

Review

# Modelling Neglected and Underutilised Crops: A Systematic Review of Progress, Challenges, and Opportunities

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**Abstract:** Developing and promoting neglected and underutilised crops (NUS) is essential to building resilience and strengthening food systems. However, a lack of robust, reliable, and scalable evidence impedes the mainstreaming of NUS into policies and strategies to improve food and nutrition security. Well-calibrated and validated crop models can be useful in closing the gap by generating evidence at several spatiotemporal scales needed to inform policy and practice. We, therefore, assessed progress, opportunities, and challenges for modelling NUS using a systematic review. While several models have been calibrated for a range of NUS, few models have been applied to evaluate the growth, yield, and resource use efficiencies of NUS. The low progress in modelling NUS is due, in part, to the vast diversity found within NUS that available models cannot adequately capture. A general lack of research compounds this focus on modelling NUS, which is made even more difficult by a deficiency of robust and accurate ecophysiological data needed to parameterise crop models. Furthermore, opportunities exist for advancing crop model databases and knowledge by tapping into big data and machine learning.

**Keywords:** crop simulation modelling; climate resilience; ecophysiology; sustainability; NUS



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## 1. Introduction

Dansi et al. [1] defined NUS as the plant species that are adapted to local environments and are culturally and traditionally important, but underutilised by society and neglected by research and conservation. Despite their status, NUS have gained attention as potential food and nutrition security crops [2] that aid in poverty reduction [3] and promote climate change adaptation [4]. The adaptability, nutritional attributes, and socio-economic potential of NUS make them appropriate crops for production and use in limited-production regions where poverty, food and nutrition insecurity, and unemployment are high [3]. While NUS can contribute to transformative agriculture, their role in mainstay agriculture remains obscure [5].

Many proponents of modern agriculture argue that many NUS are low yielding and that there is insufficient spatial and temporal data detailing their response to different agroecologies and management options [6,7]. Additionally, information about their genomics, breeding, production, management, and performance in the broader agroecosystem remains anecdotal and poorly documented in indigenous knowledge systems. By contrast,

major crops such as maize have a well-developed scientific and indigenous knowledge base, contributing to their research development and widespread use [6]. For NUS to fully partake in transformative agricultural and rural development, there is a need to consolidate and strengthen existing knowledge systems. Data to inform and design a knowledge base that is at par with major crops like maize may need innovative tools to generate relevant data. In this regard, we suggest crop growth simulation models as useful tools for bridging the existing knowledge gap.

Crop models have proven useful tools for generating data to support decision-making for sustainable resource management [8–10]. In addition, crop models have been utilised in developing optimal crop management strategies and used extensively in optimising the production of major crops and predicting the impact of environmental changes on crop ecophysiology and productivity. Crop models have been used in ideotype-based plant breeding (e.g., [11–13] for wheat) to investigate the links between crop physiology, genetics, and phenomics [14] and in assessing the impacts of innovations on transformative adaptation to climate change [15,16]. However, the application of crop models in modelling NUS has progressed at a slower rate compared to those of the staples like rice and wheat.

Crop modelling studies on NUS have focused on quinoa (*Chenopodium quinoa*) [17], amaranth (*Amaranthus* spp.) [18], bambara groundnut (*Vigna subterranea*) [19,20], sorghum (*Sorghum bicolor*) [21,22], cowpea (*Vigna unguiculata*) [23,24], pearl millet (*Pennisetum glaucum*) [25], sweetpotato (*Ipomoea batatas*) [26], and taro (*Colocasia esculenta*) [27]. However, these efforts have not been nearly the same as those for major crops. Therefore, this study aimed to assess the current progress, challenges, and opportunities for modelling NUS. The scope of the study does not include the fundamentals of NUS and other well-established concepts on orphan and marginalised crops. These have been covered extensively (see [1,4,7,28–30]). Understanding the challenges and opportunities of modelling NUS can help identify strategies to stimulate NUS modelling.

## 2. Materials and Methods

The study was structured into two phases: (i) establishing progress and challenges in modelling NUS and (ii) outlining challenges and opportunities for modelling NUS.

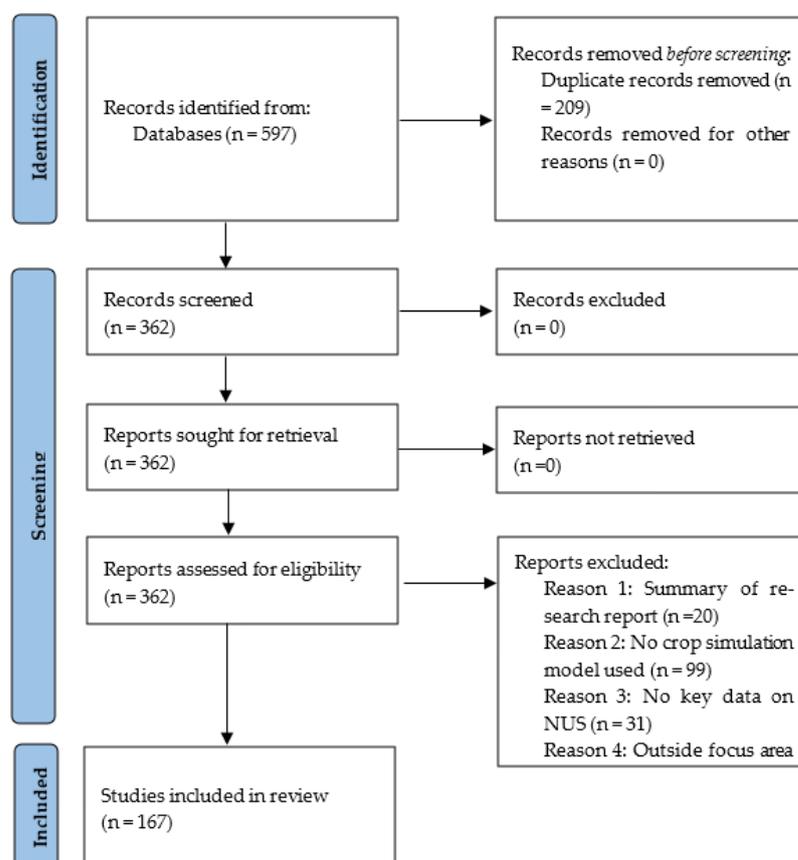
### 2.1. Phase 1 Progress: Literature Search

