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Socioeconomic Risk Factors Associated With Acute Malnutrition Severity Among Under-Five Children Based on a Machine Learning Approach: The Case of Rural Emergency Contexts in Niger and Mali

Luis Javier Sánchez-Martínez[1] | Pilar Charle-Cuéllar[2] | Abdias Ogobara Dougnon[3] | Fanta Toure[3] | Antonio Vargas[2] | Candela Lucía Hernández[1] | Noemí López-Ejeda[1,4]

[1]Department of Biodiversity, Ecology and Evolution, Unit of Physical Anthropology, Faculty of Biological Sciences, Complutense University of Madrid, Madrid, Madrid, Spain | [2]Action Against Hunger, Madrid, Madrid, Spain | [3]Action Against Hunger. West and Central Africa Regional Office, Dakar, Senegal | [4]EPINUT Research Group (ref. 920325), Faculty of Medicine, Complutense University of Madrid, Madrid, Madrid, Spain

Correspondence: Luis Javier Sánchez-Martínez (luisja02@ucm.es)

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ABSTRACT

Currently, child acute malnutrition continues to be a serious public health problem, and although its most fatal consequences are well known, its associated factors still need to be studied in more depth in different contexts. The objective of the present study is to determine the association between socioeconomic variables and acute malnutrition severity in rural emergency contexts of Niger and Mali. The present study consists of a secondary analysis of controlled trials. Data related to a total of 1447 treated children (6–59 months of age) were considered, for whom the Variable Selection Using Random Forests (VSURF) algorithm was applied to create interpretation and prediction random forest models (considering 86 variables). In Mali and Niger, the prediction models agree in pointing out aspects related to the water source and the work activity of caregivers as some of the main risk factors for developing severe acute malnutrition. However, the interpretation models highlight important heterogeneity, with the distance to the health center being the greatest exponent of this situation, being the most important factor in Niger while disappearing in Mali. The prediction accuracy in the interpretation model was 68.0% in Niger and 79.80% in Mali, while the prediction model reached similar rates of 63.17% and 75.63%, respectively. Machine learning techniques have proven to be a valid tool to interpret and predict the degree of severity of acute malnutrition based on socioeconomic characteristics, including complex interrelationships. The results obtained point out different aspects to be addressed to prevent and minimize the effects of acute malnutrition.

1 | Introduction

The prevalence figures for child acute malnutrition provided by the World Health Organization (WHO) highlight it as a serious public health problem worldwide, with Africa and Asia having the highest number of cases, affecting 12.2 and 31.6 million children between 6 and 59 months, respectively (UNICEF, WHO, & World Bank Group 2023). This condition entails serious and multiple short- and long-term consequences on the individual's health. Firstly, there is an increase in comorbidity,

Summary

- Machine learning approaches are an effective tool to fight against child acute malnutrition. Random forest models correctly identify most severe cases of child acute malnutrition only using socioeconomic/environmental variables.
- The factors that have been identified as most associated with an increase in the severity of malnutrition are those related to water, access to health care, and socioeconomic status.
- The underlying factors of acute malnutrition were different in Mali and Niger and these contextual differences reveal the importance of tailoring medical interventions to optimize case diagnosis in emergency contexts and the orientation of public policies.

as individuals become more susceptible to contracting infectious diseases (Jones and Berkley 2014). Metabolic and growth alterations occur, along with organic dysfunction in the liver, heart, and brain (Badaloo et al. 2005; Rohm et al. 2019; Lena et al. 2020). Likewise, a meta-analysis study has shown that the risk of mortality from any cause increases up to 12 times in those patients who were wasted, stunted, and underweight (McDonald et al. 2013).

The aetiology of acute malnutrition is complex and multifactorial. Biologically, it is explained as a loss of muscle and fatty tissue resulting from an imbalance between the energy consumed by the individual and the energy required to maintain vital functions and growth. However, the nutritional status of an individual is the product of multiple interactions between food intake, the presence of comorbidities, metabolism, and the endocrine and immune systems (Bhutta et al. 2017). Additionally, numerous studies have also demonstrated the influence of other socio-demographic, political, cultural and economic factors which also affect, underlyingly and to different degrees, the nutritional status of an individual (van Cooten et al. 2019; Obasohan et al. 2020; Karim et al. 2021; Katoch 2022; Alaba et al. 2023), and thus, can be associated with the problem of child acute malnutrition. However, these associations are dependent on the local context in which individuals live, and, therefore, they do not necessarily have the same importance in all regions. A study conducted by Li et al. (2020) highlights this, providing a differential ordering of the importance of different factors for a total of 35 Low- and Middle-Income Countries. Maternal nutritional status and poor household socioeconomic conditions were identified as the leading factors associated with child anthropometric failures in the pooled analysis.

Currently, the WHO recognizes two anthropometric criteria for the diagnosis of child acute malnutrition (World Health Organization WHO 2023): weight-for-height z-score (WHZ) < -2 and/or a mid-upper arm circumference (MUAC) < 125 mm. Based on these criteria we can talk about different degrees of severity. On the one hand, we define severe acute malnutrition (SAM) when the WHZ < -3 and/or MUAC < 115 mm, while we define moderate acute malnutrition (MAM) as a previous state where $-3 < \text{WHZ} < -2$ and/or $115 < \text{MUAC} < 125$ mm. The severity with which an individual is diagnosed and begins treatment is a key factor, as it has implications for both the probability of cure and the duration and speed of recovery (Atnafe et al. 2019; López-Ejeda et al. 2020), in addition to being associated with the possibility of infections and clinical complications (Rytter et al. 2014). Even in various studies, it has been found an association between the severity with which the individual was admitted to treatment and a higher risk of mortality months after recovery (Chisti et al. 2014; Kerac et al. 2014). Therefore, establishing which factors associated with acute malnutrition influence and worsen the severity of an individual is essential to optimize the results of interventions, identify the most vulnerable groups of individuals and work on prevention, thus achieving better treatment of child acute malnutrition together.

To date, there are multiple studies that have addressed the identification of risk factors for developing a severe state of malnutrition, using different statistical techniques and in various contexts. Some variables have shown a relevant impact, such as the age or sex of the child, as well as the duration of breastfeeding. (Ukwuani and Suchindran 2003; Nankinga et al. 2019; Hossain et al. 2020; Thurstans et al. 2020). Nevertheless, not only eminently biological factors or those related to eating behaviour have an impact on child acute malnutrition. The socioeconomic and educational levels of caregivers are frequently identified as key in this context (Tette et al. 2016; Imam et al. 2020; Karim et al. 2021). Additionally, a study carried out by Ketema et al. (2022) in Ethiopia established that the caregiver's employment status influences the quality of care and the nutritional status of the child. Other studies have shown a greater relevance of factors associated with hygiene, the availability, and quality of water consumed in households (Semba et al. 2009; van Cooten et al. 2019), which can be related to episodes of diarrhoea, another factor recurrently identified by more authors (Hossain et al. 2020; Donkor et al. 2022).

