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Solar Water Disinfection (SODIS): Modelling Exposure Period with Geometric Distribution

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Abstract

Solar water disinfection (SODIS) is recognised and promoted as a simple and low-cost method for water quality improvement and diarrhoea prevention. However, there is potential for underexposure and incomplete disinfection due to the uncertainty arising from variable weather/exposure period. This study presents a probabilistic methodology for obtaining exposure periods from time series of historical solar energy data capable of resolving this uncertainty. To do this, SODIS exposure period was interpreted and computed in agreement with the underlying physical processes that govern geometric distribution. The methodology was illustrated by using geometric distribution to predict monthly exposure periods at 5% exceedance probability for 324 locations in Southeastern Nigeria. The parameter of the geometric distribution was estimated from solar radiation data obtained from NASA geo-satellite database. The results revealed both spatial and temporal variation of exposure period. Two days of exposure would ensure complete disinfection 95% of the days in November to May in virtually all the locations of the region. June to September is the least favourable period for SODIS application in Southeastern Nigeria, mostly requiring more than 2 days of exposure to ensure treatment. Performance validation of the model using confusion matrix showed an overall prediction accuracy of 83%, suggesting a reliable model for the prediction of exposure period. The exposure periods were presented in the form of monthly maps to serve as a tool for guarding against underexposure.

Keywords: Solar radiation, Exposure Period, Uncertainty, Geometric distribution, Exceedance probability

1.0 INTRODUCTION

According to World Health Organisation (WHO), more than 50,000 infant Nigerians die annually from symptoms of diarrhoea disease due to the consumption of microbially contaminated water, a number that is only surpassed by India [1]. Relying on resource-intensive, centralised water treatment and supply such as piped-borne connections and tank-vended distribution will leave so many people without access to safe water because water could still be contaminated during transportation and storage [2]. World Health Organisation (WHO) favours household-based, drinking-water treatment methods, such as solar disinfection (SODIS), that allows water to be consumed directly from the container in which it was treated [3]. SODIS methods target the most vulnerable [4], improve health [5, 6], and can be employed to address the immediate water quality needs of the most disadvantaged communities of Nigeria [7]. Strategies aimed at removing some technical limitations and addressing behavioural change factors that impede the diffusion and large-scale adoption of SODIS have been the focus of SODIS research and promotion campaign [8–10]. SODIS procedure involves storing drinking water of questionable microbial quality in containers (glass or plastic bottles) that can transmit ultraviolet (UV) radiation and placing them under direct sunlight for a day or two, after which the water is rendered safe for consumption.

The effect of UV and temperature components of the sun activates a series of degradation/oxidative processes that can cause loss of membrane potential, strand breakage in cell DNA, denaturation of cell protein, and interfere with the glucose uptake of the cells, leading to cell death [11]. To date, all pathogens classically characterised as water-borne are readily responsive to SODIS treatment within 6 h of exposure to strong sunlight [12].

There are concerns about the leaching of potentially harmful compounds into SODIS water during solar exposure, notably genotoxins and endocrine disruptors. However, these concerns have been addressed through several dark-control experiments that either showed that photoproducts were either detected on the outside surface of PET bottles or detected in water at low concentrations with no health significance [13–16]. Available evidence suggests that the health risk associated with consuming water stored in PET is the same, with or without solar exposure. Numerous clinical trials have proved the efficacy of SODIS at reducing diarrhoea in human populations [5, 6, 17-19], and more than 4.5 million people,

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spread over 55 countries, have started using SODIS for their daily water treatment [20-21].

SODIS is recommended for regions and seasons where the average 5-h peak radiation intensity exceeds 500 W/m^2. This radiation intensity threshold (disinfection threshold) is required for complete and irreversible bacterial inactivation, and whether or not it is exceeded on any particular day is an uncertain/random phenomenon that can only be predicted with a certain probability of success. For this reason, the operation of SODIS systems requires variable exposure period depending on the degree of cloud cover/radiation intensity [22–26]. To address the issue of variable weather/exposure period, SODIS guidelines [21] recommended 1-day exposure during sunny days when the weather is less than 50% cloudy and 2-day exposure when the weather is more than 50% cloudy as a practical way of achieving the disinfection threshold. To operate SODIS based on this recommendation would require a means of gauging cloud coverage on a day-to-day basis through the use of weather measuring devices that may be outside the reach of most rural communities of developing countries, whom SODIS targets.

In the absence of such devices, the term "50% cloudy" cannot always be perceived by the mind and is liable to the vagueness and error of human judgement due to the diurnal variation in cloud cover. To make such a determination on a partially cloudy day would require daylong, undivided attention to the sky. Such mental focus will increase the drudgery and cognitive stress of the overall SODIS operation. Increased labour and uncertainty about exposure period may reduce user's confidence in the efficacy of SODIS and curb people's inclination to adopt this method.

Other studies have attempted to model SODIS exposure period in terms of uncertain weather and water quality parameters, such as cloud cover, water turbidity, and pathogen concentration [23, 24]. However, the utility of such models to the end-users of SODIS is doubtful, because there are no known simple methods for measuring cloud cover and pathogen concentration without the use of expensive, high-tech devices or methods. Again, models that depend on variable and uncertain parameters cannot be thoughtlessly used for the design of water treatment systems without a report on the reliability and confidence level of the model results [27, 28]. The use of chemical/electronic UV dosimeter indicators as a visual measure of UV dose that provides complete and durable disinfection has been suggested as a way of removing the uncertainty [29–31].

