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Review article

Forecasting future global food demand: A systematic review and meta-analysis of model complexity

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ABSTRACT

Predicting future food demand is a critical step for formulating the agricultural, economic and conservation policies required to feed over 9 billion people by 2050 while doing minimal harm to the environment. However, published future food demand estimates range substantially, making it difficult to determine optimal policies. Here we present a systematic review of the food demand literature—including a meta-analysis of papers reporting average global food demand predictions—and test the effect of model complexity on predictions. We show that while estimates of future global kilocalorie demand have a broad range, they are not consistently dependent on model complexity or form. Indeed, time-series and simple income-based models often make similar predictions to integrated assessments (e.g., with expert opinions, future prices or climate influencing forecasts), despite having different underlying assumptions and mechanisms. However, reporting of model accuracy and uncertainty was uncommon, leading to difficulties in making evidence-based decisions about which forecasts to trust. We argue for improved model reporting and transparency to reduce this problem and improve the pace of development in this field.

1. Introduction

The ability to feed the world's growing population is reliant on the capacity of food supply to meet future food demand (Cirera and Masset, 2010). Current estimates show increasing demand per person, from an average of 2250 kilocalories (kcal) in the early 1960s, to ~2880 kcal in 2015 (Pardey et al., 2014). Coupled within these estimates are changes in the composition of diets, with a general shift away from traditional crops (e.g. tubers and pulses) towards more "luxurious" items like animal products, vegetable oils and stimulants (Kastner et al., 2012).

Food consumption patterns are having a tremendous impact on human and environmental health. Rising fat and calorie consumption worldwide, paired with decreasing activity levels of individual people, have contributed to problems of an increasing rate of obesity and non-communicable diseases (Popkin, 2004; Tilman and Clark, 2014). Further, agriculture is the largest contributor to tropical deforestation (Geist and Lambin, 2002) and is responsible for up to 35% of global greenhouse gas emissions (Foley et al., 2011). Intensive agriculture has been a major contributor to land-use change over the last century. With demonstrated negative impacts on air and water quality, biodiversity, carbon sequestration and infectious disease transmission (Foley et al., 2005).

Rising agricultural yields have, to date, kept pace with demand, but there is evidence that yields may be plateauing, especially in intensively cropped systems (Grassini et al., 2013). The steadily increasing per capita food demand, paired with a global population that is forecast to hit 9.8 billion by 2050 (United Nations, 2017), has led to concerns about how future global food demand will be met (Godfray et al., 2010) and what impact the effort to supply sufficient future food will have on the environment (Tilman et al., 2001).

Predictions about the amount and types of food consumed in the future can inform today's agricultural policies, but current predictions vary widely. For example, while some estimates for per capita kilocalorie demand in 2050 indicate averages around 3900 (Valin et al., 2014), other estimates are as low as 3070 (Alexandratos and Bruinsma, 2012). Furthermore, a small number of predictions are disproportionately cited in the literature. The decadal reports by the FAO (Alexandratos, 1995; Alexandratos and Bruinsma, 2012; Bruinsma, 2003) have been cited over 1000 times each, David Tilman's food demand predictions from 2011 and 2014 have already been cited over 2000 times combined, and the IFPRI studies have been cited hundreds of times each (Rosegrant et al., 1995, 1999). These three sources

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constitute the majority of our understanding of the future of global food demand but take very different modelling approaches.

At an individual level, food consumption is a consequence of many interacting factors, with behavioural, cultural, environmental and economic aspects (Alexandratos, 1995; Kearney, 2010; Rosegrant et al., 2002; UN Millennium Project, 2005). The aggregate consumption behaviour of populations is less variable than an individual's consumption decisions but is nonetheless influenced by a variety of components. Some models incorporate multiple variables to represent the mechanisms driving consumption choices (e.g. prices, crop yields, climate effects, and changing diets). These "complex mechanistic" models are often built on interacting economic, ecologic, demographic and/or climate sub-models (Alexandratos, 1995; Alexandratos and Bruinsma, 2012; Bijl et al., 2017; Schneider et al., 2011).

Alternatively, a simple mechanistic approach predicts demand based on the coarse (Engel's Law) relationship between income and kilocalorie consumption (Bodirsky et al., 2015; Tilman et al., 2011; Tilman and Clark, 2014). Finally, phenomenological models assume current trends of increasing kilocalorie consumption will continue (Leach, 1995). Here, we compare predictions from two mechanistic (complex and simple) and one phenomenological (time series) model types to determine how these model choices impact predictions.

There is also debate over what scale of spatial and calorie disaggregation is best for modelling purposes. Some researchers argue that complex, disaggregated models better represent reality (Alexandratos, 1995; Alexandratos and Bruinsma, 2012; Schneider et al., 2011) while others claim that coarser, simpler analyses can avoid some of the idiosyncrasies and possibly arbitrary assumptions in fine-scale or complex models (Doos and Shaw, 1999; Tilman et al., 2011).

To improve our understanding of what shapes current perceptions of future food demand, we asked four empirical questions: 1) at what spatial scale are current food demand predictions being made, 2) what is the geographic distribution of food demand predictions, and with a meta-analysis: 3) what impact does model complexity (i.e. number of covariates and disaggregation of data) have on global food demand predictions and 4) how valid are those predictions? To answer questions 1 and 2, we examine the spatial scale and scope of published studies. For question 3, our meta-analysis compares the predictions of complex, integrated mechanistic models with simple correlative-based models (which predict food demand using GDP) and purely phenomenological models (which assume current demand trends will continue), to determine the effect of these additional data on predictions. Finally for question 4, we investigate the degree to which the various models follow current best practice in statistical analysis including model averaging (incorporating information from multiple models; Burnham, 2015; Burnham et al., 2004), model validation (reporting how well the model fits or predicts the data) and reporting of model uncertainty (using confidence intervals or standard errors). The outcome of our analyses can help inform efforts to predict future food demand patterns.