Nonetheless, a limitation of these studies is that they are based on logistic models, meaning they model the probability that the individual is severely malnourished as a linear function of parameters, thus not contemplating the more complex nonlinear relationships but generating a nonlinear relationship between input and output variables due to the sigmoid function. Furthermore, some of them consider univariate models, or models with only one or two control variables, but not multivariate models that take into account the influence of the rest of the covariates simultaneously and the possible interrelation between them, an approach that would fit better to the reality of the problem. In this sense, more complex analytical approaches have recently been developed, using machine learning methods, which can adjust models to predict the probability of malnutrition in an individual. Different studies have concluded, after evaluating different machine learning algorithms, that the one that provides the best success rates for predicting the state of malnutrition is the random forest (Talukder and Ahammed 2020; Fenta et al. 2021). Later studies, such as Bitew et al. (2022) and Anku and Duah (2024), adding a greater number of algorithms, agree in pointing out the XGBoost algorithm as a very effective tool. However, Bitew et al. (2022) also highlighted the almost identical value found using random forest: 88.1% compared to 88.0% of XGBoost, yielding almost equivalent results. The most advanced methodologies use a combination of multiple algorithms to improve prediction through an ensemble approach, Khan and Yunus (2023) show that the success rate of individual algorithms: random forest (81%), XGBoost (79%), k-nearest neighbors (74%), among others, is improved by combining their predictions.

The countries of Mali and Niger, located in the Sahel region, experience worrying living conditions for much of their population, with high levels of extreme poverty, situations of food insecurity aggravated by recurring periods of droughts and floods, which are also combined with security problems derived from chronic armed conflicts, often causing population displacement (OCHA 2022a, 2022b). The regions of Gao and Diffa, located in Mali and Niger respectively, have very high rates of child acute malnutrition according to the latest national reports, with the global acute malnutrition rate in Mali being 16.1%. (95% CI: 13.0–19.7), with SAM being 3.3% (95% CI: 2.2–4.9) (Institute National de la Statistique du Mali 2022) and 16.1% in Niger (95% CI: 13.5–19.1), with SAM being 2.2% (95% CI: 1.2–4.0) (SMART 2021). The present study consists of a secondary analysis of socioeconomic data associated with previous studies carried out in both regions of Mali and Niger, where the effectiveness of a new protocol treatment for child acute malnutrition was evaluated (Charle-Cuéllar et al. 2023; López-Ejeda et al. 2024; Sánchez-Martínez et al. 2023).

Our objective here is to determine which socioeconomic variables are associated with greater severity at admission for the treatment of acute malnutrition and to predict, based on these variables, the degree of severity of the individual. The results obtained will allow the most relevant factors, with the potential to apply that knowledge both in optimizing the collection of socioeconomic data in potential future local interventions and in the development of programs for the prevention or minimization of child acute malnutrition.

2 | Materials and Methods

2.1 | Study Design and Assessment

The present study is a secondary analysis derived from a controlled trial for the treatment of child acute malnutrition (6-59 months) carried out in the regions of Diffa in Niger and Gao in Mali, during the period from June 2020 to June 2021. Both regions are declared emergency zones, characterized by the presence of natural disasters and armed conflicts that cause population displacement, aggravating the humanitarian situation.

In Mali, a cluster-randomized controlled trial was applied throughout the Gao health area, involving a total of 12 health facilities and 20 health posts with Community Health Workers, reaching a sample size of 832 children with MAM and 1206 with SAM, treated between June 2020 and June 2021. On the other hand, in Niger a non-randomized controlled trial was conducted in two specific health areas, comprising a total of 9 health posts with health staff and Community Health Workers. For children's inclusion, treatment providers obtained signed and informed consent form to participate in the local language from all parents or caregivers. The study was approved by the National Health Research Ethics Committee of Niger with the reference number 013/2020/CNERS and by the Ethics Committee of the INSP, the reference agency of the Ministry of Health of the government of Mali (decision no. 35/2029/CE-EX-INRSP). The sample size of children treated in this case was 664 MAM and 508 SAM, between the months of December 2020 and April 2021. Regarding the admission criterion for treatment, which served to establish the severity groups, standard international criteria were used (World Health Organization WHO 2013): a child is classified as SAM if they present mild edema (+), or if their WHZ < -3, or if their MUAC < 115 mm. A child is classified as MAM if their WHZ is between -3 and -2, or if their MUAC is between 115 and 125 mm. More details about the original trials can be found in Charle-Cuéllar et al. (2023) and López-Ejeda et al. (2024).

2.2 | Socioeconomic Assessment

Initially, with the objective of evaluating the possible socioeconomic differences between the groups of individuals treated in each protocol and their influence on the treatment results, a socioeconomic survey was carried out among a subsample of participants. Specifically, the sample size reached in them, and on which the present analysis is based, was 676 individuals in Mali and 771 individuals in Niger. The socioeconomic survey was conducted by interviewing the child's caregiver at the treatment site at the first treatment visit. It consists of four dimensions of questions about living conditions: demographics, livelihoods, food security and diversity, and access to medical attention. The 86 variables included in the analysis were used with the format in which they appeared in the questionnaire except for the food security measure, which was originally measured through a questionnaire administered to the children's caregivers. This measure aimed to reflect the diversity of the diet and the frequency with which food groups were consumed in the last week. Subsequently, each food group was weighted based on its quality in terms of caloric density, resulting in a final sum or Food Consumption Score categorized into three groups: 0–21 for a poor diet, 21.5–35 for a limited diet, and > 35 for an acceptable diet (World Food Programme WFP 2008).

2.3 | Statistical Analysis

The statistical analyzes applied were carried out using the R software (R Core Team 2022). An R script template compiling the code used during data analysis is available in Supporting material. Firstly, data preprocessing tasks were carried out, including an analysis of the distribution of missing values among the variables, removing those whose percentage exceeded 5% (see Supporting Information S1: Table 1). Supporting Information S1: Table 2 presents a list of the variables that were finally included and analyzed in the present study after data cleaning. In a second preprocessing phase, individuals with a missing value in any of their variables were eliminated, reaching a final sample size of 599 in Mali and 725 in Niger (Supporting Information S1: Figure 1). Study data may be shared by the authors upon reasoned request. After these data preprocessing phases, necessary to be able to work with the VSURF algorithm as it requires complete records, the variables were selected using random forest. This algorithm, proposed by Genuer et al. (2015), is divided into three steps: In the thresholding step, the precision in the prediction of a random forest model is used to order the variables by their importance in the model, and based on a threshold, variables that are barely related to the variable of interest, in our case, severity upon admission, are eliminated. The estimation of Variable Importance (VI) is based on the out-of-bag error of the decision tree, which is a measure of prediction error (Gareth et al. 2013), using the standard deviation of the VIs, the value of this threshold is calculated. Afterwards, in the interpretation step, a nested collection of random forest models is progressively adjusted using the variables selected and ordered in the previous phase, so that the set of them that leads to the model with the lowest out-of-bag error is retained. Finally, the VSURF algorithm moves to the prediction step, in which, starting from the variables selected in the interpretation step, it adjusts a sequence of random forest models, including the variables in a stepwise manner. More precisely, the sequential variable introduction is based on the following test: a variable is added only if the OOB error decrease is significantly larger than the average variation obtained by adding noisy variables. This way, redundancy between variables is minimized, focusing more carefully on the prediction value. Figure 1 reflects a graphic summary of the process.

