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Estimating Exposure Time for Solar Water Disinfection Using Survival Models

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Abstract: This study applied Cox proportional hazards regression to investigate the effects of environmental conditions—ultraviolet (UV) intensity, water temperature, and turbidity—on the time to complete inactivation of *Escherichia coli (E. coli)* during Solar Water Disinfection (SODIS). Regression data were obtained from 33 SODIS experiments carried out in Nsukka, Nigeria, over a five-month period from April to August 2021. The results revealed that both UV intensity and water temperature were statistically significant predictors of disinfection time. Specifically, an increase of 1 W/m² above the mean UV intensity (47.05 W/m²) increased the hazard of *E. coli* inactivation by 30% (HR = 1.30, p = 0.0002), while a 1°C rise above the mean temperature (44.85°C) raised the hazard by 122% (HR = 2.22, p < 0.00001). Turbidity, however, showed no significant effect (p = 0.97). The overall model was significant (likelihood ratio $\chi^2 = 93.73$, df = 3, $p < 0.0001$), and the Nagelkerke pseudo R^2 was approximately 0.93, indicating a strong model fit. These findings suggest that UV intensity and water temperature are critical factors influencing the efficiency of SODIS, while turbidity within the studied range does not significantly alter bacterial survival outcomes.

Keywords: SODIS; *E. coli*; survival analysis; UV; temperature; turbidity

1. INTRODUCTION

The World Health Organization (WHO) reports that over 50,000 Nigerian infants die each year from diarrheal diseases linked to drinking water contaminated with harmful microbes, making Nigeria second only to India in such fatalities [1]. Relying solely on centralized water treatment systems—like piped networks and tank-distributed supplies—poses challenges, as water can still become contaminated during transit and storage [2]. To address this, WHO promotes household-level water treatment approaches such as Solar Water Disinfection (SODIS), which enables individuals to drink directly from the container in which the water was purified [3].

SODIS has been shown to particularly benefit vulnerable populations [3], improve public health outcomes [4], [5], and serve as an accessible solution for communities in Nigeria that face acute water quality issues [6]. Ongoing research and awareness campaigns on SODIS have largely focused on overcoming technical constraints and behavioural barriers that limit its broader acceptance and implementation [7] - [9].

The SODIS process involves placing water of questionable microbial quality in transparent plastic or glass bottles and exposing them to direct sunlight for one to two days. This exposure to UV radiation and heat from the sun triggers oxidative and degradation reactions that disrupt microbial cell functions—damaging DNA, denaturing proteins, impairing glucose uptake, and ultimately leading to cell death [10]. Studies have confirmed that all traditionally recognized waterborne pathogens can be effectively inactivated within six hours of intense sunlight exposure using SODIS [11]. Although concerns exist about harmful substances like genotoxins and endocrine disruptors leaching from PET bottles during solar exposure, studies have shown these are either confined to the bottle surfaces or present at negligible levels in the water, suggesting comparable health risks regardless of sunlight exposure [12] - [14].

SODIS methods are recommended for use in areas and seasons where peak solar UV radiation over a six-hour period reaches at least 45 W/m² and/or the water temperature reaches 50 °C, as these conditions are necessary to achieve complete bacterial inactivation [15]. However, whether this threshold is met on any given day depends on variable and unpredictable factors such as cloud cover, UV intensity, and ambient air temperature [16] - [18]. Selecting a functional exposure period for SODIS, which is the time required for complete die-off of a target pathogen, in any climate requires that the variabilities in these variables are accounted for.

The exposure period in SODIS is inherently a time-to-event variable and is therefore more appropriately analyzed using survival analysis techniques. However, many existing studies have used ordinary least squares (OLS) regression to estimate SODIS exposure periods, typically by predicting microbial inactivation rates based on key process parameters. For instance, Haider et al. [17] applied multivariate regression to model SODIS exposure time under different levels of turbidity, ambient temperature, and cloud cover, and found that exposure time varied significantly with turbidity and cloud conditions. Similarly, Sajjala et al. [19] employed response surface regression to analyze how solar irradiation, container volume, and exposure duration influenced the log reduction values (LRV) of total coliforms. Mansoor Ahammed et al. [20] investigated how turbidity, pH, and dissolved oxygen (DO) affect the efficiency of SODIS and observed a significant interaction between turbidity and DO. Nwankwo and Ekwueme [18] developed a comprehensive regression model to estimate the inactivation rate constant of Escherichia coli in SODIS, incorporating UV intensity, water temperature, and turbidity, along with their interactions and quadratic terms. Their study revealed interactions between UV intensity and temperature, and between temperature and turbidity, but found no significant interaction between UV intensity and turbidity within the turbidity range of 1–30 NTU.

