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Geotechnical Characterization and AI-Based Zonation of Coastal Sabkha Soils for Urban Expansion in the Eastern Province of Saudi Arabia

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Abstract- Purpose: Coastal sabkha terrains in the Eastern Province of Saudi Arabia are increasingly exposed to urban expansion, yet their geotechnical behavior remains variable because salinity, shallow groundwater, evaporite cementation, collapse upon wetting, and reclamation history interact across short distances. This review examines how integrated geotechnical characterization and artificial intelligence can support defensible zonation for expansion planning rather than reactive foundation remediation. Methods: Following a structured review approach inspired by recent Springer review models, this paper synthesizes 2020–2025 literature on sabkha characterization, saline-soil improvement, AI in geotechnical engineering, and geospatial suitability assessment. Search and screening procedures were guided by transparent review logic consistent with PRISMA 2020, while thematic synthesis was used instead of meta-analysis because sabkha definitions, laboratory protocols, and machine-learning inputs remain heterogeneous [1].

Findings: The evidence shows that coastal sabkha cannot be represented by a single index or laboratory test. Reliable characterization requires the joint interpretation of index properties, carbonate and sulfate chemistry, collapse and compressibility behavior, groundwater depth and salinity, stratigraphic variability, geophysics, and land-surface indicators derived from remote sensing [2–8]. For zonation, tree-based ensemble models and explainable AI are promising because they can fuse laboratory, field, geospatial, and environmental layers while still revealing dominant controls [16,18–20,28–30]. However, any AI map that is detached from site investigation, uncertainty reporting, and planning thresholds risks false confidence.

Originality: The paper contributes a review-based framework tailored to the Eastern Province that links sabkha geotechnics to AI-supported zoning for urban expansion. It also provides two practice-oriented artifacts: an Apple-inspired data-to-zonation workflow and an interpretable coastal risk matrix for planning, together with two synthesis tables that can be adapted in consultancy and municipal screening workflows.

Keywords- Sabkha Soils, Eastern Province, Saudi Arabia, Urban Expansion, Machine Learning, Geotechnical Characterization, Explainable AI, Zonation, Remote Sensing, Coastal Planning

I. INTRODUCTION

Urban growth in the Eastern Province has accelerated along coastal and reclaimed corridors where development pressure intersects with saline flats, shallow groundwater, and anthropogenic fill. This creates a recurring planning paradox. The same coastal locations that offer strategic access, infrastructure connectivity, and real-estate value often coincide with the sabkha environments that produce settlement, collapse, corrosivity, and drainage problems. Recent work on the Eastern Province shows that salt-bearing sabkha soils and shallow fluctuating groundwater remain among the strongest drivers of geotechnical risk for sustainable construction on reclaimed terrain [3]. At the same time, regional studies on coastal urbanization, thermal stress, and nature-based urban sustainability demonstrate that land transformation in the Arabian Gulf is no longer just a geotechnical issue; it is a coupled environmental-planning problem in which subsurface conditions, hydrology, land cover, and governance interact [9–12].

Sabkha soils have long been recognized as problematic materials, but the challenge is more specific. Municipal and project teams must decide where urban expansion should proceed, where pre-treatment is justified, and where avoidance or phased development is more rational. Such decisions cannot rely on isolated boreholes alone. They require spatially explicit zonation that integrates geotechnical evidence with terrain, groundwater, and environmental context. The Eastern Province is particularly suitable for this transition because its sabkha settings range from coastal saline flats and shallow marine deposits to reclaimed areas and mixed sand–silt–salt profiles, producing high local variability in strength, stiffness, collapse susceptibility, and durability [2,4–8]. Conventional geotechnical investigations remain indispensable, yet they are often too sparse, too expensive, and too late in the planning cycle to guide strategic expansion. Artificial intelligence offers a complementary pathway. Recent reviews show rapid growth in AI applications across geotechnical engineering, especially for nonlinear prediction, classification, and interpretable decision support [16–20]. In parallel, machine-learning methods have been used for salinity mapping, groundwater vulnerability analysis, land suitability, and urban growth assessment in arid and coastal environments [13–15]. These strands are now mature enough to be connected. The central question is not whether AI can replace geotechnical judgment; it cannot. The practical question is how AI can organize multiscale evidence into a zonation framework that remains geotechnically credible, explainable, and useful for urban decision-making.

