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Global meat consumption driver analysis with machine learning

methods

Junwen Jia^{1, 2}, Fang Wu¹, Hao Yu^{1, 3}, Jieming Chou⁴, Qinmei Han^{4, 5}, Xuefeng Cui^{1, *}

¹ School of Systems Science, Beijing Normal University, Beijing, 100875, China

² School of Earth and Environmental Sciences, Cardiff University, Cardiff, CF10 3AT, United Kingdom

³ Department of Mathematics and Statistics, University of Exeter, Exeter, EX4 4QJ, United Kingdom

⁴ Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China

⁵ National Climate Centre, China Meteorological Administration, Beijing, 100081, China

* Corresponding author.

E-mail address: xuefeng.cui@bnu.edu.cn

Abstract:

The growing global meat consumption has serious consequences on human health, the environment and ultimately impacts global food security. Therefore, identifying the drivers of meat consumption and predicting its evolution is necessary. We compared four machine learning methods in modelling meat consumption, leading to the selection of a random forest-based model to detect main drivers for global meat consumption. Our results show that per capita meat consumption is mainly driven by socioeconomic factors, such as national GDP and urbanization. However, the strength of these drivers declined between 1990 and 2018. Pork, beef, and poultry consumption are mainly driven by socioeconomic factors, whereas mutton consumption appears driven by other factors such as the per capita agricultural land. In this work, the model-agnostic interpretability method is introduced to measure the marginal effect of each driver on meat consumption. We found that there may be insufficient evidence to support the inverted U-shaped relationship between per capita GDP and meat consumption, which is reported in previous studies. Our analysis may provide avenues for predicting meat consumption at the national scale.

Key words: Meat consumption, driver analysis, interpretable machine learning, national-level prediction

1. Introduction

The world population increased by 145% between 1961 and 2018, from less than

3.1 billion to over 7.6 billion. Over the same period of time, worldwide meat consumption and production almost quintupled (4.6 times and 4.8 times, respectively; FAO, 2021). This increasing meat consumption has become a major global sustainability issue, with consequences on human health, the environment and global natural resources (Ambikapathi et al., 2018; Micha et al., 2010; Pfeiler and Egloff, 2018a; Tilman and Clark, 2014).

Meat consumption has reached a level such that it negatively affects human health in large parts of medium- and high-income countries (Andriamparany et al., 2021; Milford et al., 2019). For example, excessive animal protein and fat intake can lead to high risk of obesity, cardiovascular diseases (Popkin, 2002), stroke (Westhoek et al. 2014), and several types of cancer (Klurfeld, 2018; Knuppel et al., 2020; Sam et al., 2021; Zhao et al., 2020).

From the environmental standpoint, Heller et al. (2021) reported that meat consumption is the largest contributor (31%) to the water footprint of human diet. Over half of the protein biomass of global crop harvests is used to feed livestock (Milford et al., 2019). Approximately one quarter of the world's land area is used for grazing (Stehfest et al. 2009). The increase in animal husbandry-related land-use has become one of the main cause for human-generated environmental degradation, including deforestation, land degradation, and greenhouse gas emissions (Geldenhuys et al., 2013; Jia et al., 2023; Ratnasiri and Bandara, 2017; Yu et al., 2021).

The dietary transition toward more plant-based diets is necessary (Popkin, 2006), but needs to be guided by an understanding of the drivers of meat consumption (Milford et al., 2019). York and Gossard (2004) identified the influence of geographical and environmental factors in controlling total meat and fish consumption. Several studies have shown that income and price are also important drivers of meat consumption (Bodirsky et al., 2015). Vranken et al. (2014) identified the impacts of social and geographical variables on global meat consumption. Many studies further reported that demographic factors are also drivers of meat consumption (Aston et al., 2013; Bhandari and Smith, 2000; Gill et al., 2015; Pfeiler and Egloff, 2018b; Stoll-Kleemann, 2014; Tobler et al., 2011). Milford et al. (2019) included economic, nature endowment, social, and globalization factors to analyse total meat and ruminant meat consumption. However, questions remain about the main drivers of global meat consumption and the processes at play.