Despite the inherently stochastic nature of the SODIS exposure period, no prior studies have employed probability-based regression models to quantify the associated risks or uncertainty. Therefore, the objective of the present study is to model the exposure period using the Cox proportional hazards regression, a survival analysis method that allows for probabilistic modeling of exposure time under varying environmental conditions.

1.1 Theory of Survival Analysis

Survival data are typically analyzed using two closely related concepts: survival probability and hazard. The survival probability, also known as the survivor function S(t), represents the likelihood that an individual or group remains alive or unaffected from a defined starting point (such as the moment of exposure or diagnosis) up to a particular future time t.

$$S(t) = P(T > t) \tag{1}$$

See Clark et al. [21], Kartsonaki [22], and Jenkins [23] for more details on the theoretical background of survival analysis.

The hazard, typically represented as h(t), refers to the probability that an individual who is still being observed at time t will experience the event at that precise moment. In other words, it reflects the immediate risk or rate of the event occurring at time t, given that the individual has survived up to that point.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t | T > t)}{\Delta t} \tag{2}$$

The cumulative hazard function, H(t) is the area under the curve y = h(x) from x = 0 to x = t. For those with a calculus background H(t) can be expressed as

$$H(t) = \int_0^t h(x)\,dx \tag{3}$$

The relationship between the survival function S(t) and the cumulative hazard function H(t) is given by the following exponential formula:

$$S(t) = \exp(-H(t)) \tag{4}$$

Unlike the survivor function, which describes the probability of avoiding an event up to a certain time, the hazard function centers on the likelihood of the event actually happening at a specific time. It is particularly useful because it reveals the conditional risk of failure and serves as a foundation for defining survival models. In essence, the hazard captures the immediate rate of occurrence, while the survival function represents the accumulated chance of the event not happening.

1.2 Cox Proportional Hazards Model

Survival analysis offers a way to investigate whether, and to what extent, environmental conditions influence how long bacteria persist during solar disinfection. To evaluate these effects, regression models can be applied—much like how linear regression is used for continuous outcomes or logistic regression for binary outcomes. Among these, the Cox proportional hazards model is the most widely used approach for examining how different covariates influence survival time.

A multivariate Cox proportional hazards model [24] has the form:

$$h(t; X) = h_o(t)e^{\beta^T X}; \quad X: x_1, \ldots, x_p; \quad \beta: \beta_1, \ldots, \beta_p \tag{5}$$

In this model, $h_o(t)$ represents the baseline hazard—essentially, the risk of the event occurring when all covariates are either zero or at their average values. The X terms are the covariates (predictor variables), and the β values are the parameters estimated by the model, showing how each covariate influences the outcome. If the $h_o(t)$ is desired at the average values, the covariates are centered by subtracting their average values before using in analysis. A key assumption of the Cox proportional hazards model is that the hazard ratio—the ratio of the hazard with covariates to the baseline hazard—remains constant over time. The model estimates relative risk, not absolute risk, meaning the focus is on how much more (or less) likely an event is to occur under certain conditions. The covariates contribute additively on the log scale, and each unit increase in a covariate multiplies the hazard by e^{β}. If centering is applied X is replaced with X^c, which is defined as $X_{ij}^c = X_{ij} - \bar{X}_{.j}$. Where X_{ij} is the value of covariate j for observation i; $\bar{X}_{.j} = \frac{1}{n}\sum_{i=1}^{n} X_{ij}$. The unknown parameters β in a Cox proportional hazards model can be estimated using the partial likelihood (PL),

$$PL(\beta) = \prod_{i=1}^{n} \frac{exp(\beta^T X_i)}{\sum_{j \in R_{(t_i)}} exp(\beta^T X_j)} \tag{6}$$

Where $R_{(t_i)}$ denotes the risk set at time t_i, X_i is the covariate vector for individual i. The partial likelihood can be treated as a likelihood. Standard errors for the estimate of β are based on asymptotic results [25].