2. Materials and method

2.1. Identifying, screening & classifying papers

We frame our review questions, search strategy and inclusion/exclusion criteria using the PICOTS system (Box 1). To identify relevant papers, we used a combination of search engines that would identify both peer-reviewed and grey literature: Web of Science, Scopus and Google Scholar. A systematic search strategy was developed that would identify all relevant papers. After an iterative keyword screening process, the following keyword(s) were selected as optimal and were used for this analysis: (["Food demand" OR "crop demand" OR "human food consumption" OR "human crop consumption"] AND [trend OR historic OR predict* OR projected OR projections OR future OR model]). No time period was set for this search so all relevant papers through to June 20, 2017 were returned. This process yielded 670 papers from Web of Science, 998 papers from Scopus and 17,600 results from Google Scholar. We extracted the top 100 relevant results from Google Scholar for screening. We then supplemented the search with potentially relevant papers suggested by content experts (n = 11). After duplicates were removed, this search yielded 1190 novel references (Appendix A, Fig. 1). All references were screened by one researcher (EJF) for relevance according to the following question: "Is a major focus of this paper understanding patterns of human food consumption/demand?" All papers that were classified as "y" according to the screening question were categorized according to the spatial scale of the analysis (Table 1, Fig. 2), whether they predicted future food demand, and the level of calorie disaggregation (Fig. 1). In this process, papers were excluded when predictions were not made or reported (i.e., addressed historic patterns or used others' predictions), or when predictions were made for a subset of food types or countries. If any of the selected papers referenced the food demand predictions of another study, the referenced paper was added to the meta-analysis (n = 11). This step ensured that the literature; a) included data and forecasts from primary sources and b) included 'grey' literature sources, including reports prepared for the United Nations Food and Agriculture Organization (FAO) and the International Food Policy Research Institute (IFPRI), which are not present in Web of Science. No language was set in the search terms but only papers that were published in English were progressed beyond the initial screening stage.

2.2. Critical appraisal

Currently, no critical appraisal tool exists to guide data extraction and assess the risk of bias for non-medical predictive models, as is the focus of this review (Box 1). Therefore, a new tool was developed, modelled after the CHARMS (Debray et al., 2017; Moons et al., 2014), TRIPOD (Collins et al., 2015), REMARK (Mcshane et al., 2005) and the Cochrane (Higgins et al., 2011) internal validity tools. Our critical appraisal system has two main domains (model data, and methodology) with seven signaling questions (Table 2) to identify possible sources of error or bias in the development and reporting of future food demand. All included papers were critically appraised (and had data extracted) by two reviewers (EJF and either LB or JB).

We do not conclude this appraisal with a "bias rating" for each paper because the type of bias inherent in each data source and model method is different. Consequently, a subjective "high or low" rating of bias would not be informative nor would it enhance the meta-analysis. Therefore, the results of our critical appraisal (Table 2) did not quantitatively impact the meta-analysis but rather were used to guide the narrative comparison of the included papers.

2.3. Synthesis and meta-analysis

The purpose of the meta-analysis was to understand how model complexity influences average global food demand predictions. We only included studies that estimated future demand using definitions similar to the FAO's food balance sheets/supply utilization accounts (FAO, 2016). These predictions include all food available for human consumption (i.e. production + imports − exports ± stock variations) which excludes food used for non-human consumption (e.g., animal feed, seeds) or industry losses and wastage in the production system, but includes household-level waste. A small number of authors considered the values provided by their papers to be scenario values, not "projected" values (e.g., von Lampe et al., 2014). In these cases the authors' aim was not to forecast future demand, but rather provide a 'what if' scenario. However, these "what if" scenarios are possible futures and as such, were included in our meta-analysis.

There was only one study that reported predictions based on time trends alone. To increase the sample size for this category, we supplemented this family of predictions with our own time-trend models,

Box 1
Formulating meta-analysis question and protocol using PICOTS system.

The PICOTS system, as presented in the CHARMS checklist (Moons et al., 2014), describes key items for framing a systematic review, including the aim, search strategy, and study inclusion and exclusion criteria. These items are explained below as they apply to the meta-analysis component of our study:

- Population—defines the population being modelled. In our study, to facilitate comparisons across studies, we define the population as the global "average" person. That is, a theoretical "person" who consumes food at the global per capita average.
- Intervention (model)—defines the predictive model(s) under review. Our focus is on how model complexity impacts predictions. Therefore, we included any prognostic global food demand models.
- Comparator—what, if any, models are being compared. We compare models of different complexity (i.e., number and type of predictor variables and level of data aggregation); although the included models were built for various purposes and with different theoretical and methodological underpinnings, all report predictions of future average per capita food demand.
- Outcome(s)—define the outcome(s) being modelled or predicted. In our study, the outcome was defined as average per capita kilocalorie food demand. Papers examining specific types of demand (e.g. crop primary equivalent, wheat demand, biofuel demand) or demand for a narrow geographic region (e.g. a single country) were excluded.
- Timing—what is the predicted time frame of interest. Here, we include any models that predict future demand but we only have sufficient sample size to compare the model complexity effects for the years 2050 and 2100.
- Setting—defines the intended role or purpose of the model being examined. In this case, the intended use of these food-demand models was to predict future demand in order to inform a variety of questions about agriculture, land use, biodiversity, and human welfare. Our interest here is in examining how different modelling methods (regarding complexity) might have impacted the predictions and conclusions of those models.