A systematic literature review was performed to determine the current progress in modelling NUS. Two databases (Scopus and Web of Science) were used to search for published peer-reviewed literature for the period 1996–2022. We framed the search and recording of studies included and excluded in the screening process according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [31]. Table 1 shows the search strategy and Figure 1 shows the PRISMA flow diagram. The protocol for this review was not registered. To narrow the review's focus and provide a comprehensive evaluation of work on modelling NUS, we restricted the search to articles on priority NUS for Africa identified by [32]. Williams et al. [32] defined 20 underutilised crops as priorities based on socio-economic and biophysical importance, germplasm diversity and availability, and whether sufficient innovation could be derived from them [33]. Later, this list of priority crops was amended to give 29 crops. As such, the terms included in the search string were "Sorghum" or "Finger Millet" or "Tef" or "Barnyard grass" or "Bambara groundnut" or "Lablab" or "Pigeon pea" or "Sword bean" or "Cowpea" or "Velvet bean" or "Marama bean" or "Taro" or "Sweet potato" or "Cassava" or "African yam bean" or "Cocoyam" or "Bottle gourd" or "Blackjack" or "African Eggplant" or "Jews Mallow" or "Roselle" or "Spider plant" or "Amaranth" or "Nightshade" or "Chinese Cabbage" or "Sunberry" or "Wild mustard" or "Wild Water Melon" And "crop simulation model\*" or "crop model\*" or "crop growth model\*". The asterisk (\*) is a wildcard in scopus and web of science used to replace multiple characters anywhere in a word.

**Table 1.** The search scope for NUS used in this study.

Search Scope	NUS Database	
	Web of Science	Scopus
<b>1 NUS</b> —Title, abstract, keywords “Sorghum” OR “Finger Millet” OR “Tef” OR “Barnyard grass” OR “Bambara groundnut” OR “Lablab” OR “Pigeon pea” OR “Sword bean” OR “Cowpea” OR “Velvet bean” OR “Marama bean” OR “Taro” OR “Sweet potato” OR “Cassava” OR “African yam bean” OR “Cocoyam” OR “Bottle gourd” OR “Blackjack” OR “African Eggplant” OR “Jews Mallow” OR “Roselle” OR “Spider plant” OR “Amaranth” OR “Nightshade” OR “Chinese Cabbage” OR “Sunberry” OR “Wild mustard” OR “Wild Water Melon”	68,971	80,538
<b>2 Crop simulation modelling</b> —Title, abstract, keywords “Crop simulation model*” OR “crop model*” OR “crop growth model”	5547	6630
Combined search NUS Modelling (1 AND 2)	322	275
Retained after removing duplicates in the combined search for NUS Modelling		362
* Further screening of search by reading through titles, abstracts, and keywords for NUS Modelling		167
Retained and available for final review NUS Modelling		167

The asterisk (\*) is a wildcard in Scopus and web of science used to replace multiple characters anywhere in a word.

**Figure 1.** The study selection. Preferred items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram.

The initial search retrieved 597 articles for NUS (Table 2). Thereafter, articles were screened for duplicates and 386 articles remained. For the NUS database, studies written in English were considered, and titles and abstracts from the remaining articles were examined

to check whether studies used crop simulation models to predict resource use, growth, and productivity of the priority NUS. After the screening, 167 abstracts remained. The research study details, including the crop simulation model used, and the model development (calibration, validation, and testing), application, and improvements, were extracted from the abstracts and, if needed, also from the full-length articles. An excel sheet was created to record and quantitatively evaluate the extracted data.

## 2.2. Phase 2: Identifying Research Challenges and Opportunities

The outcomes of the first phase were used to articulate the existing challenges and possible opportunities in modelling NUS. We analysed the trends of key terms in NUS modelling using a bibliometric analysis. The bibliometric analysis method can be used to evaluate published research and has emerged as a useful tool in assessing scientific data [34,35] including secondary data [36]. Also, such an analysis can help to structure the evolution of a focal research area [37,38]. In this research, the VOSviewer (version 1.6.18, Leiden, Netherlands) [39] software was used to do the key-term investigation and the network visualisation of relevant literature for articles relating to the modelling of NUS. We used titles and abstracts from 322 and 237 articles from the Web of Science and Scopus databases retained before the screening exercise to do the analysis. Since the bibliometric analysis used the occurrence and co-occurrence of key terms and frequency distributions were computed; bias assessment was not conducted.

In addition to the information captured by the systematic review, this phase also used literature that was known and found to be relevant by the co-authors, but not captured by the searches, and it covered both grey and academic literature. Therefore, this methodology phase also served as a sanity check of the outputs of the systematic review. Such a synthesis allowed the inclusion of other literature that was not picked up by the search. The identification of literature was made on the basis that authors are experts in NUS ecophysiology as well as having contributed significantly to modelling NUS.

To effectively address the study's objectives, the review results are presented in two parts. The first part of the results explores the developments in the modelling of. The objective of this first section was to showcase the key attributes of the models for NUS, which also best exemplify their potential to deliver on creating data to expand the current knowledge base. We also detailed the challenges and drawbacks of crop model development and simulation. The second section discusses the challenges and opportunities for NUS to advance modelling and knowledge creation.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses checklist (<http://www.prisma-statement.org/>, accessed on 15 July 2022) was used as a guideline to avoid biased reporting [40,41].