Several previous studies have discussed meat consumption drivers and projected future meat demand scenarios using equilibrium models (Keyzer et al., 2005; Komarek et al., 2021; Kwasny et al., 2022; Milford et al., 2019). Traditional equilibrium procedures are based on expert judgement and kinetic equations, which often involve numerous assumptions and parameter estimations based on experiments, specific surveys, or expert opinions (Zhao et al., 2021). Solving this iterative process is very time-consuming (Mutlu and Yucel, 2018). Although conventional dynamic equilibrium models are easy to understand, the underlying processes involved are not easily revealed by kinetic equations (Arteaga-Pérez et al., 2013).

Data-driven machine learning (ML) methods, on the other hand, may provide another way to analyse meat consumption. ML-generated models, such as Gaussian

process regressions (GPR), support vector machines (SVM), artificial neural networks (ANN), and random forest (RF) are deemed to handle complex questions well (Uzun et al., 2017), and are regarded as advanced tools in a wide range of fields (Xing et al., 2019; Mora et al., 2017; Luo et al., 2023). These approaches have shown substantially superior performances compared with linear and nonlinear methods in statistical simulations (Mikulandrić et al., 2016; Elmaz et al., 2020). However, ML methods in food, especially, meat consumption analysis have not received much attention so far.

The goal of this article is to (a) develop ML methods for meat consumption driver analysis; (b) quantify relationships between meat consumption and drivers; and (c) test the predictive power of the selected model. The remainder of this article is organized as follows. Section 2 introduces data and methods; Section 3 and Section 4 discuss the results of meat consumption driver analysis; and a brief summary is provided in Section 5.

2. Methods

We trained bottom-up, data-driven, ML-generated models with comprehensive meat consumption drivers. Based on the relationships captured by our model, we then investigated the importance of different drivers of meat consumption and tested the predictive power of our developed model. Fig. 1 outlines the approach followed in the present work.