1.1 Aim of the study

The aim of this review is to develop an integrated, Saudi-relevant synthesis of how coastal sabkha soils in the Eastern Province should be characterized and how AI-based zonation can support safer and more efficient urban expansion decisions.

1.2 Objectives of the study

Four objectives guide the paper. First, it synthesizes the geotechnical and environmental characteristics that make coastal sabkha soils difficult to classify and design for. Second, it identifies the most decision-relevant variables for spatial zonation, covering laboratory, in situ, geophysical, hydrogeological, and remotely sensed indicators. Third, it evaluates AI approaches that are most suitable for transforming heterogeneous sabkha evidence into interpretable risk maps. Fourth, it proposes a review-based zoning framework aligned with planning practice in the Eastern Province.

II. REVIEW METHODOLOGY

2.1 Protocol and scope

This paper is a structured review and design synthesis rather than a statistical meta-analysis. The review scope was restricted to 2020–2025 literature in order to match the user’s temporal requirement and to reflect the period in which explainable AI, multi-source zonation, and hyper-arid urban sustainability have become prominent research themes. PRISMA 2020 informed the logic of transparency, screening, and reporting, but quantitative pooling was not attempted because the underlying studies differ substantially in soil taxonomy, testing conditions, feature engineering, output variables, and spatial scale [1].

2.2 Search strategy and eligibility

Searches were conducted across major scholarly databases and publisher platforms using combinations of the terms sabkha, coastal saline soil, Saudi Arabia, Eastern Province, machine learning, explainable AI, zonation, suitability, urban expansion, groundwater salinity, and remote sensing. Preference was given to peer-reviewed journal articles. Inclusion required direct relevance to at least one of four themes: regional sabkha characterization; geotechnical implications for construction in eastern Saudi Arabia or comparable Gulf settings; AI or machine learning for geotechnical prediction; or geospatial and environmental modeling for coastal urban suitability. Exclusion criteria removed pre-2020 sources from the formal evidence base, non-peer-reviewed items, papers focused on unrelated geomaterials, and studies that lacked method detail or planning relevance.

2.3 Data extraction and synthesis

For each paper, the review extracted location, problem setting, dominant variables, data type, modeling approach, interpretability method, and planning or design implication. Thematic synthesis then organized the evidence into five connected domains: sabkha material behavior, Eastern Province development constraints, geospatial indicators, AI model families, and interpretability for zonation. This structure follows the logic of the attached Springer review article, which moves from review method to evidence landscape and then to applied synthesis

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sections, but it is adapted here to suit the sabkha–urban expansion problem .

Table 1. Review framework linking evidence domains to planning-oriented sabkha zonation.

Domain	Representative variables	Why it matters	Typical data source
Material behavior	Grading, density, moisture, collapse, compressibility, strength	Defines load response and wetting sensitivity	Lab tests, boreholes, CPT/SPT
Soil chemistry	Sulfate, chloride, gypsum, carbonate, EC	Captures corrosivity and cementation loss	Chemical assays, groundwater samples
Hydrogeology	Groundwater depth, seasonal fluctuation, salinity	Controls softening, dissolution, and serviceability	Piezometers, well logs, hydrochemical datasets
Geophysical continuity	VP/VS, attenuation, resistivity	Bridges gaps between sparse point tests	Seismic and electrical surveys
Geospatial setting	Elevation, shoreline distance, LULC, reclamation history, thermal and salinity proxies	Supports parcel-scale zoning and update cycles	Remote sensing, DEM, GIS layers

III. LITERATURE LANDSCAPE AND REGIONAL CONTEXT

Recent sabkha research confirms that the Eastern Province must be understood as a heterogeneous coastal system rather than a single geotechnical province. Reviews from the Arabian Gulf describe sabkha as a saline, evaporitic environment in which sand, silt, clay, carbonate, gypsum, halite, and capillary groundwater processes combine to produce sharply variable engineering behavior [2]. Experimental and numerical work on Saudi and nearby Gulf sabkhas repeatedly shows that apparent crust strength can coexist with weak underlying layers, that soaked behavior can differ dramatically from dry-season conditions, and that construction performance depends not only on soil type but also on leaching, water-table fluctuation, and reclamation history [4,6,7].

