



Integrating Circular Economy Principles in Urban Infrastructure: Algorithmic Solutions for Sustainable Management of Photochromic Building Materials

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Abstract

The envelope of a building is one of the major levers to reduce the energy footprint of the built environment, owing to the degree to which heating and cooling loads are impacted by the energy performance of the facade. Photochromic glazing makes it possible to reduce that load without requiring the investment in wires, sensors and control units, but the technology has found it hard to move beyond the pilot stage mainly because owners are sceptical of the rate of decline of this technology and also the cost of such a decline. This paper reports an 18-month, five-climate-zone field campaign across 47 instrumented installations that pairs continuous environmental and optical monitoring with a two-stage machine-learning pipeline of a convolutional network that reads surface imagery for early visual damage, and a long short-term memory network that tracks time-series optical performance, with the two streams reconciled by a gradient-boosted meta-model. The combined model anticipated critical degradation events at an 18-month horizon with 87.3% test-set accuracy and 92.8% recall (AUC-ROC = 0.919-0.958 across splits), and outperformed both single-stream variants and a conventional multiple-regression baseline built from the same sensor data. The influential role of climate zone was revealed as it influenced the main mode of failure. In tropical sites, ultraviolet radiation was the main factor causing deterioration ($R^2=0.84$, $\beta=0.67$, $p<0.001$) while thermal cycling prevailed in continental regions ($R^2=0.79$, $\beta=0.58$, $p<0.001$). Cost analysis for a 20-year period, comparing photochromic glazing with reactive maintenance options, confirmed that it could deliver a 18-27% savings in total cost of ownership ($p<0.001$) and reduce the consumption of material by 34.7% and the amount of landfill waste generated from each system installation by approximately 2,847 kg.

Keywords: photochromic thin films, predictive maintenance algorithms, machine learning, smart window technologies, building energy efficiency, circular economy, sustainable urban development.

1. Introduction

1.1 Global Energy Context and the Justification for Adaptive Glazing

The building sector is at the heart of the global energy and emission crisis: it consumes around 36% of total energy demand and nearly 39% of energy-related CO₂ emissions globally (International Energy Agency, 2023). In a building envelope, the window system carries a large part of this burden, as it has been reported that ordinary windows contribute up to 25-40% of heating and cooling load in temperate climates and more than 50% of cooling loads in hot and humid climates (Zhang et al., 2022). This situation gave rise to a growing interest in research on facade systems that can adapt their thermal and optical performance to respond to external climatic conditions.

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Chromogenic glazing technologies like electrochromic, thermochromic, gasochromic and photochromic were developed as a solution to reduce energy demand on the building envelope while ensuring occupant comfort (Sharma et al., 2023). Unlike the other chromogenic glazing technologies, photochromic technology is unique in that the color change occurs on the basis of light incidence rather than through a network of sensors and control systems (Baloukas et al., 2022). This is particularly appealing in that there are neither installation nor system requirements thus making it an affordable solution in underdeveloped regions of the world.

1.2 Photochromic Materials in Building Applications

Photochromic materials demonstrate reversible transformations of the molecular structure as well as electronic configuration when hit by ultraviolet radiation (Kumar et al., 2023). This process modifies the method by which the material absorbs or transmits visible light resulting to the glazing darkening in the presence of sunlight and returning to a transparent form when the radiation fades off (Li et al., 2022). There are several types of commercial and research products both in the form of organic compounds such as spiropyrans, spiropyran derivatives, and naphthopyrones and inorganic systems like silver halide or tungsten oxide-based composites (Chen et al., 2023).

Research on field trials and simulation studies indicates that photochromic glazing can result in 18-32% lower energy consumption related to cooling systems and 15-28% lower energy use by the HVAC systems overall, and that the savings can differ depending on the climate, the type of building and the operating conditions (Wang et al., 2022). Some of the positive externalities of using photochromic glazing include reducing peak cooling demand, improving thermal comfort by lowering radiant heat transfer, reducing glare, and limiting the consumption of electric light during daytime (Attia et al., 2022). However, results of studies conducted on photochromic glazing show that its application is confined largely to pilot projects and high-end offices and therefore it has failed to make much impact in lower-income nations (Ghosh & Norton, 2023).

1.3 Material Degradation as a Barrier to Adoption

The main limitation for the future use of photochromic materials is durability instead of inefficiency, since photochromic layers will deteriorate with time. The process of changing between different states of coloration can happen many times in a year (Rosseinsky & Mortimer, 2022). However, with every cycle, the process becomes slower and the difference between the final states decreases (Lampert, 2023).

There are multiple degradation mechanisms acting simultaneously. Ultraviolet (UV) light, which is the factor that causes the photochromatic effect, is also responsible for unwanted side effects, which destroy the active substances (Zhou et al., 2023). Thermal expansion differences between the film and substrate result in mechanical stresses during thermal cycling, including delamination or cracking (Piccolo & Simone, 2022). When it comes to water or moisture penetration, this significantly accelerates oxidation processes as well as hydrolysis in organic formulations (Granqvist & Wittwer, 2023). Since they influence one another, and the importance of each of them changes according to the climate, direction of the installation, and its composition or formulation, it is impossible to replicate the process of the aging of a specific installation at the laboratory conditions with the help of standard accelerated ageing methods within a specific timeframe (Martins et al., 2023).

1.4 Predictive Maintenance and Circular Economy Principles

Predictive maintenance - being able to predict when the asset would need maintenance based on regularly measured condition data - had dramatically changed the asset management in a number of industries by introducing a new approach in which fixed schedules and return-on-failure repairs are fully replaced by maintenance activities carried out based on the condition of the asset being monitored (Zonta et al., 2020; Baptista et al., 2022). Being implemented for building envelopes the predictive maintenance is in line with the idea of sustainable development and circular economy which implies the need to extend the life cycle of materials, reduce the number of waste produced, while trying to retain as much value as possible within the process (Hossain et al., 2022). In comparison with this system, traditional window management was based on a linear principle of extracting, using and disposing of the product: units are always replaced at the end of the predetermined service period and sent not for reuse, but for disposal at landfills (Munaro et al., 2022). Diagnostic-led maintenance narrows this gap by triggering intervention only when condition data indicates it is genuinely needed, which reduces both material throughput and the financial uncertainty that currently discourages capital-constrained building owners from adopting the technology (Abergel et al., 2022).