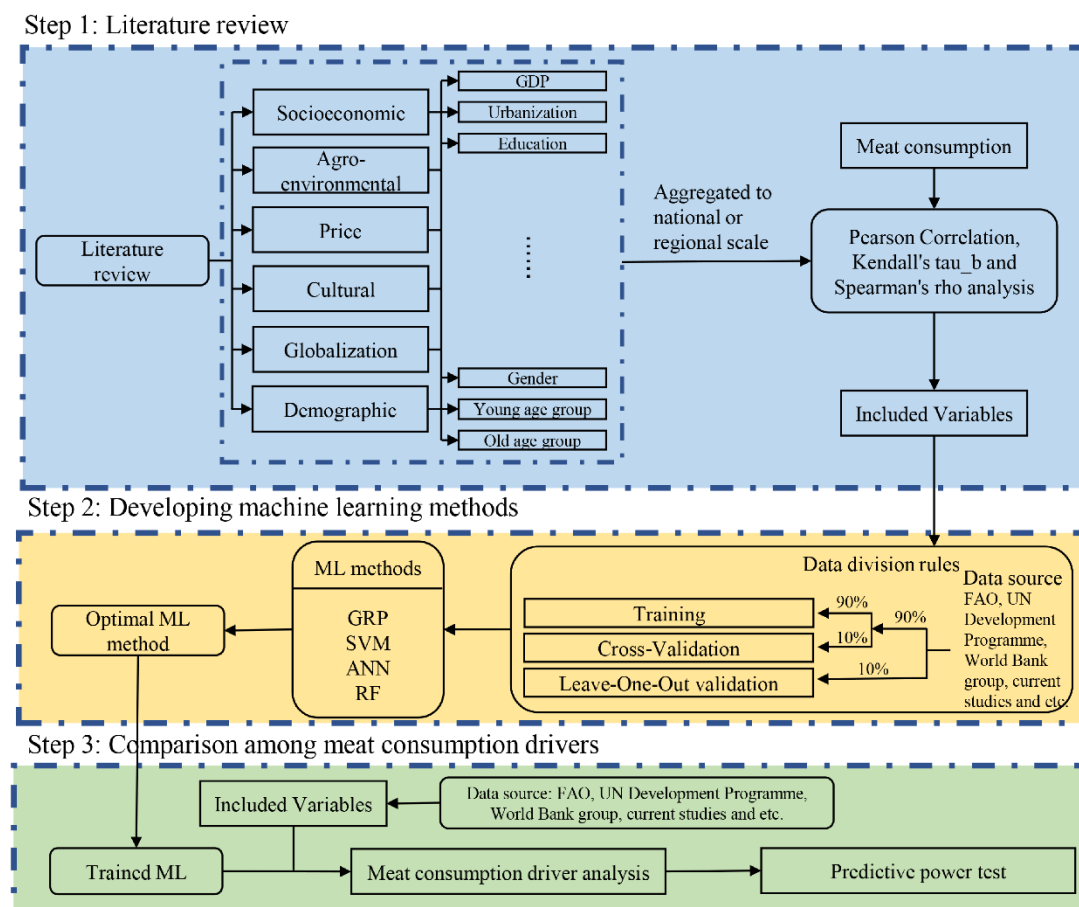


Fig. 1. Flowchart of analysis and model development for global meat consumption drivers using machine-learning methods.

2.1 Data

Drivers of meat consumption were selected from the literature (Table 1). These include socioeconomic, price, agro-environmental, globalization (Milford et al. 2019), and demographic factors (Aston et al., 2013; Bhandari and Smith, 2000; Pfeiler and Egloff, 2018b; Stoll-Kleemann, 2014; Tobler et al., 2011).

Table 1 Overview of the meat consumption drivers

Factor	Variable	Source
Consumption	Meat consumption per capita per year	FAO, food balance sheet
Socioeconomic	GDP per capita (PPPGKD)	Gütschow et al. (2021)
	Urban population share	UN development programme, demography
	Population with at least some secondary education	UN development programme, education/both sex
		UN development programme, education/female
Agro-environmental	Agricultural land per capita	FAO, land use
		FAO, annual population
	Annual mean temperature and rainfall	World Bank group, climate change knowledge portal for development practitioners and policy-maker
		FAO, temperature change University of East Anglia, climatic research unit
Price	Producer price index of meat, cereals and vegetables	FAO, producer price
Cultural	Western meat-intensive lifestyle dummy	Milford et al. (2019)
	Share of adherents to Christianity	Association of Religion Data Archives (ARDA)
	Share of adherents to Islam	
	Share of adherents to Buddhism	
Globalization	Economic globalization index	KOF globalization index
	Social globalization index	
	Political globalization index	
Demographic	Male population share	FAO, annual population
	Young age (0–14) population share	UN development programme, demography
	Elderly age (65 and older) population share	UN development programme, demography

Inclusion of variables in model development (Table 1) was based on the following rationale, derived from the literature:

Socioeconomic factors have been mainly accounted for by economics and social development. Per capita GDP (constant 2011 Purchasing-Power-Parity-adjusted Geary–Khamis Dollar; PPPGKD) was included as an income variable (Gütschow et al., 2021). Urbanization and education were included to represent societal conditions (Milford et al., 2019). Female education levels were taken into

consideration separately (Bhandari and Smith, 2000).

Price factors have been usually described as relative prices (Milford et al., 2019), which include corresponding meat prices. Cereal and vegetable prices were also involved as prices of meat substitutes.

Agro-environmental factors have been expressed by per capita agricultural land area and climate variables (York and Gossard, 2004). Empirically, temperature, precipitation and available agricultural land are important factors of agricultural production (Varadan et al., 2017; Yu et al., 2021).

Cultural factors include religious variables and western meat-intensive lifestyle (Milford et al., 2019). Religious variables were expressed as the share of adherents to Christianity, Islam, or Buddhism (Bobyreva and Dmitrieva, 2018; Zhang, 2020). A western meat-intensive lifestyle variable was included in our study with reference to a variable of western culture as defined in Milford et al. (2019) and Miller (2020).

Demographic factors include gender and age distributions (Pfeiler and Egloff, 2018a, b). Gender was represented by the proportion of males in a population. Age was represented by the proportions of individuals aged 0-14 (“young”) and of individuals aged 65 and older (“elderly”).

Globalization may be a driver of dietary structure transformation (Milford et al., 2019; Popkin, 2006). We used the globalization indexes generated by the KOF Swiss Economic Institute of ETH Zürich along the economic, social and political dimensions.

