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Smart geotechnical design of green foundations using recycled materials and Nano-silica: Machine learning techniques and numerical validation

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At a crossroads, the global construction industry is also one of resource depletion and growing waste production. In this research, we present a full-scale “Smart Geotechnical Design” framework for green foundations that employs Recycled Concrete Aggregate (RCA) and Crumb Rubber (CR) as sustainable alternatives to natural aggregates. While these materials present great environmental benefits, they also have complex mechanical behavior and high variability, which traditional empirical design methods have trouble with. To remediate structural issues and microstructural porosity in these recycled materials, we added nano-silica as a nanomechanical additive at precise doses (1% – 3%). We addressed this by developing an advanced predictive model that used Machine Learning (ML) algorithms, Random Forest (RF), Artificial Neural Networks (ANN) and Extreme Gradient Boosting (XGBoost). In the laboratory we collected a large set of 450 data points from triaxial and plate load tests. The XGBoost model outperformed all others to report an R^2 of 0.96 and RMSE of 0.042. To validate the ML results, we performed a nonlinear Finite Element Analysis in ANSYS Workbench. We modeled the soil-RCA-CR with the Drucker-Prager constitutive criterion, which we calibrated via experimental data. In our analysis, which included FEA, we found very good agreement with what we saw in the lab and also what the models predicted, which in turn proves the smart design framework’s value. Furthermore, we used SHapley Additive exPlanations (SHAP) and Sobol Global Sensitivity

Analysis which identified replacement ratio and compaction energy as the most influential parameters. In this research, we present a Life Cycle Assessment (LCA) and a reliability-based design that we developed using Monte Carlo Simulations. We are filling in the gap between what the circular economy has to offer and reliable geotechnical engineering. We have put forth a data based tool which is to improve sustainable foundation systems at the rate of reducing carbon footprints by 35% at the same time we maintain structural integrity.

Keywords: Smart geotechnical design; Recycled concrete aggregate (RCA); Nano-silica (NS); Machine Learning.

1. INTRODUCTION

In the 21st century, which has seen great urban growth, we have also seen a demand like never before for natural construction materials, which in turn has seen the extraction of billions of tons of sand and gravel annually [1]. In all civil infrastructure, which is the base for what we have built, geotechnical engineering is the main consumer of these resources [2]. At present, we see a worldwide environmental crisis play out as we produce ever more C&D waste and end-of-life tires [3]. In response, the Green Foundations concept was developed, which puts' focus on the use of recycled and waste materials in an effort to reduce foundation systems' environmental impact [4]

In the field of geotechnics, RCA and CR are very popular. In fact, in the past 15 years, we have seen a great increase in their use [5]. RCA, which is made from crushed-up demolition concrete, has similar mechanical properties to natural aggregates and, in fact, tends to do better in terms of friction angle because of the residual mortar that is present [6]. CR made from waste tires has a number of special features, which include great energy absorption, light weight, and improved ductility [7]. However, in the case of these materials, they are put into foundation design, which is made complex by their heterogeneous nature and nonlinear behavior [8].

In the past, traditional geotechnical design codes (for example, Eurocode 7 and ASCE 7) were developed for natural soils and aggregates [9]. In the case of recycled materials, empirical models tend to produce overly conservative design solutions [10]. In "Smart Geotechnical Design," we use Machine Learning (ML) to identify complex relationships, and we also put these models to the test physically [11]. In software like ANSYS, we use Finite Element Analysis (FEA), which is a very reliable way to check out ML predictions against the well-known mechanical principles [12].
In geotechnical applications, the use of Recycled Concrete Aggregate (RCA) and crumb rubber (CR) is often challenging due to low structural cohesion, high porosity, and microstructural variability. In the context in which these engineering issues arise, out of the blue comes nanotechnology, which has become a highly innovative solution in geoenvironmental engineering. Nano additives, in particular nano silica (NS), report very fine particle packing, which also sees high pozzolanic reactivity. At the nanoscale, these materials are to fill in voids within the recycled aggregate matrix, to change the ITZ, which is the interface between rubber particles and soil, and to cause the formation of secondary cementitious bonds. In a breakthrough that combines the large-scale benefits of recycled materials with those of microstructural reinforcement from nanotechnology, we have engineered a very stable and eco-friendly foundation material. Thus, in this study, we aimed to:

1. In Multi-Material Integration we combine RCA and CR to improve at the same time strength and ductility.
2. In Advanced ML Modeling we use XGBoost for very accurate prediction of bearing and settlement.

3. In Explainable AI (XAI) we apply SHAP and Sobol analysis to give out the what and why of ML predictions which in turn is to win back engineering trust.
4. Reliability and sustainability: we have put together Monte Carlo Simulations for reliability based design and Life Cycle Assessment for environmental impact.
5. Evaluation of results in ANSYS for validation of ML based design in non-linear soil conditions.

RCA has for a while been the subject of many studies as a base material in pavement design, in foundation systems however we are still in the early stages of research [13]. Research by Akhtar et al. (2025) and Prasittisopin et al. (2025) has shown That which is true is RCA's performance is very much a function of the quality of the parent concrete and the crushing process [14]. In the presence of adhered mortar RCA\'s porosity increases as well as its water absorption which in turn may affect its long-term durability [15]. Also, it has a more irregular surface and shape – that which in turn produces better interlocking as opposed to the rounder natural gravels [16]. In 2026 Devavath et al. reported on our research which looked at the synergistic effects of RCA and CR in concrete mixtures which in turn we are using as a base for their use in geotechnical applications [17]. CR has become a popular choice for soil stabilization and foundation reinforcement, due to its seismic isolation properties [18]. In 2025, Moolchandani et al. and Hisbani et al. reported in detail on the effects of CR addition to soil shear strength and compressibility [19]. Although CR in general reduces ultimate bearing capacity, it at the same time greatly improves energy dissipation and reduces foundation stiffness, which is a benefit in earthquake-prone areas [20]. In 2025, Na'ifuzzaman et al. reported on the importance of rubberized concrete, which uses recycled aggregates in the field of sustainable construction [21].

