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Machine-learning-based prediction of carbonation-induced reinforcement corrosion initiation risk in reinforced concrete under Kinshasa climate conditions

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INTRODUCTION & AIM

Why this question matters

Durability prediction is a practical issue for reinforced concrete exposed to tropical urban climates.

Carbonation progressively lowers the alkalinity of concrete. When the carbonation front reaches the steel level, the passive layer protecting the reinforcement can be lost and corrosion initiation becomes possible.

Kinshasa combines warm conditions, seasonal wetting and urban exposure. These factors make a local screening approach relevant, even when direct inspection data are not yet available.

Question Can open natural-carbonation data and Kinshasa climate descriptors provide a first quantitative estimate of corrosion initiation risk?

Objective and scientific novelty

The work sits in AI/ML for corrosion prediction by focusing on the initiation stage.

The objective was to predict carbonation-induced reinforcement corrosion initiation risk in reinforced concrete under representative Kinshasa climate conditions.

The novelty is the coupling of a curated natural-carbonation database, group-aware machine-learning validation and a transparent translation from predicted carbonation rate to corrosion initiation risk.

The output is not a measured corrosion rate from Kinshasa. It is a reproducible screening estimate that helps identify how material quality, climate scenario and concrete cover affect the timing of initiation.

DATA & METHODS

From carbonation to corrosion initiation

The risk translation follows the physical sequence that leads from environmental exposure to steel depassivation.

Carbon dioxide ingress	→	Carbonation front	→	Steel depassivation	→	Corrosion initiation
Carbon dioxide penetrates the cover and reacts with alkaline hydrates.		The predicted carbonation coefficient is converted into depth over time.		The passive layer can be lost when the front reaches the reinforcement level.		Initiation is flagged when predicted depth equals or exceeds the assumed cover.

Fig.1 : Physical sequence followed by the risk translation

For each material profile, the predicted carbonation coefficient was translated into depth using $x(t) = k\sqrt{t}$. Corrosion initiation was then assessed by comparing the depth with assumed covers of 25 mm, 30 mm and 40 mm.

Data foundation

Table 1: The analysis combined natural-carbonation records with representative Kinshasa climate descriptors.

Data element	Value used in the study
Natural-carbonation records in the RILEM database	1,744 records were available.
Mix-level observations	863 observations described concrete formulations and carbonation response.
Time-series measurements	6,879 measurements described carbonation depth over time.
Training subset	847 observations contained usable numerical climate information.
Kinshasa descriptors	Temperature, relative humidity and an atmospheric carbon dioxide proxy were used.

The database was restricted to natural carbonation because accelerated carbonation data can create a mismatch with atmospheric exposure. This choice made the Kinshasa application more defensible for a screening study.

The International Union of Laboratories and Experts in Construction Materials, Systems and Structures (RILEM) database provided the material-side evidence, while Kinshasa scenarios provided the exposure-side inputs.

Reproducible modelling workflow

The pipeline was designed to be transparent, group-aware and executable from open input data.

Natural carbonation database → Kinshasa climate profiling → Feature engineering and scenario building → Grouped machine-learning modelling → Carbonation-to-initiation risk translation

Fig.2 : Study workflow

The modelling workflow moved from natural carbonation data to climate profiling, then to feature engineering, grouped machine-learning modelling and carbonation-to-initiation risk translation.

Grouped validation by bibliographic reference was used to reduce overly optimistic testing when similar mixtures originate from the same study.

RESULTS & DISCUSSION

Model evaluation and What controlled the predictions?