The Eastern Province context deepens this complexity. Expert-based work from the province identifies sabkha soils, inadequate fill quality, poor compaction, and shallow groundwater as system-level barriers to durable construction on reclaimed sites [3]. Coastal urbanization studies across the Arabian Gulf further show that long-term shoreline transformation, filling, and infrastructure expansion alter drainage pathways, moisture regimes, and land-surface temperature, all of which can affect sabkha response and maintenance risk [9,10]. In Al Khobar specifically, recent remote-sensing analysis documents substantial land-use and land-cover change with associated thermal variation, reinforcing the need to treat urban growth as a geo-environmental process rather than a simple land allocation exercise [10].

Hydrology and salinity add another regional dimension. Groundwater and seawater intrusion research in Saudi coastal aquifers shows that machine-learning models can successfully detect vulnerability patterns from hydrochemical and environmental data, suggesting a parallel opportunity for sabkha zonation where subsurface salinity and shallow water are central controls [13]. Hyper-arid planning studies also emphasize that sustainable expansion in the Eastern Province depends on integrated ecological and institutional strategies, especially where low-lying terrain and weak environmental monitoring create cumulative risk [11,12]. The planning implication is straightforward: sabkha zonation should be built as a layered evidence model, not as a single geotechnical map.

IV. GEOTECHNICAL CHARACTERIZATION OF COASTAL SABKHA SOILS

4.1 Why sabkha resists simple classification

The geotechnical challenge of coastal sabkha lies in its contradictory behavior. In dry conditions, salt and carbonate cementation may produce an apparently competent surface crust. Under wetting, capillary rise changes, or groundwater disturbance, that same profile can lose structure as salts dissolve, cementation weakens, and collapse or excessive settlement develops. Experimental work on sandy sabkha in Saudi Arabia demonstrates this contrast clearly: compacted or unsaturated samples can yield relatively favorable strength and bearing values, but soaked material shows substantial degradation in shear strength and CBR, with settlement increasing sharply under foundation loading [4]. This means that routine index testing alone is inadequate whenever the design scenario includes moisture change, service leakage, irrigation, landscape water, tidal influence, or future drainage modification.

4.2 Core characterization domains

A reliable characterization program for coastal sabkha should integrate at least six domains. The first is index and classification testing: grain-size distribution, fines content, Atterberg limits where meaningful, specific gravity, density, moisture content, and salinity-related descriptors. The second is chemical and mineralogical testing, including sulfate, chloride, carbonate, gypsum, and total dissolved salts, because corrosivity and cementation loss are central to durability and collapse risk [2,5]. The third is mechanical response: oedometer compressibility, collapse potential under wetting, direct shear or triaxial strength, CBR where road support is relevant, and UCS for any stabilized or treated mix. The fourth is hydrogeology, especially groundwater depth, seasonal variability, and pore-water salinity. The fifth is in situ profiling through SPT, CPT, or equivalent continuous methods to identify layer variability. The sixth is near-surface geophysics, particularly where borehole spacing is too wide to capture lateral transitions.

Recent seismic work in eastern Saudi sabkhas is especially important because it demonstrates that inland and coastal sabkhas can be differentiated through VP, VS, attenuation, and anisotropy, creating an additional bridge between geotechnical interpretation and spatial zoning [8]. These geophysical parameters do not replace conventional testing, but they add continuity between point locations and can identify abrupt changes in material fabric, saturation state, and stiffness. For zonation, this matters because map boundaries drawn only from sparse boreholes tend to be either overconfident or overly generalized.

4.3 Construction implications from recent sabkha studies

Applied studies reinforce the need to move beyond descriptive characterization toward performance-based interpretation. In the Eastern Province, field and numerical assessment of stone columns shows that improvement may be significant in the upper sand and silt layers but limited within the main sabkha body, meaning treatment response is selective and stratigraphy-dependent [6]. Similarly, numerical work on deep soil mixing for sabkha excavation support indicates that the behavior of sabkha–cement systems and excavation stability is highly sensitive to wall design, embedment, and local material properties [7]. These findings are important for zonation because they show that “buildable with treatment” is not a uniform category. Some zones may be appropriate for densification or column techniques, while others may be better suited to deep mixing, drainage control, structural bridging, or even avoidance.