After the selection of interpretation and prediction variables, different random forest models were adjusted for these two sets of variables independently for each country. Different combinations of hyperparameters were evaluated in the models through a Grid Search, testing every unique combination (mtry: 3, 4, 5, 7 and node size: 2, 3, 4, 5, 10, 15, 20, 30), selecting those that maximized classification accuracy (see Supporting Information S1: Figure 2). The number of decision trees adjusted in each random forest was set to 500. The importance of the variables within their model was estimated using the Mean Decrease Accuracy, which measures the percentage of decrease in the model's accuracy when the variable in question is removed, and how much this variable contributes to the homogeneity of the nodes. Therefore, the higher these values, the greater the importance of the variable in the model (Strobl et al. 2007). To evaluate the prediction value and the reliability of the model, repeated cross-validation (cv) was applied, using parameters of 10 partitions and 5 repetitions, meaning 5 repetitions of 10-fold cv. This is a more robust approach than a train-test split, as in a 10-fold cv, the data set is randomly divided into 10 parts, and each part is then used as a prediction set (test) for the model trained on the remaining 9. This process calculates the average of the 10 error terms obtained. Subsequently, the average of the error terms from the 5 repetitions is computed (Kim 2009). This approach, compared to conventional split-train tests, minimizes potential selection bias in the validation process and ensures the reliability of its results (Cawley and Talbot 2010).

A multiple correspondence analysis (MCA) was applied independently for Mali and Niger using MCA function in "FactoMineR" R-package to delve into the relationships established between the categories of the variables in the prediction step and the severity categories. Afterwards, based on the coordinate values that each category acquired in each of the dimensions of the MCA, a hierarchical cluster analysis (HCA) was applied,

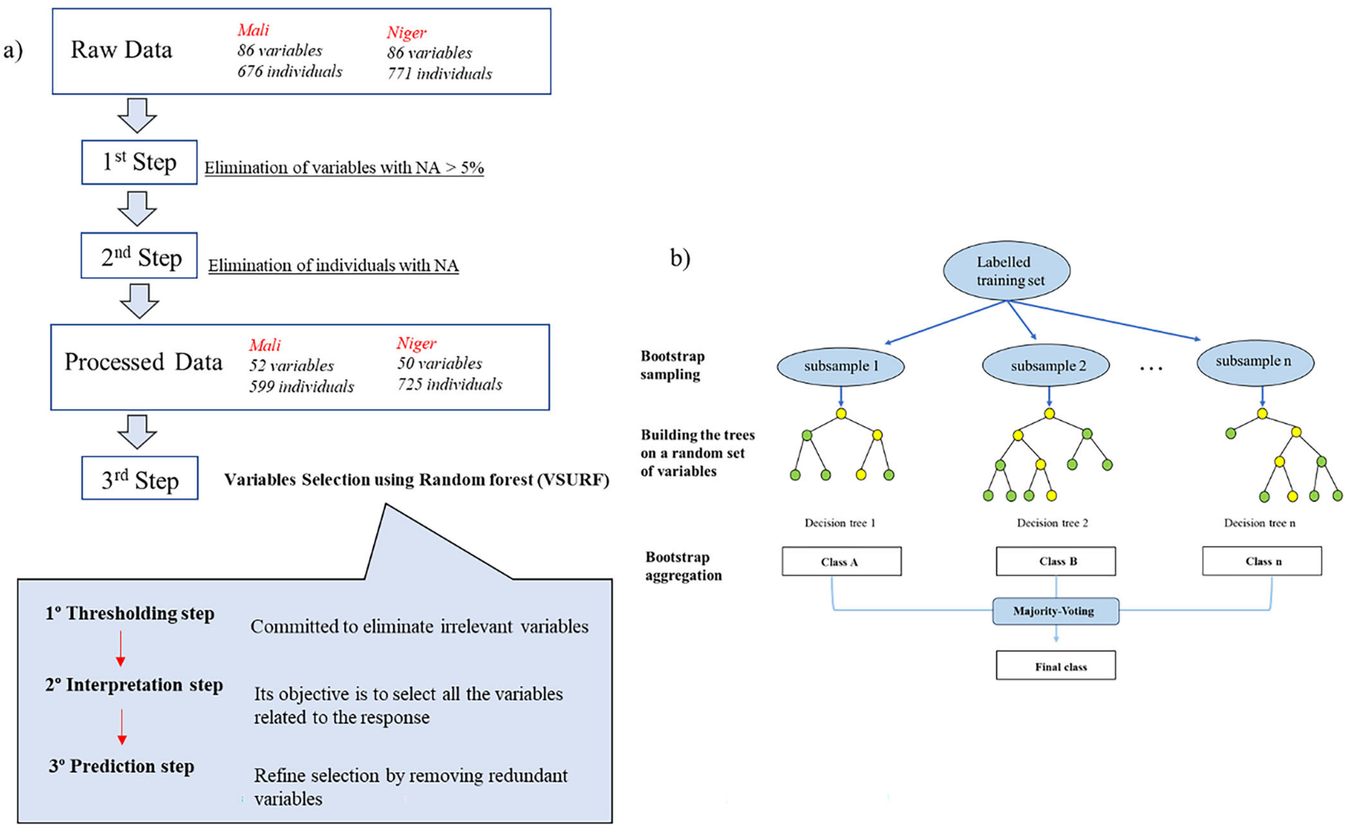

FIGURE 1 | VSURF algorithm details. (a) Workflow of preprocessing and variable selection (b) development of a random forest algorithm.

constructing a dendrogram that links the most related categories to each other based on Euclidean distances.

When performing univariate statistical comparisons between the severity conditions (SAM/MAM) for the various variables of interest, the following tests were applied: Pearson's chi-square test with Yates' continuity correction for qualitative variables, and either the Student's *t*-test or the Mann-Whitney test, depending on the normality of the data, for quantitative variables.

2.4 | Ethics Statement

The study was approved by the National Health Research Ethics Committee of Niger (reference n° 013/2020/CNERS) and the Ethics Committee of the Institut National de Sante Publique (INSP) of Mali, (reference n° 35/2029/CE-EX-INRSP). All parents or caretakers of the children included in the study signed informed consent prior participation in the study.

