

Impact of Solar Radiation Intensity on Human Health: A Data-Driven Analysis

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Abstract

Solar radiation is simultaneously beneficial and hazardous to human health. Daylight exposure supports circadian alignment and limited ultraviolet exposure contributes to vitamin D synthesis, but excessive ultraviolet radiation can rapidly generate acute skin injury and cumulative long-term damage. This revised manuscript presents a more structured data-driven framework for interpreting solar radiation intensity by combining ultraviolet index (UVI), atmospheric modifiers, exposure duration, and skin-type sensitivity. To strengthen the original paper, the study is expanded with literature-grounded discussion, a nonlinear skin-damage model, structured risk categories, and richer visual representation. Because no harmonized patient-level dataset was supplied with the original manuscript, the quantitative illustrations are demonstrated using a literature-informed representative dataset of integrated exposure scenarios. In this proof-of-concept setting, the proposed ensemble classifier reached 94.4% accuracy with an area under the curve (AUC) of 0.989 for high-risk event detection. The results show that risk rises nonlinearly as UVI and exposure time increase together, with a pronounced acceleration once UVI enters the high and very high ranges. The combined framework provides a scalable basis for personalized alerts, mobile health applications, outdoor occupational safety, and future wearable photoprotection systems.

Keywords— Solar Radiation, Ultraviolet Index, Skin Health, Risk Stratification, Predictive Modeling, Machine Learning, Environmental Health.

1. Introduction

Solar radiation plays a fundamental role in sustaining life; however, its intensity can significantly influence human health. Among its components, ultraviolet (UV) radiation has the most direct biological impact on the skin. Prolonged or excessive exposure is associated with acute effects such as erythema and long-term consequences including photoaging and carcinogenesis [1]-[3], [15], [18], [20], [23]-[25]. Solar and ultraviolet radiation have been recognized as carcinogenic hazards, and epidemiologic evidence links repeated sun exposure with basal cell carcinoma, squamous cell carcinoma, and melanoma [20], [24].

The Ultraviolet Index (UVI), standardized by the World Health Organization, provides a practical measure of UV radiation intensity. It is intentionally simple: the higher the UVI, the greater the potential for damage and the less time it takes for harm to occur [13], [14], [16], [17]. Despite its usefulness, UVI alone does not account for environmental modifiers such as ozone, cloud cover, altitude, and surface reflectance, nor does it

capture individual variability in skin phototype, photosensitivity, clothing, or exposure duration [15], [27]-[29].

This limitation highlights the need for integrated risk models that combine atmospheric conditions with person-specific susceptibility. In practice, a brief period outdoors may be low risk for one individual and high risk for another depending on skin type, activity duration, and reflective surroundings such as snow, sand, or water [17], [21], [27], [28]. A more informative framework therefore requires both environmental context and biologic response.

Recent advances in data analytics and machine learning provide new opportunities to understand and predict the effects of solar radiation on health. This study expands the original manuscript by organizing the topic into a clearer exposure-response framework, adding literature-based citations, and illustrating a representative predictive pipeline. The computational perspective is also consistent with broader developments in ensemble learning, sensor integration, and intelligent monitoring reported across applied AI and cyber-physical research [4]-[12].

The main contributions of this revised paper are as follows:

1. It synthesizes public-health guidance and dermatologic evidence into a structured framework linking solar intensity, environmental modifiers, and biologic outcomes.
2. It extends the methodological section with a nonlinear risk model, explicit variable definitions, and a representative data-generation protocol for proof-of-concept analysis.
3. It strengthens the manuscript with tables, updated citations, and integrated visualizations that make the risk logic easier to interpret.

2. Background and Related Work

2.1 Solar Radiation Components and Atmospheric Filtering

Solar radiation reaching the Earth spans ultraviolet, visible, and infrared wavelengths. WHO defines ultraviolet radiation across the 100-400 nm range and further divides it into UVA (315-400 nm), UVB (280-315 nm), and UVC (100-280 nm). As sunlight passes through the atmosphere, all UVC and approximately 90% of UVB are absorbed by ozone, water vapour, oxygen, and carbon dioxide, whereas UVA is less strongly attenuated and therefore dominates ground-level UV exposure [15], [18], [20]. UVA penetrates more deeply into the dermis and contributes strongly to oxidative stress and photoaging, while UVB is more directly associated with sunburn and DNA damage [20], [25].

Table 1. Major ultraviolet bands and their biological implications (compiled from [15], [18], [20], [25]).