Nagelkerke R^2 also known as Adjusted Cox-Snell R^2 is an important R^2-like performance indicators for survival analysis because it is more interpretable and comparable across models when compared to others such as Cox-Snell R^2 as well as Royston and Sauerbrei's R_D^2. Nagelkerke R^2 is given by

$$Nagelkerke\ R^2 = \frac{R^2_{Cox\ \ Snell}}{1 - L_0^{2/n}} \tag{7}$$

where

$$R^2_{Cox\ \ Snell} = 1 - \left(\frac{L_1}{L_0}\right)^{\frac{2}{n}} \tag{8}$$

L_1 is the full model with all the covariate (predictors) and L_0 is the null model, with predictors omitted.

2. MATERIALS AND METHOD

2.1 Description of Study Location

The experiments were carried out in Nsukka, located in Enugu State in the southeastern part of Nigeria. Geographically, Nsukka lies between latitudes 6.83°N and 6.86°N and longitudes 7.36°E and 7.42°E. The town sits on a plateau within an escarpment zone, with elevations ranging from 280 to 530 meters above sea level, averaging around 429 meters. Recent weather records for Nsukka Urban indicate a peak monthly rainfall of 231 mm, atmospheric temperatures ranging from 22 °C to 36 °C, and an average annual relative humidity of 77%. The region experiences heavy rainfall between June and October, followed by a prolonged dry season from November to March. During the dry months, sunlight is notably reduced due to aerosol particles and dust carried by the Harmattan wind—dry, dusty northeasterly trade winds that blow from the Sahara Desert toward the Gulf of Guinea.

Previous research [26] examining seasonal patterns in solar radiation and maximum air temperature confirmed the feasibility of SODIS in Nsukka. Their findings showed that, on average, only July, August, and September failed to meet the minimum recommended solar radiation threshold of 500 W/m² required for effective SODIS. This assessment was based on monthly averages of 5-hour midday solar radiation and maximum air temperature, supporting the suitability of Nsukka's climate for SODIS applications for most of the year.

2.2 Experimental Setup

The regression data were obtained from 33 SODIS experiments conducted over a five-month period from April to August 2021. Each experiment used a 1.5 L Coca-Cola PET bottle—chosen for its global availability, durability, and thermal stability—fitted with a mercury-in-glass thermometer and placed on a black polyethylene surface to enhance heat absorption. This setup aimed to accelerate water heating by transmitting absorbed solar energy directly to the water. To ensure a tight seal without adhesives, the thermometer was inserted through a catheter hub and mounted into a hole in the bottle's cap. Water temperature was recorded every 30 minutes to determine daily maximum values, with thermometer accuracy regularly verified against a reference digital thermometer at the National Centre for Energy Research and Development (NCERD), showing a deviation of no more than ±0.2 °C. Before each use, the bottles were disinfected overnight in Hypo™ (a hypochlorite solution), then thoroughly rinsed with tap water followed by the test water.

Figure 1. Experimental setup

2.3 Preparation of Test Water and Microbial Analysis

E. coli was chosen as the model organism in this study because it serves as a reliable indicator of faecal contamination and is widely studied in SODIS research due to its relatively high resistance to solar disinfection [11]. All test water was collected at once from a borehole and stored in a 200 L plastic drum to ensure uniform physicochemical characteristics throughout the study, which were checked monthly. Prior to each experiment, the water was sterilized and then inoculated with a previously cultured *E. coli* stock, diluted to achieve a concentration of approximately 10^6 CFU/mL. Each PET bottle was filled two-thirds full and shaken to promote oxygen dissolution, then topped off to full volume, yielding a consistent dissolved oxygen (DO) level of 6.1 ± 0.21 mg/L. No residual chlorine was detected in the water. Turbidity was adjusted using kaolin (China clay) and varied randomly between 0 and 30 NTU. Initial samples were collected before solar exposure, while subsequent samples were taken at 30-minute intervals or longer, using sterilized hypodermic syringes depending on cumulative UV exposure.

UV radiation was monitored using a General Tools UV513AB Digital UVA/UVB Meter (280–400 nm), which displays irradiance in mW/cm² or µW/cm². To automate data collection, an Android app (Open Camera 1.48.3) was used to take periodic snapshots of the UV meter's LCD every 60 seconds between 10 a.m. and 4 p.m. This enabled the estimation of daily UV profiles and calculation of the 5-hour average maximum UV intensity for each experiment. All experimental runs were conducted between April and August 2021. *E. coli* inactivation rates were calculated based on first-order kinetics.

$$N_t = N_o\, e^{-kt} \qquad (9)$$

Here, k denotes the inactivation rate constant per hour, N_t represents the *E. coli* population at time t, N_o is the starting population, and e is the base of the natural logarithm.