## 2.3. Limitations of the Review

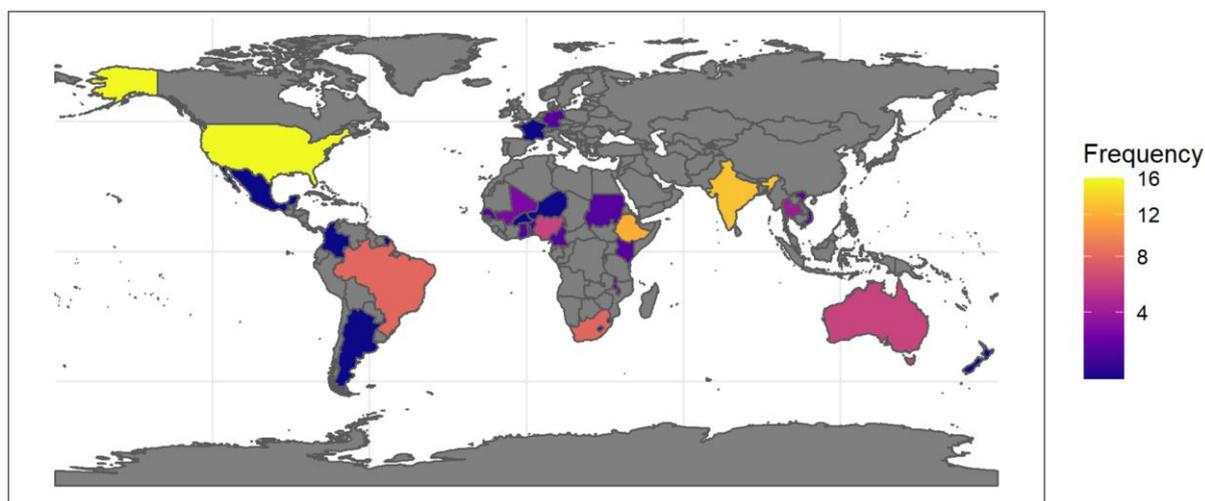
Our search process excluded several potential sources of information about modelling NUS. We sought only resources published in English and the peer-reviewed literature captured in Scopus and Web of Science. Many researchers worldwide publish in English and their native language, but we acknowledge this limitation. We also did not access grey literature such as conference proceedings, dissertations, theses, and evaluation reports, which can be problematic to search efficiently. Given that our review relied solely on academic database searching, the relevant research that did not use the exact search terms we employed would not have been captured. Despite missed contributions, we believe our findings are based on a diverse enough sample to offer meaningful insight and implications.

The basic assumption of this study, however, is another limitation. We have attempted to identify modelling work on what we regard as priority NUS. We relied on the authors (who work on NUS and crop modellers) to describe what opportunities there are in the modelling of NUS. However, we excluded work on other potentially relevant modelling studies that did not showcase priority NUS. A synthesis of these types of publications could

expand our understanding of progress made and provide useful insights into innovative ways to enhance the development of models for lesser-known crops.

### 3. Results

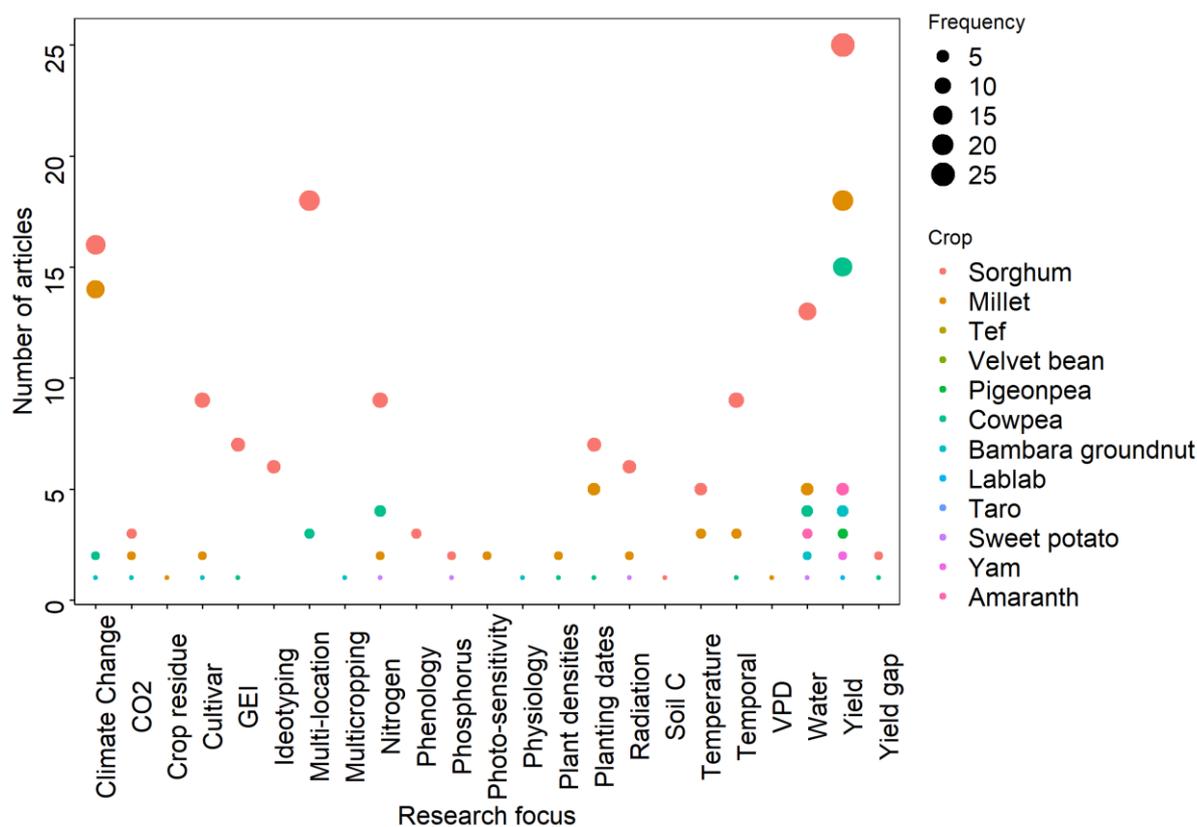
The articles on modelling NUS (an ensemble of several crop species) represented 0.3% of the published articles on NUS. The ensemble of NUS identified by the literature search covered a wide range of crop types, including cereals (sorghum, millet, and teff), legumes (pigeon pea, bambara groundnut, velvet bean lablab, and cowpea), root and tuber crops (sweet potato, cassava, yam, and taro), and African leafy vegetables (amaranth). These crop species represent 12 of the 29 priority crops outlined by Mabhaudhi et al. [6]. Sorghum and millet had the largest share (44 and 20%, respectively) of the articles on modelling. The geographical spread for the modelled NUS comprised 25 countries (Figure 2), 14 of which were from Africa (Supplementary Information). Six studies presented multi-county experiences [42–47] and 18 studies were regional (Supplementary Information). The prominence of modelling work emerging out of western, eastern, and southern Africa confirms reported efforts by these countries to incorporate NUS into their agricultural strategies.