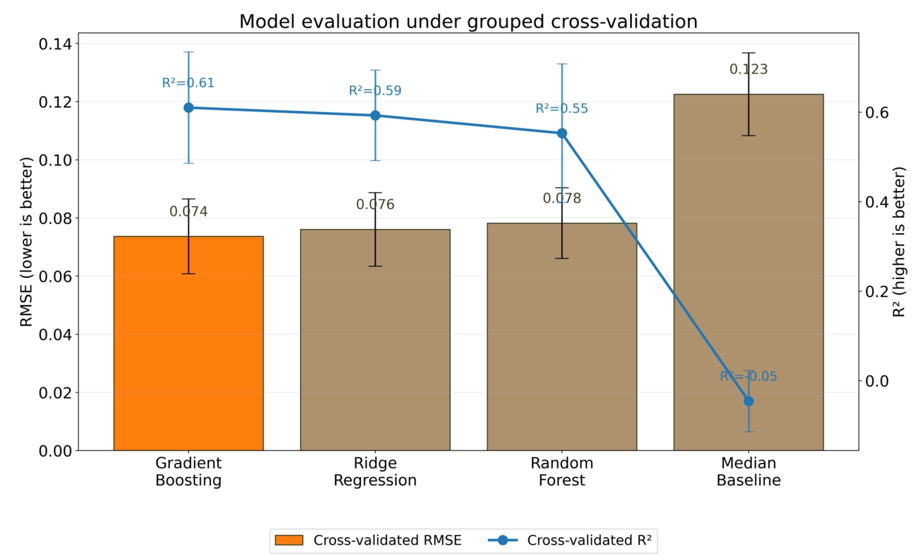

Fig.3 : Model evaluation under grouped cross-validation

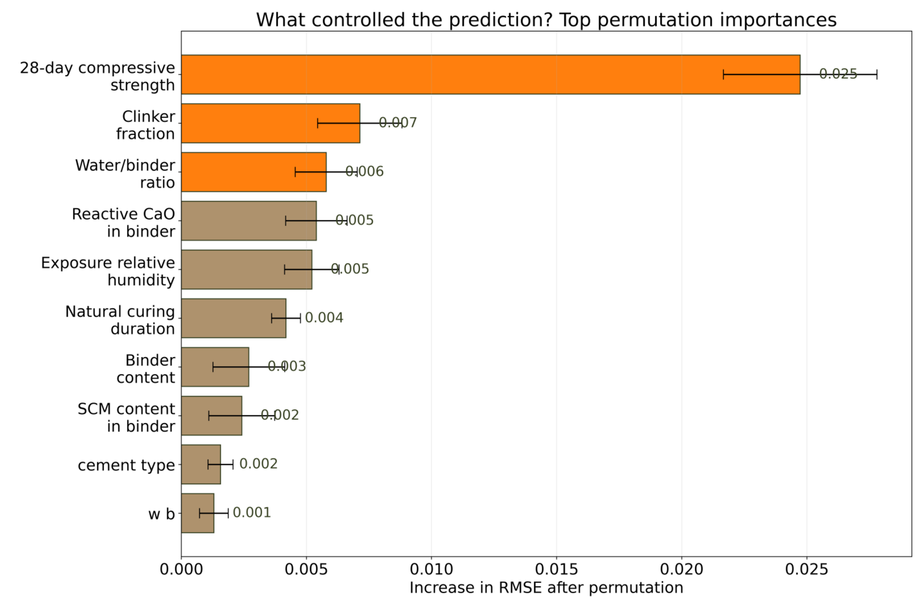

Fig.4 : What controlled the prediction

Four models were compared (Ridge regression, Random Forest, Gradient Boosting and a median baseline), and Gradient Boosting was retained for downstream risk translation. See Fig,3,

Material quality was more influential than the climate descriptor alone, but relative humidity remained visible in the model (Fig,4)

Kinshasa exposure scenarios and model domain

Only the typical dry and annual mean scenarios were retained as primary results.

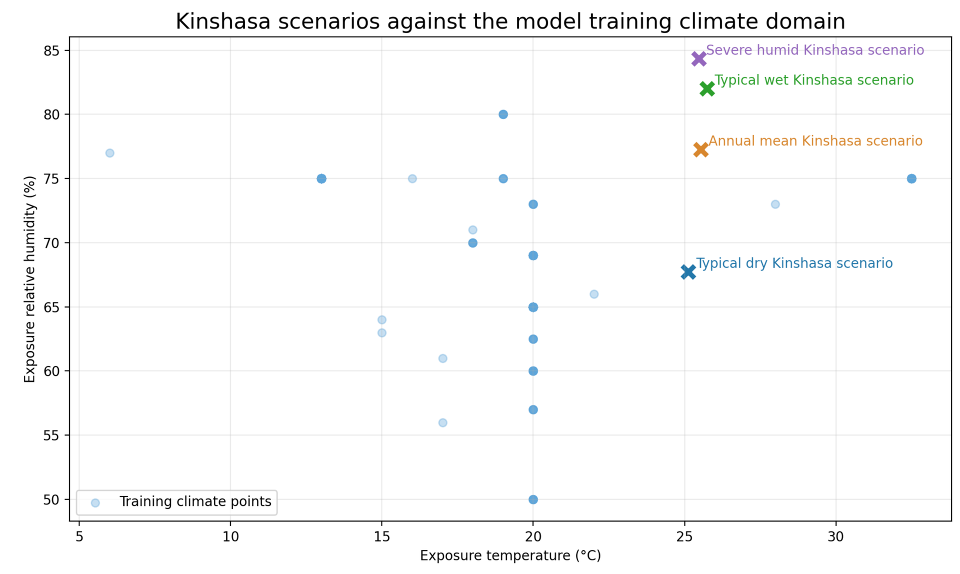

Fig.5 : Kinshasa climate scenarios versus the training climate domain

The typical dry Kinshasa scenario and the annual mean Kinshasa scenario remained inside the learned temperature–humidity domain.