4.4 Geotechnical variables most relevant for zonation

From the review, the most decision-relevant sabkha variables are not merely the standard design parameters used later in foundation analysis. The variables that matter most for pre-development zonation are those that combine strong geotechnical meaning with spatial mappability. These include groundwater depth, electrical conductivity or salinity proxies, sulfate and chloride content, dry density, moisture ratio, fines content, carbonate–gypsum indicators, CPT resistance, low-strain seismic velocity, elevation, slope, distance to shoreline, land-reclamation history, drainage modification, and land-surface thermal or moisture signatures [3–15]. The value of zonation emerges when these variables are interpreted together. For example, a site with moderate density but extremely shallow saline groundwater may present greater long-term serviceability risk than a slightly weaker site with better drainage and lower chemical aggressiveness.

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4.5 The role of temporal change

A further complication in coastal sabkha characterization is time. Many project investigations treat the site as static, yet sabkha response evolves with seasonal water-table variation, leakage, landscaping, utility operation, and continuing urbanization. Hydrochemical work from the eastern Saudi coast shows that brine composition and salinity pathways are not random background features but part of an active coastal system that can influence dissolution, crystallization, and corrosivity [5]. Similarly, vulnerability and seawater-intrusion studies in Saudi coastal aquifers demonstrate that groundwater quality can be mapped as a changing probability field rather than a fixed boundary [12,13]. For sabkha zoning, this means that some variables should be treated as dynamic layers. Groundwater depth, vegetation stress, surface moisture proxies, land-surface temperature, and even reclamation footprints may need periodic updating. A sabkha map prepared at the outset of an expansion programme should therefore be conceived as a living geospatial asset rather than a one-time figure placed in an appendix.

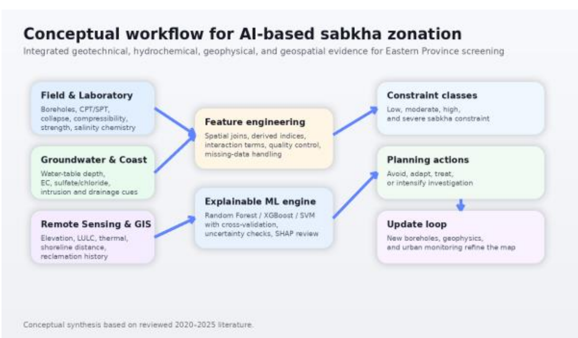

Figure 1. Apple-inspired conceptual workflow linking geotechnical, hydrochemical, geophysical, and geospatial evidence to explainable machine-learning zonation outputs.

V. AI-BASED ZONATION FRAMEWORKS FOR URBAN EXPANSION

5.1 Why AI is appropriate for sabkha zonation

Sabkha zonation is a nonlinear, multiscale, and mixed-data problem. Laboratory tests yield continuous variables, in situ tests provide depth profiles, remote sensing contributes raster layers, and planning data introduce categorical information such as land use or reclamation history. Conventional linear models struggle to preserve these interactions. AI methods are attractive because they can model threshold behavior, variable interactions, and cross-domain data without assuming that the relationship between inputs and risk is simple or monotonic [16–20]. That is exactly the kind of structure expected in sabkha terrain, where high salinity may be manageable in one stratigraphic context but destabilizing in another.

5.2 Suitable model families

The literature suggests that no single algorithm is universally best, but certain model families are especially well suited to zonation. Ensemble tree methods such as Random Forest and gradient boosting are often the strongest candidates for integrated sabkha mapping because they perform well on tabular, heterogeneous datasets, tolerate nonlinear interactions, and provide built-in measures of variable importance [16,18,19]. In geotechnical applications they have repeatedly matched or exceeded alternatives when predicting strength or classifying performance categories [21–27]. Support vector machines remain useful when datasets are moderate in size and boundaries between stable and unstable classes are complex [21]. Artificial neural networks can capture strong nonlinearities, but their opacity and sensitivity to training-data design make them less desirable for regulatory mapping unless paired with careful interpretability and uncertainty checks [17,23,24].

The geotechnical AI literature also provides practical lessons for sabkha zoning. Studies on stabilized soils show that model performance improves when input variables reflect process knowledge rather than convenience. UCS prediction is stronger when binder content, curing time, moisture state, and density are jointly represented, not when models rely on generic descriptors alone [21–28]. The same principle should guide sabkha zonation. A land-use raster or elevation layer may be useful, but it cannot substitute for subsurface evidence. The most credible models will combine geotechnical, hydrological, chemical, and geospatial features in a single architecture.

