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A BIOMATHEMATICAL SYSTEMS MODEL OF ENVIRONMENTAL RISK EXPOSURE AND POPULATION HEALTH BURDEN IN INDIA

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ABSTRACT
Background: Sanitation, drinking water, and household energy are environmental factors that greatly contribute to the population's health, but their effects are usually evaluated separately. The biomathematical systems approach gives an organized approach to combine various exposures to the environment and the interaction of such exposures with the burden of health.
Aim: To develop and evaluate a biomathematical systems model of environmental risk exposure and population health burden at the district level in India.
Methodology: An ecological, cross-sectional study was conducted using district-level data from the National Family Health Survey (NFHS-5), India (2019-2021). Three environmental variables: lack of clean cooking fuel, unsafe drinking water, and poor sanitation, were used to construct an Environmental Risk Index. A Health Burden Index was derived from indicators of diarrheal disease, acute respiratory infection, child undernutrition, and anaemia. Variables were standardized using z-scores. Descriptive statistics, Pearson correlation, and multivariable regression were applied within a biomathematical framework.
Results: A total of 706 districts were analyzed. Poor sanitation showed the strongest association with health burden ($r = 0.57$). The model explained 33.0% of variance ($R^2 = 0.330$; $p < 0.001$). Poor sanitation was the strongest predictor ($\beta = 0.024$, $p < 0.001$), while unsafe drinking water showed a weaker inverse association ($\beta = -0.006$, $p = 0.012$). Lack of clean cooking fuel was not significant ($p = 0.486$).
Conclusion: The most predominant environmental pathway that is linked to the district-level health burden is poor sanitation. The biomathematical framework provides a practical system-level method of analyzing the environment in terms of health.

KEYWORDS: biomathematical modeling, environmental risk, sanitation, population health burden, biomathematical systems model

1. INTRODUCTION

India presents a complex epidemiological context as the determinants of population health that affect the occurrence as well as distribution of disease. These determinants also comprise the wide scope of conditions, such as water quality, sanitation, and household energy consumption, all of which predetermine exposure to biological and chemical hazards (Gibson, 2018). Environmental risk factors are major contributors to morbidity and mortality on a global scale, and a large percentage of the total disease burden is attributed to them (Clark et al., 2025). Low- and middle-income countries experience such risks especially strongly, with the infrastructural constraints and socioeconomic inequalities contributing to the exposure to the unfavorable environmental conditions. India is a complicated epidemiological situation due to swift demographic change and the continued environmental crisis. The presence of communicable diseases, nutritional deficiencies, and the development of new chronic ones is the result of the interaction between environmental exposures and the vulnerability of the population (Kumar, 2024). As an illustration, the scale of environmental health impacts is indicated by the fact that exposure to air pollution has been found to severely decrease mortality and decrease life expectancy across Indian states (Balakrishnan et al., 2019). The findings indicate the significance of conceptualizing environmental determinants as a system that cannot be broken down into single factors but as a network of interrelated determinants of population health.
Numerous works of literature have discussed particular avenues through which the environment affects health. Poor sanitation is closely linked to fecal-oral pathogen spreading that is prevalent among children, which increases the risks of

diarrheal diseases and associated problems (Reid et al., 2018). On the same note, unsafe drinking water is one of the primary causes of waterborne diseases, which are highly problematic regarding the population's health in resource-limited environments (Pal et al., 2018). Another exposure pathway is household energy consumption. Polluting fuels are used to cook the food, thus polluting the indoor air, which has been associated with respiratory illnesses and the effects of pollution on health in general (Raju et al., 2020). The attempts in the shift to using cleaner energy sources have proved that it can be beneficial not only in the context of health but also in environmental sustainability as well (Ravindra et al., 2021). On a larger scale, research investigating the relationship between water, energy, and food systems has suggested the significance of the integrated approach in the interpretation of individual household well-being and environmental risk (Asaki et al., 2024).

The improvement of quantification of disease burden that can be attributed to environmental exposures has also been the subject of current developments in environmental health research. Improved models have helped in better estimations of health risks in the world, and it is necessary to consider the global nature of health risks through the implementation of holistic systems that integrate a wide range of environmental factors (Shaffer et al., 2019). Moreover, the effects of environmental factors are not limited to infectious diseases, as they impact the physiological systems and cause such diseases as sleep disorders and chronic kidney disease (Johnson et al., 2018; Xu et al., 2018). To address these complexities, quantitative and biomathematical methods in environmental health research have become increasingly popular. These methods allow combining various variables into a single analytical framework that helps to understand exposure-outcomes relationships at a deeper level (Mendes, 2024). The environmental risk assessment has also utilized biomathematical modeling to measure health effects of environmental contaminants, proving its usefulness in the context of public health (Otugboyega et al., 2024).