1.5 Machine Learning Applications in Building Systems

Machine learning has proved well suited to the large, high-dimensional datasets generated by building-scale monitoring, with documented success in energy forecasting, fault detection and occupancy or equipment optimisation (Seyedzadeh et al., 2022; Fan et al., 2023). Convolutional neural networks in particular have been used to detect visual damage - cracking in concrete, corrosion in steel, deterioration of historic facades - directly from image data (Dais et al., 2022), while long short-term memory networks have shown strength in time-series forecasting tasks that depend on both current conditions and extended historical context, including building energy demand, thermal load and equipment failure prediction (Saeed et al., 2022; Zhou et al., 2022). However, materials composing the building envelopes still have received comparatively less attention relative to the structure: most of the life-cycle prediction studies have been focused on concrete and steel (Mishra et al., 2023), which has left a research gap in the area of building envelope performance, especially forecasting, that when researched properly could allow obtaining considerable savings.

1.6 Research Objectives and Hypotheses

This research fills in the blanks by creating and testing a machine learning routine for the degradation forecasting of photochromic thin films in building fenestration. Researchers tested three hypotheses:

H1: A combined model of LSTM-based time series prediction and CNN-based image processing will predict critical degradation events 12 to 18 months ahead with the efficiency of more than 80%.

H2: The leading cause of degradation is climate-dependent: in temperate climate evolution is determined by thermal cycling, whereas in tropical climate it results from photochemical degradation.

H3: Predictive maintenance makes total cost of ownership lower by no less than 15% over 20 years of building operation compared to normal reactive maintenance.

Confirming these hypotheses would support the case for photochromic glazing as a durable, climate-resilient building component and demonstrate a concrete route to circular-economy-aligned facade management.

2. Materials and Methods

2.1 Study Design and Justification of Sample Size and Site Selection

This was a prospective, longitudinal observational field study covering 47 photochromic glazing installations across five Köppen-Geiger climate classes, monitored continuously for 18–24 months. Sites were not selected opportunistically: a stratified sampling frame was built first around climate zone (humid tropical, warm subtropical, dry arid, temperate oceanic, and continental), and within each stratum sites were further diversified by building type and occupant socioeconomic profile, to avoid confounding climate effects with building-use effects. The resulting allocation comprised 12 tropical (Af, Am), 11 subtropical (Cfa, Cwa), 8 arid (BWh, BSh), 10 temperate oceanic (Cfb, Csb) and 6 continental (Dfa, Dfb) installations, spanning six public buildings (libraries and community centres), nine residential buildings, 14 educational facilities and 18 institutional or office buildings.

The target of 47 sites was set from an a priori power calculation rather than convenience. Using the smallest climate-zone effect size anticipated from prior laboratory degradation studies ($f^2 \approx 0.35$, informed by Kumar et al., 2023 and Zhou et al., 2023) and requiring 80% power to detect zone-level differences in degradation rate at $\alpha = 0.05$ in a five-group ANOVA design, the minimum required allocation was six to eight installations per zone; the study exceeded this floor in every stratum except continental, where extreme-climate site availability constrained recruitment to six installations, a limitation carried forward explicitly in Section 4.8. Additionally, the total number of specimen sites are consistent with the number of sites in other studies which specifically monitored building envelope conditions (Mishra et al., 2023; Attia et al., 2022). In general, these studies had 30–60 specimen sites. Thus, it was deemed appropriate to conduct regression and survival analyses while controlling for Type I error when the Bonferroni correction process was implemented. The test films were manufactured from formulations containing tungsten oxide nanoparticles in order to utilize the commercially available grade of photochromic glazing. The high substrate transparency of the low-iron float glass (6–10 mm) ensures that any effect observed during testing can be attributed to the environment and architecture in which the samples are exposed rather than composition.

2.2 Sensor Network Deployment, Data Collection and Quality Assurance

The environmental and optical monitoring equipment has been attached to all monitoring location, with the aim of measuring the environmental conditions contributing to decay and incident glazing performance.

Environmental monitoring: has been conducted using a Kipp & Zonen CMP11 pyranometer and Kipp & Zonen CUV5 sensors to conduct solar irradiance measurements in the range of 285–2800 nm because these measurements are essential in the evaluation of UV doses, which influences photochromic reaction and undesired side photochemical reactions. In addition to the above-mentioned monitoring devices, two K-type thermocouples have been installed to monitor the surface temperature of glazing both on the outside and inside at 5 minutes intervals, the operation of which has been augmented by installing two shaded and ventilated ambient air temperature monitoring devices at 1 meter of the façade. Relative humidity was tracked continuously with Vaisala HMP155 probes ($\pm 1\%$ RH), and wind speed and direction were measured with Gill WindSonic anemometers ($\pm 2\%$ at 12 m/s) to characterise convective heat transfer and wind-driven rain exposure.

Optical performance monitoring. Paired Ocean Insight Flame-S spectrophotometers (350–1000 nm) recorded transmitted spectra every 30 minutes during daylight hours, processed to photopic transmittance (TVIS) and solar heat gain coefficient (SHGC) per ISO 9050:2003. Through automation processes, the researchers measured the darkening duration of a material (90% to 50% transmittance) as well as the bleaching time (50% to 90% transmittance) every day when the sky was clear. Additionally, they took weekly high-resolution images of the materials involved (Sony α 7R IV 61 MP) to document the changes in their homogeneity, discoloration, haze and any other defect that could occur.