3 | Results

After preprocessing of missing values, the sample of 1447 children (Mali = 676, Niger = 771) with acute malnutrition was reduced to 1324 children (Mali = 599, Niger = 725). The elimination of variables with an occurrence of NAs > 5% also meant a reduction from 86 variables to 52 in Mali and from 86 variables to 50 in Niger (Supporting Information S1: Table 2).

Subsequently, the VSURF algorithm carried out screening in its three steps of analysis of the variables most related to the severity at admission (MAM/SAM). After eliminating the most irrelevant variables in the first step (thresholding step), the interpretation step selected those variables that were associated, up to a certain threshold, with the target severity variable. In the case of Niger, 13 variables were selected and in the case of Mali, 6 variables were selected. Supporting Information S1: Table 3 and 4 show, ordered by their importance according to the mean decrease accuracy, the interpretation variables and their frequencies between the group of severe children (SAM) and the moderate group (MAM) for both countries.

Interesting differences between severity groups in Niger can be seen in Supporting Information S1: Table 3. Firstly, it can be seen how the MAM show greater ease in making the trip to the health center on the same day (VN50). On the other hand, a greater proportion of children's caregivers in the MAM group are observed to work 8 h or less (VN17). However, this difference may be due to the category proportion of caregivers who do not know the information. Additionally, heads of households in the MAM group tend to engage in a greater proportion of unskilled manual labor (VN14). The difference in the variable "reduction of usual food portions in the last 4 weeks" (VN44) is also very noticeable, with it being more frequent in the SAM group compared to the MAM group. Along with this, the time to go to get water supplies (VN11) is longer in the SAM group. Likewise, other variables related to family economic resources, such as possession of a mobile phone (VN25) or mattress (VN24). Finally, the Food Diversity Index (VN52) seems to be more limited in the MAM group than in the SAM group.

Regarding the case of Mali (see Supporting Information S1: Table 4), relevant differences are observed compared to Niger due to the geographical context. In this case, the source of water supply (VM9) has great relevance, such that MAM usually consume water from covered and protected wells, while SAM consume water from their homes. Furthermore, the occupation of the head of the household (VM14) differs between the MAM and SAM groups in Mali. MAM typically work in agriculture or as household employees, while SAM are more likely to work in livestock farming, transport, or skilled manual labor. A higher occurrence of going a whole day without eating in the last 4 weeks was reported in the MAM group (VM45). The MAM group exhibits greater access to arable land (VM34), while the SAM group has greater access to electricity (VM32). Additionally, a higher proportion of caregivers in the SAM group are dedicated to agriculture (VM15).

It is interesting to analyse the importance of each of the interpretation variables within the model as a whole. To do this, Table 1 shows the Mean Decrease Accuracy values when including them in a random forest model. It can be seen, how in the case of Mali, it is noticeable that all variables have a very similar importance in decreasing the precision of the model when each one is eliminated (~20–25). The behaviour of variables in Niger is less uniform, finding variables with greater importance within the model and others with a more subtle influence. This could be due to certain groups of variables being dependent and not informative in the presence of others. Notably, in Niger, the variable 'distance to the health center' stands out with the highest mean decrease accuracy.

Table 1 shows the variables that are part of this prediction model in both Mali (VM9 and VM15) and Niger (VN50, VN15, VN15 and VN11). It is interesting that in both scenarios, variables related to the availability and quality of the consumed water appear. Also, in both cases, variables related to the occupation of the child's caregiver are selected. In Niger, another interesting variable appears, which is related to the distance to the health center.

Subsequently, different random forest models were trained and validated independently for Niger and Mali using the interpretation and prediction variables. This was done through cross-validation, modifying the combination of hyperparameters to find the optimal Accuracy value (see Supporting Information S1: Figure 2). It is interesting to observe how both the country and the analyzed set of variables influence the definition of a different combination of hyperparameters as the optimal one in each case. Figure 2 displays the different confusion matrices and their resulting Accuracy for the optimal random forests in differentiating between the two severity states, both in Mali and Niger, using the interpretation and prediction variables. Using these confusion matrices, we can contrast the values predicted by the model in rows and the real values in the columns, in such a way that each cell numerically represents the agreement, or not, of each category predicted by the model and the actual one. The diagonal of the matrix is especially interesting as it reflects the values predicted by the

TABLE 1 | Importance of the interpretation variables within a random forest model for the case of Mali and Niger. It is also indicated if the variable was selected for the prediction step by VSURF.

Country	Interpretation variables	Cod	Mean Decrease Accuracy	Prediction variables
Niger	Can you make the round trip to the health center in one day?	VN50	23.56	Yes
	Main occupation of the child's caregiver	VN15	17.36	Yes
	How many hours does the child's caregiver dedicate to their job?	VN17	16.65	No
	At some point during the year has the number of meals at home been reduced?	VN41	15.58	No
	In the last 4 weeks, have you reduced the number of usual meals?	VN44	14.73	No
	Food Diversity Index	VN52	14.31	No
	Main occupation of the head of the household	VN14	14.25	Yes
	How many days of the week does the caregiver dedicate to their job?	VN16	13.25	No
	Do you have a mobile phone?	VN25	11.79	No
	Do you have a mattress?	VN24	10.37	No
	How many people live in the child's household?	VN18	7.33	No
	How long does it take to get water supplies?	VN11	7.29	Yes
	Age of the child's main caregiver	VN2	5.64	No
Mali	Main occupation of the head of the household	VM14	26.07	No
	Main source of water supply	VM9	25.73	Yes
	Do you have access to arable land?	VM34	25.71	No
	In the last 4 weeks, has anyone in the household gone an entire day without eating?	VM45	22.85	No
	Do you have access to electricity?	VM32	21.42	No
	Main occupation of the child's caregiver	VM15	20.96	Yes

Abbreviations: VN, variable of Niger; VM, variable of Mali.

model that coincide with the real values of those individuals, that is, we would be talking about the success rate or Accuracy of the model.

Firstly, we observe that in both Mali and Niger, the highest Accuracy is provided by the set of interpretation variables, with 79.80% and 68.00%, respectively. This result is expected given the more comprehensive nature of the model. However, when we examine the prediction models, they do not show such a marked decrease in terms of their Accuracy value, with only a slight decrease of around 5% in both cases. Meanwhile, the reduction in the number of variables is very appreciable, dropping from 13 to 4 variables in Niger and from 6 to 2 in Mali, thus achieving much simpler and easier to use models in practical terms.

It seems evident that the prediction made by the models is better for the case of Mali than for Niger, both using the interpretation variables (79.80% vs. 68.00%, respectively), and using the prediction variables (75.63% vs. 63.17%, respectively). This fact points to a very plausible difference between both contexts. Additionally, the variables selected in each case are very different, with only two variables shared within the set of interpretation variables. If we examine the prediction of SAM cases, which are especially noteworthy due to their severity, very marked differences appear again between both models. While the models in Niger struggle to predict SAM cases [211/347 (60.8%) and 208/347 (59.94%)], very high sensitivities are achieved in Mali [413/446 (92.60%) and 435/446 (97.35%)].