Equation (1) can be expressed in its linearized form:

$$\log_e N_t = \log_e N_o - kt \qquad (10)$$

E. coli survival time (t_s, i.e., time taken for $N_t = 0$) was estimated by applying a regression line to the paired data [log $N(t)$, t] before evaluating t_s as t at $N_t = 0$.

3. RESULTS AND DISCUSSION

3.1 Cox Proportional Hazards Regression Result

A Cox proportional hazards regression model was used to evaluate the effects of UV intensity, water temperature, and turbidity on the time to complete inactivation of *E. coli* during SODIS. The model was statistically significant, with a likelihood ratio chi-square of 93.73 (df = 3, $p < 0.0001$), indicating that the full model with predictors jointly provide a much better fit than a null model without predictors. The log-likelihood of the full model was –38.19, compared to –85.05 for the null model. Based on these values and a sample size of 33, the Nagelkerke pseudo R-squared was calculated at approximately 0.93, showing that the predictors explained about 93% of the variability in survival time.

Centered UV intensity and centered maximum water temperature (Max. T) were both significant predictors of the hazard of disinfection. The UV coefficient (0.264, p = 0.0002) corresponded to a hazard ratio of 1.30 (95% CI: 1.13–1.49), meaning each unit increase in UV intensity above the mean of 47.05 W/m² increased the disinfection likelihood by 30%. Water temperature had an even stronger effect, with a coefficient of 0.796 ($p < 0.00001$) and a hazard ratio of 2.22 (95% CI: 1.57–3.13), indicating a 122% increase in disinfection hazard for every 1°C rise above the mean temperature of 44.85°C. Turbidity, however, showed no significant effect (coefficient = –0.0009, p = 0.97; hazard ratio ≈ 1.00, 95% CI: 0.95–1.05), suggesting that within the tested range, turbidity did not influence the rate of inactivation. The model's convergence diagnostics and covariance matrix confirmed stability and reliable parameter estimates, reinforcing the findings that UV and temperature are the primary drivers of *E. coli* inactivation in this context.

Figure 2 presents the adjusted (predicted) survival curves of *E. coli* at two turbidity levels under various UV and temperature conditions. Notably, the survival curves for 0 and 30 NTU are identical across all UV-temperature combinations, reinforcing the earlier conclusion that turbidity within this range has little to no impact on *E. coli* survival. The curves were evaluated at UV-temperature conditions that simulated realistic experimental conditions. As shown in Figure 1(a), when UV intensity is 40 W/m², even a water temperature of 45 °C is not sufficient to achieve full inactivation—some *E. coli* are likely to survive, and the probability of complete disinfection after 6 hours is only about 50%. Full inactivation is only predicted when UV intensity rises to 50 W/m², even if the temperature remains unchanged. Under these conditions, *E. coli* survival probability drops to less than 0.001 after 6 hours of exposure.

Lower survival probabilities were recorded at higher values of UV and temperature.

Table 1: Result of Cox regression

(a) Overall Fit	
Chi-sq	93.734
Df	3
p-value	<0.001

(b) Regression Summary	β	s.e.	p-value	lower	upper	exp(β)
Centered UV	0.264	0.070	<0.001	0.126	0.401	1.302
Centered Max. T	0.796	0.176	<0.001	0.452	1.141	2.217
Centered Tu	-0.001	0.025	0.970	-0.050	0.048	0.999