These methods are based on the degradation and discolouration of a chemical dye when a requisite irradiation dose has been received. However, dosimetric determination of exposure period using chemical dyes does not seem realistic in practice because it will increase the complexity of the treatment process and create a need for the establishment of a supply chain for such chemicals. Moreover, if a chemical substance is to be added to the water, it may as well be one that disinfects the water without creating an additional need for irradiation (e.g., chlorination) [21].

Whenever uncertainty and randomness are present, it is a general engineering practice to select an appropriate probabilistic model that can quantify such uncertainty so that it can be taken into account in parameter selection and design [32, 33]. Despite the stochastic nature of SODIS exposure period, no studies have used a probability theory to quantify the associated uncertainty in order to produce location- and season-specific exposure periods that capture the variations in radiation intensity. Therefore, the objective of this study is to propose and verify a probabilistic methodology, using geometric distribution to model and extract exposure period (days) from time series of historical insolation data in order to eliminate the uncertainty arising from variable weather/exposure period. An exposure period determined in this way will be a character of that location and season, i.e., a characteristic exposure period (CEP)

2.0 FRAMING SODIS EXPOSURE PERIOD (DAYS) AS A GEOMERIC RANDOM VARIABLE

A geometric random variable describes the number of trials until the first occurrence of success, assuming each trial has equal success probability. Exposure period, if viewed as the number of exposure days (trials) until the occurrence of a threshold day (success), can be interpreted and modelled as a geometric random variable. The key assumption here is that complete disinfection is only achieved if the SODIS is exposed on a threshold day, i.e, a day whose radiation intensity is higher that the disinfection threshold. Table 1 compared the properties of geometric distribution with those of SODIS exposure period.

Table 1: Similarities between the properties of geometric random variable and exposure period

Properties of a Geometric Random Variable	**Properties of SODIS Exposure Period in days**
(i) Consist of a series of independent trials. (ii) Each trial results in two possible outcomes: success or failure. (iii) The probability of success stays the same for every trial.	(i) Consist of a series of exposure days. (ii) Each exposure day can either be above the disinfection threshold (success) or below the disinfection threshold (failure). (iii) The probability of meeting the disinfection threshold in a single trial stays the same in a short time frame (weekly, monthly).

The cumulative density functions (CDF) of geometric distribution is given by:

$$\forall \boldsymbol{k} \in N, \qquad F_o(k;p) = 1 - (1-p)^k \qquad (i)$$

Where N is a set of positive integers.

Equation (i) gives the probability that the first occurrence of success (a day with the disinfection threshold) requires k exposure days. Cumulative probability (F_o) is also known as the probability of non-exceedance and can be expressed as the complement of exceedance probability $(1 - F_o)$. It is formed by summing the probabilities of occurrence of all events less than k. Exceedance probability represents the risk of underexposure associated with a given exposure period. Exposure time for any month and location can be evaluated based on this risk.

Making the exposure period k in Equation (i) the subject, we have:

$$k = \frac{log_e(1 - F_o)}{log_e(1-p)} \qquad (ii)$$

If the parameter p is known, the exposure period k can be evaluated for different exceedance probabilities $(1 - F_o)$, (notably 10%, 5%, 1%) depending on the acceptable risk of underexposure. The greater the probability of exceedance the higher the risk of underexposure. The value of k given by Equation (ii) is always a decimal fraction and has to be rounded up to the nearest whole number. The resulting k is slightly higher and will provide some safety margins. The parameter p is usually estimated from the data as $\hat{p}_n$. Where $\hat{p}_n$ is the maximum likelihood estimator of p, which is given by:

$$\forall \boldsymbol{k} \in N, \qquad \hat{p}_n = \left(\frac{1}{n}\sum_{i=1}^{n} k_i\right)^{-1} \qquad (iii)$$

Equation (iii) is the inverse mean of the observed k.

The variability of SODIS exposure period matches the assumptions of geometric distribution listed above. If a disinfection threshold is chosen for SODIS, i.e., radiation dose that must be received in a day to ensure adequate treatment, solar energy data can be converted to exposure (days) as demonstrated in Table 2. The key assumption here is that effective and irreversible damage to microbial pathogens can only be achieved if the disinfection threshold is reached in a single day. Receiving less-than-threshold irradiation would not achieve complete and irreversible inactivation, even if the bottles remain exposed for days.

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3.0 APPLICATION OF GEOMETRIC DISTRIBUTION FOR THE ESTIMATION OF EXPOSURE PERIOD

3.1 Data Collection and Processing

Southeastern Nigeria was used to demonstrate the proposed procedure for determining monthly characteristic exposure period (CEP). Thirty-five years of solar energy data (Jul. 1983 – Dec. 2018 daily all-sky insolation incident on a horizontal surface) were collected for 27 locations monthwise in Southeastern Nigeria (lat. 4.5 – 7.5ºN, log. 6.5 – 8.5ºE) from the NASA geo-satellite database [34], which amounted to 324 datasets (27 locations multiplied by 12 months). The data is available for $^1/_2 \times {}^1/_2$ degree for the entire globe. The intersections of the lines of longitude and latitude in Figure 1 corresponds with the geographical locations whose CEPs were estimated.