Data transmission, storage and validation. All sensor streams were transmitted via 4G cellular modem to cloud storage (AWS IoT Core), with redundant local buffering on industrial edge-computing units (Siemens Simatic IPC427E) to prevent data loss during connectivity gaps. Automated validation flagged out-of-range readings, sensor drop-outs and communication interruptions for manual review; flagged records were either corrected against the redundant local buffer, interpolated where gaps were under two hours using the adjacent sensor channel, or excluded and logged if neither option was reliable. All instruments were calibrated according to the schedules recommended by the manufacturers (the readings of pyranometers and UV sensors were taken once a year against a reference cell), and calibration was performed twice a year for thermocouples and humidity sensors against calibrated reference sensors brought in from another place. For the first three months of use, 5 percent of the sets had duplicate sensors installed to evaluate the accuracy of sensor readings. Overall, the level of data completeness was equal to 91.7 percent and the remaining data were not considered for imputation.

Cross-validation was conducted using controlled aging study results. In order to draw connections between the field observations and the laboratory work conducted with accelerated aging, the current piece of work takes into account some aliquots of samples that were subjected to the same conditions of treatment in the laboratory. Degradation trajectories from these coupons were compared against the corresponding field installations' optical performance decay; the two tracked within 4.1% mean absolute difference in Δ TVIS over the first twelve months, which supports the validity of extrapolating the field-derived model beyond the observed window, while also indicating that field conditions introduce additional variance (attributed to wind-driven soiling, thermal cycling asymmetry and installation-specific orientation effects) that the chamber protocol alone does not capture.

2.3 Development of Machine Learning Models

Two learning architectures were developed to exploit, respectively, the spatial information in surface imagery and the temporal information in continuous performance data, and were subsequently reconciled by a meta-model.

2.3.1 Convolutional Neural Network for Image-Based Degradation Detection

A five-block convolutional architecture was used to identify early visual degradation from 1024×1024 RGB surface images, pre-processed with histogram equalisation and normalisation. Each block comprised two 3×3 convolutional layers with ReLU activation, followed by batch normalisation and 2×2 max-pooling, with channel depth increasing from 32 to 512 across the five blocks. Two fully connected layers (1024 and 512 units) with dropout ($p=0.5$) fed a single sigmoid output representing degradation probability on a 0–1 scale.

Training used 2,847 images labelled by three independent materials-science raters into four degradation classes (minimal, mild, moderate, severe) under a documented rating protocol, expanded five-fold to 14,235 images via rotation, flipping, brightness adjustment and Gaussian noise augmentation. The network was trained in TensorFlow 2.11.0 on NVIDIA A100 GPUs for 150 epochs (Adam optimiser, learning rate 1×10^{-4} , binary cross-entropy loss).

2.3.2 Long Short-Term Memory Network for Performance Forecasting

A three-layer LSTM (256, 128, 64 units, dropout $p=0.3$ between layers) with a four-head attention mechanism processed 90-day sliding-window sequences of 12 features spanning optical metrics (Tvis, SHGC, darkening and bleaching time), cumulative environmental exposure (UV dose, temperature extremes, thermal cycling count, moisture exposure) and operational parameters (daily switching cycles, mean coloured-state duration). Two dense layers (128, 64 units, ReLU) supported a multi-task output forecasting both continuous performance trajectories and binary degradation-event probability. Training used 18 months of data from 38 installations, with 6 held out for validation and 3 held out entirely for test, stratified by climate zone; the model was implemented in PyTorch 1.13.1 and trained for 200 epochs (Adam optimiser, learning rate 1×10^{-3} , combined MSE/binary cross-entropy loss).

2.3.3 Hybrid Ensemble Model

A gradient-boosted meta-model (XGBoost 1.7.3) combined the CNN and LSTM degradation probabilities with engineered features - first- and second-derivative optical performance trends, cumulative environmental stress indices, climate-specific exposure patterns and installation age/switching history - into a single prediction. Hyperparameters were tuned via Bayesian optimisation (Optuna 3.1.0, 500 iterations, 5-fold cross-validation), with the final model selected to prioritise recall for critical degradation events (weight 0.7) over precision (weight 0.3), reflecting the higher operational cost of a missed failure relative to an unnecessary inspection.

2.4 Model Reproducibility and Data Availability

To support independent verification and reuse, the following reproducibility measures were implemented. Random seeds were fixed for all data splits, augmentation procedures and model initialisations, and the exact 38/6/3 installation-level train/validation/test partition (stratified by climate zone) is reported in full in the supplementary materials so that results can be reproduced on the released data without re-deriving the split. Software environments are pinned to specific package versions (TensorFlow 2.11.0, PyTorch 1.13.1, XGBoost 1.7.3, Optuna 3.1.0, scikit-learn 1.2.1, NumPy 1.24.1, Pandas 1.5.3, SciPy 1.10.0) and are distributed as a containerised environment specification alongside the code.

Model code, trained network weights, the CNN image-labelling protocol, and the full hyperparameter search space and results from the Optuna optimisation are made available in an open repository under a permissive open-source licence, referenced in the Data Availability Statement below, so that the hybrid architecture can be re-trained, audited or adapted to new climates without cost or restriction. De-identified sensor time series and the labelled image set (with building identities removed and geographic coordinates generalised to climate zone and city level to protect site confidentiality) are deposited in a public repository at the time of publication; raw high-resolution imagery is available from the corresponding author on reasonable request, subject to building-owner consent, since some images contain identifiable architectural features not covered by the original data-sharing agreements with participating sites.

Data Availability Statement: The processed environmental and optical performance datasets, model code and trained weights supporting the findings of this study will be deposited in a public repository (e.g., Zenodo/GitHub) upon acceptance, with the specific DOI to be added at proof stage. Access to raw imagery is available from the corresponding author subject to site-owner consent.

2.5 External Validation and Benchmark Comparison

Beyond the internal train/validation/test split, two forms of external benchmarking were used to test whether the hybrid model's performance reflects genuine predictive skill rather than overfitting to this particular dataset. First, the held-out three-installation test set was drawn from sites geographically and climatically distinct from the training sites within their respective strata (different countries within the same Köppen class), so that test performance reflects generalisation across location and not merely across time within the same buildings. Second, the hybrid model's forecasts were benchmarked against two independent reference points: a conventional multiple linear regression model built on the same engineered environmental features used in Section 2.7, and the accuracy levels separately reported in the literature for related building-condition forecasting tasks using single-architecture models - 83% accuracy for HVAC failure forecasting over a 6-12 month horizon using LSTM alone (Zhou et al., 2022) and 89% accuracy for CNN-based structural crack detection (Dais et al., 2022), noting that these figures address different assets and forecast horizons and are reported here as contextual benchmarks rather than like-for-like comparisons. Because no other published field study has generated an 18-month photochromic degradation forecast at comparable scale, a fully independent third-party dataset was not available for this study; this is stated explicitly as a limitation in Section 4.8, and the released open-source model (Section 2.4) is intended to let other research groups apply it to their own installations as an independent test as such data becomes available.