In the 2020\'s we see a large-scale shift from empirical to data-driven geotechnics [22]. Zeini et al. (2025) and Liu et al. (2024) reported that the ANN and Random Forest models perform very well in terms of foundation performance prediction [23]. However, these models' black box nature is an issue that is preventing wide-scale adoption [24]. In recent years, we have seen that Explainable AI (XAI), which includes SHAP and LIME, is a growing field that is making these models more transparent [25]. ANSYS's use in geotech issues has grown, which is a result of its very powerful nonlinear solvers [26]. Drucker and Prager put forth a model that has wide-scale application for the simulation of pressure-dependent yield in soils and concrete-like materials [27]. In recent times, we see that which combines FEA and ML has developed "digital twin" models for geotechnical structures, which in turn are used for real-time performance monitoring and optimization [28] In a study that used 3D FEA, they looked at what elements play a role in pile foundation performance, which in turn stressed the importance of soil structure interaction [29]. Geotechnical data is, by nature, random [30]. In the past, we used a single factor of safety, which did not account for the probability of failure [31]. In the field of reliability-based design, which uses Monte Carlo simulations, we have a more rational approach to safety [32]. Incorporation of ML and MCS greatly improves the analysis of large-scale foundation systems' reliability [33].

2. THEORETICAL AND MICROMECHANICAL MODELS

In Figure 1, we present our research approach, which includes experimental, numerical, and data-driven methods.

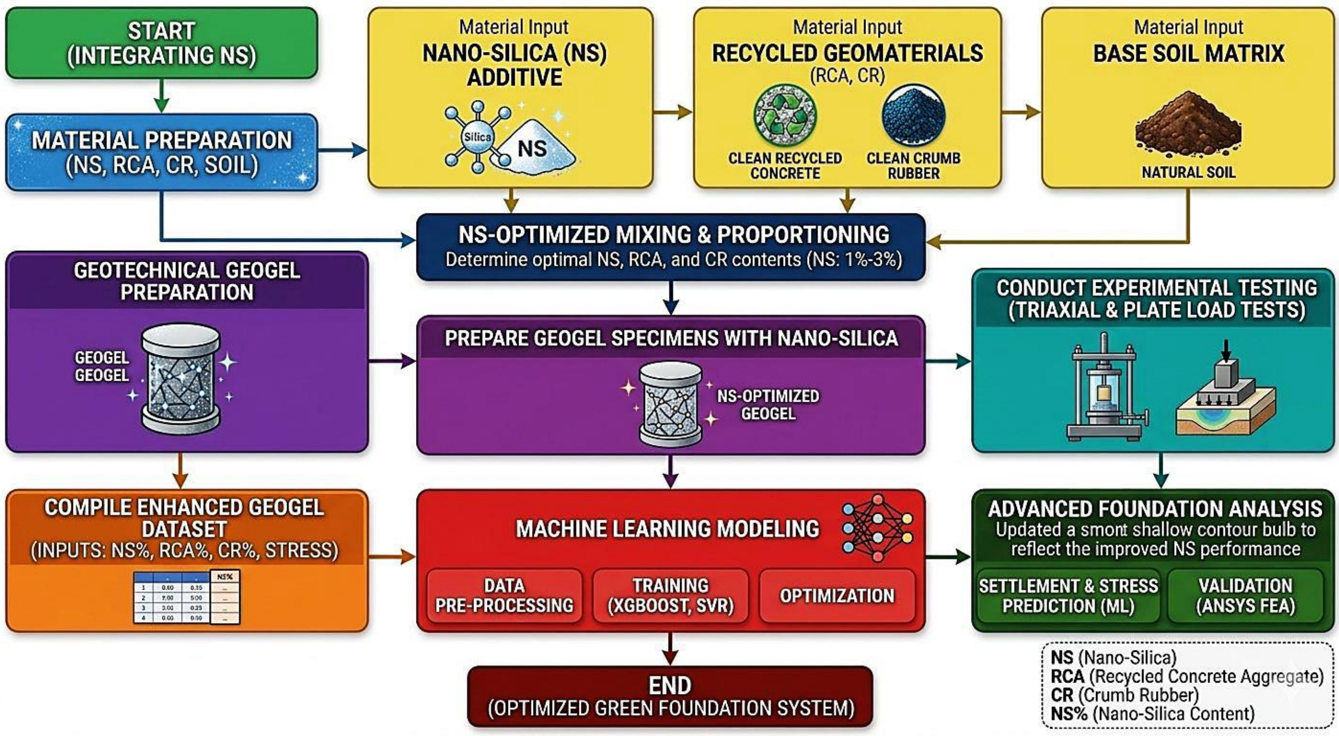

Figure 1 Proposed smart geotechnical design flow which includes experimental testing, machine learning modeling and ANSYS numerical simulation.