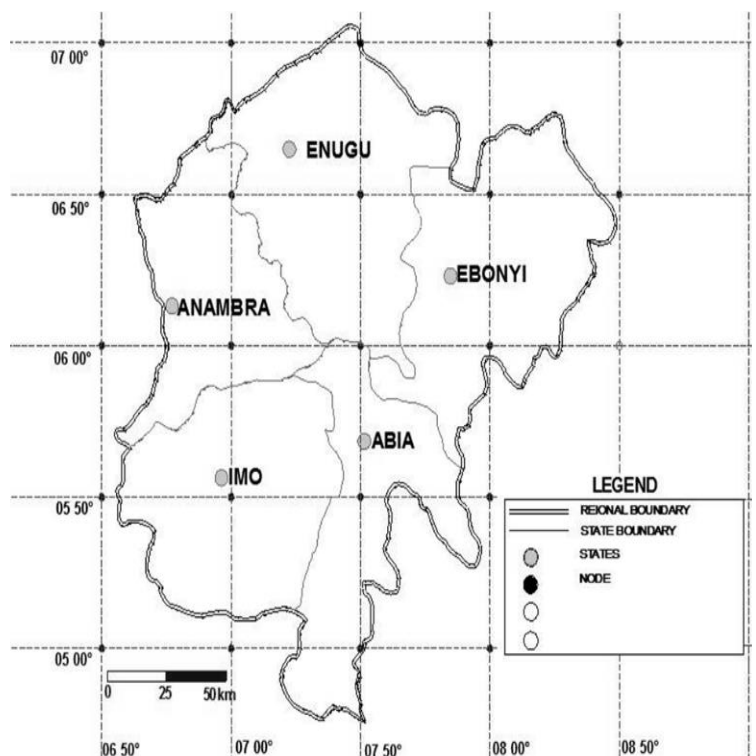


Figure 1: Map of Southeastern Nigeria divided into half by half degree NASA grid

Truncated data for the location of Nsukka (6.80ºN, 7.40ºE) was reproduced in Table 2 to demonstrate the procedure for transforming solar energy data to exposure period.

Daily cumulative solar irradiance (insolation) value of 4 kWh/m^2 was selected as the disinfection threshold for every location in Southeastern Nigeria. However, the actual disinfection threshold will vary slightly from location to location, depending on the ambient air temperature and UV content of solar radiation. Preliminary studies show that the occurrence of 4 kWh/m^2 can be associated with the occurrence of an average of 500 W/m^2 for 5 h, which is the SODIS radiation threshold, water temperature of > 50 ^{0}C, and irreversible damage to bacterial pathogens in relatively clear SODIS water (< 10 NTU) contaminated to the tune of 10^6 CFU/ml.

Another study carried out in Southwestern Ethiopia reported irreversible damage of faecal coliform after 4 h of exposure in a region with a daily cumulative solar irradiance of 3.99 kWh/m^2 [35].

Table 2: Procedure for Converting Solar Energy Data to Exposure Periods

1	2	3	4	5	6	7
SN	**Location coordinate**	**Date (d/m/y)**	**All-sky insolation on horizontal surface (kWh/m^2)**	**Cutoff Threshold (kWh/m^2)**	**Treatment/no treatment**	**Exposure period (EP) (days)**
1	6.8ºN, 7.4ºE	1/7/1983	3.32	4.00	No treatment	2
2	6.8ºN, 7.4ºE	2/7/1983	4.24	4.00	Treatment	1
3	6.8ºN, 7.4ºE	3/7/1983	4.06	4.00	Treatment	1
4	6.8ºN, 7.4ºE	4/7/1983	2.97	4.00	No treatment	2
5	6.8ºN, 7.4ºE	5/7/1983	4.30	4.00	Treatment	1
6	6.8ºN, 7.4ºE	6/7/1983	5.05	4.00	Treatment	1
7	6.8ºN, 7.4ºE	7/7/1983	3.43	4.00	No treatment	2
8	6.8ºN, 7.4ºE	8/7/1983	5.34	4.00	Treatment	1
9	6.8ºN, 7.4ºE	9/7/1983	5.30	4.00	Treatment	1
10	6.8ºN, 7.4ºE	10/7/1983	4.82	4.00	Treatment	1
11	6.8ºN, 7.4ºE	11/7/1983	5.71	4.00	Treatment	1
12	6.8ºN, 7.4ºE	12/7/1983	4.79	4.00	Treatment	1
13	6.8ºN, 7.4ºE	13/7/1983	4.16	4.00	Treatment	1
14	6.8ºN, 7.4ºE	14/7/1983	3.98	4.00	No treatment	4
15	6.8ºN, 7.4ºE	15/7/1983	3.87	4.00	No treatment	3
16	6.8ºN, 7.4ºE	16/7/1983	2.48	4.00	No treatment	2
17	6.8ºN, 7.4ºE	17/7/1983	4.02	4.00	Treatment	1
18	6.8ºN, 7.4ºE	18/7/1983	4.95	4.00	Treatment	1
19	6.8ºN, 7.4ºE	19/7/1983	4.51	4.00	Treatment	1
20	6.8ºN, 7.4ºE	20/7/1983	4.17	4.00	Treatment	1
21	6.8ºN, 7.4ºE	21/7/1983	5.44	4.00	Treatment	1
22	6.8ºN, 7.4ºE	22/7/1983	4.39	4.00	Treatment	1
23	6.8ºN, 7.4ºE	23/7/1983	4.50	4.00	Treatment	1
24	6.8ºN, 7.4ºE	24/7/1983	4.13	4.00	Treatment	1
25	6.8ºN, 7.4ºE	25/7/1983	4.37	4.00	Treatment	1
26	6.8ºN, 7.4ºE	26/7/1983	4.59	4.00	Treatment	1
27	6.8ºN, 7.4ºE	27/7/1983	4.23	4.00	Treatment	1
28	6.8ºN, 7.4ºE	28/7/1983	3.78	4.00	No treatment	5
29	6.8ºN, 7.4ºE	29/7/1983	3.12	4.00	No treatment	4
30	6.8ºN, 7.4ºE	30/7/1983	2.10	4.00	No treatment	3
31	6.8ºN, 7.4ºE	31/7/1983	3.76	4.00	No treatment	2
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
12968	6.8ºN, 7.4ºE	31/12/2018	5.42	4.00	Treatment	1