**Figure 2.** Spatial distribution and frequency of studies where neglected and underutilised crops (NUS) have been modelled.

Results of the literature search also showed that most of the modelling initiatives were done using generic crop models with well-established sub-models (Figure 3; Supplementary Information). These sub-models consider the interdependency of physiological processes and responses to various management levers and growth factors. These generic crop models have been developed from a handful of landmark models such as APSIM Agricultural Production Systems Simulator (APSIM), AquaCrop, Cropping Systems simulation (CROPSYST), Decision Support System for Agrotechnology Transfer (DSSAT) and Environmental Policy Integrated (EPIC) [14]. AquaCrop was the most versatile crop model as it has been used for most crop types (cereals, legumes, roots and tubers, and leafy vegetables) (Supplementary Information). APSIM and DSSAT have also been used widely (45% of the identified articles), but mainly on a handful of underutilised cereals (sorghum and millet) and legumes (pigeon pea, cowpea, and lablab). It is also worth noting that among the modelled NUS, sorghum has received the most attention, and has been calibrated and applied in models such as the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC), APSIM, AquaCrop, CROPSYST, DSSAT, EPIC, SORghum, Kansas, A&M (SORKAM), Simulator of crop trait Assembly, Management Response and Adaptation (Samara), and Simulateur multIdisciplinaire pour les Cultures Standard (STICS). The reviewed articles also showed that specific simulation models have

been developed for crops such as sorghum (SORKAM) and bambara groundnut [Bambara Groundnut (BamGRO) model].

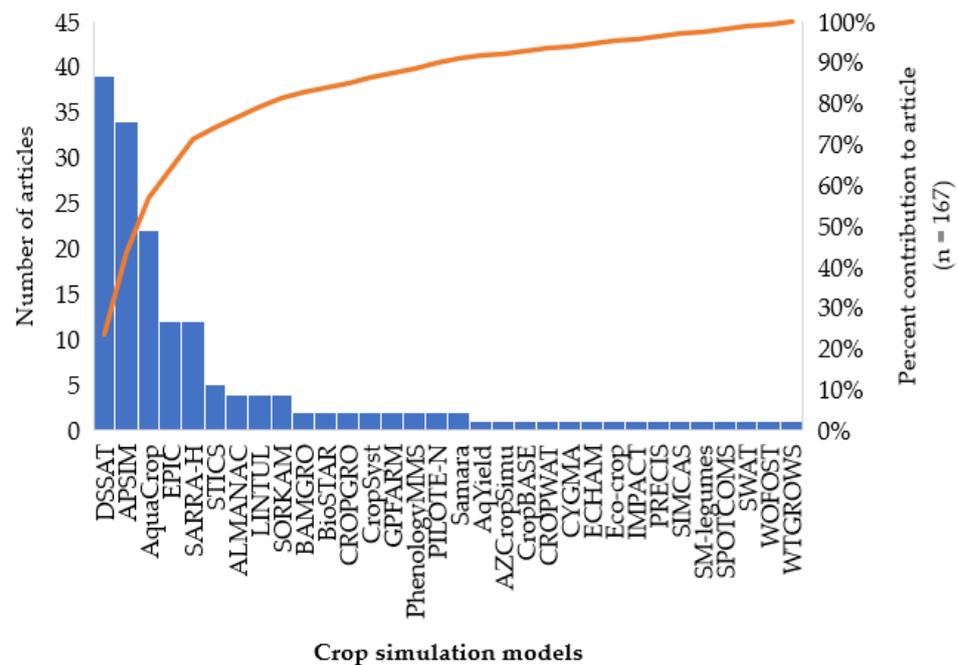


**Figure 3.** An overview of the model application across the identified neglected and underutilised crop species. The size of the bubble corresponds with the number of articles identified.

From the survey of the 167 papers published on modelling NUS, the researchers considered a wide range of issues. These included the effects of water-use efficiency [48] nitrogen-use efficiency [49], phosphorus uptake [50], solar radiation [51,52], yield gaps [53–55], planting densities [19] and growing crops in marginal environments [27,56] (Figure 3). Sorghum had most of these themes identified, followed by millet and cowpea, and this observed large number of themes is consistent with the number of articles on modelling sorghum. The geographic importance of sorghum makes it underutilised as it has a high economic value in northern and western Africa but remains a minor crop in central and southern Africa. In addition, the advancements in sorghum modelling are attributed to its inclusion in global research initiatives as an alternative biofuel and fodder crop to maize, especially under climate risk circumstances.

### 3.1. Progress and Challenges in Modelling NUS

Out of the 75 crop and plant growth models identified by Paola et al. [57], we identified 33 crop models that have been calibrated and/or validated for NUS (Figure 4; Supplementary Information). As far back as 2001, Xie et al. [58] applied the ALMANAC model for sorghum simulations, while Bello et al. [25] calibrated and validated the AquaCrop model for pearl millet. Chimonyo et al. [24] recently simulated crop growth and water usage of a sorghum–cowpea intercrop in South Africa using the APSIM model, while Akinseye et al. [42] assessed APSIM, DSSAT, and Samara in predicting diverse sorghum germplasm in West Africa. While crop models have been applied in different regions such as the USA, India, and Africa, the number of modelling studies on NUS is low compared to staple crops like maize, rice, and wheat, which have more than 20 crop models each that simulate growth, resource use, and yield.