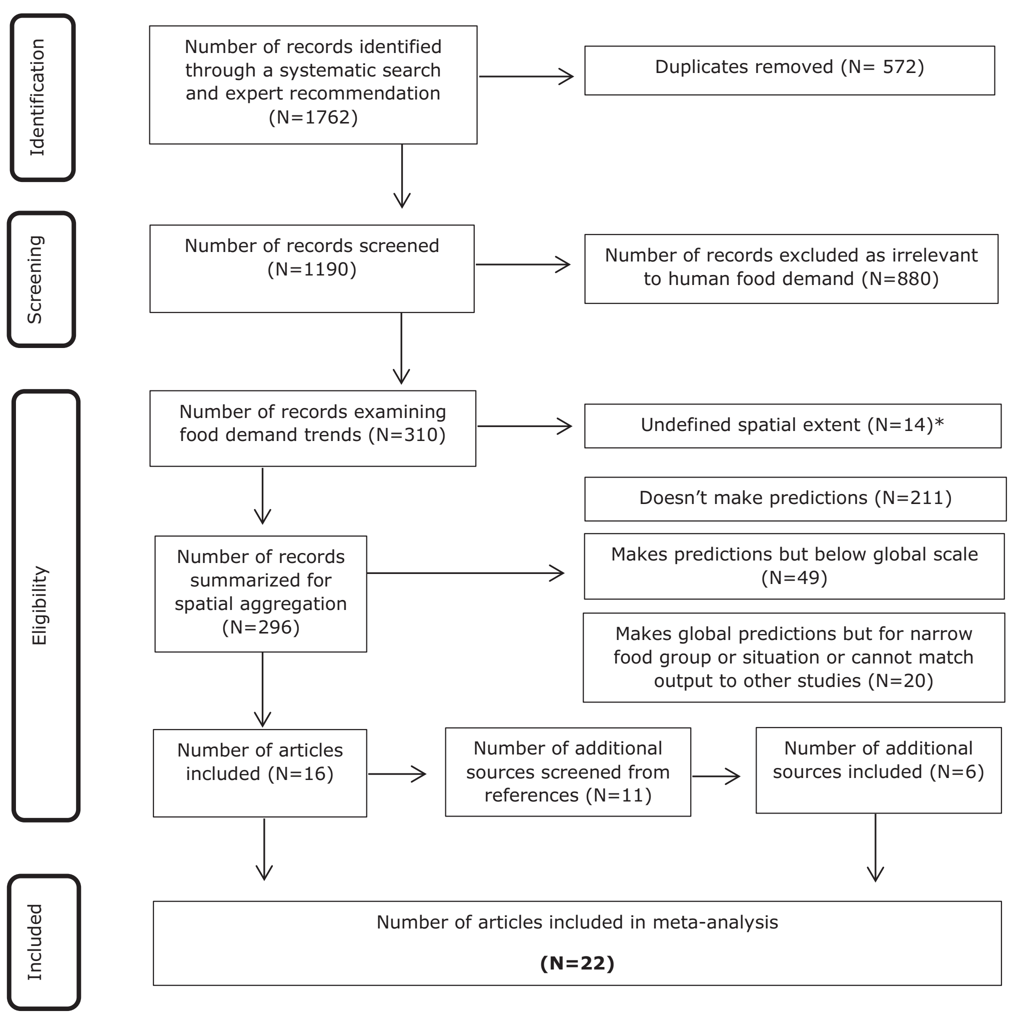

Fig. 1. Screening protocol and included papers, based on protocol from Moher et al. (2009).
*None of the 13 undefined spatial extent papers made predictions.

Table 1
Spatial extent of food demand papers.

Spatial scale of analysis/paper	Number of papers
Global	56
Regional	32
Country	156
Within-country	52

based on a suite of commonly used functional forms. To make these predictions, we acquired data on food supply (kcal/cap/day) from FAOSTAT's Food Balance Sheet (FAO, 2016) for 158 countries for each year ($kcal_{iy}$) from 1961 to 2013.

Population weighed global average kcals ($Gkcal_y$) were calculated by the following equations:

$$Skcal_y = \sum_{i=1}^{n} \left(kcal_{iy} * \frac{Pop_{iy}}{KcalPop_y} \right) \tag{1}$$

$$Mkcal_y = \mu kcal_y * \frac{TPop_y - KcalPop_y}{TPop_y} \tag{2}$$

$$Gkcal_y = Skcal_y + Mkcal_y \tag{3}$$

Eq. (1) calculates the population weighted average kcal for the sample countries (n = 158; $Skcal_y$). The average kcal for each country each year ($kcal_{iy}$) were multiplied by the percent of the total global population (covering 158 countries; $KcalPop_y$) represented by that country in the given year (Pop_{iy}). The "missing" global calories ($Mkcal_y$) were then calculated using Eq. (2), with the unweighted (absolute) average kcal for that year ($\mu kcal_y$) being multiplied by the percent of the global population missing from the data. The missing population was computed by subtracting the total "semi-global" sample population ($KcalPop_y$) from the total global population (according to United Nations (2017); $TPop_y$) and dividing by the total global population. The final population-weighted global average kcals for each year ($Gkcal_y$) were calculated by summing the sample kcal and the missing kcal (Eq. (3)). Projections were made from this dataset using different functional relationships between kcal and year; kcal was predicted assuming a linear, logarithmic, power and square root dependence on "year" out to 2050.

Some studies that met our criteria for inclusion in the meta-analysis only reported the predictions in the form of a graph, rather than a table (Bijl et al., 2017; Kii et al., 2013; Kriegler et al., 2017). We used Plot Digitizer (Huwaldt, 2015) to extract the projected average global food demand values from these figures. Values that were reported in percent or relative change from a given date (Gouel and Guimbard, 2017; Schneider et al., 2011; Tweeten, 1998; Valin et al., 2014) or gave values in total global kcal per year (Kii et al., 2013; Kriegler et al., 2017) were converted into kcal/cap/day using either our calculated values from the comparison data, or global population values from whatever source was used for population predictions in that paper (see Appendix B for details).

