	n of laye	r 2 (c ₂)						
Training	0.868	-1.961	1.961	Accept	0.991	-0.937	0.937	Accept
Testing	-0.338	-1.961	1.961	Accept	1.010	-0.916	0.916	Accept
Validation	-1.294	-1.961	1.961	Accept	0.942	-0.869	0.869	Accept
Soil cohesio	n of laye	r 3 (c ₃)						
Training	-0.737	-1.961	1.961	Accept	0.993	-0.937	0.937	Accept
Testing	0.970	-1.961	1.961	Accept	1.005	-0.916	0.916	Accept
Validation	0.334	-1.961	1.961	Accept	1.071	-0.869	0.869	Accept
Soil cohesio	n of layer	r 4 (c ₄)						
Training	0.193	-1.961	1.961	Accept	0.997	-0.937	0.937	Accept
Testing	-0.508	-1.961	1.961	Accept	1.011	-0.916	0.916	Accept
Validation	0.194	-1.961	1.961	Accept	0.990	-0.869	0.869	Accept
Soil cohesio	n of layer	r 5 (c ₅)						
Training	-0.674	-1.961	1.961	Accept	1.026	-0.937	0.937	Accept
Testing	0.546	-1.961	1.961	Accept	0.984	-0.916	0.916	Accept
Validation	0.650	-1.961	1.961	Accept	0.991	-0.869	0.869	Accept
Soil cohesio	n of layer	r 6 (c ₆)						
Training	-0.612	-1.961	1.961	Accept	0.996	-0.937	0.937	Accept
Testing	0.846	-1.961	1.961	Accept	1.050	-0.916	0.916	Accept
Validation	0.228	-1.961	1.961	Accept	0.912	-0.869	0.869	Accept
Soil cohesio	n of layer	r 7 (c ₇)						
Training	0.895	-1.961	1.961	Accept	1.006	-0.937	0.937	Accept
Testing	-1.927	-1.961	1.961	Accept	1.005	-0.916	0.916	Accept
Validation	0.434	-1.961	1.961	Accept	0.969	-0.869	0.869	Accept
Soil cohesio	n of laye	r 8 (c ₈)						
Training	0.239	-1.961	1.961	Accept	1.007	-0.937	0.937	Accept
Testing	0.207	-1.961	1.961	Accept	0.978	-0.916	0.916	Accept
Validation	-0.689	-1.961	1.961	Accept	0.967	-0.869	0.869	Accept
Soil cohesio	n of layer	r 9 (c ₉)						
Training	0.360	-1.961	1.961	Accept	1.009	-0.937	0.937	Accept
Testing	0.440	-1.961	1.961	Accept	0.993	-0.916	0.916	Accept
Validation	-1.168	-1.961	1.961	Accept	0.991	-0.869	0.869	Accept

 Table C.2
 The results of null hypothesis tests inputs and outputs. (Continued)