To analyse meat consumption drivers, we estimated the per capita annual consumption of meat, pork, beef (beef and veal), mutton (sheep and goat), and poultry (FAO, 2021). We collected 20 global variables from 1990 to 2018, depending on the availability of data. Detailed sources and availability of data selected are provided in Supplementary Table S1. A detailed description of the data selected and methods of data pre-processing is provided in Supplement A2.

2.2 Simulation models

GPR, SVM, ANN, and RF models are widely used ML-generated models (Uzun et al., 2017). GPR and ANN models were built, trained, and tested with packages *fitrgp* and *fitnet*, respectively, using *MATLAB* (see Rasmussen and Williams, 2006; Beale et al., 2023, for protocol details). The optimal hyper-parameters for GPR and ANN models were selected through quasi-Newton and Levenberg–Marquardt algorithms, respectively, with reference to Zhao et al. (2021) and Uzun et al. (2017). SVM and RF models were built based on the package *sklearn* from *Python 3.8* (See Pedregosa et al., 2011, for protocol details). The optimal hyper-parameters of the SVM and RF models were selected with the package *Bayesian-optimization* from *Python 3.8* (See Brochu et al., 2010, for protocol details). To evaluate the performance of the ML-generated models, 10% of the sample data was randomly split into a testing set firstly used for leave-one-out validation. The remaining 90% of the sample data were used

as training set (Zhao et al., 2021; Lipton, 2018). Within the training data set, 10% of the data were selected randomly for cross-validation, repeated 10 times to avoid overfitting (Fushiki 2011; Zhou et al. 2022). After 10-fold cross-validation, model performance evaluation indicators for training data set were calculated. Figure 1 and Supplementary Table S9 provide details.

2.3 Model performance evaluation indicators

We briefly explain the properties of the four assessment measures (Buitinck et al. 2013) that were used to evaluate the performance of the four ML-generated models: the mean absolute percentage error (MAPE), the root mean square error (RMSE), the determination coefficients (R^2) and the explained variance score (EVS). R^2 , EVS, RMSE, and MAPE were calculated as follows:

$$R^2 = 1 - \frac{\sum_{j=1}^N (Y_j^{model} - Y_j)^2}{\sum_{j=1}^N (Y_j - Y_{ave}^{act})^2} \quad (1)$$

$$EVS = 1 - \frac{\sum_{j=1}^N Var(Y_j^{model} - Y_j)}{\sum_{j=1}^N Var(Y_j)} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^N (Y_j^{model} - Y_j)^2}{N}} \quad (3)$$

$$MAPE = \frac{1}{N} \sum_{j=1}^N \left| \frac{Y_j^{model} - Y_j}{Y_j} \right| \times 100\% \quad (4)$$

where N is the number of samples, Y_j^{model} is the model simulated value of the j th sample, Y_j is the observed value of the j th sample, and Y_{ave}^{act} is the average value of the observed value. Var is the calculated variance.

2.4 Feature importance and partial dependence plots

ML interpretation approaches can be split in two broad categories: model-specific or model-agnostic (Guidotti et al., 2018). Model-specific procedures are only applicable for certain model, for example, regression weight in a linear model, whereas model-agnostic approaches can be used in multiple machine learning methods (Azodi et al., 2020; Zhao et al., 2021). Two widely used model-agnostic approaches (Luo et al. 2023), which feature importance and partial dependence plots (PDPs), were used in this study.

Feature importance analysis is based on the fact that the more the model error increases due to the permutation of a specific feature, the more important the feature is (Friedman, 2001). The feature importance index used in our research is the normalized ratio of the model fitting error of the training set before and after permuting a feature. To avoid the influence of short-term fluctuations, we measured the importance of meat consumption drivers over approximately 30 years with a ten-year sliding time window (from 1990-1999 to 2009-2018).

PDPs were used to display links between selected input variable and dependent output variable while accounting for the mean value of other input variables (Zhu et

al., 2019). The PDPs of a dependent variable on input factor x_s is:

$$\hat{f}_{x_s}(x_s) = E_{x_c}[\hat{f}(x_s, x_c)] = \int \hat{f}(x_s, x_c) dP(x_c) \quad (5)$$

where $\hat{f}$ represents the ML-generated model, x_s is selected input variable, and x_c is the other variables also input in the model. Equation (5) could be evaluated on the training dataset by

$$\hat{f}_{x_s}(x_s) = \frac{1}{n} \sum_{k=1}^n \hat{f}(x_s, x_c^{(k)}) \quad (6)$$

where $x_c^{(k)}$ ($k = 1, 2, \dots, n$) is the value of x_c for every individual sample in the training dataset. PDPs depict the marginal effect of simulation selection probability for a given value of the selected independent variable x_s .