UV – Ultraviolet intensity; Max. T – maximum water temperature; Tu - Turbidity

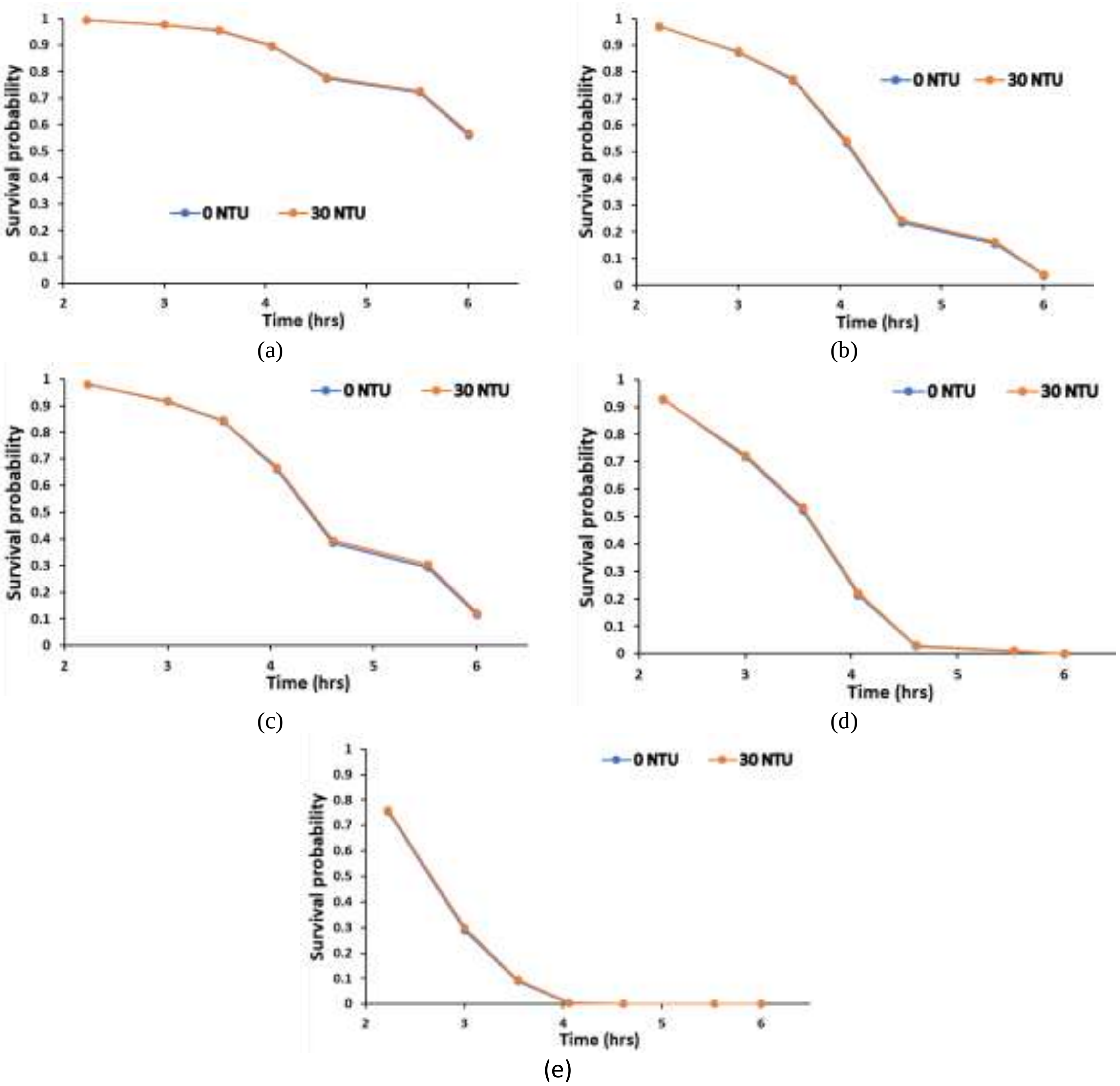

Figure 2. Adjusted (predicted) survival curves of E. coli at two turbidity levels, evaluated under different combinations of UV intensity and maximum water temperature: (a) UV = 40 W/m^2, Max. temp. = 45 °C; (b) UV = 47 W/m^2, Max. temp. = 44.8 °C; (c) UV = 45 W/m^2, Max. temp. = 45 °C; (d) UV = 50 W/m^2, Max. temp. = 45 °C; (e) UV = 55 W/m^2, Max. temp. = 45 °C

3.2 Effect of UV Intensity and Temperature on the Survival of *E. coli*

The survival analysis revealed a strong linear relationship between the survival time of *E. coli* and two key environmental variables: the 5-hour average of midday UV intensity and the maximum water temperature. This finding is consistent with recent studies by Brockliss et al. [27] and Samoili et al. [28], which similarly linked the cumulative die-off rate of *E. coli* to solar irradiance and water temperature. The hazard ratio of 1.30 for UV intensity and 2.22 for maximum water temperature indicate that a unit increase in maximum temperature has a greater impact on the survival of *E. coli* than a unit increase in UV intensity. This result is somewhat surprising, given that UV radiation is widely acknowledged as the primary source of hazard in SODIS [29], [30]. However, prior studies have shown that high water temperatures—particularly above 45 °C—can significantly diminish bacterial survival capacity, even under relatively low UV exposure [31], [32]. This temperature effect likely explains the stronger influence of temperature observed in this study. Indeed, water temperatures above 45 °C were recorded in approximately 48% of the experimental runs.