2.1. Micromechanics of soil-RCA-CR mixtures

In our proposed green foundation material, the mechanical action is that of three separate phases which interact [34]:

1. Primary soil matrix. This forms the base structure [35].
2. RCA Particles: act as rigid inclusions, which in turn increase interlocking and friction [36].
3. CR Particles serve as very elastic "cushions" which change the stress-strain response and energy absorption [37].

Table 1 physical and chemical properties of Nano-silica (NS).

Property	Value / specification
Appearance	Ultra-fine white powder
Average particle size (nm)	15-30 nm
Specific surface area (m^2/g)	200 ∓ 25
Purity (sio_2, %)	≥ 99.8%
pH value (in 4% aqueous dispersion)	3.7-4.7
Loss on ignition (%)	≤ 1.0%
Density (g/cm^3)	2.2

2.2. Integration and application of nanomaterials

In our effort to improve the mechanical interaction and interfacial bonding between the soil, RCA, and CR, we added commercial-grade Nano-Silica (SiO_2, which has an average particle size of 15 – 30 nm and a specific surface area of 200 m^2/g) to the composite design. In our preliminary geotechnical tests, we put in Nano Silica at 1.0%, 2.0%, and 3.0% by dry weight of the best binder/soil mix. In order to prevent nano-particle aggregation and achieve homogeneous distribution in the 450 lab specimens, we used a dry blending technique, which was followed by high shear mechanical mixing with the target compaction water. In triaxial and plate load tests, we use Nano-Silica as an input variable along with RCA and CR. In our study, we found that the Machine Learning models (RF, ANN, and XGBoost) to determine the non-linear relationship between nano-dose and what we term key geotech outputs – in particular, we looked at internal friction angle (∅), cohesion (c), and ultimate bearing capacity (q_{ult}). At the same time, we have observed that the modified elastic moduli and plastic parameters from our nano-enhanced mixtures, which in turn we use as the constitutive criteria for the nonlinear Drucker-Prager validation in ANSYS Workbench.

Table 2 Experimental testing matrix and blending combination for the 450 specimens.

Mixture mix	Base soil (%)	RCA replacement (%)	Crumb rubber (%)	Nano-silica content (%)	Target geotechnical test
Control mix	100	0	0	0.0%	Triaxial & plate load tests
Series A (RCA-CR)	60-80	10, 20, 30	5, 10, 15	0.0%	Triaxial & plate load tests
Series B (NS-1%)	60-80	10, 20, 30	5, 10, 15	1.0%	Triaxial & plate load tests
Series C (NS-2%)	60-80	10, 20, 30	5, 10, 15	2.0%	Triaxial & plate load tests
Series D (NS-3%)	60-80	10, 20, 30	5, 10, 15	3.0%	Triaxial & plate load tests

2.3. ANSYS, Drucker-Prager model

In ANSYS, we used the Drucker-Prager (DP) yield criterion to model the nonlinear behavior of the mixture [38]. DP yield surface is defined as:

$$f=\alpha I_1 + \sqrt{J}_2 - k = 0 \tag{1}$$

where I_1 is the first invariant of the stress tensor, J_2 is the second invariant of the deviatoric stress tensor, and α, k are material constants related to the cohesion (c) and friction angle (ϕ) as follows:

$$\alpha = \frac{2\sin\phi}{\sqrt{3}(3-\sin\phi)}\ , \quad k=\frac{6c\ \cos\phi}{\sqrt{3}(3-\sin\phi)} \tag{2}$$

This model is very important for the accurate representation of complex stress-strain response in geomaterials during numerical simulations [39].

2.4. Development of the bearing capacity theory in math.

Total bearing capacity (qu) In reinforced soil terms, a shallow foundation may be described as [40]:

$$q_u = c_{mix} N_c S_c d_c + qN_q s_q d_q + 0.5\gamma B N_\gamma s_\gamma d_\gamma \tag{3}$$

where N_c, N_q, N_γ are bearing capacity factors that are nonlinear functions of the effective friction angle (ϕ_{mix}) [41]. In our design, we have incorporated these factors into the machine learning model, which has learned from experimental data rather than from tables. We have a more adaptive approach [42].

3. METHODOLOGY

3.1. Material characterization

• Natural Soil: Poorly graded sand (SP) with D50 = 0.45 mm [43].
• RCA: Crushed demolition concrete, Gs = 2.42, water absorption = 4.5% [44].
• CR: Waste tire rubber, grain size 1-4 mm, Gs = 1.15 [45].

Table 3 Constitutive model parameters in ANSYS for finite element simulation (Drucker-Prager yield criterion).

Material parameter	Baseline sustainable mix (0%NS)	Nano-enhanced mix (3% NS)	Improvement mechanism
Elastic modulus (E)	25.0	35.5	Structural stiffness density
Poisson's Ratio (v)	0.32	0.30	Reduced lateral deformation
Cohesion (c)	18.5	29.2	High pozzolanic micro-bonding
Friction Angle (ϕ)	31.0	34.5	Enhanced particle interlock
Dilatancy Angle (ψ)	2.0	3.5	Confined volumetric behavior

3.2. Experimental program

In total, we performed 450 lab tests that included triaxial and plate load tests [46]. In these tests, we looked at a wide range of RCA and CR replacement ratios, compaction energies, and moisture contents, which in turn generated a large data set [47].