All predicted average global food demand values were grouped according to model characteristics (e.g., time series, simple and complex models; Table 3, Appendix B) and the mean and 95% confidence intervals were calculated for each group for the years 2050 and 2100. These predictions are presented in Table 4 and the predicted demand trends for the different levels of model complexity are shown in Fig. 3.

2.4. Complex vs simple categorisation

We define phenomenological models as those that base future predictions purely on time trends. Simple mechanistic models base predictions only on income (i.e., GDP) data. Complex mechanistic models as those that include prices and any additional variables; prices based on both partial and complete equilibrium are included in this category.

3. Results

3.1. Systematic review

The majority of unique papers returned by our search terms (74%) did not have the major focus of understanding human food demand patterns (i.e., false positives; Fig. 1). Many of these false positives focused on the implications of growing food demand (e.g., land-use patterns, how to mitigate environmental impacts) or the ability of the agricultural sector to meet food demand under different scenarios (e.g., different management or policy options or under climate-change scenarios). Other false positives involved food consumption in non-human

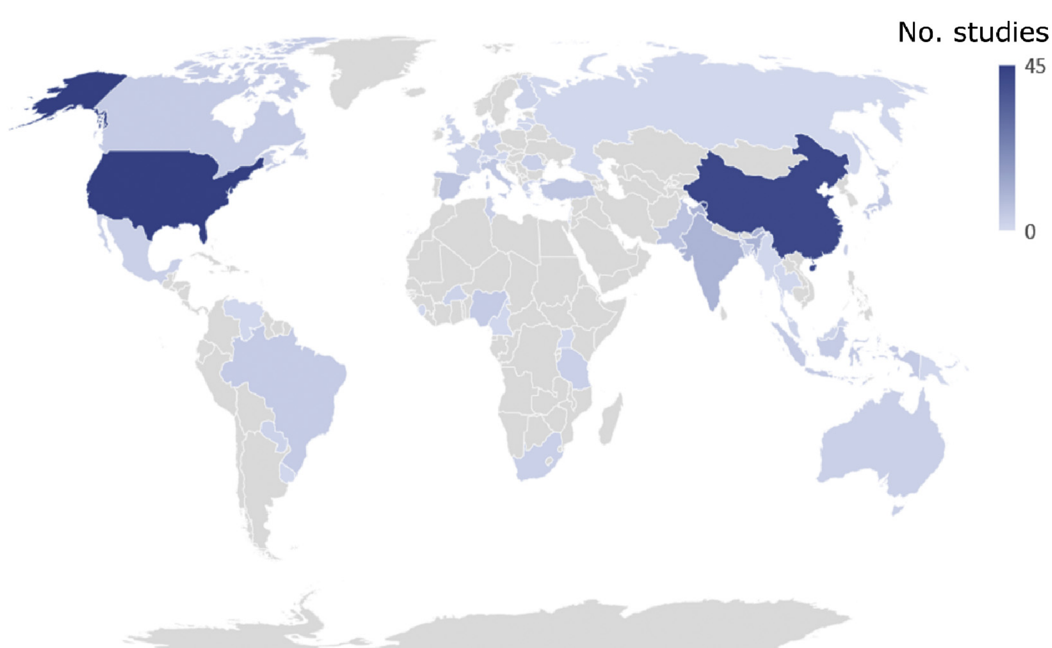

Fig. 2. Map of the number of country or within-country scale food demand analyses.

Table 2
Critical assessment of methodological quality and possible sources of bias for each included study across two domains (model methods and data sources) and seven signaling questions.

Citation	Model methods				Data sources for model		
	Reports model uncertainty?	Uses expert opinion?	Reports model validation?	Employs model averaging?	Historic food demand	Future GDP	Future population
(Alexandratos, 1995, 1999, 2009; Alexandratos et al., 2006; Bruinsma, 2003; Alexandratos and Bruinsma, 2012)	N	Y	N	N	FAO (own model)	World Bank	United Nations, medium variant
(Bijl et al., 2017)	Scenarios & sensitivity analysis	N	N	N	FAO	TIMER model (Stehfest et al., 2014)	TIMER model (Stehfest et al., 2014)
(Bodirsky et al., 2015)	Scenarios	N	Y	N	FAO	CIESIN database	CIESIN database
(Dorin, 2011)	Scenarios	Y	N	N	FAO	Own model, based on MEA global orchestration	Own model, based on MEA global orchestration
(Gouel and Guimbard, 2016, 2017)	Scenarios & confidence intervals	N	N	N	FAO	EconMap version 2.4. (based on World Bank historic data)	EconMap version 2.4. (based on World Bank historic data)
(Kii et al., 2013)	N	N	Y	N	FAO	IPCC (2000); B2 scenario	IPCC (2000); B2 scenario
(Kriegler et al., 2017)	Scenarios	N	N	N	FAO	Samir and Lutz (2017)	Dellink et al. (2017)
(Kruse, 2010)	N	Y	N	N	Unspecified	Unspecified	Unspecified
(Leach, 1995)	Scenarios	N	N	N	FAO	NA	United Nations, medium variant
(Pardey et al., 2014)	Standard error & confidence intervals	N	Y	N	FAO	World Bank and IMF sources, as reported by Fouré et al. (2012)	United Nations, medium variant
(Rosegrant et al., 1995, 1999)	Scenarios	Y	N	N	FAO	World Bank & Asian Development Bank	United Nations, medium variant
(Schneider et al., 2011)	Scenarios	Y	N	N	FAO	MEA (2005)	MEA (2005)
(Tilman and Clark, 2014)	N	N	N	N	FAO	Own model; calculated using a Kuznets curve equation for each of the income groups	United Nations, medium variant
(Valin et al., 2010, 2014)	Scenarios & standard deviation	N	N	N	FAO	O'Neill et al. (2014)	O'Neill et al. (2014)
(Tweeten, 1998)	N	N	N	N	FAO	World Bank	United Nations, medium variant