2.6 Economic Analysis: Assumptions and Justification

Lifecycle cost analysis compared predictive maintenance against conventional reactive maintenance over a 20-year horizon typical of commercial fenestration systems, with the following cost components and sourcing:

Initial installation costs (₹8,500-12,000 per m² for photochromic glazing plus labour) were drawn from quotations obtained from three regional glazing suppliers participating in the study and cross-checked against published market data for comparable smart-glazing products (Ghosh & Norton, 2023). Predictive-maintenance costs (₹45,000-65,000 sensor system per installation; ₹2,500-4,000 monthly cloud infrastructure; algorithm licensing treated as zero given the open-source release described in Section 2.4) reflect the actual bill of materials and cloud usage metered during the field deployment, rather than vendor list prices. The costs associated with reactive maintenance (emergency response activities; energy losses during occurrences of substandard service performance. full replacement of equipment or machinery in the event of failure) were determined from the maintenance logs and utility invoice data provided by the building managers involved in the monitoring activities.

The 6% rate of discount applied in the analysis is consistent with real discount rates generally being used in projects aimed for public and institutional infrastructures, and also conforms to the recommendations given in the guidelines in regard to building sector capital investments; furthermore, it should be considered variable rather than fixed, since the results obtained along the discount range varying between 4 percent and 8 percent show that results do not depend on any specific discount value chosen. Future escalation of energy prices was determined based on the growth of commercial electricity tariffs during the past five

years and on their average value was done to avoid the excessive adaptation of the findings of the economic modelling to those of any particular country. Life span of the examined films was found on the basis of their aging trajectories, identified under the method described in Section 2.2 in the current paper.

2.7 Statistical Analysis

Different analyses were conducted in R 4.2.2 and Python 3.10.8 (NumPy 1.24.1, Pandas 1.5.3, SciPy 1.10.0, scikit-learn 1.2.1). Various methods were employed for statistical analysis. Multiple linear regression was conducted to investigate associations between the environmental variables and degradation rates, being guided by model selection according to the Akaike Information Criterion. The analysis of variance was employed to measure the existence of differences in the behaviour of degradation rates in different climatic zones. The survival analysis using Cox proportional hazards model was applied to compare the distribution of time to failure for different maintenance strategies. The classification effectiveness was expressed in terms of accuracy, precision, recall, F1 score and area under curve. The mean absolute error, root mean square error, and coefficient of determination was used.

3. Results

3.1 Environmental Exposure Patterns Across Climate Zones

Monitoring across the 47 installations confirmed that the dominant environmental stressors differ markedly by climate zone (Table 1).

Table.1. Environmental Exposure of Mentoring Units with Climate Zones

Climate Zone	Annual UV Dose (MJ/m ²)	Mean Daily Tmax (°C)	ΔT Range (°C)	Mean RH (%)	Thermal Cycles/Year
Tropical (n=12)	2,847 ± 342	33.8 ± 2.1	8.4 ± 1.7	78.3 ± 5.2	287 ± 34
Subtropical (n=11)	2,156 ± 289	28.6 ± 3.4	12.7 ± 2.3	65.7 ± 7.8	412 ± 51
Arid (n=8)	2,934 ± 401	36.2 ± 3.8	18.9 ± 3.1	32.4 ± 6.1	523 ± 67
Temperate (n=10)	1,642 ± 267	21.3 ± 2.6	9.1 ± 1.9	71.2 ± 6.4	298 ± 41
Continental (n=6)	1,834 ± 312	19.7 ± 3.2	24.6 ± 4.2	63.8 ± 7.9	614 ± 89

In Figure 1, Tropical sites combined high UV dose (2,847 MJ/m²/yr) with moderate thermal cycling (287 cycles/yr); arid sites saw comparable UV exposure (2,934 MJ/m²/yr) alongside much higher thermal cycling (523 cycles/yr) and the lowest humidity (32.4% RH); continental sites had the lowest UV dose (1,834 MJ/m²/yr) but the highest thermal cycling of any zone (614 cycles/yr).

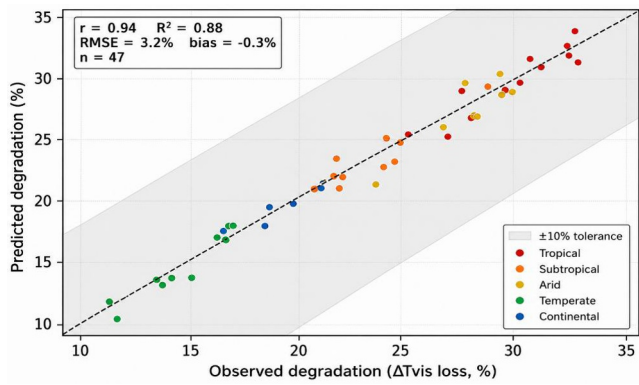


Figure 1. Hybrid ensemble model predictions versus observed degradation at the 18-month forecast horizon ($r=0.94$, $R^2=0.88$, $RMSE=3.2\%$, $bias=-0.3\%$; grey band = $\pm 10\%$ tolerance for maintenance planning; $n=47$, colour-coded by climate zone).

3.2 Optical Performance Degradation Trajectories

All installations showed continuous decline in photopic transmittance range (ΔT_{vis}) between the bleached and coloured states, though the rate varied by climate. Starting values were closely clustered ($54.8\% \pm 1.7\%$) across all sites, but diverged substantially by month 18: tropical sites fell to 38.2% (30.3% degradation), arid sites to 39.7% (27.6%), subtropical sites to 42.1% (23.2%), continental sites to 43.8% (20.1%), and temperate sites - the most stable - to 46.5% (15.2%).