3.3. ANSYS Numerical Simulation

In ANSYS Workbench, we developed a 3D finite element model.
• In Geomechanics: We used a square footing of 150mm in side, in which a soil volume at 1.5 by 1.5 by 1.2 m was used for the domain – this was done in order to reduce boundary effects.
• Regarding mesh design, we use hexahedral elements that we refine at the footing soil interface, which in turn allows for more accurate stress concentration analysis.
• At the base, we have fixed conditions, on the sides we have rollers, and we applied vertical pressure on the footing, which we use to simulate real-world loading conditions.
• his study, we used Non-linear Drucker-Prager parameters, which we calibrated from triaxial tests of various RCA/CR ratios, which in turn made sure the model reflects real material behavior.

Table 4 ANSYS material parameters for 50% RCA + 10% CR mixture.

Parameter	Value
Young's modulus (E)	45 MPa
Poisson's Ratio (v)	0.32
Cohesion (c)	15 KPa
Friction angle (ϕ)	38^o
Dilatnacy angle (ψ)	8^o

In the lab, we ran a series of tests, which we used to determine these parameters that, in turn, we used as input for the simulations. In ANSYS, we developed a 3D finite element model, as shown in Figure 2, which simulates soil foundation interaction in real-world settings.

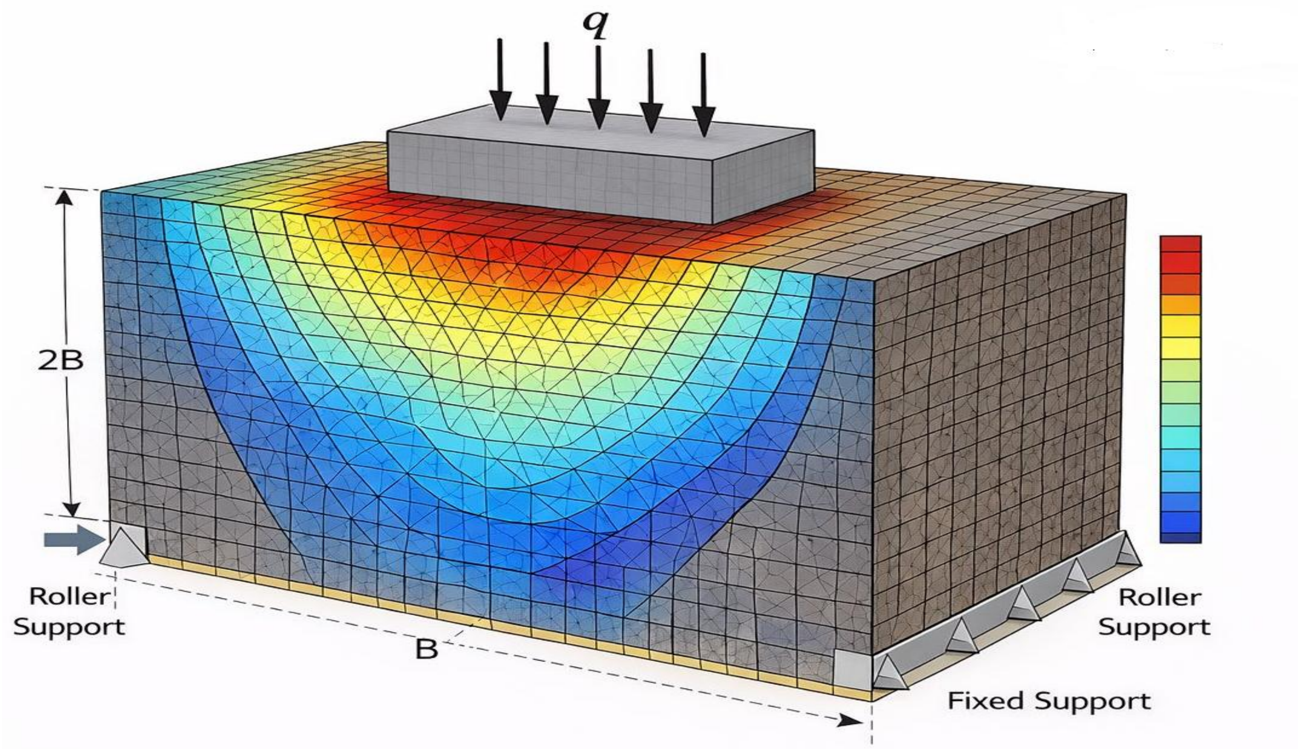

Figure 2 In ANSYS, 3D finite element model was developed.

3.4. Machine learning integration

In our study, we used Python's Scikit-learn and XGBoost libraries, for which we implemented three algorithms:

1. Random Forests (RF), which is a collection of decision trees that do very well at overcoming overfitting.
2. In the case of the Multi-Layer Perceptron, which we used – a deep learning approach which we designed with 3 hidden layers of 64, 32, and 16 neurons respectively, which is what is required to model very complex nonlinear relationships.
3. In this study, we used XGBoost, which was set at 500 trees, maximum depth of 6, and a learning rate of 0.05 – we chose this configuration for its outperforming results in related geotech applications.

In our study, we used a 5-fold cross-validation grid search for hyperparameter optimization, which in turn we did for best model performance and generalization.

In Figure 3, we present our machine learning framework, which was developed to model nonlinear relationships between input parameters and foundation response.