Table 3
Model classification from studies included in meta-analysis. A summary of Valin et al., 2014 is not included in this table because that paper examines multiple models with varied methods. The classification for each model used in Valin et al. (2014) can be found in the Meta-analysis datasheet of Appendix B. Prices are either incorporated at partial equilibrium (PE; i.e., incorporate a narrow set of food-related prices/expenses) or general computable equilibrium (GCE) which accounts for food expenditure/prices as a subset of total household expenses (e.g. including housing, clothing, transport, etc.).

Model complexity	Spatial groupings (≤45 regions, ≥100 countries)	Food groupings (few = 1–2, many = 7 +)	Model name	Citation	Main determinants of per cap food demand	Reported purpose of study
Complex	Countries	Many	World food model (FAO)	(Alexandratos, 1995, 1999, 2009; Alexandratos et al., 2006; Alexandratos and Bruinsma, 2012; Bruinsma, 2003)	GDP, prices (PE)	Assess prospects for trade and sustainable development for food and agriculture
Complex/simple	Countries	Many	GLOBIOM	(Valin et al., 2010)	GDP, prices (for complex models; PE when present)	Examine how climate change policies could alter the way agricultural supply meets demand
Complex	Countries	Many	GLOBIOM	(Dorin, 2011)	GDP, prices (PE)	Imagine different possible states of food and agriculture in 2050 in order to understand and debate where to go in the future, and how
Complex	Countries	Many	IHS-GI	(Kruse, 2010)	GDP, prices (PE)	Develop a detailed forecast of global food demand to 2050
Complex	Regions	Many	IMPACT	(Rosegrant et al., 1995, 1999)	GDP, prices (PE)	Develop a shared vision and a consensus for action on how to meet future world food needs while reducing poverty and protecting the environment.
Complex/simple	Countries	Many	NA	(Gouel and Guimbard, 2016, 2017)	GDP, prices (for complex models)	Represent the nutrition transition and project future food demand based on a set of plausible futures
Complex	Regions	Few	REMIND-MAgPIE	(Kriegler et al., 2017)	GDP, prices (GCE), ecology	Provide useful reference points for future climate change, climate impact, adaption and mitigation analysis, and broader questions of sustainable development
Complex	Regions	Many	GLOBIOM	(Schneider et al., 2011)	GDP, prices (PE)	Quantify the food production impacts of four alternative development scenarios
Complex	Regions	Many	NA	(Bijl et al., 2017)	GDP, income inequality, regional dietary patterns, animal feed efficiency, waste, industrial use	Understand future food demand, the agricultural system, and the interactions with other natural and human systems
Simple	Regions (economic groups)	Few	NA	(Tilman and Clark, 2014)	GDP	Quantify relationships among diet, environmental sustainability and human health
Simple	Regions	Many	iAP	(Pardey et al., 2014)	GDP, population age structure	Project global agricultural consumption and production
Simple	Countries	Few	NA	(Bodirsky et al., 2015)	GDP, time	Study global food security and for analysing the environmental impacts of agriculture
Simple	Regions	Many	NA	(Kii et al., 2013)	GDP, economic disparity	Analyze food availability and risk of hunger under the combined scenarios of food demands and agroproductivity
Simple	Regions	Few	NA	(Tweeten, 1998)	GDP	Understand the implications of crop yield growth and population growth for food security
Time	Regions	Many	NA	(Leach, 1995)	Year	Systematically explore sustainable futures, including for the land and food sector

Table 4
Model predictions by category, in units of kcal per capita. We found no papers with time trend estimates past 2050.

Forecast type		2050			2100		
		n	Mean	95%CI	n	Mean	95%CI
Food aggregation	Few	14	3320	3224–3416	9	3597	3310–3884
	Many	28	3215	3116–3314	5	3401	2971–3831
Spatial aggregation	Countries	17	3163	3061–3265	4	3773	3386–4160
	Regions	25	3310	3212–3408	10	3428	3148–3708
Model complexity	Time	5	3360	3161–3559	0	NA	NA
	Simple	11	3167	3017–3317	6	3503	3060–3946
	Complex	26	3264	3171–3357	8	3545	3270–3819

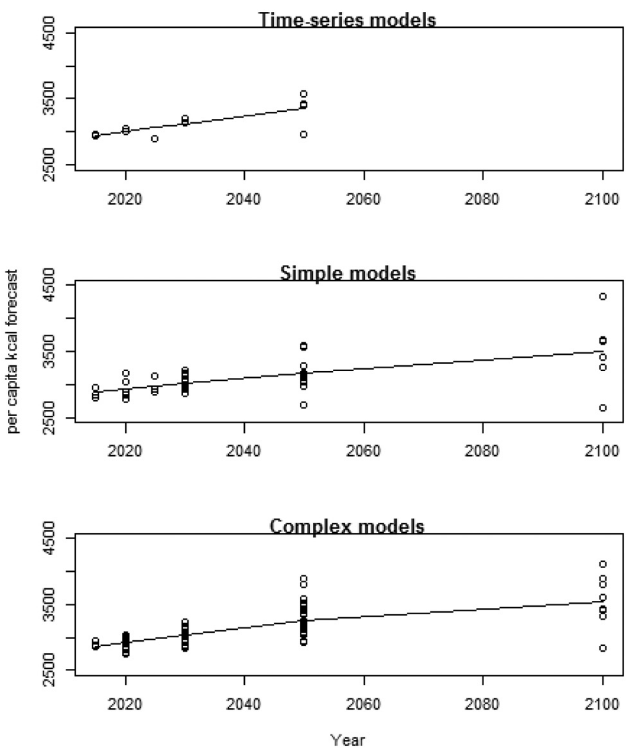

Fig. 3. Predictions for global average per capita kcal demand for each of the categories of model. No predictions exist past 2050 for the time-series models.

species (e.g., rats, birds), or examining consumer choice in response to labelling or marketing. We were not able to develop exclusion terms that could reliably remove all of these false positives without potentially excluding relevant papers.