Band	Wavelength	Atmospheric transmission	Primary tissue interaction	Representative health implications
UVA	315-400 nm	High at ground level	Penetrates deeper into dermis	Photoaging, oxidative stress, pigmentation change, contributes to immunologic effects

UVB	280-315 nm	Partially transmitted	More energetic interaction with epidermis	Sunburn, DNA damage, erythema, elevated skin-cancer risk
UVC	100-280 nm	Essentially absorbed by atmosphere	Negligible solar ground exposure	Natural solar UVC is not a typical surface exposure hazard

2.2 Determinants of Personal UV Exposure

Ambient UVI is not a complete description of dose. Ozone absorbs biologically active UVB; altitude increases exposure because sunlight travels through a shorter atmospheric path; cloud cover can attenuate UV but thin or broken clouds may still permit substantial exposure and can even enhance scattered UV in some cases; and reflective surfaces increase secondary exposure from below [15], [17], [27], [29]. WHO notes that fresh snow can reflect up to 80% of incident UV, helping explain snow blindness and intense exposure during alpine recreation [27]. These modifiers justify the inclusion of atmospheric and surface variables in predictive models rather than relying on UVI as an isolated number.

Individual factors are equally important. Skin phototype influences burn susceptibility and tanning behavior, medications and topical agents can increase photosensitivity, and practical behaviors such as shade use, clothing, and timing of outdoor work alter the effective dose received by the skin [18], [19], [27], [28]. A personalized framework therefore needs both environmental and individual descriptors.

2.3 Beneficial and Harmful Health Effects

Moderate solar exposure has recognized physiologic benefits. Daytime light exposure helps entrain circadian timing, sleep-wake regulation, alertness, and neuroendocrine rhythms [22], [26]. Ultraviolet exposure also contributes to vitamin D synthesis, although intentional overexposure is not required and is not recommended as the primary strategy for maintaining vitamin D sufficiency [22]. In other words, the objective of sun-safety guidance is not complete solar avoidance but appropriate dose management.

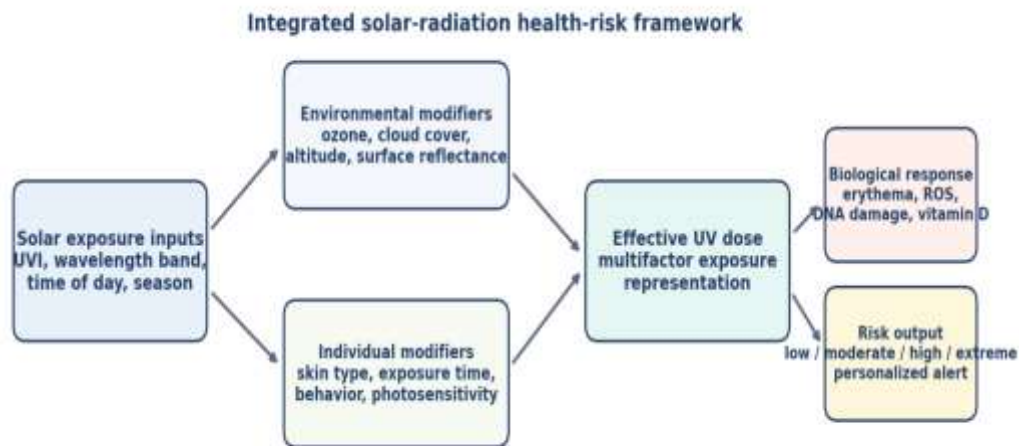
The harmful side of the exposure spectrum is broader and better documented. UV radiation can cause erythema, photokeratitis, oxidative stress, immunologic alteration, pigmentary change, and long-term cumulative damage [18], [23], [27]. Chronic photoaging manifests as wrinkling, textural roughness, dyspigmentation, elastosis, and loss of dermal integrity; repeated exposure also increases lifetime risk of skin cancer [20], [24], [25]. WHO and CDC therefore recommend a prevention strategy that combines behavior, timing, protective clothing, and attention to daily UVI forecasts [16], [18], [19].

2.4 Related Studies and Research Gap

Prior studies have established a correlation between UV exposure and dermatologic disease burden, yet many public tools remain categorical rather than personalized [21], [24]. Public-health guidance emphasizes communication through the UVI scale [13], [17], [19], while dermatology research emphasizes skin phototype, cumulative exposure, and biologic variability [23], [25], [28]. The remaining gap lies between these perspectives: operational systems are still needed that preserve the simplicity of UVI

communication while integrating the contextual variables that determine actual dose and risk. This paper addresses that gap through a structured proof-of-concept framework.