It is particularly interesting to explore the relationship between the prediction variables and the severity categories (MAM/SAM) to determine precisely which factors contribute most to the dispersion of individuals. Figure 3 shows the conceptual map created by the MCA of Niger. The MAM category and the other categories of the predictor variables most associated with it are highlighted in green based on the HCA based on the coordinates of the variables. Similarly, the SAM category and the other predictor categories most associated with it appear in red.

However, it is interesting not to limit ourselves only to the results of the HCA and also analyze the relative position of the categories with respect to the degrees of severity. As can be seen, SAM is located in lower coordinates of dimension 1 but higher in dimensions 2 and 3 (Supporting Information S1: Table 3). In the same direction, interesting categories are also

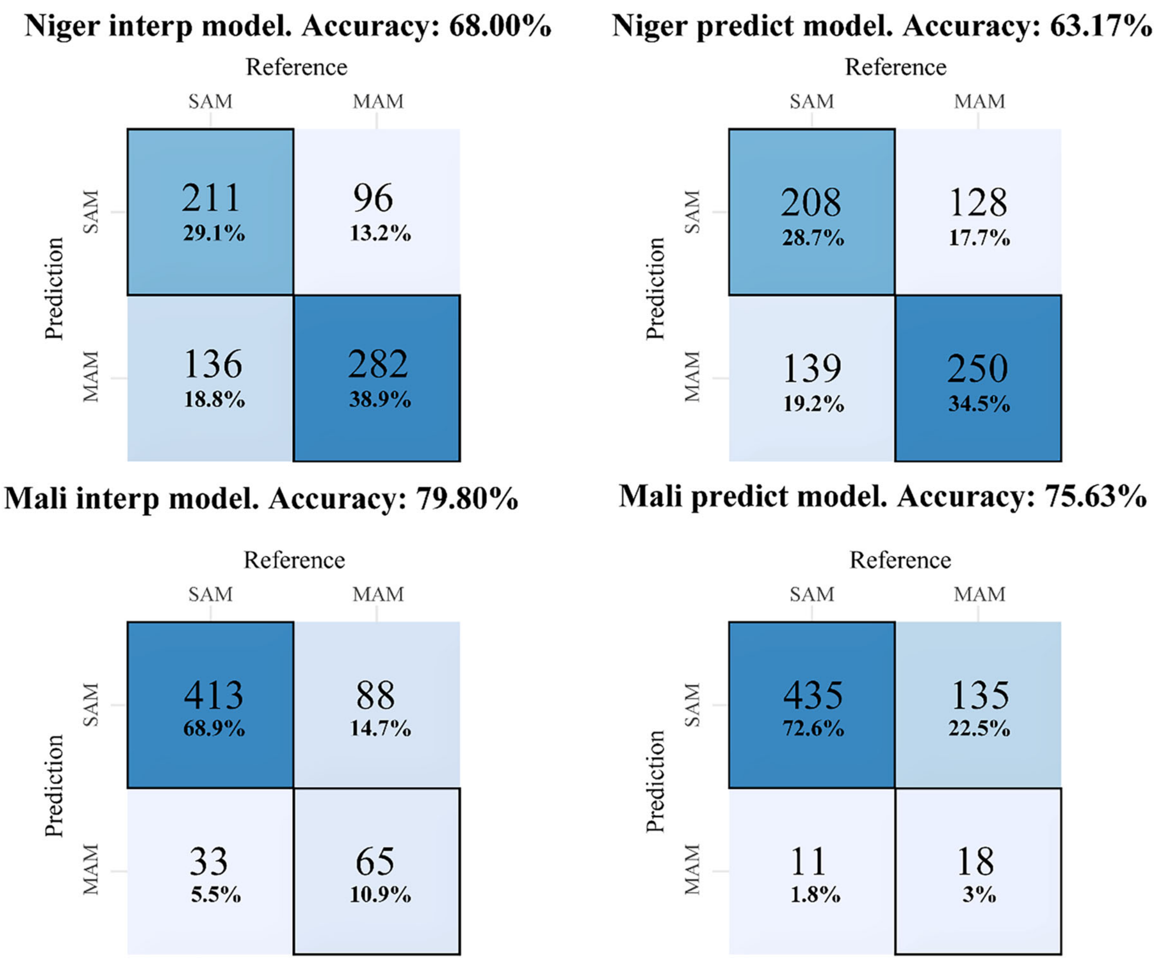

FIGURE 2 | Confusion matrix for the random forests models adjusted with the interpretation and prediction variables in Niger and Mali.

oriented, such as not being able to make the trip to the health center in a single day, agriculture being the main occupation of caregivers, and the head of the household. On the other hand, the MAM category tends towards a more positive sense of dimension 1 and a more negative sense of dimensions 2 and 3 (Supporting Information S1: Table 3). This is associated with variables such as being able to make the trip to the health center in a single day, taking between 30 min and 1 h to stock up on water, engaging in unskilled manual labor, and being a domestic worker as the main caregiver and head of the household.

As can be seen in the case of Mali, the separation between the severity groups is greater in the result provided by the MCA (Figure 4). The MAM category is located in positive coordinates of dimensions 1 and 3 but negative of 2, while the SAM category presents a completely opposite orientation (Supporting Information S1: Table 4).

By examining the distribution of the remaining categories, we can interpret the associations with the degree of severity in Mali. In the MAM category, the distributed categories are: The origin of drinking water is purchased water or from a protected well, skilled manual labor as the primary occupation of the child's caregiver, transport, and sales and services. While in the case of greater severity (SAM), the distributed categories are: The origin of drinking water from an unprotected well, home tap, and rainwater. Regarding the main occupation of the child's caregiver, it is associated with unskilled manual labor, household employee, agriculture, and cattle raising.

4 | Discussion

From an anthropometric point of view, child acute malnutrition is defined by two distinct states, an intermediate state known as MAM and a more severe state which is SAM. As a result, the WHO officially recommends treating them independently and applying different protocols (World Health Organization WHO 2012; 2013). However, a recent guideline has included recommendations for high-risk contexts, where there is a recent or ongoing humanitarian crisis. In these contexts, all infants and children aged 6-59 months with moderate wasting should be considered for specially formulated foods (SFFs). Along with counselling, they should also receive provisions of home foods for themselves and their families (World Health Organization WHO 2023). The present study investigates, in emergency contexts of Mali and Niger, the association of certain socioeconomic factors with greater severity at the time of diagnosis of acute malnutrition in children under 5 years of age.