3.2 Model formulation and performance evaluation

As shown in Equation (ii) based on the inverse transformation of the cumulative density function (CDF) of geometric distributions

$$k = \frac{log_e(1 - F_0)}{log_e(1 - \hat{p}_n)} \qquad (iv)$$

Where "log_e" is the natural logarithm; F_o and $\hat{p}_n$ are the same as in Equation (ii).

For 95% confidence level (or 5% exceedance of exposure periods); that is, $F_o = 0.95$, Equation (iv) becomes

$$K_{cep} = \frac{-2.996}{log_e(1 - \hat{p}_n)} \qquad (v)$$

Where k_{cep} is the theoretical estimate of the CEP such that only 5% of exposure periods fall above k_{cep}. Once $\hat{p}_n$ is computed for any month, Equation (v) can be used to estimate the k_{cep}. Setting $F_o = 0.95$ guarantees that the estimated values of k_{cep} (days) have a 95% chance of containing at least a day whose total radiation energy exceeds the selected disinfection threshold value of 4 kW/m^2.

Using Equation (v), k_{cep} for the 324 datasets, representing 27 locations in Southeastern Nigeria (January to December) was determined. The parameter, $\hat{p}_n$, was estimated for each month using 60 data points of EP randomly selected from the 35 years of EPs. The model performance was evaluated by comparing the observed and estimated CEPs (k_{cep}) for all the months and locations using a multiclass confusion matrix (matching matrix). The confusion matrix features the frequencies of the observed and predicted CEPs in a format that allows the visualisation of the model performance. The generalised formulae and derivations for comparing the actual and the predicted classes in confusion matrix are in Garillos-Manliguez [36].

3.3 Goodness-of-Fit Test

Anderson-Darling (AD) goodness-of-fit (GOF) test was used to test the hypothesis of geometric distribution. Anderson-Darling test is the most powerful among the GOF tests that are based on empirical density function (EDF) and is used as a benchmark for comparing the power of other GOF statistics [37–39]. It is suitable when the data are small and the sample takes observed values comprising lots of 1s and 2s [38]. This is largely the case with the observed exposure periods in Southeastern Nigeria, especially for the sunny months.

If F_n is the empirical density function (EDF) of the sample $K_1, \ldots, K_n$,

$$\forall k \in N, \qquad \boldsymbol{F_n}(k) = \frac{1}{n}\sum_{i=1}^{n} 1_{(K_i \le k)} \qquad (vi)$$

The general principle of the EDF test is to reject the null hypothesis if the $\mathbf{F_n}$ and F_o are significantly different, where F_o is the cumulative density function (CDF) of a geometric distribution given in Equation (i).

The AD statistic is generally given as

$$\mathrm{AD} = \mathrm{n}\sum_{\mathrm{k}=1}^{\infty} \frac{[\mathbf{F_n}(\mathrm{k}) - \mathrm{F_o}(\mathrm{k})]^2[\mathrm{F_o}(\mathrm{k}) - \mathrm{F_o}(\mathrm{k}-1)]}{\mathrm{F_o}(\mathrm{k})\big(1 - \mathrm{F_o}(\mathrm{k})\big)} \qquad (vii)$$

The statistic was further developed to provide GOF test for discrete and geometric distribution [38, 40]:

$$\mathrm{AD} = \mathrm{n}\sum_{\mathrm{k}=1}^{\infty} \frac{[\mathbf{F_n}(\mathrm{k}) - \mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})]^2[\mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n}) - \mathrm{F_o}(\mathrm{k}-1;\hat{\mathrm{p}}_\mathrm{n})]}{\mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})\big(1 - \mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})\big)} \qquad (viii)$$

To compute the AD statistic, the sum must be finite. Henze [40] gave a truncation criterion:$\mathrm{M_l} = 1$;

$$\mathrm{M_u} = \min\left\{\mathrm{k} \ge \mathrm{K}_{(\mathrm{n})};\ \big(1 - \mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})\big)^3 \le {}^{10^{-4}}\!/_{\mathrm{n}}\right\} \qquad (ix)$$

So that:

$$\mathrm{AD} = \mathrm{n}\sum_{\mathrm{k}=\mathrm{M_l}}^{\mathrm{M_u}} \frac{[\mathbf{F_n}(\mathrm{k}) - \mathrm{F_o}(\mathrm{k};\mathrm{p})]^2[\mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n}) - \mathrm{F_o}(\mathrm{k}-1;\hat{\mathrm{p}}_\mathrm{n})]}{\mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})\big(1 - \mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})\big)} \qquad (x)$$