5.3 Explainable AI and the problem of false confidence

Explainability is not optional in this context. Urban expansion maps influence land value, permitting, infrastructure sequencing, and public risk. If a zoning model cannot explain why an area was classified as severe, high, moderate, or low sabkha risk, the result is difficult to defend in professional review. Recent geotechnical studies using SHAP and related explainable AI tools show how model reasoning can be made visible, whether for stabilized soil strength, road-embankment safety, or liquefaction-related hazards [28–30]. These methods are especially valuable because they can separate global patterns from local anomalies. A model may indicate, for example, that shallow groundwater and CPT weakness dominate risk across the province, while one individual coastal polygon is classified as severe because reclamation history and high surface salinity interact with those subsurface conditions.

This matters for practice because black-box accuracy is not the same as trustworthy mapping. A model can achieve high validation metrics and still fail under new site conditions if it is learning spurious correlations. The broader AI-in-geotechnics literature repeatedly warns that generalization, not headline accuracy, is the decisive criterion [16–20]. For sabkha zoning, the preferred workflow is therefore explainable and uncertainty-aware: train the model, inspect feature importance, test spatial stability, identify zones of low confidence, and flag areas where additional boreholes or geophysics are required before planning decisions are finalized.

5.4 From susceptibility mapping to zonation classes

AI outputs must be translated into categories that planners can use. A practical scheme is to convert continuous model scores into four interpretive classes: low, moderate, high, and severe sabkha constraint. Low-constraint land would show relatively favorable strength, manageable groundwater depth, limited chemical aggressiveness, and stable geomorphic context. Moderate-constraint land might require drainage management and conventional ground improvement. High-constraint land would normally require project-specific treatment, staged development, or foundation systems that bypass weak layers. Severe-constraint land would be reserved for essential infrastructure only, or development would proceed only after intensive treatment and monitoring. The value of AI is not in creating these classes automatically, but in identifying where the class boundaries probably lie and how stable those boundaries remain when new data are introduced.

5.5 Feature engineering for zonation models

If AI models are to be trusted, feature engineering must reflect geotechnical causality. Raw variables should be accompanied by derived indicators that improve physical meaning. Examples include groundwater-normalized cone resistance, salinity–moisture interaction terms, distance-weighted exposure to shoreline or tidal flats, thickness ratios between crust and weak sublayers, and neighborhood statistics that capture the degree of spatial continuity around each investigation point. In remote sensing, spectral salinity indices, surface albedo, and thermal anomalies can serve as indirect indicators of evaporite concentration, moisture retention, or anthropogenic disturbance, but these features should never be interpreted in isolation from ground truth [10,14]. For Eastern Province applications, historical reclamation polygons and development chronology may also be powerful predictors because recently filled areas can mask young, poorly consolidated or chemically active ground beneath engineered surfaces. The most reliable zonation models will therefore combine raw measurements, physically informed derived variables, and explicit spatial context.

5.6 Validation logic for a planning-scale model

Validation strategy is as important as algorithm choice. Standard random train–test splitting can give an overly optimistic impression of performance because nearby samples often share the same geomorphic and hydrogeological context. For zonation, spatial cross-validation is preferable. In this approach, model training and testing are separated by location so that the model is challenged with areas it has not already “seen” through neighboring points. This is particularly important in sabkha terrain because local continuity can be strong over short distances even when regional variability is high. Model evaluation should also include class balance, calibration, and threshold stability. A model that

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accurately predicts the majority of moderate-risk cells but misses small clusters of severe sabkha may still be unacceptable in planning practice. Consequently, confusion matrices, precision–recall behavior for high-risk classes, and uncertainty maps should accompany overall accuracy. In consultant and municipal workflows, the preferred outcome is not the single "best" model but a stable model ensemble whose class assignments remain broadly consistent under resampling and variable perturbation [16,18–20,28–30].

Table 2. Geotechnical indicators and zoning implications for coastal sabkha settings in the Eastern Province.