Although a lot of research has been conducted on the environmental determinants of health, there are still a number of limitations. Numerous current investigations attempt to measure the effects of single risk factors or disease outcomes alone, and research has not yet been able to measure the combined and interacting effects of the various environmental exposures. This piecemeal method may fail to capture the cumulative effect of environmental risks, especially in an environment where there are several exposures operating in a similar population. Also, although large-scale datasets are important, there is no analytical infrastructure that can incorporate a variety of environmental and health indicators in a single system that can make sense. There has been limited research that has tried to measure the relative contribution of various environmental factors in a single model, especially at the district level in India. This gap shows the necessity of methods that would combine both statistical rigor and system-level interpretation in order to understand the dynamics of environmental health better.

Against these considerations, the current research will formulate and test a biomathematical systems model in order to test the association between environmental risk exposure and population health burden at the district level in India. Particularly, the investigation aims at building composite indicators of environmental hazard and well-being load, evaluating the connection between environmental exposures and health effects, as well as quantifying the (compared) input of sanitation, drinking water, and household energy in a combined analytical structure.

2. METHODOLOGY

2.1 Study Design

This research was based on an ecological, cross-sectional analytical design with secondary data summed to the district level in India. This design was chosen to test population-level associations between environmental risk exposures and health outcomes, and not the individual-level effect. The study used district-level variation to examine the spatial heterogeneity of both the nature of the environment and the associated health burdens.

The methodology is a combination of a statistical model and a simplified biomathematical approach, where environmental factors are conceptualized as inputs into the system that drives a compound health burden outcome. This design allows exploring the structural relationship between exposures to the environment and population health in a unitary, system-based approach, yet it is relevant to the nature of cross-sectional data.

2.2 Data Source

The data were sourced from the National Family Health Survey (NFHS-5), India (2019- 2021), which is a national representative survey administered by the Ministry of Health and Family Welfare (Gopan, 2024). It is a survey offering standardized district-level projections of demographic, environmental, and health indicators in India.

2.3 Variable Selection

Variables were also chosen in terms of their relevance to environmental exposure pathways and population health outcomes. Three environmental indicators at the household level were used to reflect the exposure to environmental risk: the absence of clean cooking fuel, unsafe drinking water, and poor sanitation. These variables were obtained based on the NFHS indicators that denote access to better household facilities. To ensure a consistent interpretation, all the environmental variables were converted to ensure that the higher the value, the greater the exposure to the environmental risk.

A composite measure of indicators was used to show population health burden by using a set of indicators that defined important adverse health outcomes at the district level. These were the occurrence of diarrheal disease, acute respiratory infection (ARI) symptoms, child undernutrition (stunting, wasting, and underweight) and anaemia in children and women. Markers of treatment-seeking behaviour or healthcare use were eliminated to make sure that the measure that has been constructed captured outcome-based health burden as opposed to differences in healthcare access or service use.

2.4 Data Processing and Cleaning

Systematic cleaning and validation procedures were used to prepare data so as to maintain consistency and reliability of the data. The non-numeric entries, such as symbols that represent missing values, were changed to standard missing values. Next, all the variables were converted to a number format in order to perform statistical analysis. Values that were implausible, like negative percentages, were recognized and set as missing. In cases where the data was inadequate, a preset measure of completeness was used to filter out the districts.

2.5 Index Construction

Composite indices were built in order to capture environmental exposure and health burden in a single framework of analysis.

2.5.1 Environmental Risk Index (ERI)

Environmental variables were standardized using z-score normalization:

$$Z = \frac{X - \mu}{\sigma}$$

The Environmental Risk Index was computed as the mean of standardized environmental variables:

$$ERI = \frac{1}{n}\sum_{i=1}^{n} Z_{E_i}$$

2.5.2 Health Burden Index (HBI)

Similarly, health outcome variables were standardized and combined:

$$HBI = \frac{1}{m}\sum_{j=1}^{m} Z_{H_j}$$

This strategy allowed the inclusion of various health measures into one continuous population health burden measure.

2.6 Biomathematical Systems Framework

The relationship between environmental exposure and health burden was formulated as a simplified biomathematical system:

$$H = f(E_1, E_2, E_3)$$

where Hrepresents the health burden index, and E_1, E_2, and E_3correspond to environmental risk components (sanitation, water, and fuel).