The typical wet and severe humid scenarios were kept only as exploratory extrapolations because their relative humidity values exceeded the main training range.

Predicted corrosion initiation risk

The screening curves show how cover depth changes the service-life interpretation.

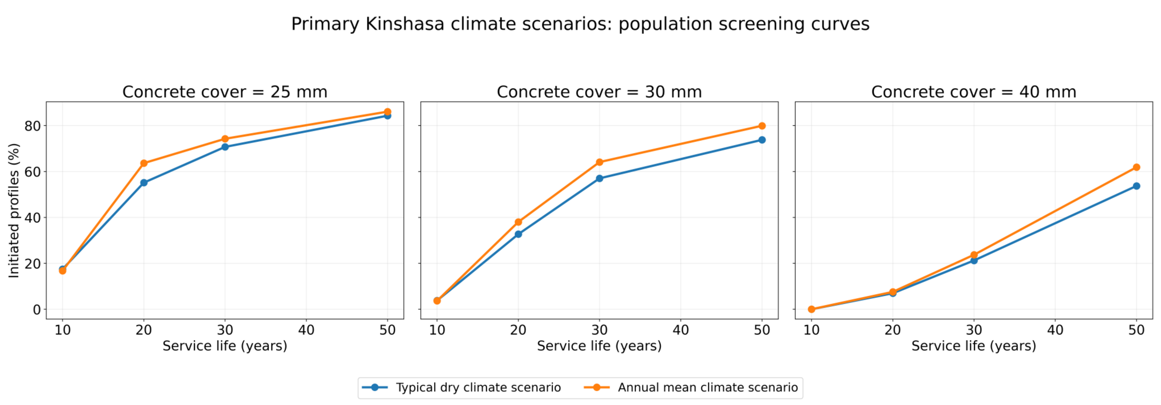

Fig.6 : Primary Kinshasa climate scenarios: population screening curves

For 25 mm cover, the median time for the carbonation front to reach the reinforcement level was 18.30 years under a typical dry scenario and 16.05 years under an annual mean scenario.

At 30 years and 25 mm cover, 70.72% of profiles reached initiation under the typical dry scenario, compared with 74.26% under the annual mean scenario.

Material profile sensitivity

The same Kinshasa climate can produce very different initiation times across material profiles.

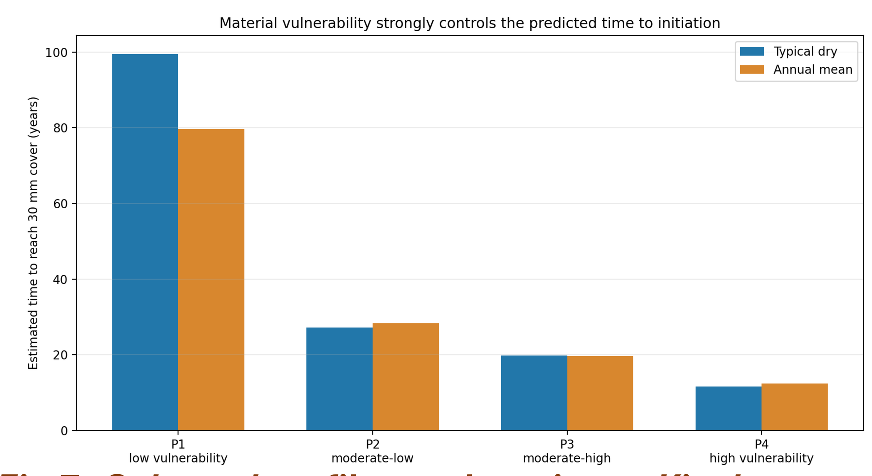

Fig.7 : Selected profiles under primary Kinshasa climate scenarios

Under the annual mean scenario, the estimated time to reach 30 mm cover ranged from 79.67 years for the lower-vulnerability profile to 12.46 years for the higher-vulnerability profile.

This spread means that material quality and cover depth may be as important as the local climate descriptor when screening carbonation-driven corrosion initiation.

CONCLUSIONS

The approach is useful as a first screening tool, but it requires local validation before design-level use.

The study demonstrates that open natural-carbonation data can be converted into a machine-learning framework for predicting carbonation-induced corrosion initiation risk under Kinshasa climate conditions.

Scientifically, the contribution is a transparent and reproducible bridge between material data, climate exposure and corrosion initiation screening for an African tropical urban context.

Practically, the results suggest that small covers and vulnerable material profiles may reach initiation thresholds within service-life windows of interest, making quality control and cover specification central to durability planning.

FUTURE WORK / REFERENCES

Limitation and Future Work: The main limitation is that the current framework is based on transferred open data. Future work should add local carbonation measurements and a richer representation of wet exposure in Kinshasa.

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