3. Results

3.1 Performance of Machine Learning-generated models

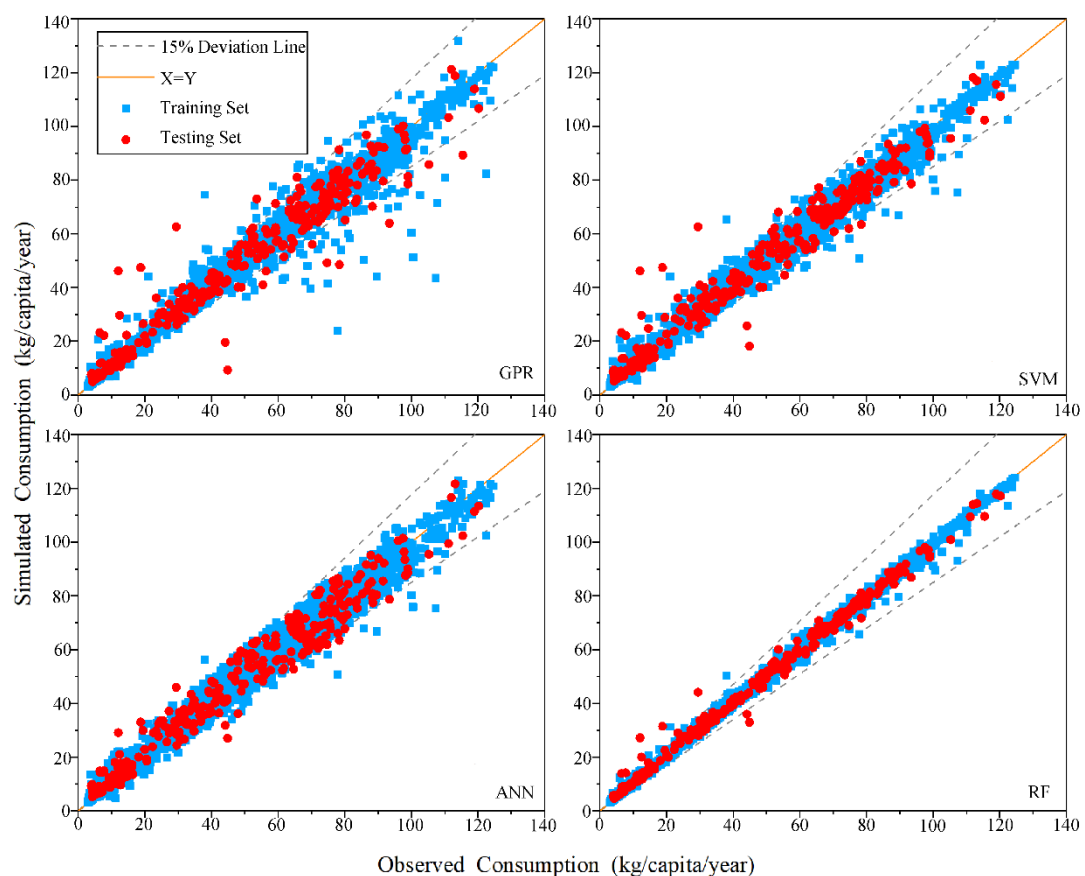


Fig. 2 Simulations of four types of machine learning -generated models with meat consumption fitting results from the training set and testing set (reference line in red: one-to-one line for $X = Y$)

Table 2 Evaluation indicators for simulating meat consumption of four models.