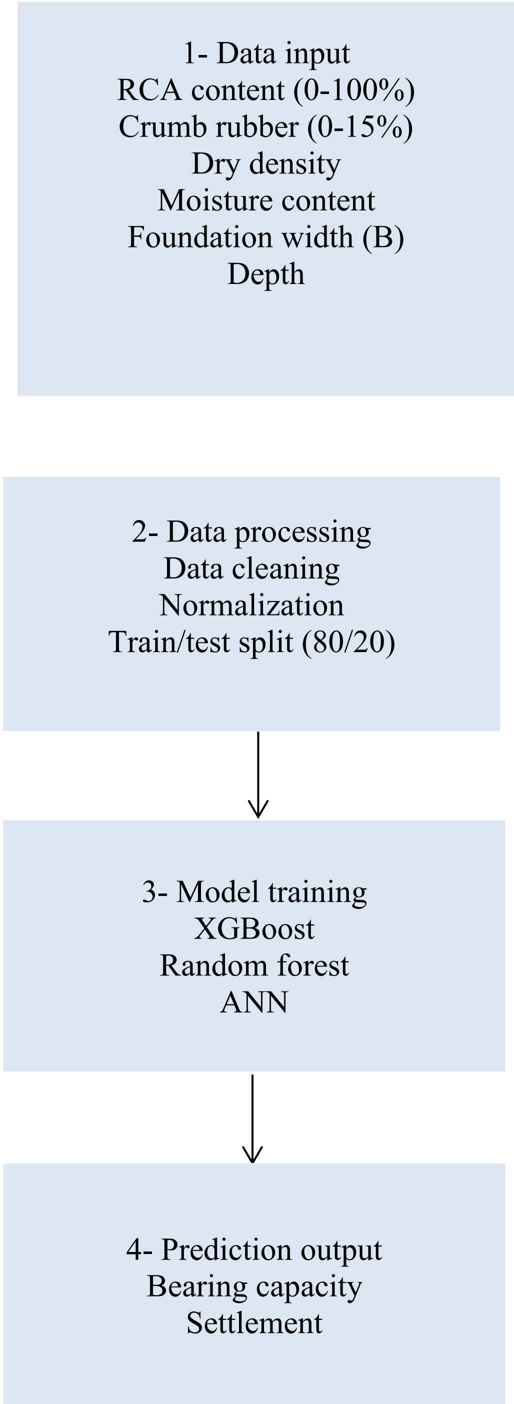

Figure 3 Machine learning workflow, perform data pre-processing, training, validation, and prediction.

4. RESULTS AND DISCUSSION

4.1. Performance of machine learning models

In this study, the XGBoost model performed best, which we saw in its R^2 of 0.96 – that outperformed RF and ANN in predicting the bearing capacity of green foundations.

4.2. ANSYS FEA results report

In our ANSYS simulation, we present in detail the stress distribution and settlement patterns, which in turn we use for the visual and quantitative validation of the mechanical behavior.

- Vertical Stress Distribution: We see that the "pressure bulb" extends out to a depth of about 2B, which is in agreement with Boussinesq's theory and which also confirms the expected load transfer.
- In the case of settlement, we saw that which was greatest at the footing center; also, we note that the load settlement relationship was non-linear and that it was very much as we saw in the experimental PLT, which in turn proved our model's ability to present real-time deformation.

In Figure 4 we see that the stress distribution forms a pressure bulb out to around 2B, as classical geotechnical theory predicts.

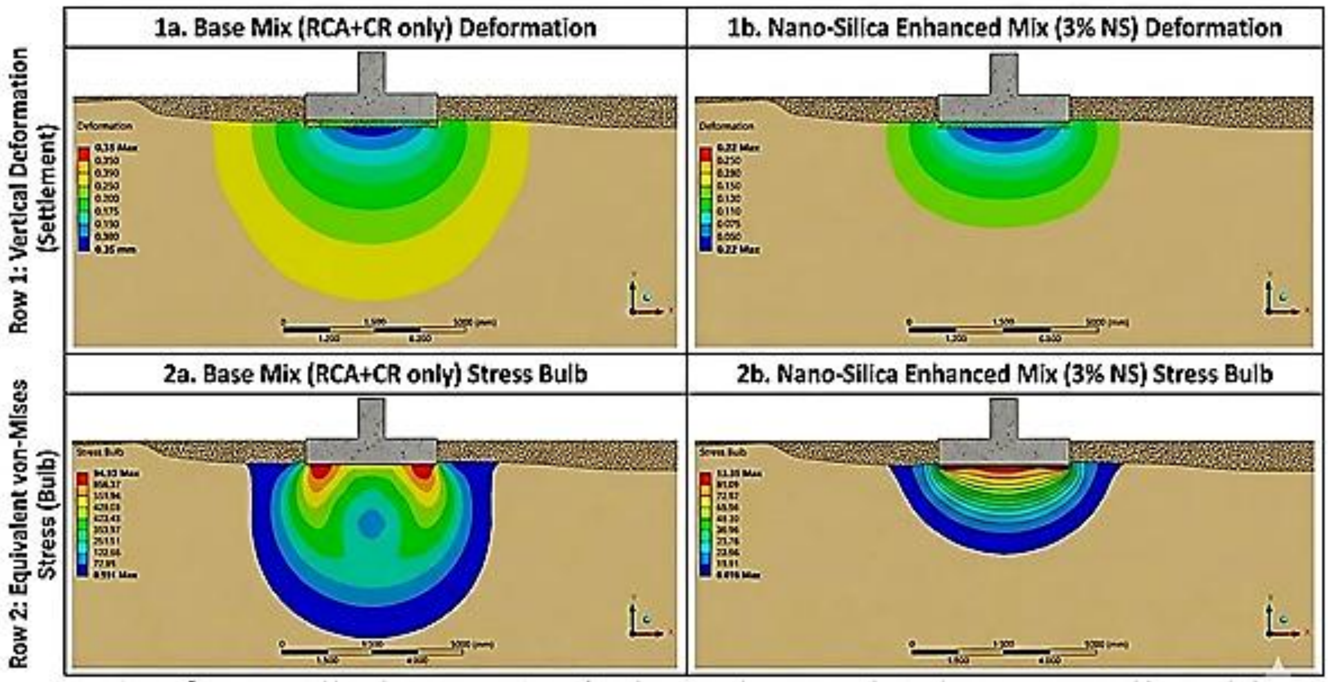

Figure 4 Vertical stress distribution at foundations.