Our results confirmed the great complexity that characterizes child acute malnutrition. This disorder is influenced by factors

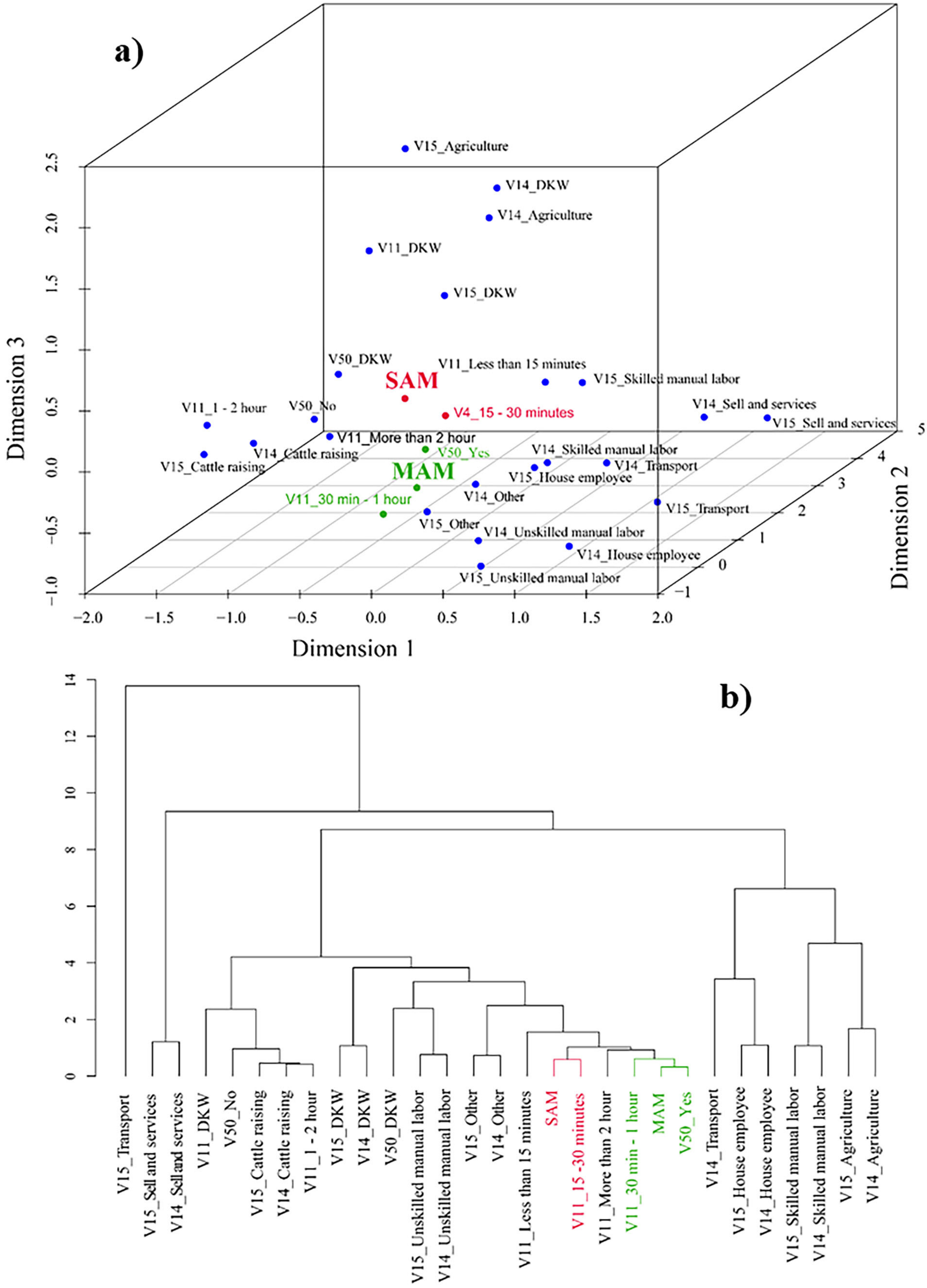

FIGURE 3 | Interrelationship between the categories of the prediction variables in the case of Niger. (a) The coordinates of the categories in the multiple correspondence analysis are shown. (b) Dendrogram based on the multiple correspondence analysis distances between the categories.