Model Variable and Data Sets	<i>t</i> -value	Lower Critical value	Upper Critical value	t-test	<i>F</i> -value	Lower Critical value	Upper Critical value	F-test	
Soil cohesion of layer 10 (c ₁₀)									
Training	0.159	-1.961	1.961	Accept	0.990	-0.937	0.937	Accept	
Testing	0.634	-1.961	1.961	Accept	1.009	-0.916	0.916	Accept	
Validation	-1.015	-1.961	1.961	Accept	1.034	-0.869	0.869	Accept	
Soil friction	n angle of	layer 1 (ø	l)						
Training	-0.530	-1.961	1.961	Accept	1.006	-0.937	0.937	Accept	
Testing	0.788	-1.961	1.961	Accept	0.978	-0.916	0.916	Accept	
Validation	0.125	-1.961	1.961	Accept	1.025	-0.869	0.869	Accept	
Soil friction	n angle of	layer 2 (ϕ_2	2)						
Training	0.309	-1.961	1.961	Accept	0.997	-0.937	0.937	Accept	
Testing	-0.970	-1.961	1.961	Accept	1.025	-0.916	0.916	Accept	
Validation	0.475	-1.961	1.961	Accept	0.995	-0.869	0.869	Accept	
Soil friction	n angle of	layer 3 (ø	s)						
Training	1.227	-1.961	1.961	Accept	0.972	-0.937	0.937	Accept	
Testing	-1.626	-1.961	1.961	Accept	1.059	-0.916	0.916	Accept	
Validation	-0.596	-1.961	1.961	Accept	0.912	-0.869	0.869	Accept	
Soil friction	n angle of	layer 4 (ø	l)						
Training	0.174	-1.961	1.961	Accept	0.992	-0.937	0.937	Accept	
Testing	-0.994	-1.961	1.961	Accept	1.021	-0.916	0.916	Accept	
Validation	0.764	-1.961	1.961	Accept	1.050	-0.869	0.869	Accept	
Soil friction	n angle of	layer 5 (ø	5)						
Training	1.130	-1.961	1.961	Accept	0.992	-0.937	0.937	Accept	
Testing	-1.373	-1.961	1.961	Accept	1.011	-0.916	0.916	Accept	
Validation	-0.642	-1.961	1.961	Accept	0.946	-0.869	0.869	Accept	
Soil friction	n angle of	layer 6 (ø	<u>(</u>)						
Training	-0.473	-1.961	1.961	Accept	1.003	-0.937	0.937	Accept	
Testing	0.935	-1.961	1.961	Accept	0.995	-0.916	0.916	Accept	
Validation	-0.142	-1.961	1.961	Accept	0.996	-0.869	0.869	Accept	
Soil friction	n angle of	layer 7 (ϕ	<i>,</i>)						
Training	0.050	-1.961	1.961	Accept	1.003	-0.937	0.937	Accept	
Testing	0.079	-1.961	1.961	Accept	0.985	-0.916	0.916	Accept	
Validation	-0.184	-1.961	1.961	Accept	1.005	-0.869	0.869	Accept	

 Table C.2
 The results of null hypothesis tests inputs and outputs. (Continued)

Model Variable and Data Sets	<i>t</i> -value	Lower Critical value	Upper Critical value	t-test	<i>F</i> -value	Lower Critical value	Upper Critical value	F-test	
Soil friction	angle of	layer 8 (ø	3)						
Training	0.158	-1.961	1.961	Accept	0.985	-0.937	0.937	Accept	
Testing	-1.015	-1.961	1.961	Accept	1.038	-0.916	0.916	Accept	
Validation	0.809	-1.961	1.961	Accept	1.011	-0.869	0.869	Accept	
Soil friction angle of layer 9 (ϕ_9)									
Training	-0.412	-1.961	1.961	Accept	1.016	-0.937	0.937	Accept	
Testing	0.195	-1.961	1.961	Accept	0.974	-0.916	0.916	Accept	
Validation	0.561	-1.961	1.961	Accept	0.997	-0.869	0.869	Accept	
Soil friction	angle of	layer 10 (g	¢10)						
Training	0.861	-1.961	1.961	Accept	0.992	-0.937	0.937	Accept	
Testing	-1.787	-1.961	1.961	Accept	1.024	-0.916	0.916	Accept	
Validation	0.325	-1.961	1.961	Accept	0.969	-0.869	0.869	Accept	
Soil thickne	ess of laye	er 1 (<i>h</i> ₁)							
Training	-0.027	-1.961	1.961	Accept	0.974	-0.937	0.937	Accept	
Testing	-0.611	-1.961	1.961	Accept	1.070	-0.916	0.916	Accept	
Validation	0.713	-1.961	1.961	Accept	0.986	-0.869	0.869	Accept	
Soil thickne	ess of laye	r 2 (h ₂)							
Training	-0.152	-1.961	1.961	Accept	1.004	-0.937	0.937	Accept	
Testing	-0.561	-1.961	1.961	Accept	0.989	-0.916	0.916	Accept	
Validation	0.917	-1.961	1.961	Accept	1.054	-0.869	0.869	Accept	
Soil thickne	ess of laye	er 3 (h ₃)							
Training	-0.755	-1.961	1.961	Accept	0.994	-0.937	0.937	Accept	
Testing	1.393	-1.961	1.961	Accept	1.033	-0.916	0.916	Accept	
Validation	-0.088	-1.961	1.961	Accept	0.941	-0.869	0.869	Accept	
Soil thickne	ess of laye	er 4 (h ₄)							
Training	0.113	-1.961	1.961	Accept	1.008	-0.937	0.937	Accept	
Testing	0.786	-1.961	1.961	Accept	0.983	-0.916	0.916	Accept	
Validation	-1.097	-1.961	1.961	Accept	0.968	-0.869	0.869	Accept	
Soil thickne	ess of laye	$= 5 (h_5)$							
Training	0.346	-1.961	1.961	Accept	0.995	-0.937	0.937	Accept	
Testing	-0.265	-1.961	1.961	Accept	1.042	-0.916	0.916	Accept	
Validation	-0.365	-1.961	1.961	Accept	0.949	-0.869	0.869	Accept	