**Figure 4.** Frequency and crop simulation models used on neglected and underutilised crops (NUS).

Asseng et al. [59] noted that the modelled impacts of climate change varied across different crop models due to variances in the structure and values assigned to parameters in the models. Asseng et al. [59] concluded that the uncertainties in impact modelling could be better quantified and minimised using multi-model ensembles. This notion was also supported by Hao et al. [60] who stated that combined predictions from an ensemble of models can produce a more reliable mean forecast and reduce the risk of reporting erroneous results (e.g., a Type II error). Multi-model ensemble methods have gained popularity as an approach to improving model predictions by adjusting model biases and taking advantage of complementary individual models [61,62]. Martre et al. [63], for example, used the mean and median values of 27 wheat crop simulations using a multi-model ensemble and concluded that using a multi-model approach provided more accurate results than individual models. The limited number of capable models for NUS reflects a limited investment in NUS research and development, and specifically, apathy towards their modelling.

Paulo et al., Raymundo et al., and Ke et al. [57,64,65] showed how crop model and module improvements have often resulted in developing new models. For models adapted for NUS modelling, the number of publications on improvements is relatively small. For instance, a canopy algorithm improvement of the MADHURAM model for sweet potato has led to the Sweet Potato Computer Simulation (SPOTCOMS) model [66]. For bambara groundnut, the Predicting Arable Resource Capture in Hostile Environment (PARCH) model [67] was adapted from the Crop Growth (CROPGRO), Bambara nut (BAMnut) [68] and Bambara Food (BAMFOOD) project models [69] to model bambara groundnut, but this has not been used by any of the studies showcased (Supplementary Information). The sorghum module in APSIM has advanced due to the ongoing development and improvement since 1994 [70]. Researchers have continuously developed aspects of sorghum crop models such as crop growth, phenology, nutrient use, and canopy development [71–73]. Consequently, many sorghum models share a similar structure with some selected changes (Supplementary Information). Researchers have sometimes modified the code to create versions of crop models. For example, APSIM was modified to simulate complex plant traits important to adaptation and to make genotype-to-phenotype forecasts [74]. Even so, such efforts are complicated by the models' design and the lack of adequate documentation.

According to Jones et al. [75], model development and use have typically been driven or motivated by the need to increase scientific understanding and to support or inform decision/policy formulation. Model development to advance scientific knowledge often addresses research questions regarding the quality, quantity, magnitude, and interactions of the research subject/s. The focus across NUS modelling articles is limited to a few key research themes, mostly related to agronomy. For the research articles included in this study, the main focus has been on climate change adaptation and yield. What seems to be lacking are the thematic areas that deal with the environmental and policy aspects such as system optimisation and spatiotemporal assessments on climate impacts, as well as the genotype-by-environment-by-management interactions.

Beyond the efforts highlighted in the Supplementary Information, there are few indications of the development and application of crop models for NUS. An example is AquaCrop, where several NUS have been calibrated, but there have been inadequate follow-up studies on using the calibrated models. In the case of bambara groundnut, Mabhaudhi et al. [27] applied a previously calibrated and validated AquaCrop model to assess the effects of climate change on crop yield and water productivity. The lack of follow-through is evident because the AquaCrop still does not include any NUS crop files in its data folder. This could be due to inadequate knowledge sharing amongst crop-model developers, modellers, and policymakers. Furthermore, when we say policymakers, we are not just referring to government agencies, but a broader network of actors that formulate a course or principle of action for agricultural innovation.

Another bottleneck to modelling NUS may be the lack of validated empirical information and data sets for NUS [3]. For most of the major crops, modellers have been able to tap into existing global databases from spatial and temporal trials (Figures 4 and 5). Experimentation on NUS continues to be descriptive and not nomothetic, limiting the ability of crop modellers to develop well-calibrated models [3]. However, one of the limitations of the current study is that it did not go further to assess the methodological quality of the included studies.

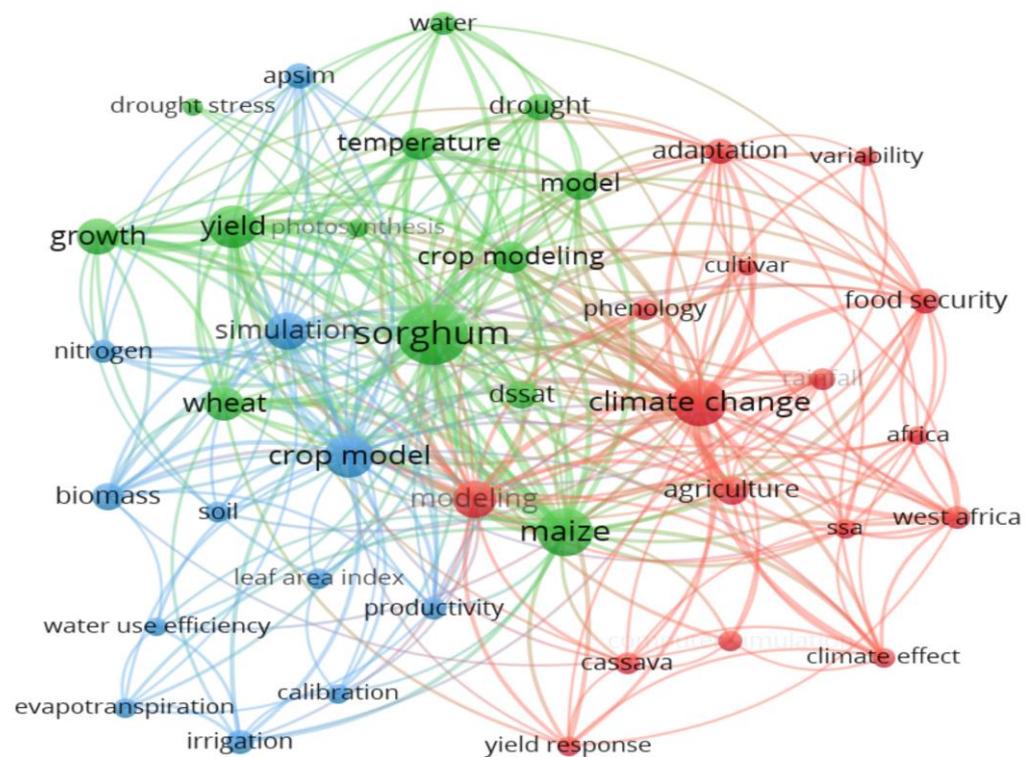
The limited research on the application of modelling to NSU found in this review confirms the previous reports that identify the lack of an articulated research agenda [6] and the low research incentives [30] possibly emanating from the misalignments with international, regional, and national policies. Conversely, models are useful in generating data for evidence-based policy formulation. In addition, if model development is motivated primarily by academic and research outcomes, then crop modelling might remain only loosely connected to user needs.