Most papers that did examine human food demand trends (73%) only examined historic patterns and did not make quantitative predictions about the future. Of the papers that did make predictions (n = 85), 81% did so for a subset of countries, food types or situations (e.g. in the event of a natural disaster). Of the 296 studies assessing food demand trends, 70% were done at the country or within-country scale with only 19% at the global scale (Table 1). The best-studied countries, by far, are the USA and China while countries from Africa, the Middle East and South America are poorly represented (Fig. 2).

3.2. Food-demand predictions

The 22 studies that met our inclusion criterion for meta-analysis were critically appraised by authors EJF, JCB and LB. Most of these studies used complex models in which food demand estimates are influenced by production through prices and trade. There was substantial overlap in the confidence intervals for predictions for the various model complexities (Fig. 3, Table 4).

Although there are differences among the means of these different categories, the confidence intervals overlapped among all categories at each time point, indicating high inter-study variability and lack of significant differences. There is no clear trend related to our model complexity categories or levels of aggregation. For instance, in 2100, the lowest estimate (2654 kcal per capita) comes from a forecast that has a simple structure with many food types. But the next smallest (2830) is from a complex model with few food types. The highest forecast at 2100 (4335) came from a simple/countries/few model. The next highest estimate at 2100 was from a complex/regions/few model (4110), and then two complex/regions/many models. No pattern emerged linking estimates to model complexity or level of aggregation.

All categories predict higher food consumption in 2100 compared to 2050. Surprisingly, though, the confidence intervals for 2100 overlapped those of 2050 for almost all of the categories presented here. Averaging all predictions, the estimate for 2050 is 3250 (95% CI = 3176–3324) and for 2100 it is 3527 (95% CI = 3290–3763), suggesting an increase of 277 kcal on average, per capita. However, these confidence intervals overlap, underlining the generally accepted slowing down of the increase in per capita demand during this period. Sometimes the complex models were paired with a simple form where prices were held constant and demand was forecast with income only (Gouel and Guimbard, 2017; Valin et al., 2010). When this pairing occurred, and paired predictions were reported, the model estimates were within about 40 kcal of one another (3052 for simple model and 3095 for complex model; Hugo Valin et al., 2010).

There was no reported model validation in the papers associated with the complex models, although many of these are built upon integrated or sub-models which may have undergone validation in their initial development stages. Several of the simple models did report model validation or selection techniques in the form of coefficient of determination (R^2), Akaike information criterion (AIC) or cross-validation. None of the models described the use of model averaging/ensemble models and few (4; 18%) explicitly reported uncertainty in the form of confidence intervals, standard error or sensitivity analysis, though many (12; 55%) employed scenarios to indicate the possible range of future demand levels.

4. Discussion

Past studies have predicted future global food demand for a variety of reasons (Table 3), using different methods and have envisaged a diversity of potential futures. All models assessed in this systematic review predicted increasing per capita food demand, but the end-point confidence intervals were wide, ranging from 3060 to 3819 kcal per capita (Table 4, Fig. 3). The predicted increase of 277 kcal per capita from 2050 (3250 ± 56) to 2100 (3527 ± 104) would represent an increase of about 8.5% over the mean of the predictions for 2050 which, paired with the increasing population, would have significant implications for global food production systems. Surprisingly, our analysis shows that this cross-study variability in predictions is not attributable to any obviously different characteristics of their approach, such as model complexity or aggregation. Indeed, predictions for 2050 from the FAO's complex models are within 100 kcal of prediction from David Tilman's group (Tilman and Clark, 2014) which are based simply on GDP, further reinforcing the idea that additional variables do not alter general predictions for food demand in any consistent way.

Other forces may be constraining demand predictions as well; specifically, biological limits (represented in models as explicit thresholds or asymptotic functional forms) and shared data sources (e.g., a universal reliance on FAO's historic demand estimates) may force predictions to fall within a relatively narrow range (see Bias section, below). Therefore, rather than model complexity, differences in forecasted future food demand might derive principally from attributes like the underpinning economic models (Yu et al., 2004), projected prices, assumed economic-growth scenarios (Valin et al., 2014; von Lampe et al., 2014), and whether income inequality is explicitly included and/or expected to change (Cirera and Masset, 2010; Kii et al., 2013).

Two thorough previous studies, which compared predictions from 10 different integrated assessment type models (after unifying socio-economic, climate and energy data), found that assumed prices (von Lampe et al., 2014) and socioeconomic assumptions (income inequality and economic models used; Valin et al., 2014) exerted a greater influence on model predictions than did climate or bioenergy assumptions. Given our finding that complex mechanistic model predictions were not significantly different to those from simple mechanistic models, we agree that the addition of ecological or climatological data does not seem to alter model predictions in a consistent direction. However, the simple mechanistic models also yielded comparable predictions to phenomenological time-trend models, making it unclear whether the added effort of specifying economic relationships acts to enhance model predictions either. This somewhat surprising finding does not suggest that food demand is independent of economics. Rather, we find that phenomenological models (which represent the observed pattern of a given phenomenon, e.g. time and GDP) and mechanistic models (which represent the probable underlying mechanisms, e.g. prices, driving an observed phenomenon) make similar predictions for future (kilocalorie) demand. There can be an argument made for using phenomenological models, when predicting future metrics, if the data (e.g., GDP) can be more reliably predicted than mechanisms underpinning process-based models (e.g. prices and production). However, the additional variables in complex models may add flexibility needed to answer certain research or policy questions.