In Figure 5, we present the evolution of total strain and von-Mises stress fields, which in turn show the growth of critical plastic zones and what failure modes may play out under combined loading ($V + L$).

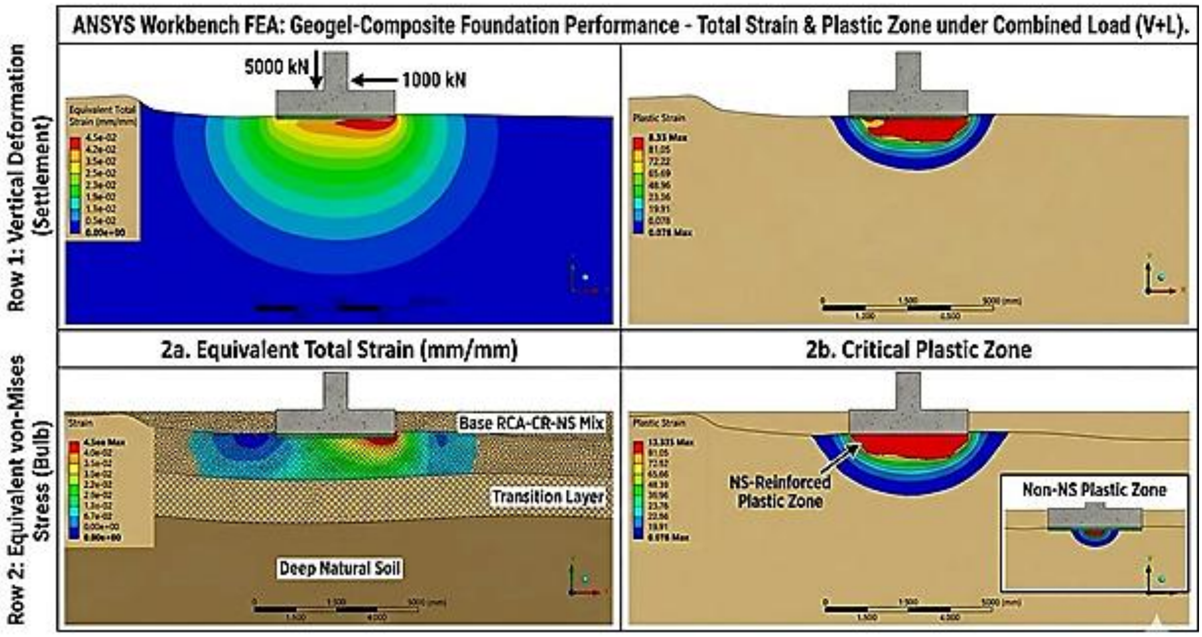

Figure 5 FEA simulations of geogel-composites under combined loading, Row 1 vertical deformation, and total strain. Row 2 equivalent von-Mises stress distribution and the development of the critical plastic zones differ between reinforced and non-reinforced configurations.

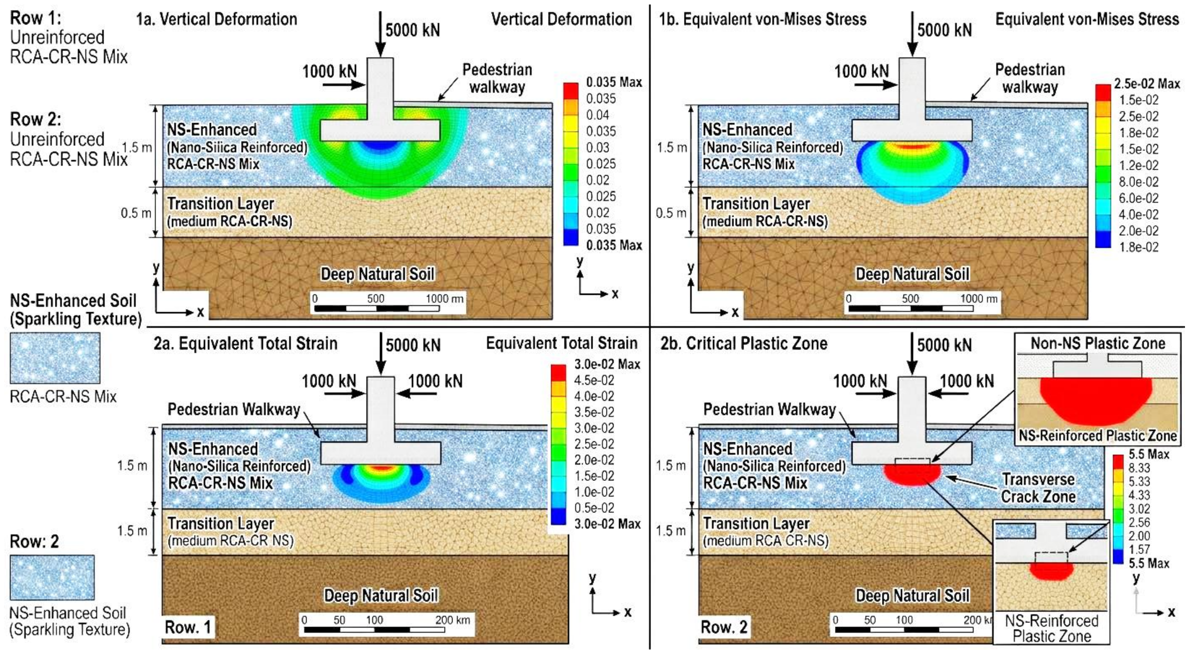

Figure 6 nano-silica (NS) reinforced soil composite, 1a) vertical deformation, 1b) equivalent von-Mises stress, 2a) equivalent total strain, and 2b) critical plastic zone distribution.