Another challenge in modelling NUS is that crop production systems are complex [76,77]. This complexity comes from the inherent multifaceted processes that drive the interactions within the plant, soil, and atmosphere continuum [78]. These combined interactions produce an infinite set of inherently dynamic outcomes in space and time [76]. This complexity tends to be more pronounced in NUS, as most NUS exhibit wide within-species genetic variability compared to the well-developed major crops [79].

Most crop models need a considerable quantity of data as input [80,81]. Modellers need these input parameters in a range of temporal (hourly, daily, weekly, or monthly) and spatial (point, field, catchment, and regional) scales. In addition to the biophysical data, models also require crop physiology and morphology information. The number of parameters and the rigour used to obtain data for parameterisation often limits the model usefulness for research. The biggest challenge met by many researchers working on NUS has been the absence of a detailed description of these interactions and hypotheses. Adapting the current crop suite to many existing crop models has been challenging. This gap in understanding is due to the lack of data for constructing the biophysical processes governing the plants within the models.

While advances in genomics, phenomics (phenotyping), and computational technologies within the last century have allowed plant scientists to understand the constructs of a given crop phenotype [82], the genomic studies of many NUS are still in their infancy

with a limited number of known improved cultivars. The lack of data has resulted in gaps in the knowledge base regarding the ecophysiology, the resource use, and the yield potential of NUS. Then again, Washburn et al. [83] suggested that integrating molecular phenotypes, machine learning, and physiological crop models could enable accelerated progress in predictive breeding for maize. Chapman [84] used crop models to understand genotypic-by-environmental expressions for drought in real-world and simulated maize breeding trials. Also, Chenu [85] applied a gene-to-phenotype modelling approach to understand the impacts on crop yield of organ-level quantitative trait loci linked to drought response in maize. In this regard, crop models may offer a solution to consolidating the available information on NUS genomics and addressing some of the knowledge gaps. However, genetics and genomics reduce the uncertainty associated with crop modelling by improving the characterisation of cultivar differences and plant processes [86]. As such, NUS genetics and genomics information is required to advance their modelling.



**Figure 5.** The visualization of thematic areas assessed across 167 research articles on the modelling activities for neglected and underutilised crop species (NUS) using VOSviewer. The network map designated neglected and underutilised crop (NUS) modelling studies into three thematic areas, namely, modelling of major cereals (green), climate change and food security (red), and model use in understanding crop water use (blue).

### 3.2. Opportunities for Modelling NUS

According to Antle et al. [87], most crop models have been established using limited data ranges. The limited data could be because most modellers, in the absence of crop physiologists and ecologists, generally collect their data for model calibration and validation. The subsections below describe several opportunities to improve data availability in order to address the data availability and quality challenges for NUS.

### 3.3. Genomics Opportunities

There are two schools of thought about advancing the information on NUS genomics for modelling. One side of the discussion suggests it is instructive to look back at historic genomic studies of related crops and use these as a framework to construct crop modules

in generic models (see, for example, Chivenge et al., Mabhaudhi et al. [3,27]). On the other hand, some researchers believe there is a need to promote genetic studies of NUS to understand better gene expression and responses. The latter has been met with considerable resistance from researchers owing to the wide genetic diversity within a single collection or population of most of the NUS species. However, for the past 30 years, the developments in mapping the major crop genomes have been remarkable. For instance, genetic-map construction, which is a critical tool for in-depth genomic studies, has been carried out for the economically important crop species [88].

Taking maize as an example, Washburn et al. [83] noted that since 1998 the American National Science Foundation's Plant Genome Research Program had prioritised the sequencing of the maize genome. This prioritisation has culminated in the development and use of the novel clone-by-clone approach to sequence the genome of the maize inbred B73 [83]. Such scientific advances in conducting genomic analyses on crops have resulted in quick and reasonably priced genotyping that has resulted in significant changes in the breeding and understanding of the underlying response of specific genes to crop physiology and morphological responses to the environment. The prospective worth of this information on molecular genetics involves enhancing the crop models' ability to predict the performance of the different crop varieties under specific climate and management conditions.

### 3.4. Mapping the Underlying Eco-Physiology in NUS

The principles of system dynamics have been around for decades, and the empirical nature of most crop models represents this. Developing the knowledge used in the design of the GECROS model, Yin et al. [89] have suggested that model developers could make models that are less empirical if they employed the existing physiological understanding and mathematical tools. This rhetoric emanates from research that believes that the genetic fundamentals of NUS genomics can be studied with greater ease by using existing examples.

On the other hand, to address gaps in the knowledge on function–ecophysiology, resource use, and crop responses to climate extremes for NUS, the use of Functional–structural plant models (FSPMs) can be employed [90]. Functional-structural plant models clearly describe the growth of the three-dimensional form of plants over time as influenced by the plant's physiology [91]. As such, they allow for a hierarchical and systematic representation of a plant in response to the environmental factors [91–93]. Therefore, the FSPM framework considers that the plant response to the environment is a function of the ecophysiological adaptation (e.g., N allocation) and plant structure (e.g., the shape and orientation of organs). In turn, the ecophysiological adaptation and structure modify the conditions in which functions operate [91]. Consequently, feedback within and between components is expressed at the individual level (organ level), and at the plant or the plant population levels (the global level) [93]. Therefore, FSPMs explicitly allow the feedback between the structure and the function of complex NUS species to be easily captured.

### 3.5. NUS Phenology

For NUS, there is a pressing need to increase their yields as the current yields in the farmer's fields are far below those of the major staple crops like maize that are already approaching maximum yields for existing cultivars. Against the backdrop of water scarcity and the increasing calls to minimise environmental degradation from extensive homogenous production systems, improving the use efficiencies of various resources through sustainable intensification has received attention in agriculture (see, for example, Lipper et al. [94]). There is also a need to assess the relevant NUS traits related to agricultural production.