It was difficult to make comparisons in how model complexity impacts regional and food-group predictions due to the variability in how countries and food items were aggregated. However, when we compare studies with the same regional classifications, there is no clear effect of model complexity when looking at regional or food group estimates (Appendix B). For example, for two studies which aggregated data into the same six regional classifications, the complex model estimated higher calorie consumption for two regions (Asia and OECD; Dorin, 2011) and the simple model estimated higher calories for the other four regions (Bodirsky et al., 2015). Similarly, for three studies that used the same eight regional aggregations, a simple model predicted the highest value for four of the regions (Valin et al., 2010), whereas a complex model predicted the highest value for two of the regions (Alexandratos et al., 2006), and a different simple model predicted the highest value for the final two regions (Bodirsky et al., 2015).

Likewise, there was no consistent pattern in how model complexities predicted the percent of the diet composed of animal products ("animal percent"; Appendix B). A complex model (Dorin, 2011) predicted a higher animal percent than a simple model for three of six regions (Bodirsky et al., 2015) and for three of eight regions, a complex model (Alexandratos et al., 2006) predicted a higher animal percent than a simple model (Bodirsky et al., 2015).

This study can make no claims about which models more accurately predict food demand, and we have not seen such an analysis, although it would be beneficial to the field. Future studies should endeavour to report model accuracy using the coefficient of determination, structural goodness-of-fit or, ideally, some form of cross validation.

We encountered substantial variation across studies in how the data were aggregated. Food balance sheets provide data for most countries in the world (n = 176) for up to 87 individual food items (or 68 crops primary equivalents in food supply sheets). Some studies model food items individually (e.g. FAO), while others group food into general categories (e.g. meats, fruits and vegetables, etc.; Gouel and Guimbard, 2017) or into total kilocalories (Tilman et al., 2011). Likewise, some studies aggregated national data into regions (based on spatial or economic similarities). Aggregation can smooth out irregularities but could also miss important information, rendering predictions less accurate. However, our meta-analysis determined that predictions were similar regardless of how food and national data were aggregated.

Most studies examining food-demand trends were done at the country or within-country spatial scale (70%) and were mainly from China and the United States. Such studies provide a strong foundation for understanding and predicting food consumption trends in these specific locations. However, the lack of national-level data in developing regions, particularly Africa, South America and the Middle East (Fig. 2), reduces our understanding of food-demand patterns (and therefore our capacity to make reliable predictions) for these regions. The world's developing regions, especially sub-Saharan Africa, are experiencing rapidly changing food consumption patterns, and rising per capita food consumption (Kearney, 2010), along with the fastest population growth (United Nations, 2017). The outcome of these combined changes is that uncertainty surrounding predictions for food-calorie demand in these regions (due to few country-level studies) will have a disproportionately large effect on future global predictions.

4.1. Biases

In any review, particularly those including a meta-analysis, it is important to consider the potential for many forms of biases to impact conclusions. We considered three tiers of bias: systemic (publication) bias, reviewer (search strategy) bias, and the bias present in the included studies (Table 2). The broad search strategy used here identified potentially relevant papers from five sources: Web of Science, Scopus, Google Scholar, expert knowledge and citations from relevant papers. All initial papers were screened by one reviewer (EJF), leaving room for potential screener bias. However, < 2% of uniquely identifiable papers were suitable for our meta-analysis (Fig. 1), suggesting that the search was comprehensive. In medical and experimental fields, it can be difficult to publish studies where "no effect" is seen, leading to a positive publication bias that can affect meta-analyses (Dickersin, 1990). However, projections of food demand are less subject to this bias; predictions of no change in global consumption are just as interesting as predictions of substantial increases or decreases in demand.

The sources of bias in the predictive modelling studies are quite different from traditional sources of bias in for example, medical experiments and studies (Cohen et al., 2016; G. S. Collins et al., 2015; Debray et al., 2017). The main sources of bias identified in food demand models were in the data employed and the modelling techniques used. All food demand predictions (excluding time trends) relied on estimates of the future economy and/or populations. Many studies used predictions from the World Bank (GDP; The World Bank, 2018) and United Nations Population Division (United Nations, 2017), while others used scenario-based predictions from various sources or made their own calculations (Table 2). All of these data are subject to different biases, although without reporting the accuracy of each data source's predictions (e.g., using an out-of-sample method like cross validation), it is unclear how these various data sources are impacting demand predictions.

Importantly, all included studies relied on the same historic data, from the FAO, to determine relationships between economic conditions and demand. Therefore, bias present in FAO data is a ubiquitous and unifying force across studies. That said, FAO future estimates are derived through a rigorous set of integrated demographic, economic, production, and trade models which result in generally accurate predictions. For example, the prediction of Alexandratos (1995) for global average consumption in the year 2010 (2860) was only 10 kcal off from the FAO reported value of 2850 in 2010. However, we are not aware of any report of the accuracy of FAO's estimates of historic demand. The FAO's historic data estimates rely on official reports from various countries; missing data at the country-level means many values have to be "guesstimated" (Alexandratos, 1995). Errors are likely to be present in the values for certain countries or products, but are not expected to be consistently skewed. Systematic bias does arise from the FAO's definition of food demand which includes household level waste. This definition over-estimates consumption in all countries but has a greater impact on higher-income countries where household-level waste is more prevalent. The FAO estimates also do not account for gathered and hunted food, resulting in a systematic under-estimation of consumption in some less developed countries. Nevertheless, at the global scale, these biases will tend to cancel each other out, and as a consequence, FAO data probably remains the best uniform source of information on global food demand that we have (or are likely to get).