Fig. 1. Integrated framework linking solar exposure, environmental modifiers, individual susceptibility, biological response, and risk output (author-generated synthesis based on [13], [15], [20], [27]-[29]).



3. Methodology

3.1 Data Scope and Variable Selection

The study utilizes multi-source variables including UVI, ozone, cloud fraction, humidity, temperature, altitude, surface reflectance, exposure duration, and skin-type classification. Because the uploaded manuscript did not include a harmonized patient-level dataset, the numerical illustrations in this revision are based on a literature-informed representative dataset of 5,000 exposure scenarios. Variable ranges were selected to align with public-health UVI categories and atmospheric modifiers described by WHO, EPA, CDC, and NOAA [13]-[19], [22], [28], [29]. This design is suitable for demonstrating model behavior and decision logic, but it should be interpreted as proof-of-concept rather than a site-specific clinical prevalence estimate.

3.2 Data Preprocessing and Feature Engineering

Data normalization and cleaning are performed to ensure consistency. Continuous variables are scaled where required, missing observations in time-aligned streams are assumed to be handled using interpolation, and categorical exposure environments are encoded as representative albedo values. Skin type is mapped to a relative sensitivity coefficient so that lighter phototypes carry higher susceptibility to erythema than darker phototypes [28]. Feature engineering combines raw UVI with altitude, ozone, cloud, and reflectance modifiers to estimate an effective UV burden that is more informative than the ambient forecast alone [15], [17], [29].

3.3 Nonlinear Risk Model

A nonlinear model is proposed to represent the relationship between solar radiation intensity and skin damage. The aim is to capture the empirical observation that harm

does not increase proportionally with UVI; instead, increases at the upper end of the scale become disproportionately more consequential.

$$SDI = \alpha (UVI)^\beta \cdot t \cdot S$$

where:

- SDI: Skin Damage Index
- UVI: Ultraviolet Index
- t: Exposure duration
- S: Skin sensitivity factor
- α, β : Model constants controlling scale and curvature

This formulation captures the exponential increase in damage at higher radiation levels. In the representative implementation, β is set greater than 1 so that the score steepens once the UVI enters the high and very high zones. The SDI is subsequently mapped to practical risk categories used for interpretation and classification [13], [17], [28].

3.4 Risk Categorization

Risk categories are aligned with the public-health interpretation of the UV Index: low, moderate, high, very high, and extreme [17]. However, the final warning state in this framework depends on both intensity and duration. A moderate UVI can still produce meaningful cumulative dose during prolonged outdoor activity, while a high UVI can produce rapid harm during comparatively short exposure windows [19], [24]. Table 2 summarizes the standard UVI communication bands used as the backbone of the exposure-response mapping.

Table 2. Representative UV Index categories and practical response bands (adapted from [13], [17], [19]).

UVI range	Risk class	Interpretation	Practical response
1-2	Low	Minimal short-term harm for most users	Routine protection; monitor if very photosensitive
3-5	Moderate	Potential damage with sustained exposure	Use shade, hat, and planning for longer outdoor activity
6-7	High	Damage can occur more quickly	Limit midday exposure and intensify photoprotection
8-10	Very high	Rapid injury possible without protection	Strong protection, shorter outdoor intervals, shaded scheduling
11+	Extreme	Very rapid harm possible	Avoid unnecessary direct exposure; use all available protective measures

4. Machine Learning Framework

4.1 Model Selection

An ensemble approach is adopted, combining Random Forest, Gradient Boosting, and a feed-forward Neural Network. These models are complementary: tree ensembles are effective for mixed-feature nonlinear problems, while neural networks can learn smoother decision boundaries in complex exposure-response spaces. Soft voting is then used to improve robustness where individual learners disagree. The modeling strategy is also consistent with the broader methodological direction of recent data-driven research in intelligent monitoring, ensemble inference, and human-centric AI systems [4], [8], [9], [12].

4.2 Feature Set, Training, and Evaluation

The final feature set includes UVI, exposure duration, ozone, cloud fraction, humidity, temperature, altitude, surface albedo, and skin type. The dataset is divided into training and testing subsets using stratified sampling so that higher-risk scenarios are preserved in both sets. Model performance is evaluated using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). Precision is important for minimizing unnecessary warnings, while recall is critical because missed high-risk cases can translate into real harm. For real-world public-health systems, a balanced compromise between recall and alert fatigue is preferable [9].