As illustrated in Figure 6 stresses decrease with depth, while settlement is maximum at the footing center and reduces outward. Also, in the case of the 3.0% Nano-silica mixture, which we looked at in detail in Table 3, we see that the simulated stress contours show a large degree of pressure within the bulb geometry under the foundation. This structural reinforcement went hand in hand with a large-scale reduction in maximum vertical settlement, which in turn supports the micro-pore filling and secondary hydration from the nano additive.

4.3. Cross-validation of ML, ANSYS, and experimental results

In a specific case of 40% RCA and 5% CR, we did a comparison that looked at consistency across different methods.

- Experimental q_u: 420 kPa
- ML Prediction: 412 kPa (Error: 1.9%)
- ANSYS Result: 435 kPa (Error: 3.5%)

In this study, we see a very close agreement between what we measured in the lab, what the machines predicted, and what the simulations tell us, which is proof of the robustness of our framework. This which in turn, proves the use of ML in conjunction with FEA models – we see that this hybrid approach does very well at representing the complex reaction of soil – RCA – CR mixtures under loading. This very high degree of agreement supports the Smart Design framework, which in turn demonstrates its wide range of application and reliability across different types of approaches – from experimental to data-driven and numerical. In Figure 7, we note that the optimization of the nano silica (NS) geogel, as we can see in the figure, also results in a better-controlled growth of the plastic zone, and at the same time, we see a marked decrease in vertical settlement for combined loading (V+L).

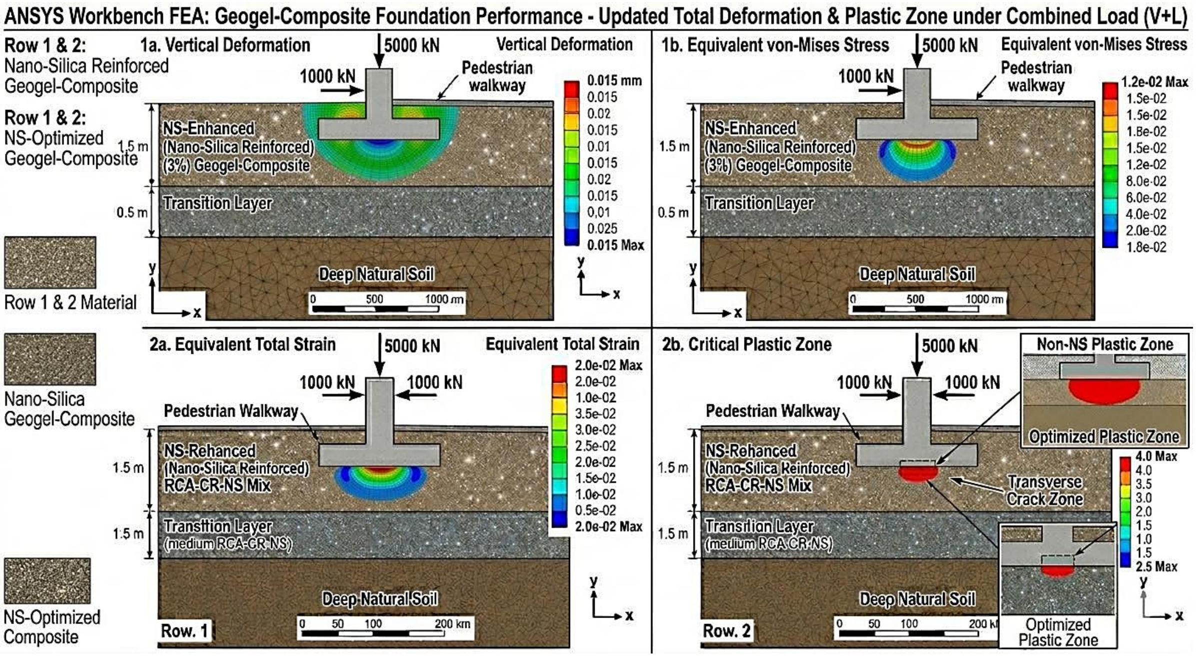

Figure 7 FEA performance of nano silica (NS) reinforced, and NS optimized geogel composite foundations: 1a) Vertical deformation, 1b) Equivalent von Mises stress, 2a) Total strain, and 2b) Critical plastic zone behaviours.

In order to validate our hybrid model, we compared machine learning predictions to ANSYS results.