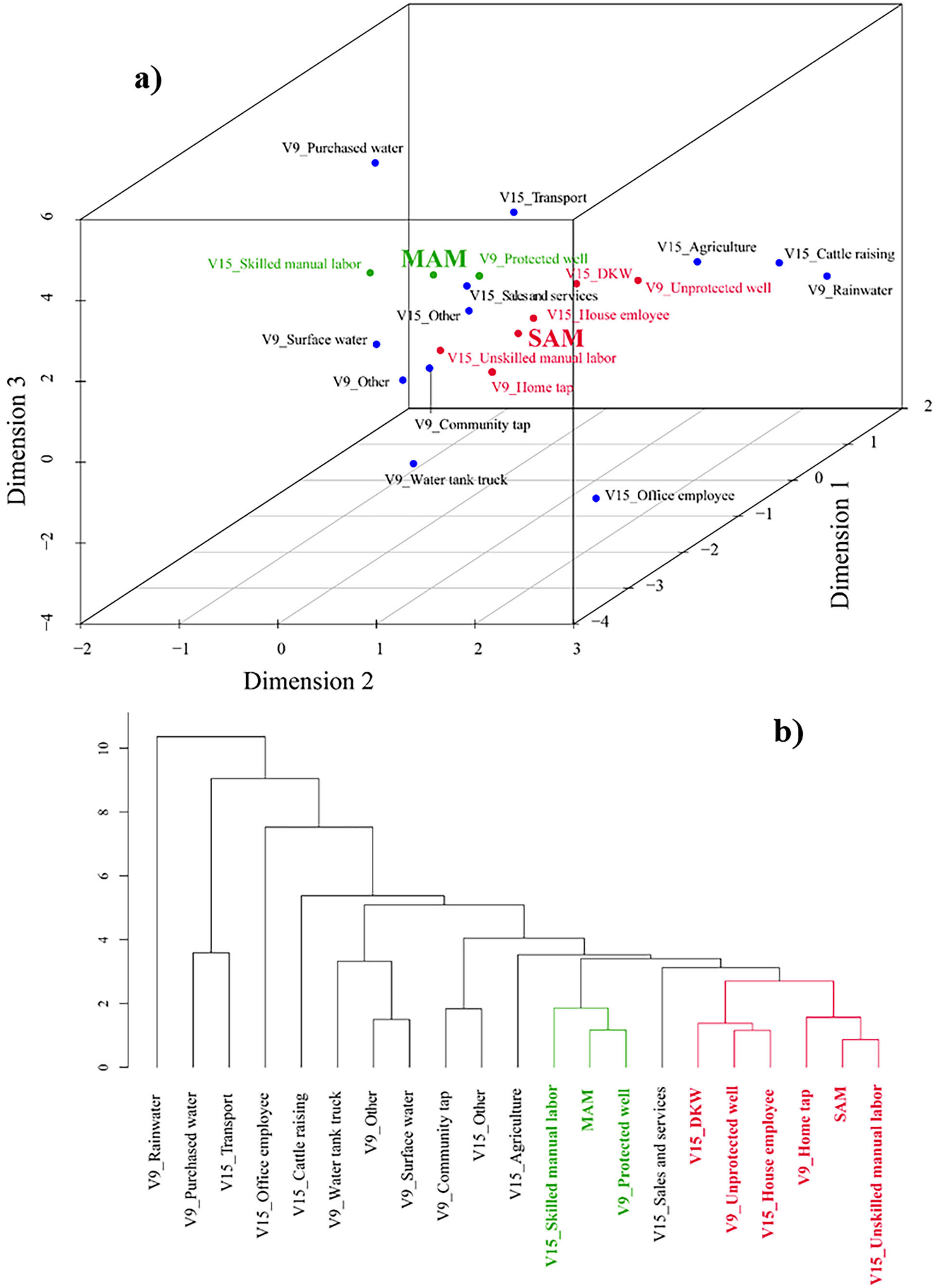

FIGURE 4 | Interrelationship between the categories of the predictor variables in the case of Mali. (a) The coordinates of the categories in the multiple correspondence analysis are shown. (b) Dendrogram based on the multiple correspondence analysis distances between the categories.

that are not exclusively biological, as demonstrated by the adjusted interpretation models. In addition, there is a clear variability between different national and local contexts. The effects of these factors and their interrelationships can vary significantly, as observed in the two regions of Mali and Niger studied. Therefore, it is essential to assess the scope of action beforehand to effectively alleviate the effects of child malnutrition. Another methodological aspect that must be considered when interpreting the results is that the algorithms used provide the advantage of managing the variables jointly, taking into account their interrelationships, which offers a better approximation to a multivariate reality. Compared to a more biased analysis, such as analysing the variables independently, the descriptive tables, in some cases show discordant results, possibly related to the existence of confounding factors.

The models adjusted in the second phase of the analysis (interpretation step) provide a broad set of variables that are associated with the severity phenomenon (MAM/SAM), which are useful for understanding the context of each region. On the one hand, in the case of Niger, the most notable significant differences between MAM and SAM are based on the greater ease of MAM children compared to SAM in making the trip to the health center on the same day. This ease of access is indicative of the distance to the center and the varying levels of accessibility to health services, which has also been linked to malnutrition in recent studies (Shahid et al. 2022; Atalell et al. 2023). On the other hand, it was detected that more caregivers of children with SAM reported having to reduce the portion of food at home during the last 4 weeks. This emphasizes the lower availability of food in the group of children with greater severity. Nevertheless, the diversity of the diet in the home of the MAM children was smaller than that in the homes of SAM children. This could be explained as a consequence of inappropriate feeding practices related to the child's age. After the first 6 months, during which exclusive breastfeeding is recommended, it has been shown that maintaining breastfeeding along with complementary feeding helps protect against falling in acute malnutrition (Akombi et al. 2017; Hossain et al. 2020). Likewise, significant differences were found in the time that both groups invested in water supply, with the MAM group having a greater frequency of families requiring 30 min to 1 h. This association of distance to the water source with child malnutrition has been supported by previous studies, which have also highlighted its impact (Kamiya 2011; Bitew et al. 2022).

If we look at the situation in Mali, we observe that the most notable differences between both severity groups are due, first of all, to the source of water supply. While MAM children usually consume water from covered and protected wells, SAM children more frequently consume water from taps in their homes, whose safety is not guaranteed. This association may be due to the quality of the water itself as a result of poor sanitation. Several studies have highlighted the importance of having access to safe water to reduce the risk of child malnutrition due to the comorbidities that it can trigger (Bhutta et al. 2013; Ercumen et al. 2015; Nagahori et al. 2015). A variable that showed interesting differences between the groups was the occupation of the head of the household. In the MAM group, it is usually in agriculture or as a house employee, while in the SAM group, they usually dedicate themselves to livestock, transport, or skilled manual labor. A previous study carried out in the Greater Horn of Africa found similar results, with the prevalence of wasting among pastoral child populations about 6-7 percentage points higher than the rates among agricultural populations or populations with mixed livelihoods. These differences have been interpreted in relation to a differential body composition of the former populations, due to the existence of a Nilote body type where the individual grows thinner but taller (Chotard et al. 2010). Other studies have linked the presence of animals in the child's environment with a worsening of health conditions that can trigger wasting (Gelli et al. 2019). Finally, the comparison between groups in the variables of access to electricity and whether someone in the household has gone a whole day without eating in the last 4 weeks is striking. The group of SAM children has greater access to electricity in their home and fewer occurrence of a cohabitant having gone a day without eating. Taken together, both variables would indicate a higher socioeconomic level that would lead to greater availability of food. However, since they are associated with the group of children with more severe malnutrition, this leads to the question of whether these households are part of a program or receive help from an organization because they actually have a low socioeconomic condition. The literature demonstrates that an increasingly lower socioeconomic level aggravates the risk of child malnutrition and its effects (Tette et al. 2016; Li et al. 2020; Alaba et al. 2023; Chowdhury et al. 2023). Nevertheless, these variables were not selected by the final predictive model.

Another interesting aspect that emerges from the analyses and that is pertinent to discuss here is the difference in the number of variables selected by VSURF in each region, which is also in line with the differences shown in the prediction values of the models. While in Niger, despite selecting more variables, success rates of 63%–68% are achieved, in Mali, with fewer variables selected, success rates of 75%–80% are achieved. This fact reflects that the behaviour of the severity of acute malnutrition is much better reflected in Mali with the analysed variables. Therefore, in the case of Niger there must be other factors not contemplated in this study that are influencing the behaviour of severity with appreciable impact. Among them, we can consider biological factors such as the incidence of certain comorbidities that have been widely associated with child acute malnutrition (Richard et al. 2013; Menalu et al. 2021; Owusu et al. 2024). Another factor that could have a high influence is the health quality to which families have access, for example, in terms of vaccination (Altare et al. 2016; Ambadekar and Zodpey 2017). There may even be population genetic factors whose variability has not been taken into account (Duggal and Petri 2018).