The models examined here range from transparent and clearly repeatable (Gouel and Guimbard, 2017; Tilman and Clark, 2014) to thoroughly opaque and non-replicable (e.g. FAO models). Some of the intermediaries report their methods and do not rely on expert opinion but are based on complex meta-models whose output can only be interpreted by experts. Though bias can be present in any model through the selection of data, covariates and the functional relationships among them, the bias can only be interpreted if it is reported.

4.2. Model reporting

Given the uncertainty surrounding data and future estimates, it is important for predictive models to report the model- and data-generated error bounds around mean predictions. In the studies we examined, few reported the uncertainty surrounding future kilocalorie demand estimates in the traditional form of confidence intervals or standard deviation. Rather, many of the studies opted to use broad scenarios by the International Panel on Climate Change (IPCC, 2000), the Center for International Earth Science Information Network (CIESIN, 2018; Stehfest et al., 2014), the Millennium Ecosystem Assessment (MEA, 2005), the International Institute for Applied Systems Analysis (IIASA, 2009) and others (Dellink et al., 2017; Fouré et al., 2012; Samir and Lutz, 2017; O'Neill et al., 2014), to showcase the variety of potential futures for food demand. While scenarios do provide a range of predictions, they may underestimate the potential range of future outcomes due to the pre-determined pairing of variables (Brook and Blomqvist, 2016), do not represent the relative likelihood of each scenario against the others, and do not accurately display the uncertainty surrounding predictions.

Some predictive models, rather than reporting uncertainty, attempt to improve the accuracy of predictions by tweaking model outputs according to expert advice (Alexandratos, 1995; Alexandratos and Bruinsma, 2012; Rosegrant et al., 1995). While this approach may effectively make predictions more accurate (given the accuracy of FAO's 2010 predictions), it also makes the model outcomes impossible to reproduce, and prone to subjective biases (often unrecognised) in the consulted experts (Burgman et al., 2011).

None of the complex studies reported any attempt at model selection or verification in the form of AIC, R^2 or cross-validation approaches. Most of the simple mechanistic models reported some form of model validation, which may be easier to do with simpler models. For the complex models, it is possible that validating tests were simply not reported, or were done only for some of the integrated sub-models. However, transparency of model uncertainty was generally lacking in the studies we examined. We also identified a complete lack of studies using ensembling or model-averaging approaches to making predictions. By including information from multiple informative models, weighted by their credibility, model averaging can produce more robust parameter estimates than if a single model is used (Burnham, 2015; Burnham et al., 2004). Based on these findings, we encourage future predictive studies to incorporate contemporary statistical best practices: transparency, model validation, model averaging (when feasible/appropriate), and consistent reporting of model uncertainty.

One of the challenges in comparing papers was the unification of definitions for food demand. We have included in our meta-analysis papers which reportedly predict food or calorie consumption, demand, or availability. Some have explicitly differentiated between these terms (Tilman and Clark, 2014), preferring "demand" over consumption since the available (food balance sheet) data overestimate consumption due to its inclusion of household-level waste (Serra-Majem et al., 2003). However, it is important to acknowledge that this use of the term "demand" in this context does not match precisely with the economic concept of demand, which refers to the amount of a good that a person wishes to buy at a given price – that is, the latter concept is not necessarily the amount a person actually buys at a given time. This terminological mire is not easily traversed, and has led to the variety of terms currently in use and the resultant difficulty in unifying model output for comparisons. Although perhaps the most accurate term would be "food available for human consumption", this term seems too passive with respect to human preferences to accurately reflect the dependence on human purchasing and consumption patterns. Therefore, although admittedly imperfect, we agree with Tilman and Clark (2014) in encouraging use of the term "demand" when referring to the available food-calorie-consumption data as reported by the FAO (2016).

5. Conclusions

Different modelling methods have resulted in a variety of forecasts for global food demand. However, these differences are not due to the complexity of the models nor to the level of aggregation of the (food or national) data. We found that purely phenomenological (time-trend) model predictions fell within the same range as simple and complex mechanistic models. While complex models are flexible to expected changes in agricultural output, food prices, and trade, they result in opaque and sometimes irreproducible models. Simpler models are easier to interpret and reproduce but may not be as accurate. Likewise, models with data aggregated across geographies and food types make similar predictions compared to models using disaggregated data. Therefore, decisions about model complexity and data aggregation can be made based on the research/policy questions of interest, without substantial impact on model predictions.

The significant overlap across predictions for future per capita food demand, despite different model methods and data sources, supports the robustness of these estimates. Likewise, the overlap between per capita demand estimates from years 2050 and 2100 underlines a generally accepted deceleration of rising demand levels.

We did not identify any studies following current best statistical methods of transparency, model validation, model averaging, and reporting model uncertainty. We suggest that better adherence to statistical best practice methods would allow for a thorough comparison of model predictive ability, which would answer some of the pressing questions in the field of food-demand modelling. A hind-casting or cross-validation assessment of model accuracy would enhance the decision-making process for researchers and policy-makers deciding what models or results to use.

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Author contributions

All authors contributed to the conceptualization of this study and writing of this manuscript. Authors EJF, JCB, and LB contributed to the screening, critical appraisal and data extraction from papers. Author BWB conducted the meta-analysis.

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