The empirical regression model is a steady-state approximation of this system, where environmental exposures are the input variables that cause the response (population health burden) in the state variable, and model coefficients are a measure of the relative contribution of each exposure pathway.

2.7 Statistical Analysis

All variables were summarized using the descriptive statistics, which include means, standard deviations and ranges. The correlation between the environmental risk variables and the health burden index was determined using Pearson correlation coefficients.

To quantify the association between environmental exposures and health outcomes, a multivariable linear regression model was fitted, expressed as:

$$HBI = \beta_0 + \beta_1 E_1 + \beta_2 E_2 + \beta_3 E_3 + \epsilon$$

where HBI represents the health burden index and E_1, E_2, and E_3represent environmental risk components. The statistical significance and effect size were reported using regression coefficients, standard errors, p-values, and confidence intervals. Standardized coefficients were also provided to determine the contribution of each predictor in the model.

Checking of regression assumptions Model diagnostics were conducted to test the validity of regression assumptions. Normality and model fit were studied using residual distributions, and multicollinearity between predictors was studied with the variance inflation factors (VIF).

3. RESULTS

3.1 Descriptive Characteristics of Environmental Risk and Health Burden

The total number of districts to be analyzed was 706. In Table 1, the distribution of environmental risk components and the index of health burden is shown. The average absence of clean cooking fuel was 45.88% (SD = 24.18), which showed a high degree of variation between districts. The mean of poor sanitation was 28.07% (SD = 14.29), and the exposure to unsafe drinking water was relatively lower (6.28%, SD = 8.72).

The standardized Health Burden Index (HBI) revealed a mean near zero (-0.026, SD: 0.616), which is indicative of proper normalization, with the range of values being between -1.79 and 1.65, indicating that there is a significant heterogeneity in the population health burden among districts.

Table 1. Descriptive statistics of environmental risk components and health burden index

Variable	N	Mean	SD	Min	Max
Lack of clean fuel	706	45.88	24.18	0.21	91.39
Unsafe drinking water	706	6.28	8.72	0.00	58.82
Poor sanitation	706	28.07	14.29	0.15	70.76
Health Burden Index (HBI)	706	-0.03	0.62	-1.79	1.65

Lack of clean fuel is another environmental risk that is depicted as the most common in the relative value of environmental exposure, as indicated in Figure 1, next comes poor sanitation with unsafe drinking water, contributing a lesser percentage of exposure in different districts.