Indicator	High-risk expression	Interpretive meaning	Likely planning response
Groundwater regime	Very shallow, saline, or strongly variable water table	Higher probability of softening, collapse, and chemical attack	Restrict land use or intensify drainage and monitoring
Mechanical behavior	High compressibility, marked wetting collapse, low soaked strength	Serviceability risk dominates even where dry crust seems competent	Require denser investigation and treatment appraisal
Chemistry	Elevated sulfates/chlorides and active evaporites	Durability, corrosion, and cementation-loss concerns	Screen material compatibility and groundwater control
Stratigraphic continuity	Weak sabkha thickness beneath stiffer crust or fill	Hidden differential settlement potential	Increase profiling density and consider bridging systems
Geophysical signature	Low stiffness or abrupt lateral transitions	Suggests heterogeneity not captured by few boreholes	Refine class boundaries before permitting

VI. PLANNING AND DESIGN IMPLICATIONS FOR THE EASTERN PROVINCE

6.1 A phased decision framework

The review supports a phased decision framework for urban expansion in coastal sabkha settings. Phase one is regional screening using available geospatial layers: shoreline distance, elevation, land-reclamation history, LULC change, thermal anomalies, groundwater salinity indicators, and environmental constraints [9–15]. Phase two adds subsurface evidence from boreholes, CPT/SPT, groundwater logging, and chemical testing. Phase three trains or updates the AI model, preferably using an interpretable ensemble framework. Phase four converts the model into zoning classes, uncertainty bands, and investigation priorities. Phase five uses project-level testing and design to confirm or revise the class assigned to each development parcel.

This sequencing helps solve a recurring problem in fast-growing urban regions: geotechnical investigations often begin only after land parcels are already committed to a use. AI-based zonation cannot replace detailed design, but it can move geotechnical thinking upstream. In the Eastern Province, where reclaimed land and shallow saline conditions repeatedly appear in both geotechnical and urban-environmental studies, this upstream shift is especially valuable [3,9–12].

6.2 Data architecture for municipal implementation

A defensible municipal workflow would combine five data blocks. The first block is geotechnical: borelogs, index tests, collapse and compressibility tests, CPT/SPT, and strength measurements. The second is hydrochemical: groundwater level, EC, sulfates, chlorides, and intrusion indicators. The third is geophysical: seismic velocity, attenuation, and where relevant electrical resistivity. The fourth is geospatial: DEM-derived elevation, coastline distance, drainage pathways, reclamation history, surface moisture or salinity proxies, and land-surface temperature. The fifth is planning context: current land use, infrastructure criticality, and ecological constraints [8–15]. AI then serves as the fusion engine, not as the sole source of evidence.

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6.3 Design philosophy: map for action, not just description

The most useful sabkha map is one that changes decisions. A descriptive susceptibility map is insufficient if it does not indicate what kind of action is appropriate. Therefore, each zonation class should be tied to planning consequences: additional investigation density, allowable land uses, preferred improvement methods, groundwater management needs, and monitoring intensity. For example, areas with high probability of collapse under wetting may still be developable if urban drainage is tightly controlled and the founding level is improved. By contrast, areas combining high salinity, shallow groundwater, and thick weak sabkha may be more rationally reserved for low-load or adaptive land uses rather than dense urban structures. This is where geotechnics and urban planning truly meet.

6.5 Governance, communication, and decision thresholds

For zoning to be actionable, the technical classes must be translated into governance language. Planning departments, utility agencies, transport authorities, and private developers do not all work with the same threshold of acceptable risk. Essential infrastructure may tolerate higher treatment cost than residential subdivisions, while environmentally sensitive corridors may require conservative avoidance regardless of improvement feasibility. The mapping process should therefore involve a shared risk matrix established before the model is finalized. Such a matrix identifies the consequences of each class in terms of investigation obligations, design review level, drainage restrictions, groundwater monitoring, and post-construction observation periods. This governance layer echoes broader Eastern Province sustainability research, which emphasizes that technical success in hyper-arid urban regions depends on coordination across institutions rather than on isolated design excellence [11]. In effect, AI-based sabkha zonation becomes a boundary object that helps multiple actors negotiate where to build, how to build, and when to defer development.


Interpretable sabkha constraint matrix for urban expansion

Suggested review-based planning classes for Eastern Province screening before detailed design

Class	Dominant cues	Typical implication	Preferred response
Severe	Very shallow saline groundwater, thick weak sabkha, high collapsibility, strong chemical aggressiveness	Avoid dense development or permit only after intensive treatment and monitoring	Avoid / reserve / redesign
High	Weak profile continuity, reclamation history, low stiffness, adverse chemistry, water-sensitive serviceability	Project-specific treatment and tighter investigation density required	Treat + monitor
Moderate	Manageable variability with localized weak zones, moderate groundwater or salinity constraints	Development possible with targeted drainage, verification testing, and suitable foundation choice	Adapt + verify
Low	Relatively favorable stratigraphy, deeper groundwater, limited aggressive chemistry	Proceed with standard geotechnical confirmation and routine design controls	Proceed + confirm

Classes should be refined with local boreholes, CPT, geophysics, groundwater logs, and model uncertainty.