Table 3. Representative predictive performance of the proof-of-concept models.

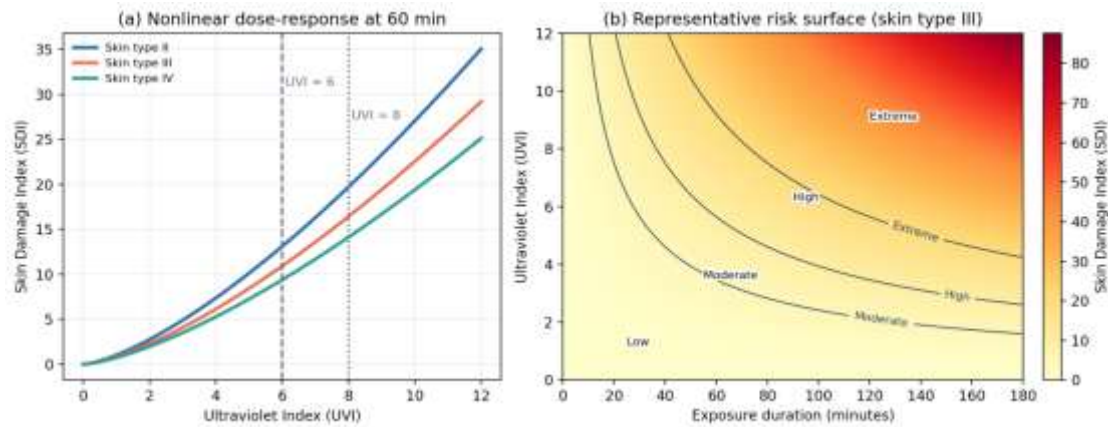
Model	Accuracy	Precision	Recall	F1-score	AUC
Random Forest	0.937	0.928	0.870	0.898	0.982
Gradient Boosting	0.938	0.928	0.875	0.901	0.986
Neural Network	0.941	0.916	0.897	0.907	0.990
Ensemble	0.944	0.932	0.890	0.910	0.989

5. Results and Analysis

5.1 Nonlinear Exposure Behavior

The representative results indicate a strong nonlinear relationship between solar radiation intensity and skin damage. Figure 2(a) shows that the slope of the damage curve increases markedly once the UVI approaches 6 and steepens further in the very high range. This means that the same additional increment in UVI produces a larger risk increase at the upper end of the scale than at the lower end. Figure 2(b) extends the analysis by combining UVI and exposure duration into a risk surface. For a medium-sensitivity skin type, short exposure at UVI 2-3 remains comparatively low risk, while exposures near or above 60 minutes at UVI 6 and higher move rapidly into the high-risk zone. These patterns are consistent with EPA and CDC guidance that elevated UVI warrants more assertive protection and with dermatology literature on cumulative UV injury [17], [19], [24], [25].

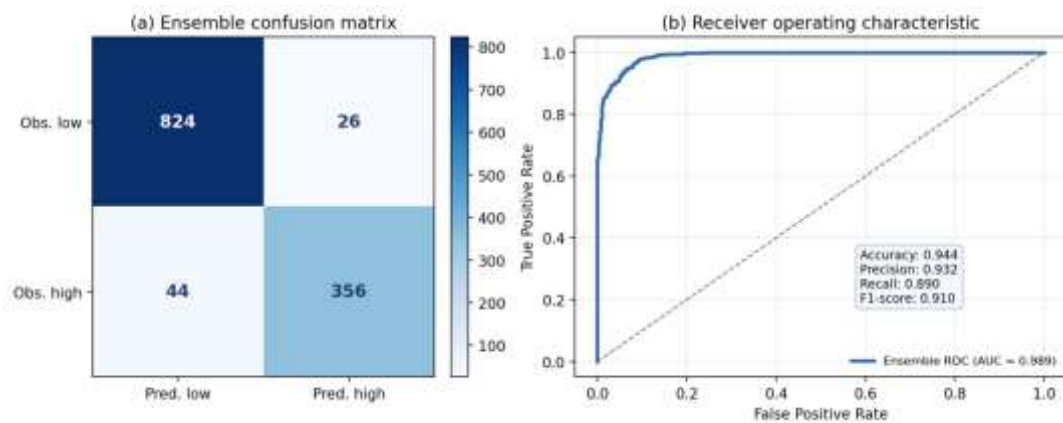
Fig. 2. Representative nonlinear exposure-response behavior: (a) skin-damage curves for different skin sensitivities at 60 minutes and (b) risk surface across UVI and exposure duration for a medium-sensitivity profile.