However, many of these traits are quantitative and complex. For instance, phenotypes at the crop level, regardless of yield or resource use efficiencies, are influenced by the multiplicative interactions of genes. The final expression often depends on the environmental conditions, the stress factors, and the stage of development. In addition, the outcome is affected by multiple intermediate processes, coordinated response mechanisms, and intra-

and interplant competition. Due to this interaction of multiple factors, changing one part of the system can often result in unexpected consequences in other parts of the system, such as for crop yield. As for cereal yields, crop scientists have applied a simple equation that considers the yield components for the analysis of factors that are limiting yields [95]. Similar equations have been derived for other crops and traits; however, in the case of NUS, applying such a simple equation might be difficult because of the broad diversity within and across the crop species. Also, the equation assumes that the set of interactions and responses occurs along a crop developmental cascade. NUS generally have a poorly developed research agenda, therefore, breeding out of indeterminacy has not yet happened, which means that many NUS may have several phenological processes occurring at any given time. Thus, a substantial increase in one part of the system may not automatically increase the yield. Cobb et al. [96] showed that the study of the genotype–phenotype relationships needs more robust crop models than those that are currently applied in the conventional agricultural systems.

### *3.6. The Role of Information and Computer Technologies and Data Management*

The history of crop science shows that significant advances can occur when different disciplines join forces. For instance, crop modelling and remote sensing researchers have worked together to create models to predict global crop yields of wheat in the 1970s and advance sustainable intensification through precision agriculture [97]. There is a need to broaden and strengthen the collaboration among biophysical modellers, engineers, agricultural practitioners, and policymakers to develop dynamic strategies for modelling NUS. Many cooperative projects like the Agricultural Model Intercomparison and Improvement Project (AgMIP) and the Consortium of International Agricultural Research Centers (CGIAR) Platform for Big Data in Agriculture launched in 2017 have emerged from the need to address global challenges. Such initiatives understand the need to increase agrobiodiversity for sustainable food systems. The researchers working on modelling NUS can leverage these collaborative initiatives; however, additional investments are required to promote the collection of freely available and quality data for NUS modelling purposes.

The way in which agriculture contributes to rural development is undergoing a new and rapid change due to the need for transformative technologies, the awareness of globalization, and the advancements in ICT. For example, advances in ICT such as digital data platforms [98] that allow farmers to share data for decision making can address the challenge of generating new and relevant data on NUS for crop modelling. Techniques such as the Internet of Things, Cloud Computing, and large-scale phenotyping methods such as the use of remote sensing with drones (unmanned aerial vehicles), nanosatellites, and planned satellite missions can leverage this development and introduce artificial intelligence into the NUS data value chain [99]. A key advantage of integrating remote sensing data into the crop models is that it allows for a more accurate representation of the crop's actual condition at various developmental stages in the growing season [97]. While moderated by Big Data, this can ensure that large quantities of information from various sources are captured, analysed, and used to build and simulate NUS in existing or new crop models.

Crop models require parameters that contribute to mechanistic and functional components within the framework. While these parameters may differ based on the needs of the model and modeller, there are generic parameters that speak to the technical attributes of most of the models. Several databases have been generated, and these are partially accessible for use. In many cases, the direct access to yield data for many commercially important crops is available through the countrywide statistics departments' websites or it is retrieved by researchers from their local statistical institutions. Unfortunately, yield data for most of the NUS is only available in grey literature and is not readily accessible. This gives false confidence about data quality, especially for many developing nations where the reporting of crop yields, in general, is not well established. There is a need to create and harmonise the standards and protocols for data collection for NUS. This harmonisation would

ensure the access and use of the same data sources “in the cloud”, from the various sources available, and the operation of various models, knowledge products, and decision support systems. While it is important to have different models and strategies, developing the guidelines and procedures to fully benefit from these developments is equally important.

### 3.7. Considerations for Informing the Modelling of NUS

Several crop models exist, and these differ in complexity, ranging from the relatively simple empirical relationships (i.e., the rule-based yield equations using climate and soil data) to the complex mechanistic models. Several reviews have summarised crop model capabilities and use. For instance, Jones et al. [99] and Antle et al. [87] discussed a possible option for designing the next-generation models by assessing the capabilities and limitations of the existing models relative to “Use Cases”. Gaudio et al. [100] reviewed the opportunities for modelling annual crop mixtures. Holzworth et al. [101] discussed the status and prospects in software capabilities and applications of crop models over time in order to inform climate change adaptation and mitigation. Huang et al. [102] gave a comprehensive overview of the latest developments and applications of crop models and the data-assimilation remote sensing techniques.

While these and other reviews have offered a sufficient critique on the capabilities and uses, very few have provided an in-depth assessment of the considerations made during model selection. Such information is essential if this is to guide the use of the current models for modelling NUS. Although many factors have influenced the research and development of crop models, four factors stand out among them: (1) the proposed use of the model; (2) the methods used to develop the model; (3) the scale of operation; and (4) the availability of data for model calibration and evaluation. The insufficient information for the calibration of models is frequently a significant challenge in applying crop models [103]. Collecting field data that are adequate for model calibration requires resources such as funding and manpower, which may be allocated based on the perceived importance of a crop. In summary, this section provides a systematic overview of the factors to be considered when selecting a crop simulation model. To overcome the challenges established by the literature review, Table 2 provides an overview of the considerations that are needed for increasing the use of models for NUS.

**Table 2.** Considerations for crop model selection.

Consideration	Description	Key Feature/Requirements	Comment
Modelling and model goals	The first criterion when choosing a crop model should be the main purpose of applying it.	Simulate plant growth and development, biophysical processes, resource use and management, inter-plant competition and climate change impacts	For NUS, one of the primary research objectives is to develop production guidelines for mainstreaming them into the existing cropping system. Hence, the selected crop model should be able to simulate various management levers and, more importantly, climate variability and change scenarios to address some of the existing knowledge gaps on NUS
	A model’s goal should be to inform what function the model is to perform and what degree of accuracy is required in the model’s outputs	Simulate plant growth and development, biophysical processes, resource use and management, inter-plant competition and climate change impacts	For NUS, models should consider the various influences of climate change drivers such as rainfall and temperature while accounting for key crop physiological processes and biophysical aspects of the crop–soil–atmosphere systems to solve crop production and natural resource management issues.