If we analyse the results obtained by the random forest models in more detail, we find success rates (Niger: 63-68% and Mali: 75%–80%) in a range approximate to those provided by previous studies. Bitew et al. (2022) achieved success rates of 86.0%–90.2% when predicting wasting in Ethiopia. Similarly, the study by Anku and Duah (2024) improved this success rate, achieving a range of 84%–98% by considering a set of seven different algorithms. These differences may be due to the fact that their analysis objective was not as specific as ours, since in these studies they considered, in a more general way, differentiating between normonourished children and children with acute malnutrition in any degree of severity. Another study carried out by Talukder and Ahammed (2020) in Bangladesh also used random forest to predict whether a child was normonourished or had wasting, achieving success rates of 66.26%–70.71%. These more moderate rates of prediction success could be related to the fact that the authors used a smaller number of variables. A subsequent study from the same 2014 Bangladesh Demographic and Health Survey (BDHS), but using a greater number of variables, showed a success rate of 87.7% (Rahman et al. 2021). Therefore, it is evident, as in our interpretative models, that increasing the number of variables used in the same model usually results in a higher success rate. Another factor that must be taken into account, and which limits a direct comparison of our results, is that our data come from emergency contexts with the presence of armed conflicts. These conflicts affect different humanitarian levels, ultimately having an impact on the nutritional status of the affected population (Azanaw et al. 2023).

If we advance to the third phase of VSURF analysis (prediction step), we find the prediction models. This step corresponds to a model that tries to avoid redundancy by focusing more closely on the prediction objective (Genuer et al. 2015). It is interesting that in both contexts, variables related to the source of water and the occupation of the child's caregiver have been selected. Additionally, in Niger, a variable that reflects the distance to the health center appears. The subsequent MCA and HCA applied to this set of variables reveal an interesting association between their categories in each context.

On the one hand, in the case of Niger, the analysis indicates that the MAM group shows more intense associations with investing 30 min to 1 h in stocking up on water and making the trip to the health center in 1 day. In turn, the SAM group is more intensely associated with not making the trip to the health center in 1 day and investing 15 min to 30 min in stocking up on water. However, although not with as much weight, the categories of investing 1 h to 2 h and more than 2 h are closer to the SAM category. That is, we are finding that in Niger, the most determining factors for severity would be factors related to the distance to the treatment and the water source. A previous study reported distance as the primary barrier to accessing malnutrition treatment (Puett and Guerrero 2015). It has also been shown that a greater distance to the health center is a factor that negatively contributes to the treatment of other diseases (Mbuba et al. 2012; Debsarma et al. 2022). Added to this is the challenging situation in Niger in this regard, where a geospatial study found that the distribution of community health posts was inefficient, with only 22.1% of the population having access to a treatment site within a reasonable 60-min walk (Oliphant et al. 2021).

On the other hand, in the case of Mali, the MAM group is more intensely associated with consuming water purchased or water from a protected well. Their caregivers are primarily engaged in skilled manual labor, transport, and sales and services. In contrast, the SAM group is more associated with consuming water from the home, unprotected wells, and rainwater. Additionally, their caregivers are mainly involved in unskilled manual labor, housekeeping, agriculture, and cattle raising. In short, the most logical interpretation would be that children with MAM consume water in better condition and their caregivers have jobs that may indicate a higher socioeconomic level. It is widely contrasted and accepted in the literature that a higher household income is related to greater food security, due to its link with a higher educational level of the parents and the possibility to invest a greater number of economic resources in access to sufficient food of adequate quality and access to basic health care services (Akombi et al. 2017; Katoch 2022). In this sense, a recent study using machine learning techniques has agreed to identify the educational level of both caregivers as the best predictors of the wasting condition in their model (Islam et al. 2024).

The results indicate, therefore, that access to and availability of water are essential factors for understanding and predicting the severity of child malnutrition. The Sahel region consists of a semi-arid area where water availability is reduced. Many surface water bodies are heavily dependent on precipitation, reaching capacity during the rainy season, and disappearing completely during the dry season (Snorek et al. 2014). This low availability in dry and isolated areas means that natural and artificial water sources are frequented by humans, livestock, and wild animals, which favours an environment conducive to the transmission of diseases (Schelling et al. 2016). The great importance of this environment regarding the severity of acute malnutrition lies in the fact that a vicious circle is created between malnutrition and diseases. Malnutrition in children increases their susceptibility to contracting infectious diseases, and diseases cause serious effects on nutrition, all accompanied by a prolonged deterioration of the individual's immune function (Rodríguez et al. 2011). All of these relationships are mediated by leptin, a pleiotropic hormone whose levels increase acutely during infection and inflammation (Faggioni et al. 2001). Nevertheless, leptin levels are reduced during acute malnutrition due to the loss of fatty tissue. These low levels initiate a series of physiological adaptation responses, such as reduced appetite and increased energy expenditure, raising the metabolic rate, suppressing immune, reproductive and thyroid function, and stimulating the hypothalamus-pituitary-adrenal (HPA) axis (Amorim et al. 2023).

Overall, this study has shown the enormous complexity surrounding acute malnutrition, considering its multifactorial nature and emphasizing the association of certain factors with greater severity of the pathology. The specific results will serve to optimize the questionnaires for collecting socioeconomic data at the local level, by including key variables associated with acute malnutrition and, especially, with its most severe manifestation. The information provided by these questionnaires can be used to target prevention plans more effectively or improve existing interventions. This may include adding new water and sanitation components to treatment models, bringing treatment points closer to families in remote locations through Community Health Workers, or implementing training programs to enhance the employability and entrepreneurship of caregivers. It is worth mentioning that possible differences may exist between specific contexts. Therefore, it would be necessary to be cautious when extrapolating the results shown in the present study to other regions. Instead, we should use this study as a practical approach that could be applied in different contexts with the aim of better characterizing child acute malnutrition and optimizing the fight against it. Regarding method limitations, the most common problems with machine learning algorithms are underfitting and overfitting. To mitigate these issues, we have applied robust cross-validation methodologies to enhance the reliability of the results. Furthermore, the simulation study by Rajput et al. (2023) demonstrated that a sample size of $n = 500$, similar to our study, marks a point beyond which the efficiency of the algorithms becomes asymptotic, rendering further improvements negligible.

5 | Conclusions

The present work has demonstrated, using machine learning techniques, the existence of socioeconomic risk factors involved in an increase in the severity of child acute malnutrition. Good success rates have also been obtained from the random forest algorithm when predicting the degree of severity of an individual using only socioeconomic variables. However, there was high variability between countries and in the weight and interrelationships that occur between these factors. Risk may change depending on the conditions of each population.

In the emergency context of Gao in Mali, the main risk factors identified by the prediction model were: the source of drinking water and the work activity of the caregiver of the child in treatment. Conversely, in the emergency context of Diffa in Niger, the identified risk factors were: the distance to the health center, the distance to the water source, the work activity of the caregiver and the head of the household. This knowledge holds great potential in providing concrete guidelines for lines of action to be undertaken at the level of public policies, aiming to prevent and minimize the effects of acute malnutrition in the future, as well as to design future humanitarian interventions.

Author Contributions

L.J.S.-M. performed database cleaning, analysed, and interpreted the data, write the manuscript. P.C-C. and N.L.-E., designed the study, validated the field implementation of the study and revised the manuscript. A.O.D. supervised and validated field implementation of the study. F.T., C.L.H., A.V. revised the draft manuscript, advised and validated the manuscript. All authors contributed to the article and approved the submitted version.

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Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.