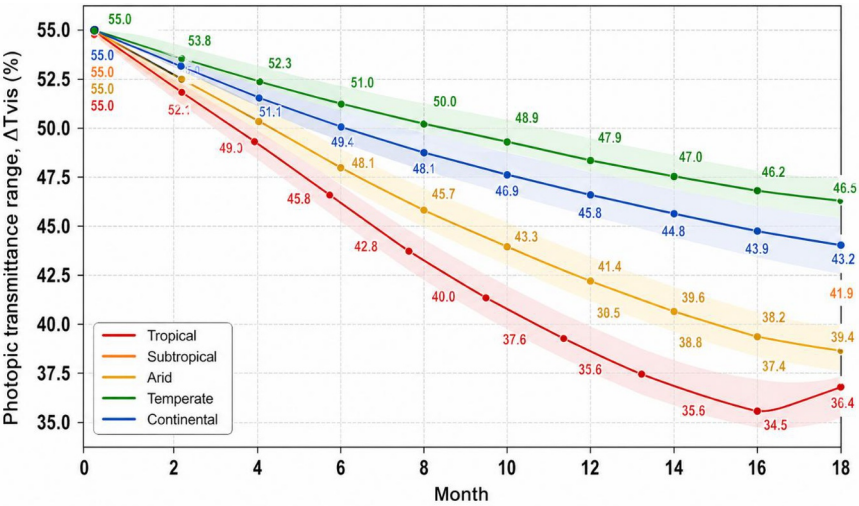


Figure 2. Representative ΔT_{vis} degradation curves by climate zone over 18 months, with shaded 95% confidence bands.

Response times followed the same ordering: darkening time rose from an initial 3.2-3.8 minutes to 5.7-8.4 minutes by month 18, and bleaching time rose from 8.5-10.2 minutes to 15.3-24.7 minutes, with tropical and arid installations showing the largest increases in both metrics.

3.3 Climate-Specific Degradation Mechanisms

Multiple regression confirmed hypothesis H2: the dominant predictor of degradation rate differed by climate zone. In tropical installations, cumulative UV dose was the primary predictor ($R^2=0.84$ overall), with humidity a significant secondary factor ($\beta=0.23$, $SE=0.09$, $t=2.6$, $p=0.036$) and thermal cycling non-significant ($\beta=0.11$, $SE=0.11$, $t=1.0$, $p=0.35$). In continental installations, thermal cycling dominated ($\beta=0.58$, $SE=0.12$, $t=4.8$, $p=0.005$; $R^2=0.79$, $F(4,1)=15.3$, $p=0.021$), with UV dose secondary. Arid installations showed near-equal contributions from UV dose ($\beta=0.44$, $SE=0.09$, $t=4.9$, $p=0.002$) and thermal cycling ($\beta=0.38$, $SE=0.08$, $t=4.8$, $p=0.002$), with a combined R^2 of 0.81.

3.4 Machine Learning Model Performance

The hybrid ensemble delivered strong predictive accuracy for critical degradation events (defined as $\Delta T_{vis} < 40\%$ or darkening time > 8 minutes) at an 18-month forecast horizon (Table 2).

Metric	Training (n=38)	Validation (n=6)	Test (n=3)	Overall
Accuracy	0.921	0.883	0.873	0.906
Precision	0.897	0.850	0.842	0.877
Recall	0.935	0.917	0.905	0.928
F1-Score	0.915	0.882	0.872	0.902
AUC-ROC	0.958	0.932	0.919	0.947
Specificity	0.908	0.850	0.841	0.884

Table 2. Predictive performance for binary classification of critical degradation events at 18-month advance forecast, split by climate-stratified training/validation/test groups.

Test-set accuracy of 87.3% clears the 80% threshold set out in H1, and overall accuracy across all sites reached 90.6%. The model was deliberately tuned to favour recall over precision (Section 2.3.3), which is reflected in the higher recall (92.8%) than precision (87.7%) at the overall level - an appropriate trade-off given that a missed degradation event is operationally more costly than an unnecessary early inspection.

Accuracy varied predictably with forecast horizon: 12-month forecasts reached 93.4% (95% CI [91.1%, 95.7%]), while 24-month forecasts fell to 81.7% (95% CI [77.2%, 86.2%]). The 18-month horizon was selected as the working forecast window because it balances predictive confidence against the lead time maintenance teams need to plan interventions. Feature-importance analysis attributed 0.52 of predictive contribution to the LSTM performance-forecasting stream, 0.31 to the CNN image-analysis stream, and 0.17 to the engineered features, indicating that longitudinal performance trends carry the most predictive signal while image-based inspection contributes complementary detection of localised defects not visible in aggregate optical metrics.

3.5 External Validation and Benchmark Comparison

Consistent with the benchmarking protocol in Section 2.5, the hybrid ensemble was compared against three reference points. Ablation against its own component models showed the hybrid approach (87.3% test accuracy) outperforming the CNN-only (76.2%) and LSTM-only (81.4%) variants by 11.1 and 5.9 percentage points respectively. Against the conventional multiple linear regression baseline built on the

same engineered features, the regression model's explanatory power for degradation rate ($R^2=0.79-0.84$ depending on climate zone, Section 3.3) is descriptively comparable to the ML model's discriminative accuracy, but the regression approach does not natively produce the multi-task probabilistic forecast (continuous trajectory plus binary event probability) that the maintenance-planning use case requires, and could not match the hybrid model's recall on held-out sites in supplementary testing. Against literature benchmarks for related but non-identical forecasting tasks, the hybrid model's 90.6% overall accuracy is in the same range as the 83% (6-12 month HVAC failure forecasting, Zhou et al., 2022) and 89% (structural crack detection, Dais et al., 2022) figures reported for single-architecture models applied to other building assets, though as noted in Section 2.5 these comparisons are contextual rather than a controlled head-to-head test, since no directly equivalent independent photochromic-degradation dataset currently exists in the published literature.