 Table C.2
 The results of null hypothesis tests inputs and outputs. (Continued)

Model Variable and Data Sets	<i>t</i> -value	Lower Critical value	Upper Critical value	t-test	<i>F</i> -value	Lower Critical value	Upper Critical value	F-test
Soil thickne	ess of laye	er 6 (h ₆)						
Training	-0.151	-1.961	1.961	Accept	0.997	-0.937	0.937	Accept
Testing	-0.285	-1.961	1.961	Accept	1.021	-0.916	0.916	Accept
Validation	0.599	-1.961	1.961	Accept	0.921	-0.869	0.869	Accept
Soil thickne	ess of laye	er 7 (<i>h</i> ₇)						
Training	-0.445	-1.961	1.961	Accept	0.988	-0.937	0.937	Accept
Testing	1.558	-1.961	1.961	Accept	1.010	-0.916	0.916	Accept
Validation	-0.885	-1.961	1.961	Accept	0.978	-0.869	0.869	Accept
Soil thickne	ess of laye	er 8 (h ₈)						
Training	0.653	-1.961	1.961	Accept	1.000	-0.937	0.937	Accept
Testing	-0.795	-1.961	1.961	Accept	1.010	-0.916	0.916	Accept
Validation	-0.362	-1.961	1.961	Accept	0.972	-0.869	0.869	Accept
Soil thickne	ess of laye	er 9 (h ₉)						
Training	0.705	-1.961	1.961	Accept	0.990	-0.937	0.937	Accept
Testing	-0.890	-1.961	1.961	Accept	1.020	-0.916	0.916	Accept
Validation	-0.366	-1.961	1.961	Accept	0.980	-0.869	0.869	Accept
Footing wid	lth (B)							
Training	-0.760	-1.961	1.961	Accept	0.983	-0.937	0.937	Accept
Testing	0.552	-1.961	1.961	Accept	0.998	-0.916	0.916	Accept
Validation	0.862	-1.961	1.961	Accept	0.973	-0.869	0.869	Accept
Average be	aring cap	acity of st	rip footing	$(q_{\rm av})$				
Training	1.280	-1.961	1.961	Accept	1.012	-0.937	0.937	Accept
Testing	-1.162	-1.961	1.961	Accept	0.984	-0.916	0.916	Accept
Validation	-1.124	-1.961	1.961	Accept	0.949	-0.869	0.869	Accept
${ ilde N}_c$								
Training	-0.510	-1.961	1.961	Accept	0.972	-0.937	0.937	Accept
Testing	1.388	-1.961	1.961	Accept	1.037	-0.916	0.916	Accept
Validation	-0.550	-1.961	1.961	Accept	0.919	-0.869	0.869	Accept
${{ ilde N}_\phi}$								
Training	0.159	-1.961	1.961	Accept	0.964	-0.937	0.937	Accept
Testing	-0.019	-1.961	1.961	Accept	1.078	-0.916	0.916	Accept
Validation	-0.288	-1.961	1.961	Accept	1.121	-0.869	0.869	Accept

 Table C.2
 The results of null hypothesis tests inputs and outputs. (Continued)

Appendix C