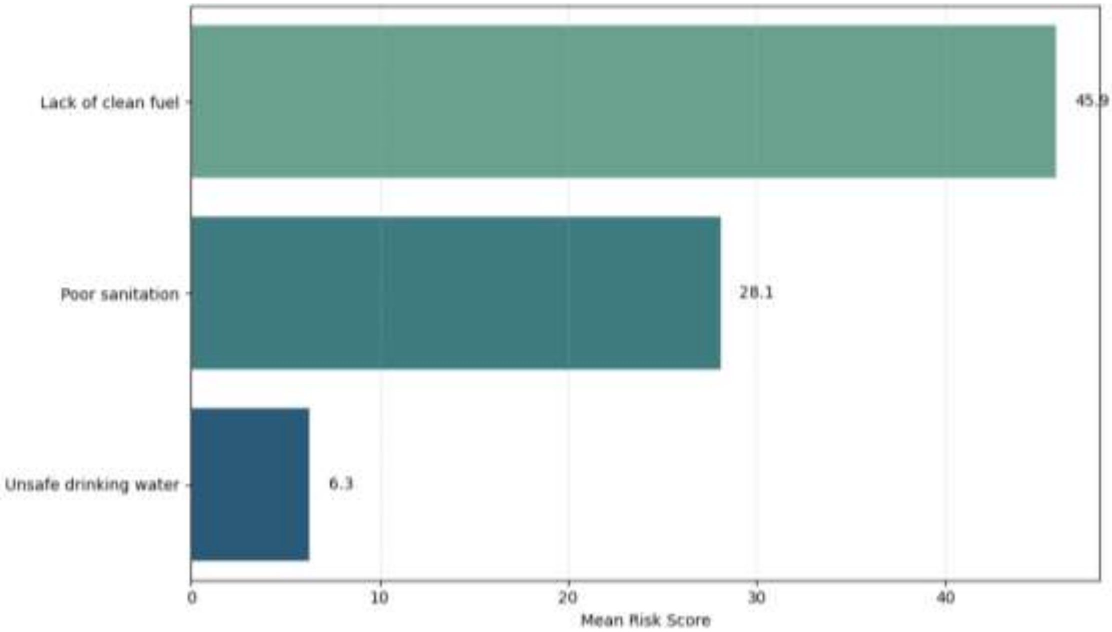

Figure 1. Mean environmental risk profile across districts

3.2 Correlation Structure of Environmental Risk Components and Health Burden

Table 2 demonstrates the correlation between the environmental risk variables and the index of health burden, and Figure 2 visualizes the correlation. There was also a relatively strong positive correlation between poor sanitation and health burden ($r = 0.57$), which means that districts with poorer sanitation have a significantly higher disease burden. Absence of clean fuel was associated with health burden ($r = 0.26$) and poor sanitation ($r = 0.46$) in a moderate positive manner, showing that these two environmental risks partially co-exist. Unsafe drinking water, on the contrary, was not significantly correlated with health burden ($r = -0.01$), which confirmed that it has a negligible linear correlation in the current dataset.

Table 2. Correlation matrix of environmental risk components and health burden

Variable	Lack of clean fuel	Unsafe drinking water	Poor sanitation	HBI
Lack of clean fuel	1.00	0.34	0.46	0.26
Unsafe drinking water	0.34	1.00	0.11	-0.01
Poor sanitation	0.46	0.11	1.00	0.57
HBI	0.26	-0.01	0.57	1.00

Figure 2 also illustrates the overwhelming association of sanitation and health burden and the rather weak association of water-related exposure in the heatmap.

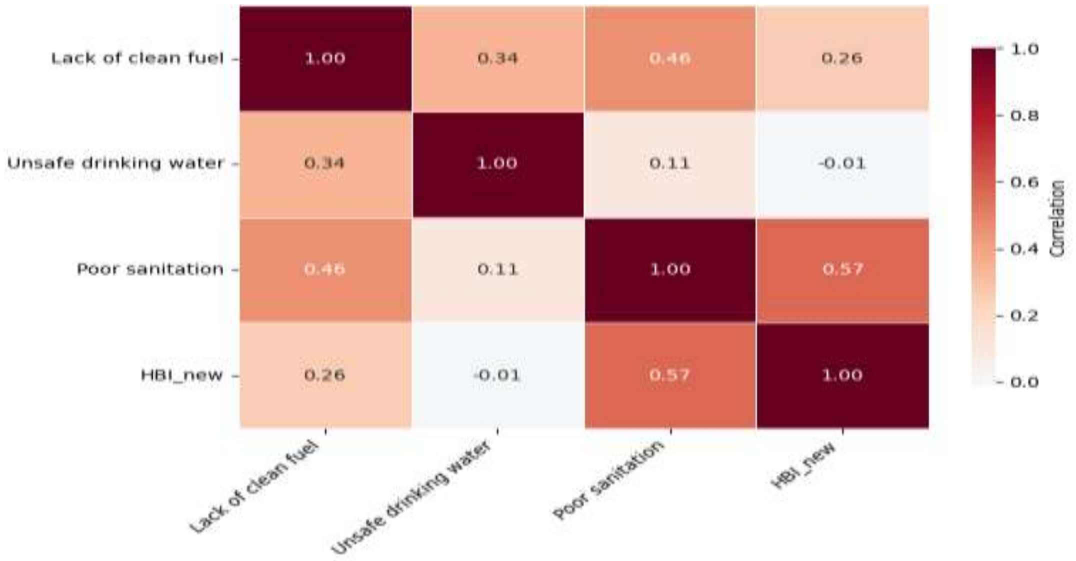

Figure 2. Correlation matrix of environmental risk components and health burden

3.3 Multivariable Biomathematical Systems Model

The multivariate linear regression model was developed to estimate the significance of the individual environmental risk factors to the population health burden. The model was statistically significant (F = 115.1, $p < 0.001$) and associated with an explanation of 33.0% of the variance in the Health Burden Index (R2 = 0.330).

Table 3 presents the health burden as highly predictable by poor sanitation ($\beta = 0.024$, 95% CI: 0.021-0.027, $p < 0.001$). Unsafe drinking water showed a statistically significant, but not that large, effect ($\beta = -0.006$, $p = 0.012$), whereas insufficiency of clean cooking fuel was not found to have a significant bearing on health ($p = 0.486$).