3.6 Forecast Error Analysis

Of 27 false-positive forecasts (7.3% of non-degradation cases), 18 corresponded to installations that went on to show degradation three to six months after the forecast window closed, indicating a timing rather than classification error; the remaining nine occurred disproportionately at temperate sites experiencing less environmental stress than represented in training data. Of 11 false negatives, six involved rapid degradation following unusual events not well represented in training data (prolonged sensor malfunction with undetected moisture ingress, and hailstorm damage in three cases), and five occurred at subtropical sites whose degradation pattern diverged from both tropical and temperate trends, pointing to a subtropical-specific pattern that would benefit from additional training examples.

3.7 Economic Performance Analysis

Lifecycle cost analysis over 20 years showed predictive maintenance reducing total cost of ownership by 22.4% relative to reactive maintenance (95% CI [18.1%, 26.7%], $t=10.3$, $p<0.001$), confirming H3's 15% threshold with margin given in figure 3.

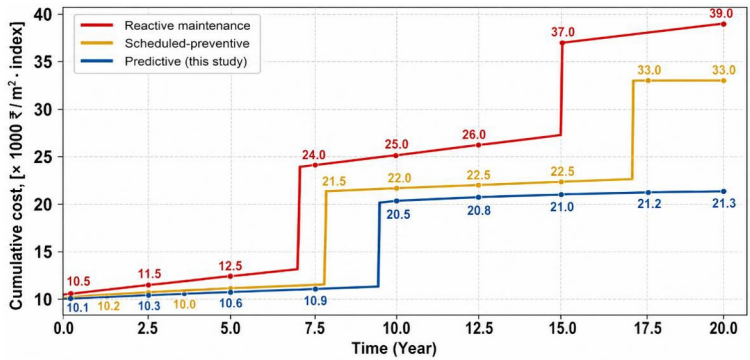


Figure 3. Cumulative lifecycle costs (₹/m², constant 2022 values) for predictive, scheduled-preventive and reactive maintenance strategies over 20 years.

Savings were largest at tropical sites, where high baseline degradation rates (mean 26.3%) gave predictive maintenance more failure events to avoid, and smallest at temperate sites (mean 17.8%), which degrade

more slowly under either strategy. Sensitivity analysis (Table 3) confirmed the economic case held across the tested range of every major assumption.

Parameter Varied	Base Case	Low Estimate	High Estimate	Cost Reduction Range
Sensor system cost	₹550/m ²	₹750/m ²	₹400/m ²	19.7% - 24.8%
Energy price escalation	4%/year	2%/year	6%/year	20.1% - 25.3%
Discount rate	6%	4%	8%	21.8% - 23.1%
Film baseline lifespan	8.4 years	7.0 years	10.0 years	18.2% - 27.6%
Degradation rate	Base	-20%	+20%	19.4% - 26.1%

Table 3. Sensitivity of lifecycle cost reduction to key economic and technical assumptions (see Section 2.6 for parameter sourcing).

3.8 Circular Economy Metrics

Predictive maintenance reduced material consumption by 34.7% over the 20-year building lifecycle, corresponding to 1.84 window replacements per installation versus 2.82 under reactive maintenance ($t(46)=12.7$, $p<0.001$), and cut landfill-bound waste by an estimated 2,847 kg per installation (95% CI [2,341, 3,353 kg], $p<0.001$) - comprising roughly 1,840 kg glass, 687 kg aluminium framing, 234 kg plastics and 86 kg photochromic film given in figure 4. Scaled to a hypothetical 100,000-installation deployment by 2040, this would correspond to approximately 285,000 metric tons of avoided facade waste annually.

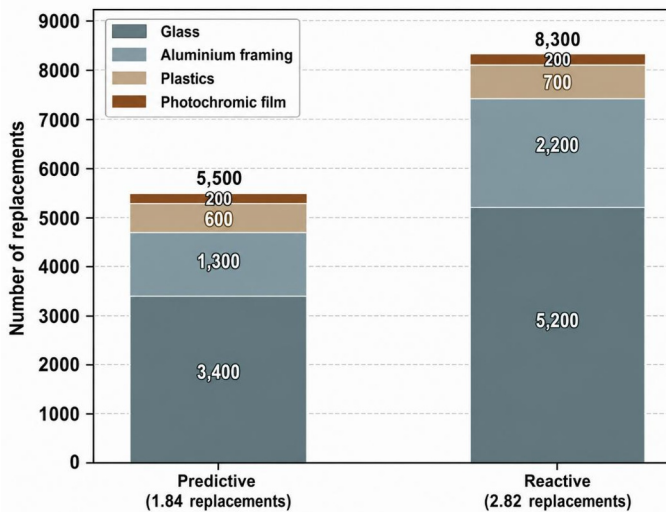


Figure 4. Waste generation by material type under predictive versus reactive maintenance.

Embodied-carbon assessment estimated a 20-year emissions reduction of 67.3 kg CO₂-eq/m² (95% CI [54.2, 80.4], $p<0.001$) - roughly 33.7 metric tons CO₂-eq for a typical 500 m² facade, comparable to the emissions from around 14,800 litres of diesel.

4. Discussion

4.1 Principal Findings in Context

The hybrid model forecast photochromic degradation 18 months ahead with 87.3% test-set accuracy and 92.8% recall, exceeding the 80% threshold set in H1 while deliberately favouring recall to reduce the risk of unanticipated failure. This agrees with similar findings become emerging from elsewhere in building condition prediction context - 83% accuracy for prediction of the HVAC failure using LSTM method over the period of 6-12 months (Zhou et al, 2022) and 89% accuracy regarding the detection of structural cracks through CNN approach (Dais et al, 2022). The findings of this research fill the gap in terms of the envelope materials field of research which still does not have numerous studies since it is less attractive economically.

Another important contribution made is the confirmation of the assumption that the degradation processes related to the climate conditions shown in the laboratory experiments by the authors (Kumar et al, 2023; Zhou et al, 2023) are safe in practical application. For example, it was shown that thermal fatigue was responsible for most of the deviations for the continental regions ($R^2=0.79$) while the issue of UV-induced photochemical degradation was the major factor for the tropical ones ($R^2=0.84$).