In practice, while UV intensity can be estimated using cloud cover observations as recommended by SODIS guidelines [15], the daily maximum water temperature can also be determined through simple methods, such as using a temperature bottle [6], [26]. A temperature bottle is a specially designated SODIS bottle used in the field to monitor and record the highest water temperature reached during exposure to sunlight. Since UV intensity and maximum temperature are often strongly correlated, either can be used to predict treatment outcomes. This correlation is largely attributed to the tropical climate, where strong sunlight is typically accompanied by high temperatures, making "sunny but cold" conditions uncommon [26]. Measuring the maximum water temperature around 2 p.m. has proven to be a dependable indicator of SODIS performance: complete *E. coli* inactivation can be expected after a single day with temperatures reaching 50 °C or after two consecutive days of 45–50 °C. In contrast, estimating cloud cover requires continuous observation, which can be error-prone and mentally taxing, potentially reducing user confidence and consistent use of SODIS

3.3 Effect of Water Turbidity on Survival Probability of *E. coli*

Water turbidity is a crucial factor in the effectiveness of SODIS. Many studies have shown that higher turbidity reduces the efficiency of the disinfection process [16], [33], [34]. For example, Amirsoleimani and Brion [34] found that increasing turbidity from 0 to 200 NTU reduced the *E. coli* die-off rate from 5 to 1 log units. This is primarily because light penetration is hindered in turbid water, which interferes with the solar disinfection mechanism [35]. However, these findings apply to much higher turbidity levels than those tested in this study. The 30 NTU threshold has since become a standard upper limit for turbidity in water treated with SODIS. Luzi et al. [15] described a simple field method for checking if water turbidity is below this threshold, and SODIS protocols recommend pretreatment for water that exceeds it.

In this study, there was no evidence that turbidity levels between 0 and 30 NTU affected exposure time. When tested as a variable, turbidity was not statistically significant—whether alone or alongside other predictor variables. This aligns with the findings of Brockliss et al. [27], who reported a weak correlation ($R^2 = 0.15$) between turbidity and bacterial die-off using natural water sources under 30 NTU. One explanation is that only UVB is strongly blocked by suspended particles, whereas UVA, though absorbed and scattered, continues to generate reactive oxygen species (ROS) within the water. These ROS can migrate through the water column and destroy pathogens, even without direct light exposure [15].

Interestingly, turbid water can also retain more heat due to the heat-absorbing nature of suspended particles. Amirsoleimani and Brion [34] observed significantly higher temperatures in 30 NTU water compared to clear water under the same solar conditions. This temperature gain can improve disinfection, as shown by Meera and Ahammed [36], who found higher SODIS efficiency at 38 NTU than at turbidity below 5 NTU. Joyce et al. [37] also reported complete bacterial inactivation at turbidity levels above 30 NTU, provided temperatures exceeded 55 °C. Despite this temperature advantage, high turbidity water is generally discouraged in SODIS. Studies have shown that water treated at lower turbidity levels offers more stable disinfection outcomes and better user acceptance, especially when complete inactivation and adequate UV exposure are ensured [38], [39].

4. CONCLUSION

The survival analysis indicates that solar water disinfection (SODIS) efficiency in inactivating *E. coli* is strongly influenced by both UV intensity and water temperature. The Cox proportional hazards model revealed that a unit increase in UV intensity above the mean leads to a 30% higher hazard of disinfection, while a 1°C rise in temperature above the average is associated with a 122% increase in the likelihood of bacterial inactivation. Therefore, optimizing SODIS protocols should prioritize maximizing sunlight exposure and water temperature, particularly in locations with variable weather conditions. In contrast, within the tested range (0–30 NTU), turbidity did not have a significant impact on survival outcomes. Overall, the model's excellent fit (with a Nagelkerke pseudo R^2 of approximately 0.93) supports the conclusion that UV intensity and water temperature are critical determinants of SODIS performance in Nsukka, Nigeria. These findings not only provide valuable insights for optimizing SODIS protocols but also underscore the importance of considering environmental variables when evaluating water disinfection strategies.

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