Table 3. Multivariable biomathematical systems model of environmental risk exposure and health burden

Variable	Coefficient (β)	Std. Error	t-value	p-value	95% CI
Intercept	-0.705	0.047	-14.95	<0.001	-0.798 to -0.613
Lack of clean fuel	0.001	0.001	0.70	0.486	-0.001 to 0.002
Unsafe drinking water	-0.006	0.002	-2.51	0.012	-0.010 to -0.001
Poor sanitation	0.024	0.002	16.24	<0.001	0.021 to 0.027

The standardized coefficient plot (Figure 3) also highlights the relative predictor significance, in that the effect of poor sanitation ($\beta = 0.35$) is much more significant than that of drinking water ($\beta = -0.05$) and cooking fuel ($\beta = 0.02$).

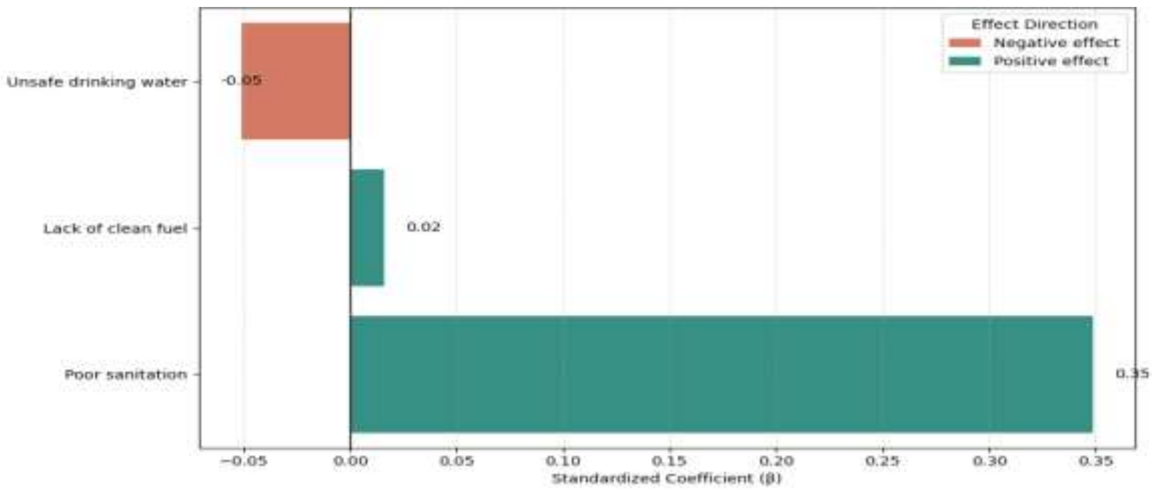

Figure 3. Standardized effects of environmental risk components on health burden

3.4 Relative Contribution of Environmental Components

Comparison of standardized coefficients reveals that poor sanitation has an inordinate impact on the health burden of the population, which is about 6 to 7 times more than drinking water and much larger than the impact of cooking fuel. This underscores the importance of the sanitation-related exposure pathways in the framework of the environmental health system.

4. DISCUSSION

The results of the environmental risk factors did not consistently relate to population health burden by district, meaning that some exposure pathways under the modeled system contribute more significantly than others. The outstanding result was the primary role of poor sanitation, which exhibited a strong correlation with the health burden index, besides the highest effect size in the multivariate model. The implication here is that exposures associated with sanitation are still a key contributor to the poor health outcomes at the population level. Systems Sanitation is also a major route by which environmental pollution is converted into disease burden, especially by the fecal-oral route, repeated infections and the ensuing nutritional repercussions. Conversely, unsafe drinking water showed a relatively weak and negative relation to health burden. This observation must be taken with care since it is probably indicating measurement restrictions but not a protective effect. The indicators of "improved" water access might not be sufficient in recording changes in water quality, water storage, or intermittent contamination. This may be because the lack of a strong association can be used to suggest that the variable does not fully depict actual exposure conditions in the system. In a similar vein, the non-significance of the relationship between the lack of clean cooking fuel and health burden indicates that the impact of the phenomenon might not be well represented in the chosen composite outcome. Household air pollution has been identified to have a significant impact on respiratory and chronic diseases, but such effects might not be well captured by the measures taken that are used to create the health burden index. In the context of biomathematical, this means that some exposure pathways can have indirect or more long-lasting effects that are not well modeled by a cross-sectional approach.