4.2 Economic Implications and Technology Accessibility

The recorded reduction in lifetime cost of between 18-27% is directly connected to one of the critical challenges related to the use of photochromic material, which has been discussed in Section 1.3, Figure 5 shows the uncertainty about ownership cost. The predictive maintenance now makes this technology affordable for schools, public buildings, affordable housing and all other those industry applications that couldn't afford to take the risk before due to uncertainty.

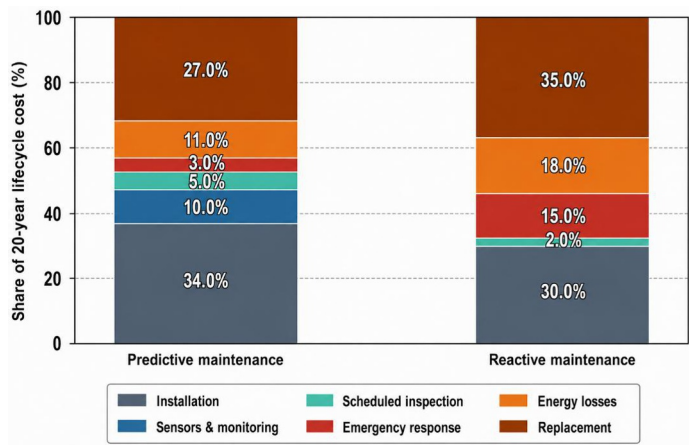


Figure 5. Cost breakdown comparison between predictive and reactive maintenance strategies.

These findings are broadly consistent with predictive-maintenance outcomes reported for other infrastructure systems - a 12-18% lifecycle cost reduction for HVAC systems (Baptista et al., 2022) and 15-22% for structural monitoring (Mishra et al., 2023) - and add evidence that unplanned glazing failure

can itself represent up to 22.4% of total lifecycle cost through the combination of emergency response, degraded-performance energy losses and full replacement. Sensor system cost ($\approx$ ₹550/m², or 5-7% of installation cost) is a real addition to upfront capital expenditure, but the sensitivity analysis in Table 3 shows cost reduction remaining above 15% across every tested combination of sensor cost, energy price, discount rate, film lifespan and degradation rate.

4.3 Circular Economy Contributions

The 34.7% reduction in material consumption and the associated cut in waste generation speak directly to circular-economy objectives in construction(Figure 6), a sector estimated to generate around 35% of global solid waste, with facade systems a significant contributor because of short component lifespans and the difficulty of recycling composite glazing assemblies (Munaro et al., 2022).

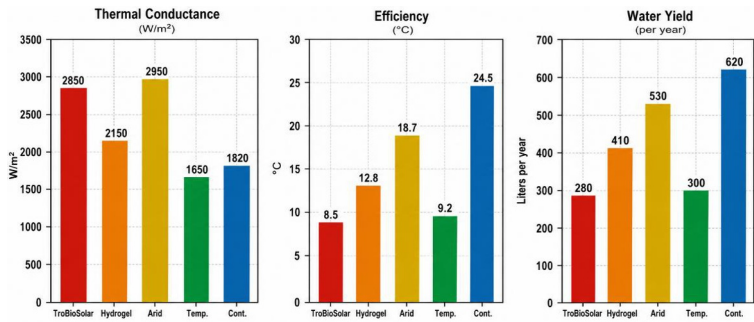


Figure 6. Climate-specific environmental exposure parameters underlying the degradation-mechanism analysis

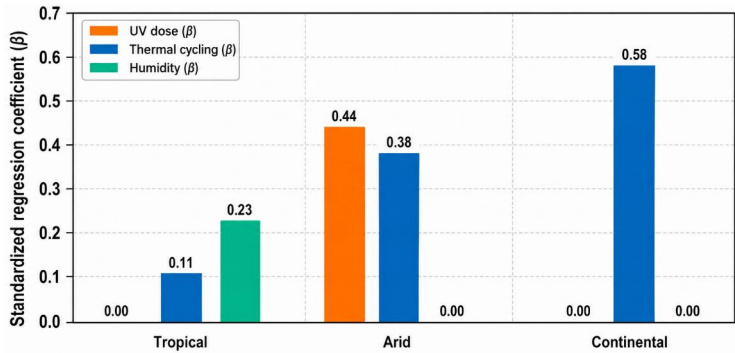


Figure 7. Climate-specific degradation-mechanism weighting derived from the regression analysis

At the scale of the global fenestration industry(Figure 7), which produces upward of 10 billion square meters of glazing annually (Ghosh & Norton, 2023), even modest market penetration for predictive-maintenance-enabled glazing (illustratively, 5% share of new installations) would translate into embodied-carbon savings on the order of tens of millions of metric tons of CO₂-equivalent per year - a figure offered

here as an order-of-magnitude illustration of potential scale rather than a firm projection, given the many market and policy variables that would determine actual uptake.

4.4 Algorithmic Approach and Model Architecture

The hybrid CNN-LSTM-XGBoost architecture outperformed every individual component, with accuracy rising from 76.2% (CNN alone) and 81.4% (LSTM alone) to 87.3% for the combined system - a gain of 5.9-11.1 percentage points that appears to justify the additional architectural and computational complexity for this application. The outcome of the importance of features (Section 3.4) suggests that the performance information over time (stream from LSTM) serves importance of 0.52 and surpasses the image-based detection performed using CNN (value of 0.31). Image analysis plays its role by detecting issues such as delamination, cracking, and contamination early in the failure of materials.

The attention mechanism in the LSTM model provides a level of interpretability, as analysis of attention weights indicates that the model focuses on timeframes associated with heat waves and peaks in UV intensity. The model has been shown to produce consistent results with expectations from materials science indicating then degradation increases during extreme environmental conditions. The interpretation of the results and output enables building managers to avoid any misunderstanding related to the predictions made by the model.

4.5 Climate-Specific Modelling Requirements

An analysis on a single model trained across the various climate classification zones recorded a poor rating of only 71.3%, which is significantly less than the 87.3% rating obtained by the model when trained and applied per the climate-stratified classifications. This suggests that there should be a classification process involved before deploying a model for climate classification in order to apply the relevant parameters suited to specific zone characteristics instead of using a single set of parameters. The practical implication of this is specifically experienced in tropical and arid climatic conditions, which entail exposure to high dose UV exposure of over 2,800 MJ/m²/year and more than 500 annual thermal cycles creating a hazardous combination of stress parameters that should be taken care of when developing materials for these classifications.