Datasets	Evaluation indicators	GPR	SVM	ANN	RF
Training set	MAPE (%)	7.32	4.16	5.90	2.11
	RMSE	2.55	1.86	1.93	1.28
	R ²	0.92	0.97	0.95	0.99
	EVS	0.91	0.95	0.95	0.99
Testing set	MAPE (%)	14.77	9.15	9.10	5.43
	RMSE	3.87	3.22	3.09	2.41
	R ²	0.89	0.93	0.95	0.99
	EVS	0.89	0.93	0.94	0.99

The simulation performances of four types of ML-generated models based on training and testing data sets are shown in Fig. 2. Table 2 shows the evaluation indicators for GPR, SVM, ANN, and RF models to quantify performances of these four methods. RF model outperforms the other three ML-generated models in the training and testing sets, with MAPE, RMSE, R², and EVS values of 2.11% and 5.43%, 1.28 and 2.41, 0.99 and 0.99, and 0.99 and 0.99, respectively. SVM and ANN models perform similarly in both sets, whereas GPR model performs poorly.

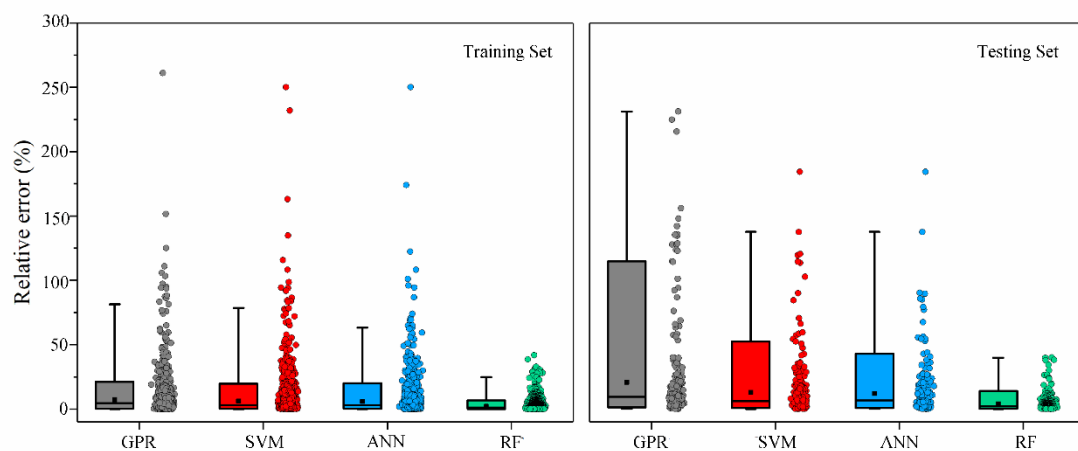


Fig. 3 Distributions of relative error of four machine learning-generated models using the training and testing dataset. Relative error were calculated on the simulated consumption and observed consumption values of the training (left) and testing sets (right). Each point represents the relative error of simulated vs observed per capita annual consumption of one country.

The distributions of relative error of ML-generated models plotted in Fig. 3 further describe the robustness of the considered modelling methods. Relative errors were calculated from the absolute differences between model outputs and observed values divided by the observed values. The RF-generated model has the lowest relative error among four ML-generated models, followed by ANN and SVM-generated models, which yielded similar results. There is a clear difference between the performance of

GPR model in the training and testing datasets. In both training and testing datasets, relative errors for the RF-generated model are generally below 25%, whereas relative errors using the other three modelling methods are much higher, some values exceeding 100%.

3.2 Drivers of meat consumption

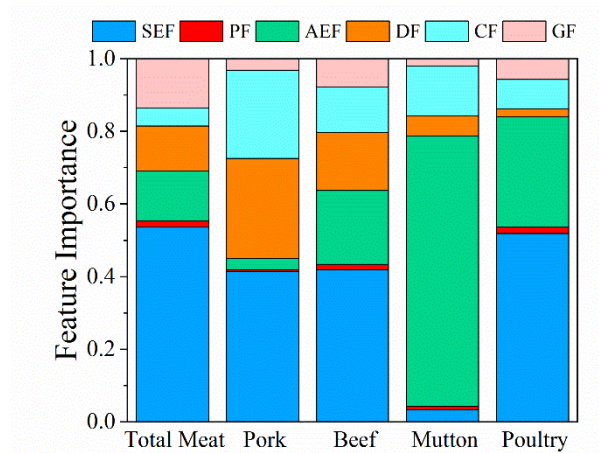


Fig. 4 Feature importance of different driving factor for meat consumption from 1990 to 2018 (SEF: Socioeconomic factors; PF: Price factors; AEF: Agro-environmental factors; DF: Demographic factors; CF: Cultural factors; GF: Globalization factors). A detailed description of the factors is provided in Supplementary A1 and supporting data is provided in Supplementary Table S2.