The critical values (C_α) were estimated by the parametric bootstrap method. To do this, the inverse function of $\mathrm{F_o}(\mathrm{k};\hat{\mathrm{p}}_\mathrm{n})$ was used to simulate 10,000 replications of each of the 324 datasets using Scilab (version 5.5.2). Anderson-Darling (AD) statistic was computed for each of the 10,000 samples. The critical values (C_α) were estimated as the empirical percentile of order $(1 - \alpha)$ for all the values of AD statistics computed from the replications, where α is the significant level of a $\mathrm{p} - \mathrm{value}$. The null hypothesis is rejected if the value of the AD statistic is greater than C_α. The significant level (α) was chosen as 0.05 (i.e. 5% level of significance) for all the test. Henze [40] validated this method by showing that as n and N tends to infinity, the significant level of the test tends to α.

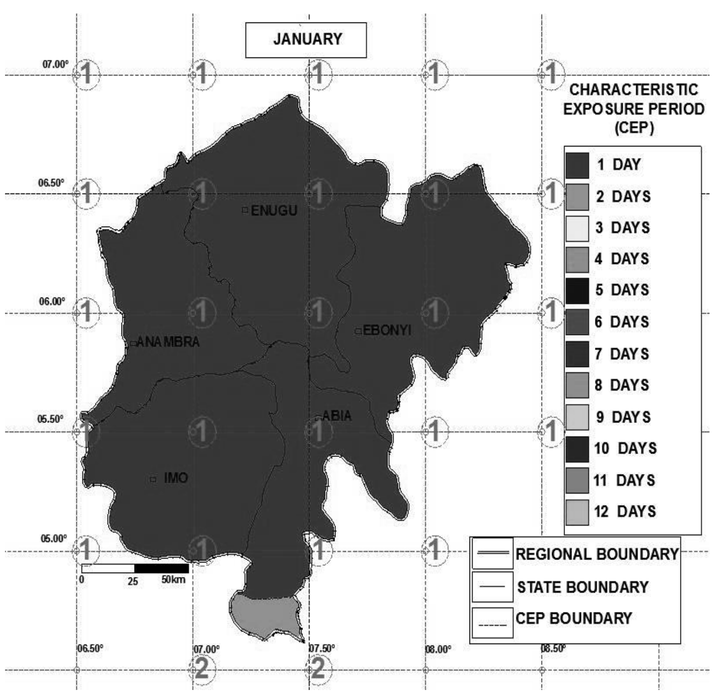
4.0 RESULTS AND DISCUSSION

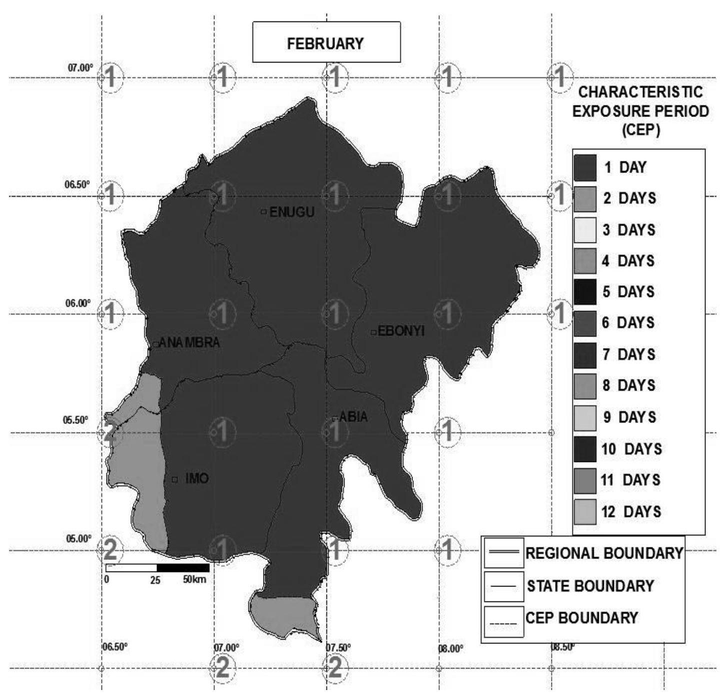
The maps of monthly CEPs estimated for the region of Southeastern Nigeria are shown in Figures 2 – 3. The CEPs were determined based on the inverse cumulative density function (CDF) of geometric distribution given in Equation (v). The parameter, $\hat{p}_n$, for each month and location was estimated from 60 data point of exposure periods (EP) values (equivalent to 2 years of solar energy data) randomly selected from the 35 years of EPs computed from the NASA solar energy data for the corresponding locations. Monthly estimates of CEP, k_{cep}, is defined as the value of EP (days) such that only 5% of the observed EPs for that month are higher than k_{cep}. The numbers contained in the maps are the estimated CEPs. They are displayed at the coordinates of the geographical location they represent, which correspond with the points of intersection between the lines of longitude and latitude. The same shade of grey was used to represent locations of equal CEPs so that SODIS users, just by knowing their location in the region, could select the appropriate CEPs for the application of SODIS.