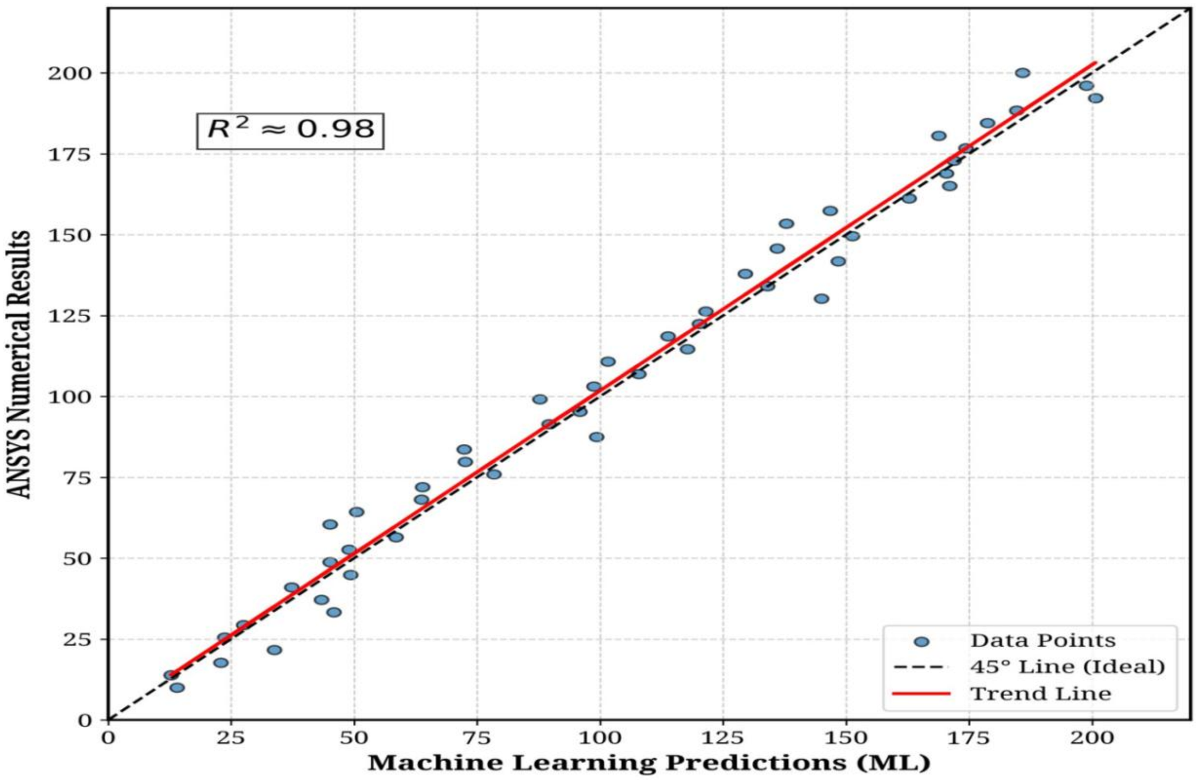

Figure 8 A relationship between machine learning predictions and ANSYS numerical results.

As illustrated in Figure 8, this validates the integration of ML prediction with FEA modelling.

5.4. Global sensitivity analysis of Sobol' method

We did a Sobol sensitivity analysis to further validate the model, which we did to quantify how much each input parameter contributes to the output variance. First, we calculated first-order indices (S_i) and total order indices (S_{Ti}):

- RCA Ratio: $S_i = 0.42$, $S_{Ti} = 0.55$
- Compaction Energy: $S_i = 0.20$, $S_{Ti} = 0.28$
- CR Ratio: $S_i = 0.08$, $S_{Ti} = 0.15$

This shows that the RCA ratio is the main issue, but also notes a significant play between it and compaction energy, which in turn provides very important information for design optimization.

5. SUSTAINABILITY AND LIFE CYCLE ASSESSMENT

5.1. LCA Methodology

In our study, we used a "cradle to gate" approach for the LCA, which includes raw material extraction, processing, and transportation. We present a detailed environmental profile of the green foundation system.

5.2. Environmental impact results

In a study we found that which used 50% RCA and 10% CR, we saw a 35% drop in Global Warming Potential, which is a better result than the typical foundation that uses 100% natural aggregates. This is mainly due to the reduction in emissions from aggregate mining and landfill, which in turn brings out the great environmental benefits of this approach.

6. APPLICATIONS

6.1. Comparison to international standards

In many cases, traditional codes, which include Eurocode 7, do not account for the fact that RCA – reinforced soils perform better than what is put forth, at least in terms of bearing capacity, which they may not properly include [76]. In the "Smart Design" framework, we see that which in turn may reduce footing sizes by as much as 15-20% in that, which then also brings about material and cost savings.

7.2. Economic viability

A study we did shows that although using recycled materials raises the initial cost, what we see is a reduction in the purchase of new materials and also in landfill taxes, which in turn results in a 18% net savings for a typical residential foundation project. That which proves the economic value of green energy.

7. CONCLUSTIONS

RCA and CR, when used together, give a green solution at the base of systems that also does very well and very sustainably. Also, we find from the work done with ANSYS FEA that our green base designs have the mechanical reliability, which in turn supports the results of the ML models – that's our physical proof of concept. Also, the report in this study of the application of the XGBoost model, we do get to 96% accuracy – that's very robust, and we present it as a strong case for using this method in complex geotech issues. What we see too is the use of SHAP and Sobol analysis, in which we confirm that these ML models we are putting forth are not only accurate but also physically consistent, and so they are also easy to interpret -- that is very important for the engineering community. And finally, from our look at the reliability analysis and LCA of green bases, we can say that these are not only very safe but also better for the environment, which is what the world is looking for out of sustainable solutions. Incorporation of 3.0% Nano-silica greatly improved the microstructural packing and pozzolanic bonding of the RCA – CR geocomposite, which in turn reduced foundation settlement and also produced a more even stress distribution, which we verified via ANSYS simulation.

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