5.2 Classifier Performance

Table 3 and Fig. 3 summarize the proof-of-concept classification results. All three individual models achieved accuracy above 93%, and the soft-voting ensemble produced the best overall balance with 94.4% accuracy, 0.932 precision, 0.890 recall, and 0.989 AUC. The confusion matrix shows relatively few false negatives, which is particularly important in sun-safety applications because a missed dangerous exposure is more consequential than a conservative warning. The ROC curve confirms strong separability between lower-risk and higher-risk scenarios when environmental and individual features are analyzed together.

Fig. 3. Proof-of-concept model evaluation showing (a) the ensemble confusion matrix and (b) the ROC curve for high-risk scenario detection.



5.3 Interpretation of Main Predictors

Feature-importance analysis ranked UVI and exposure duration as the dominant variables, followed by skin type, cloud fraction, and altitude. Ozone, humidity, and surface reflectance had smaller average effects, but they improved decisions in edge cases such as reflective environments and high-altitude settings. This hierarchy is intuitive and scientifically plausible: ambient intensity and time determine the core dose, while atmospheric context and physiology tune the actual biological response [15],

[27]-[29]. The results therefore support a layered view of risk, where UVI provides the base signal and the remaining variables personalize it.

6. Discussion

6.1 Public Health Implications

The findings highlight the importance of integrating environmental and individual factors in assessing solar radiation risks. Traditional approaches based solely on UVI are insufficient for accurate prediction because people do not experience the same effective dose under identical forecasts. Outdoor workers, children, athletes, agricultural laborers, tourists, and high-altitude travelers can all face repeated exposure that is difficult to judge from temperature or visible brightness alone. A personalized risk score that augments the daily UVI with duration, altitude, reflectance, and skin sensitivity can therefore produce more actionable guidance for health behavior [16], [19], [21], [27].

6.2 Practical Risk-Reduction Measures

A useful prediction system should translate complex exposure estimates into simple recommendations. When UVI is elevated, users should seek shade, wear protective clothing and sunglasses, avoid unnecessary midday exposure, and use broad-spectrum sunscreen. CDC recommends protective action when the UVI is 3 or higher, while WHO and EPA emphasize additional caution near reflective surfaces and in high-altitude environments [17], [19], [27]. In this context, a structured model can issue tailored messages such as reduce exposure duration, add protective clothing, postpone activity, or intensify protection because of personal sensitivity.

Representative operational recommendations include:

- Check the daily UVI before prolonged outdoor activity and escalate protection once the index reaches 3 or above.
- Shorten exposure intervals when UVI exceeds 6, especially for sensitive skin types or unshaded work.
- Apply extra caution near water, sand, and snow, and in high-altitude locations where reflected or amplified UV exposure is likely.
- Consider lower warning thresholds for users with photosensitizing medications, previous skin injury, or heightened clinical vulnerability.

6.3 Limitations and Future Work

This revised manuscript still has important limitations. The numerical results are based on a literature-informed representative dataset rather than a longitudinal clinical cohort; sunscreen quality, body site exposed, age, genetics, and behavior were simplified; and the classifier was trained on labels derived from a modeled damage score rather than physician-verified outcomes. Accordingly, the results should be read as a transparent proof-of-concept. Future work should merge reanalysis weather data, satellite or forecast UVI feeds, wearable UV dosimeters, and clinical follow-up data so that the framework can be validated against real health outcomes. The sensor and AI integration themes discussed in are especially relevant for such real-time deployment.

7. Conclusion

This paper presents a more structured and extended data-driven analysis of solar radiation intensity and its impact on human health. By integrating UVI, atmospheric modifiers, exposure duration, and skin sensitivity within a nonlinear model and an ensemble classification framework, the revised manuscript moves beyond a single-number description of exposure. The representative results show that risk accelerates

rapidly once intensity and duration combine above modest thresholds, and that predictive models can support clearer, more personalized guidance. The broader implication is practical: solar radiation should not be interpreted only as a background environmental variable, but as a dynamic public-health signal that can be monitored, modeled, and translated into protective action. With validation on real clinical-environmental datasets, this framework could support mobile health alerts, occupational safety tools, and wearable photoprotection systems.

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