To validate the procedure, the estimated CEPs (k_{cep}) for all the locations and months were compared with the observed CEPs using the confusion matrix shown in Table 3. The observed CEPs were computed as the 95th percentile of the 35 years of monthly exposure periods. The main diagonal values in bold texts (from top left of the matrix down to bottom right corner) represent the frequency of accurate estimations, i.e., the number of times the estimated equals the observed. The overall accuracy, which is the proportion of accurate estimation, is 83 %, suggesting a reliable model for the prediction of exposure period. However, the accuracy of the estimation decreased with increasing values of CEP. It remained acceptably high until the CEP value of 4 days, after which the performance of the model declined drastically.

The low estimation accuracy of the model for CEP values higher than 4 days may not affect the utility of the model, since the use of SODIS in regions where more than 4 days of exposure is required is hardly recommended [21]. The guidelines recommend the use of other household water treatment and safe storage (HWTS) options in such situations [21].

Moreover, extended exposure periods could render SODIS laborious and unattractive. Therefore, obtaining a CEP value of greater than 4 using the model may as well serve as an indication that SODIS will not work well for that particular month and location.





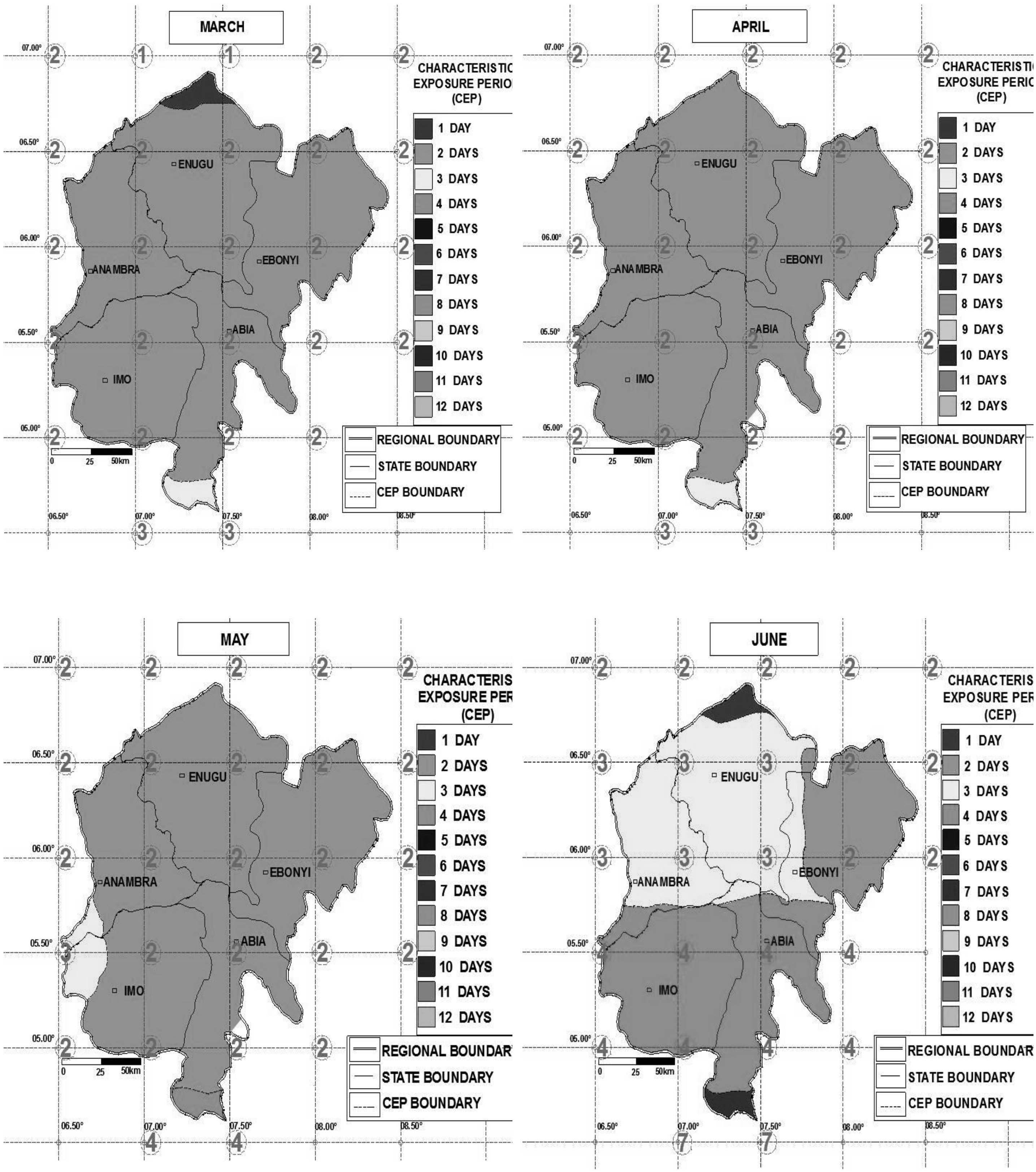
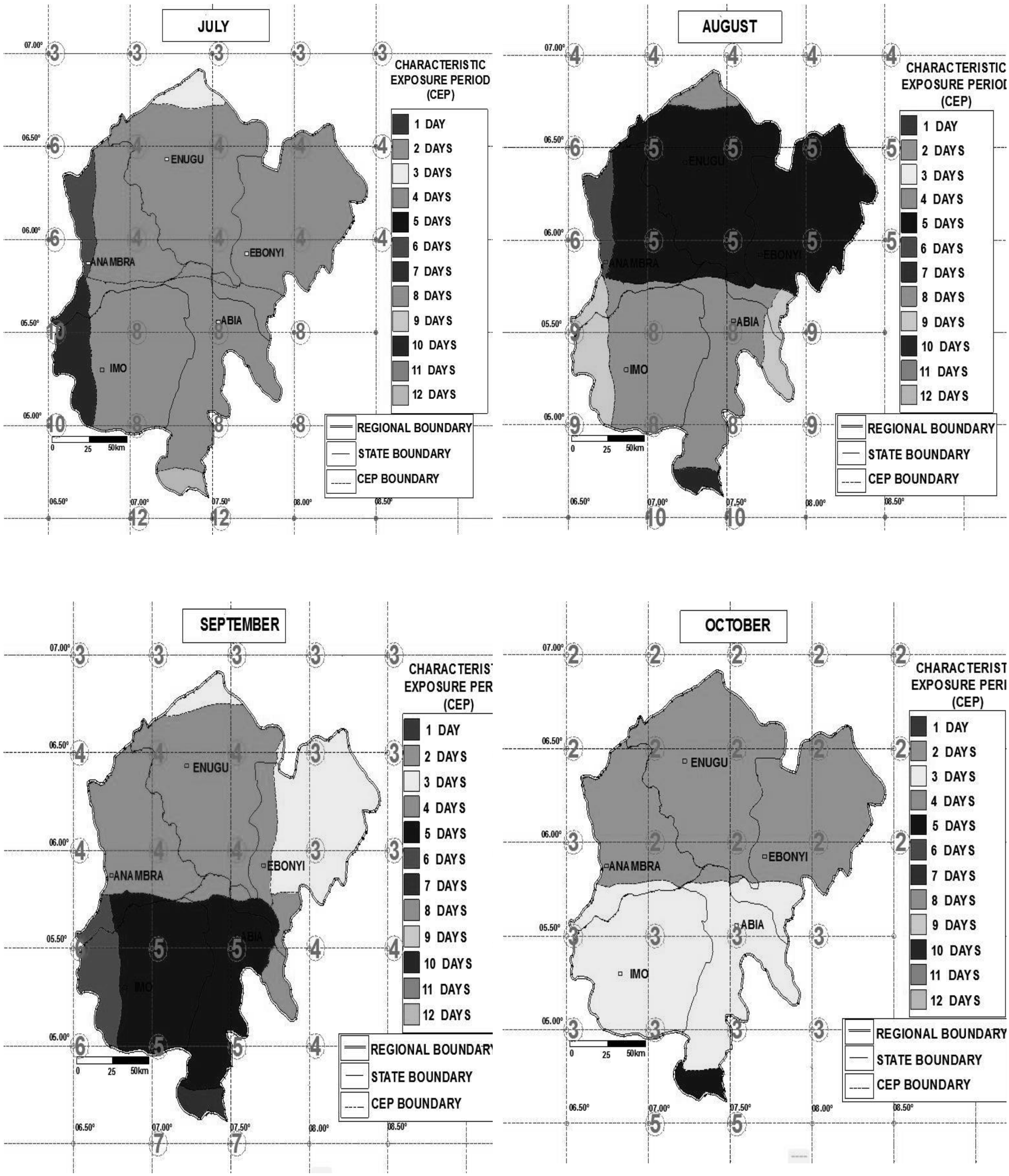