Figure 2. Apple-inspired review-based sabkha constraint matrix showing class logic and preferred planning responses before detailed design.

VII. RESEARCH GAPS AND FUTURE DIRECTIONS

Three major gaps recur across the literature. The first is the gap between point data and spatial decision-making. Many sabkha studies are rich in geotechnical detail but poor in map integration, while many environmental mapping studies are spatially sophisticated but geotechnically shallow. Future work should build shared datasets that link geotechnical logs, chemistry, geophysics, and remote-sensing layers at consistent coordinates. The second gap is interpretability under uncertainty. Explainable AI has improved rapidly, but most geotechnical applications still emphasize accuracy before uncertainty and transferability [28–30]. For municipal use, zonation models should report confidence, not just class. The third gap is physics integration. Emerging work on physics-informed machine learning in geotechnics suggests a route beyond purely statistical fitting by embedding domain constraints into model training [20]. For sabkha, this could help ensure that predicted risk patterns remain consistent with groundwater processes, collapse mechanics, or geophysical signatures rather than reflecting accidental correlations.

A fourth and specifically Saudi gap is the limited coupling of urban-growth studies with foundation-level risk layers. Eastern Province planning research now discusses thermal variation, ecological design, and coastal sustainability in much greater detail than before [10–12], but these agendas are rarely connected to the geotechnical realities of sabkha. A

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mature zonation system should support both infrastructure resilience and broader urban policy, including open-space design, drainage strategy, and climate adaptation.

7.2 Sustainable expansion and treatment hierarchy

The review also suggests a treatment hierarchy for coastal sabkha expansion. The first preference should be avoidance of the most severe zones where the required engineering effort is disproportionate to urban benefit. The second is low-disturbance adaptation, such as land-use reallocation, drainage preservation, or open-space designation. The third is selective improvement, where the mapped mechanism of weakness indicates a plausible intervention, for example densification in overlying sandy layers, deep mixing in chemically aggressive soft zones, or structural systems that bridge localized weak pockets [6,7]. Only after these options are examined should highly intensive treatment become the default. This hierarchy aligns geotechnical prudence with sustainability because it treats land suitability as a planning question before it becomes an expensive foundation problem.

7.3 A proposed research agenda

A focused research agenda for the Eastern Province should include five priorities. First, build open, spatially referenced sabkha datasets that integrate laboratory, field, groundwater, and remote-sensing observations. Second, test spatial cross-validation protocols for municipal-scale zonation rather than relying on random validation alone. Third, compare Random Forest, gradient boosting, and support vector approaches against simpler baselines so that model complexity is justified by actual gain. Fourth, embed explainability and uncertainty as standard outputs rather than optional post-processing. Fifth, evaluate the planning utility of zonation maps through real case studies, including how they change site selection, investigation scope, and treatment cost. Progress on these priorities would move the field from promising prototypes to institutionally usable tools.

VIII. CONCLUSION

This review shows that coastal sabkha soils in the Eastern Province cannot be treated as a uniform constraint zone. Their engineering behavior depends on the interaction of salinity, groundwater, fabric, cementation, moisture change, and anthropogenic transformation. The practical consequence is that characterization must be integrated and spatially aware. Index tests, mechanical behavior, chemistry, hydrogeology, geophysics, and land-surface evidence all matter, and none is sufficient in isolation. AI becomes useful precisely at this point of complexity. Ensemble learning, support vector approaches, and explainable AI provide a defensible way to combine multiscale evidence into planning-oriented zonation, provided they remain anchored to field data and uncertainty reporting.

For urban expansion in the Eastern Province, the most robust path is neither purely empirical nor purely algorithmic. It is a hybrid workflow in which geotechnical investigation, environmental sensing, and interpretable AI are staged together. In that workflow, zonation is not the final answer but the decision bridge between regional planning and site-specific design. Used in this way, AI-based zonation can reduce avoidable construction risk, improve investigation efficiency, and help direct development toward locations where engineering effort is proportionate to urban benefit.

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