Table 2. Cont.

Consideration	Description	Key Feature/Requirements	Comment
Model availability	The essential aspect to consider is whether the selected model is freely available for use. Not all crop models are freely available. Based on 70 models reviewed by [104], only 29 are freely available	Most established models can be downloaded free of charge	The use of generic crop models can allow several NUS to be adapted for individual crop varieties under specific conditions.
Model type	The complexity, degree of detail, level of comprehensiveness, and the scale of application (specific cultivar, field, catchment, and region) of crop models differs  Most models are “source-driven”, thus assuming that growth is limited by factors that drive the production and partitioning of assimilates	Models can be described as either simple empirical types or complex mechanistic models  Growth engine can be either carbon-driven (World Food Studies simulation WOFOST model), solar radiation-driven (APSIM) or water-driven (AquaCrop)	Mechanistic crop models exhibit increased robustness  Across sub-Saharan Africa, current climate change projections indicate increased atmospheric CO <sub>2</sub> concentration and weather excesses like heatwaves, droughts, and floods. It is in this context of the expected impacts of climate change and climate change adaptation that carbon-, solar radiation and water-driven models should be considered
System boundaries	Predictive capabilities are generally most robust within the boundaries of the data used to develop a model	To rely on a model’s results to make decisions, it is vital to use a model that is not “built on oversimplified and unrealistic assumptions about natural processes.”	
Model input	Model complexity increases with the number of input parameters required by the model	A model’s descriptive or predictive ability depends on the data quality used to populate it.	As shown by [59], the number of cultivar-specific parameters ranged from 2 (e.g., AquaCrop) to 22 (General Large Area Model GLAM)
Spatialisation	The impacts of climate variability and change on the agricultural system are interrelated, with cascading and interchanging biophysical layers of air, water, soil, and crops at spatiotemporal scales	To run the models non-stop and at a regional and national level	NUS have been produced and studied in a few agroecologies, where the temporal drivers for their growth and production operate at much smaller resolutions than the courser scale at which most crop models are presented
Model output	Outputs generated by the model allow the user to fully answer and analyse the questions or objectives of the modelling exercise		
Intersectionality	Intersectionality refers to how different processes within the model interact to create a distinct outcome based on different management levers	The model needs to include the representation of several physiological processes to describe or predict outcomes	

#### 4. Discussion

The application of crop models for understanding crop growth, yield, and resource use in NUS is still in its early stages, with a limited number of articles published. A pressing need exists for more significant commitments in NUS research, funding, and training to increase their knowledge base. This should also be accompanied by developing and/or improving crop models capable of modelling NUS. A paradigm shift is required regarding how the NUS modelling research is funded and can move away from a system that has only prioritised the major staple crops linked to industrial agriculture. As such, policy-makers need to transform policy-making processes that support research and promote

collaborations across different fields in crop modelling. This ensures that the modelling research on NUS can also inform the policy making and that there are the co-creation and co-development of crop models for NUS.

This review highlighted the significant challenges to modelling NUS, including data availability and accessibility. Other challenges included the large agrobiodiversity present within NUS. The limited data availability and the large ensemble of NUS and, to an extent, the misalignment in research priorities make it challenging to develop the conservative crop coefficients needed to parameterise crop models. To bridge the gaps in data availability and accessibility, the use of pre-existing crop databases, as well as the use of the Functional-structural plant type models, the data value chains and ICT, and the promotion of research collaborations should all be included for use with NUS. In addition, GIS and remote sensing can be integrated into crop models to collate high-resolution data.

The current food systems have contributed to the present environmental and socio-economic challenges, especially in marginalised communities [105]. The emphasis on a few economically important crop species has increased the risk from climate variability and change, economic volatility, and the increased vulnerability of marginalised communities. According to Jones et al. [75] and the Royal Society [106], policy shifts and operationalisation of research agendas on NUS (e.g., Mabhaudhi et al. [33]) can only occur after a need presents itself.

In the wake of the challenges mentioned above, the current need to transform agricultural systems has created a window of opportunity for advancing NUS modelling. Thus, there is a need to tap into the available tools to promote the development of models that are capable of simulating growth, yield, and resource use for a broader range of NUS. Numerous crop models have been created with various detail, complexity, and scale levels. For example, the simple generic crop model (SIMPLE) [106] requires 14 parameters to specify a crop, while the EPIC model [107] and the AquaCrop [108] models require 24 and 29 parameters, respectively.

Furthermore, crop modelling requires reliable experimental data to describe plant processes accurately. For most of the major crops, crop modellers have been able to tap into existing global data sets from long-term trials. Hence, another bottleneck to modelling NUS may be the lack of empirical information and available long-term data sets for NUS, thereby, limiting the ability of the crop modeller to develop well-calibrated NUS models. In most cases, there are no bred varieties of NUS, but rather a wide range of landraces with different characteristics. This presents a challenge when developing the conservative crop coefficients needed to drive the crop models. The incomplete and fragmented nature of the information on NUS has been cited as an obstacle to their modelling [79].

The history of model development indicates that many existing models result from questions formulated around scenarios and then adapted to address the user needs. As reiterated by Jones et al. [75], having one “perfect” model cannot capture the level of diversity within the full suite of the crops used in agriculture. Instead, the aim should be to develop component/modular models that can be applied individually or in tandem to answer direct questions (e.g., when to apply a climate change response or management option). The fundamental structure of models—climate, soil, and management modular structures—are easily transferable; however, biophysical and economic models (i.e., bioeconomic models) are required to address the socio-economic issues.

## 5. Conclusions

Several crop models exist; however, not all can be used to advance the knowledge base for NUS. Several factors must be considered, notably the model and the modelling objectives, the model inputs and outputs, and the spatialisation. Using the current crop models requires understanding their strengths and weaknesses and knowing when to apply them for the maximum benefit. Therefore, consulting experts and key stakeholders should ensure the future progress in co-developing robust and versatile crop models for NUS.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su142113931/s1>, Table S1: Overview of selected neglected and underutilised crop varieties, models used to simulate crop growth and productivity, level of application, and the country where the simulations were performed.

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