The importance of factors in different meat consumption types widely varies (Fig. 4). Socioeconomic factors generally play the most important role in the consumption of total meat, pork, beef and poultry, followed by agro-environmental and demographic factors. Mutton consumption is however mainly driven by agro-environmental factors. It is interesting to point out that the price factors do not show substantial impacts on any kind of meat consumption. The supporting data for the importance of each variable is provided in Supplementary Table S2.

3.2.1 Total meat

The results show that socioeconomic factors remain the most important drivers of meat consumption, while a slight but consistent downtrend from 1990 to 2018 is observed, followed by agro-environmental, demographic and cultural factors (Fig. 5).

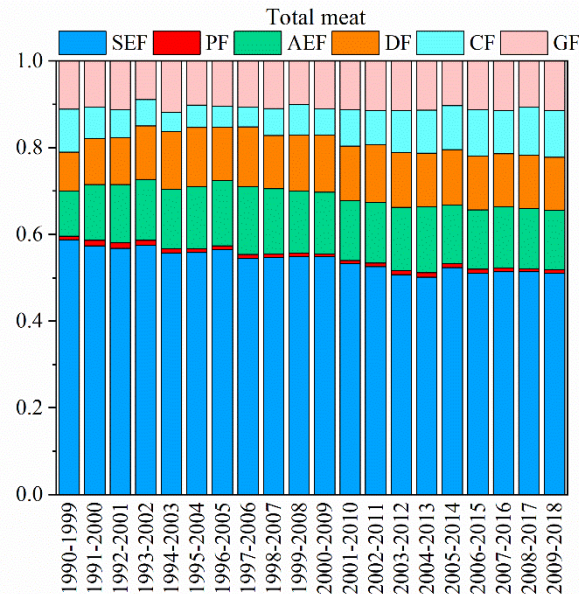


Fig. 5 Factors importance variation tendency (SEF: Socioeconomic factors; PF: Price factors; AEF: Agro-environmental factors; DF: Demographic factors; CF: Cultural factors; GF: Globalization factors). A detailed description of the factors is provided in Supplementary A1 and data is provided in Supplementary Table S3.

Per capita GDP is the most important variable among the socioeconomic factors considered (Table S3). Urbanization is also a positive factor on meat consumption; i.e., a 5% rate increase leads to a 1.3 kg per capita annual consumption rise. Education is also an important factor, especially the level of female education. Globally, a 2% increase in the population with at least a secondary education level results in a 2.2 kg per capita annual meat consumption increase.

Among the agro-environmental factors, agricultural land per capita is the most influential variable (Table S3). A rise of one hectare per capita in agricultural land results in a 3.8 kg per capita annual meat consumption increase. Individuals who live in regions with annual mean temperatures between 5 and 15°C consume nearly 28 kg more meat a year than those in high-temperature areas (higher than 15°C) and 3 kg more meat a year than those in cold areas (under 5°C). Nations with annual mean rainfall between 500 and 1,500 mm consume more meat than those under 500 mm (+10.6 kg per capita a year) and over 1,500 mm (+10.4 kg per capita a year). The above results show that warm climates, as well as drought or high humidity, suppress meat consumption.

Western, meat-intensive lifestyle and Muslim culture are more sensitive to cultural factors (Table S3). The proportion of elderly (65 and older) in a population is an influential demographic variable; nations with an index (the proportion of elderly in population) higher than 20% consume approximately 33 kg meat per capita a year more than others. However, both the young age (0–14) population share and the male population share are not as important as the proportion of elderly in meat consumption.

Social globalization holds a strong position among the variable importance ranking list (Table S3). A 5-point value rise in the social globalization index leads to a

+2.7 kg per capita annual meat consumption change. Similar to previous studies such as Milford et al. (2019), we also found that economic globalization is a negative variable in meat consumption. Per capita annual consumption decreases by approximately 3.1 kg responding to a 5-point value rise in economic globalization. Policy globalization is not a particularly prominent positive variable, and a +5-point value change leads to a responding +1.3 kg of per capita annual consumption.