The importance of sanitation observed is consistent with the current mathematical and epidemiological studies that underline the importance of environmental conditions on the dynamics of diseases. Infectious disease transmission models proved that environmental contamination may sustain the transmission process and increase the risk at the population level, especially in environments without proper sanitation systems (Kumari and Sharma, 2018). This helps to view sanitation as one of the key channels in the environmental health system. The recent advances in the modeling of the environment further underscore the usefulness of combined methods in the modeling of complex exposure-outcome relationships. System-based models have been demonstrated to enhance the modeling of environmental interactions and uncertainties, and this supports the necessity of models that integrate the presence of many variables in a single structure (Dey et al., 2025). The current results can be related to this point of view because the biomathematical model could separate the relative weight of various environmental factors. The moderately low relationship found with respect to drinking water also indicates some problems that are noted in environmental health studies. Research has highlighted that exposure measures might not capture the nature of environmental hazard, especially when one bases measurements on infrastructural categories and not actual contamination measurements (Staessen et al., 2020). In the same way, the methods of environmental exposure evaluation have shown that it is necessary to combine various data to precisely predict the risk on a population level (Shaddick et al., 2018).

This could be because the present model of household fuel exposure has a limited contribution due to the nature of the outcomes that are included in the health burden index. Mathematical experiments of exposure to toxicants indicate that the effect of environmental factors may depend on the pathways and effects included, and some effects would be more visible when the model includes the chronic or long-term health indicators (Achema, 2025). Wider environmental health analysis has also demonstrated that the impact of emissions and pollution can be widely spread across systems, and they may not be fully reflected in any one single analytical model (Eckelman & Sherman, 2018). Besides, cumulative environmental exposures have been shown to have quantifiable health effects, when combined, even in the population when individual pathways do not seem to be significant on their own (Eckelman et al., 2018). Large-scale burden of disease studies of China also show that environmental exposures have the potential to greatly affect the mortality and life expectancy at subnational scales, which supports the relevance of spatially disaggregated analysis (Yin et al., 2020).

This research has significant implications for the policy of health and for the methods of analysis of environmental health. Policy-wise, the powerful effect of sanitation implies that the enhancement of sanitation infrastructure can provide significant decreases in population health burden, especially within high-exposure districts. Sanitation-focused interventions can then be a high-impact intervention in resource-limited environments. Analytically, the application of a biomathematical systems framework shows the usefulness of having several variables of the environment as a single variable. This technique represents the environmental exposures as interplaying elements in a system and enables one to have a more detailed view of the contribution of various factors towards health outcomes. The decision-making process can be supported by such models on the basis of prioritizing areas of intervention as well as quantifying the relative significance of various environmental pathways.

The findings are limited in a number of ways that need to be taken into account. To begin with, ecological and cross-sectional designs do not make it possible to determine causal relations and evaluate temporal dynamics. Second, aggregated district-level data can conceal the variability within districts and create the threat of ecological fallacy. Third, there are environmental indicators that might be imperfect proxies to actual exposure conditions, especially in the example of drinking water and household energy consumption. In future research, adding longitudinal data, a finer spatial resolution and more direct measures of environmental exposure are the aspects on which future studies should seek to overcome these limitations. More sophisticated biomathematical methods, such as nonlinear and dynamic models, may be used to offer more insight into feedback and interactions in the environmental health systems. By examining more health outcomes, such as chronic and long-term ones, one can also increase the coverage of particular exposure pathways. Together, the above directions would improve the capacity to simulate the environmental risk and its effect on the population health in a systems framework that is more comprehensive.

5. CONCLUSION

India does not have a homogeneous effect of household exposures on environmental health burdens. Under the biomathematical systems model constructed in this paper, the poor quality of sanitation was found to be the most significant environmental factor that was related to the burden on population health, with a much greater contribution to the burden than either unsafe drinking water or the lack of clean cooking fuel. This trend indicates that sanitation-related exposure pathways continue to be the focal point of the continued occurrence of diarrheal disease, undernutrition, anaemia, and their related undesirable outcomes at the district-level. The study illustrates the usefulness of a simplified biomathematical method of characterizing the dynamics of environmental health at the population level by incorporating numerous environmental inputs and health outcomes into composite indices. The model provides a well-organized method to measure relative contributions of environmental risk pathways without losing interpretability to be used in the context of public health. These results confirm the importance of prioritizing sanitation-based interventions in a high-environment-risk district, as well as the need to increase the accuracy of water and household energy exposure measurements. This framework should be extended to future work through longitudinal data, smaller spatial scales, and dynamic modeling strategies to enhance the ability of this framework to capture temporal change and interaction among environmental health systems.

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