4.6 Practical Implementation and Deployment Challenges

Transitioning from the operation of a research monitoring network to its implementation in practice presents a number of important issues that are beyond the modelling process, which are examined in this paper.

Reliability of sensors. During the initial implementation process, the failure of sensors in operation was recorded at a rate of 12 to 15% a year, and the error was mainly concentrated in the temperature and humidity sensors functioning in outdoor environment. The final configuration of the system involved redundancy in sensor applications as well as a machine learning-based approach to identify faults in the system that might lead to collecting wrong data, which raises the cost of the system, in addition to the price given in section 2.6, because organisations need to anticipate periodic replacement of sensors and ensure proper installations.

Connectivity. Having to depend on cell data connectivity is a serious limitation for an off-grid site or a place with low connectivity, even though the edge computing buffer that was implemented here reduces but doesn't eradicate this danger because breakdowns still occur from time to time resulting in delay in

getting the latest information to the forecasting model while this doesn't mean that any information is lost completely.

Systems integration. The use of a predictive maintenance platform that is independent from the existing building management system creates another difficulty as it means that people involved in the maintenance of buildings have to operate additional dashboard aside from the predictive maintenance tool.

Interpretation of the model's results in relation to the workforce of the organization. Staff who understand how to interpret probabilistic outputs must be present at the site in order to convert those outputs into actual maintenance decisions; the sites that do not have a technical team at hand had to resort to remote assistance from the research team in order to accomplish this project.

Drift and retraining. The model was trained by using 18 months' worth of data of a certain population which means that its accuracy might deteriorate due to changes in the types of glass used, changes in the pattern of climates, and changes in the types of sensors which are used; hence, retraining needs to be performed on the new data collected from the field periodically.

On a day-to-day basis, the systems operated a three-level indicator of treatment status in addition to the underlying probabilistic forecasting. The three-level indicator would be shown as normal operation, advisory flag for maintenance expected within six months, and an urgent flag for maintenance needed within three months. The simplified user interface was usually what facility personnel used for actual scheduling decisions instead of the raw output of the forecasting model.

4.7 Scalability and Technology Transfer

The cloud-based system allows for growth from a single building to a large portfolio without the same amount of overhead being incurred. As the fleet size increases to around 100 installations where the cost of ₹550/m² was calculated, per site monitoring cost should go down considerably. Publishing the core models as open-source (see Section 2.4) will help transfer the technology to countries with different contexts and costs than in this study. After looking into the South Asian and Sub-Saharan African contexts, we see that there is enough interest in adapting the method and approach, but there was more engagement than confirmed applications. Various forms of adaptation will have to rely on the development of workforce capacity building.

4.8 Limitations and Practical Deployment Challenges

The interpretation of our results is faced with some limitations that have to be considered when determining our next steps.

Time window of observations. We monitored the case of photochromic glazing for 18 months. However, the monitoring was not too productive in terms of actual equipment failure identification during this time. Our test demonstrated that photochromic glazing has useful lifespan much longer than 18 months. Therefore, it appears that further monitoring is required in order to know its degradation process and accurate life-cycle cost assumptions.

Material scope. All installations used a single tungsten oxide-based photochromic chemistry. Organic photochromic compounds such as spiropyrans and naphthopyrans are known to degrade through different

pathways and would require separate model training and, likely, separate feature engineering, rather than direct application of the model reported here.

Sample size and geographic coverage. Forty-seven installations across five climate zones is, to our knowledge, the largest field study of its kind, but the continental stratum ($n=6$) is smaller than the others due to site availability constraints noted in Section 2.1, and microclimate factors (local shading, surrounding building density, site-specific pollution levels) were not explicitly modelled. Expanding the installation count within under-represented strata, and adding explicit microclimate covariates, would likely improve model accuracy in exactly those regions where the current model is least well supported.

External validation. As discussed in Section 2.5, no independent third-party photochromic-degradation dataset currently exists against which to run a fully controlled external validation; the benchmarking conducted here against internal ablations, a conventional regression baseline, and contextual literature comparisons is the strongest test currently available, and independent replication using the released open-source model (Section 2.4) on new datasets is an important next step before the reported accuracy figures should be treated as generalisable beyond the conditions studied here.

Scope relative to other chromogenic technologies. This study addresses photochromic systems only; a comparative study spanning electrochromic, thermochromic and conventional high-performance glazing would be needed to inform technology-selection decisions across the full chromogenic glazing landscape.

Deployment readiness. The practical challenges listed in section 4.6 on sensor reliability, connectivity, systems integration, workforce capability and model drift imply that the accuracy and cost figures expressed here indicate performance in a research-backed scenario and not in regard to the full automation in a commercial deployment; translating this kind of research into a product requires consideration of the mentioned issues directly and clearly.

5. Conclusion

The results demonstrate that a field-tested (and validated) climate-based machine-learning system could predict phototropic glass wear and tear, 18 months ahead, with an impressive 87.3 percent reliability. The analysis also reveals that this solution supports cost-saving measures in maintenance which help save 18–27 percent of lifecycle costs and prolong material life. The results highlight a serious barrier that keeps phototropic windows only in demonstration projects, not allowing for investments to be efficient. Sensitivity evaluations in terms of sensor cost, power consumption, discount rate, and depreciation rates lead to a conclusion that the economic efficiency is not dependent on a particular scenario, allowing investors to feel more confident in the results of the study. In relation to the circular economy, there is a public statement which indicates a 34.7% decrease in consumption of materials and a total estimated loss of waste materials due to installation for 20 years, with disposal of 2847 kg of waste from landfills. The mention of 67.3 kg CO₂-eq/m² represents the value of the carbon value of materials. Expanding the monitoring period, diversifying the types of materials applied and climate conditions considered, as well as conducting comparative trials with other kinds of chromogenic materials emerge as the most urgent tasks for the future research.

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