Figure 2: Maps of characteristic exposure periods (CEPs) for Southeastern Nigeria (January to June)


JULY
CHARACTERISTIC EXPOSURE PERIOD (CEP)
1 DAY
2 DAYS
3 DAYS
4 DAYS
5 DAYS
6 DAYS
7 DAYS
8 DAYS
9 DAYS
10 DAYS
11 DAYS
12 DAYS
REGIONAL BOUNDARY
STATE BOUNDARY
CEP BOUNDARY
ENUGU
ANAMBRA
EBONYI
ABIA
IMO
0 25 50km
07.00°
06.50°
06.00°
05.50°
05.00°
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AUGUST
SEPTEMBER
OCTOBER

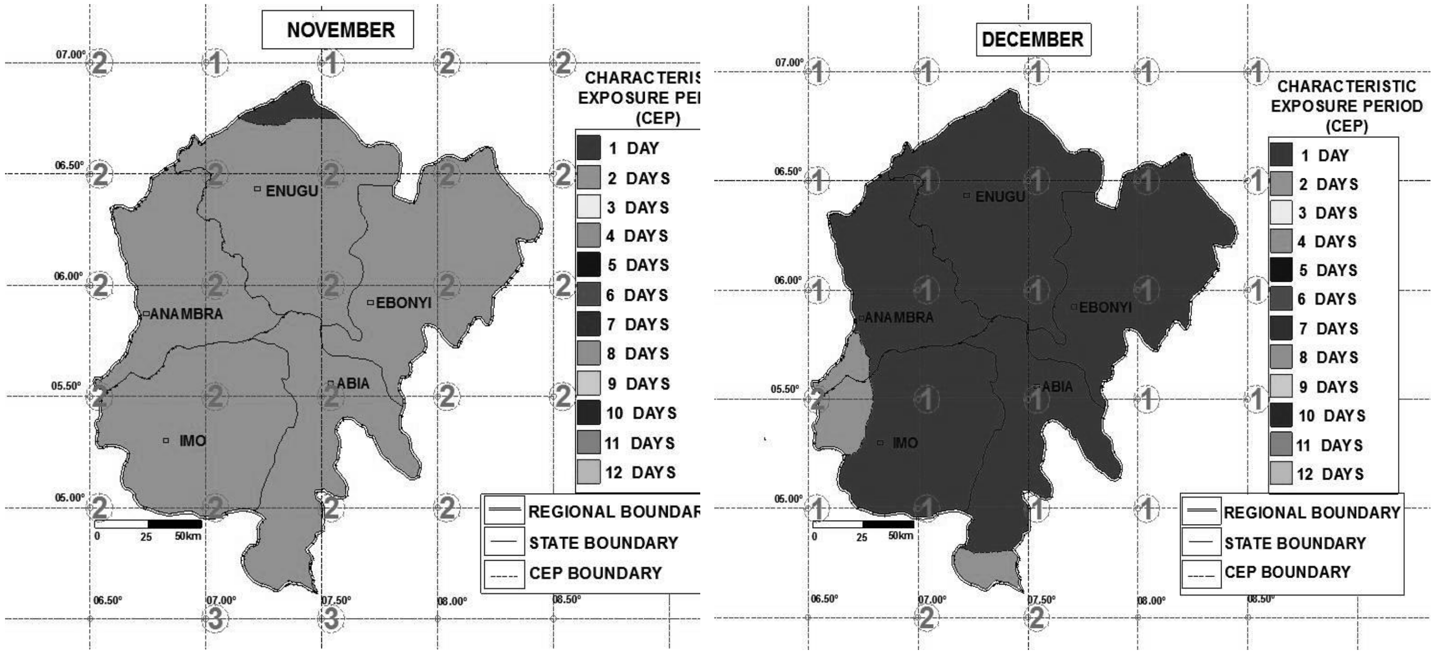

Figure 3: Maps of characteristic exposure periods (CEPs) for Southeastern Nigeria (July to December)

Table 3: Confusion matrix and the class frequencies of the observed and estimated CEPs for different month and location in Southeastern Nigeria

	Estimated CEPs															
	CEP (Days)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Acc. (%)
Observed CEPs	1	82	6	0	0	0	0	0	0	0	0	0	0	0	0	93.2
	2	0	114	1	0	0	0	0	0	0	0	0	0	0	0	99.1
	3	0	5	39	2	0	0	0	0	0	0	0	0	0	0	84.8
	4	0	0	0	24	0	0	0	0	0	0	0	0	0	0	100
	5	0	0	0	7	10	0	0	0	0	0	0	0	0	0	58.8
	6	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0
	10	0	0	0	0	0	0	0	6	2	0	0	0	0	0	0
	11	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
	13	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
	14	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0

Maps displaying monthly CEPs, such as the ones shown in Figure 2 – 4, can be developed to assess the applicability of SODIS in any region of the world. The probability model presented in this document proved to be an effective tool for estimating monthly CEPs for this purpose. Presenting the estimated monthly CEPs as maps will improve the utility of the model results, especially among rural users. It will also clear up the confusion and uncertainty arising from variable weather/exposure period, thereby minimizing the risk of underexposure and incorrect application of SODIS.

One would only need to obtain daily insolation values of the location (say, from NASA) and convert the data to exposure periods in order to calibrate the model. The

NASA data should be applied with caution because their spatial resolution does not capture the presence of microclimates within $^1/_2 \times {}^1/_2$ degree longitude and latitude, which can cause inaccurate predictions for specific locations [41]. This means that the model estimations can only be as accurate as the solar energy data used in calibrating the model. Therefore, even though NASA data was used to validate the probability model, actual ground measurement of solar radiation should be used to estimate the model parameter if available.

Exposure period has an implication on SODIS productivity (litre/day), PET utilisation, and labour input for SODIS operation. The maps will allow potential users to weigh these factors in the context of other HWTS technologies in order to determine if and when to use SODIS, depending on preference and the capacity of their resources. The maps will also eliminate the cognitive stress associated with day-to-day gauging of cloud cover recommended by the guidelines for SODIS users [21], and replace it with the simple task of knowing the current month and one's location in their region. Locations and months unsupportive of the SODIS process can be easily identified on the maps.

The need to be certain of complete inactivation at all times led to an unusually high estimate of exposure periods displayed in some locations, even when treatment could well be affected long before the end of the CEP. For example, location (5.0ºN, 8.0ºE) in July has an estimated exposure period of 10 days to stand a 95% chance of meeting the radiation threshold, but two days of exposure in the same location and month would give more than 50% chance of meeting threshold. Therefore, it should be noted that this study focused on recommending exposure periods that will work at all times in order to prevent underexposure and incorrect application of SODIS. Such a long exposure period could be relaxed if SODIS users are certain of the operating solar radiation and water temperature.

5.0 CONCLUSIONS

A methodology/model for estimating SODIS exposure period based on the cumulative density function (CDF) of geometric distribution has been presented. The methodology can always be applied to determine the characteristic exposure period (CEP) for any location in the world once solar radiation data are available. CEP represents a fixed, location-specific exposure period that captures and quantifies the day-to-day variation in cloud cover depending on the acceptable risk of underexposure. This is better than relying on the vagueness of human judgement to determine days that met the disinfection threshold, which could lead to massive underexposure and incomplete disinfection. The model demonstrated satisfactory prediction accuracy and is adequate for its purpose. Presenting the exposure periods obtained from the model in the form of maps could be a valuable tool in regions where there is high variability in cloud cover and there are no solar measuring devices to gauge the degree of cloud coverage.

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