3.2.2 Pork and Poultry

Pork and poultry consumption are both mainly driven by socioeconomic factors (Fig. 6). However, trends in driver importance differ between pork and poultry consumption. For pork consumption, the importance of socioeconomic factors remains stable at approximately 0.4 from 1990 to 2018. Cultural factors play an important role in pork consumption (mainly due to the influence of Islamic religion and western meat-intensive lifestyle; Table S4), but the importance of cultural factors shows a clear downward trend. In recent years, the importance of demographic factors has exceeded cultural factors. For poultry consumption, the importance of socioeconomic factors shows an obvious downtrend. In contrast, globalization is becoming more important. The influence of cultural and demographic factors on poultry consumption is not as strong as that on pork consumption, while agro-environmental factors have more influence.

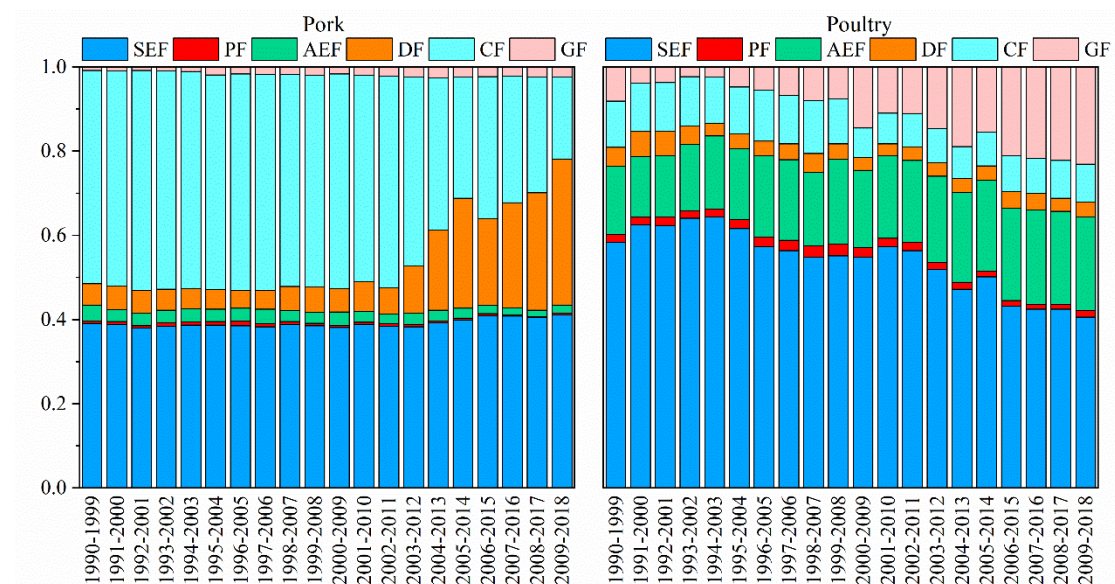


Fig. 6 Factor importance variation tendency on pork and poultry consumption (SEF: Socioeconomic factors; PF: Price factors; AEF: Agro-environmental factors; DF: Demographic factors; CF: Cultural factors; GF: Globalization factors). Supporting data is provided in Supplementary Table S4 and Table S7.

In pork consumption, the Muslim population share has a substantial negative impact. Nations with a Muslim population share over 80% consume nearly 65 times

less pork than others. Additionally, population structure has a close relationship with pork consumption. The young population share is generally a negative factor on pork consumption, and per capita consumption in nations with a share over 60% is nearly 15.7 kg less than that in other nations. The elderly population share is a positive driver, and countries with an elderly population share over 20% consume approximately 24.5 kg of pork per capita a year more than others.

In poultry consumption, social globalization is an important driver; i.e., a 5-point value rise in the social globalization index contributes to an approximately +1.0 kg per capita annual consumption. Urbanization has a positive impact on poultry consumption; a 5% increase leads to an approximately +1.7 kg per capita annual consumption. Agro-environmental factors are more important in poultry consumption than in pork consumption. The annual mean temperature is the most influential agro-environmental variable. The per capita annual consumption of nations with 5–15°C annual mean temperatures is 0.7 kg and 3.7 kg higher than those with higher and lower annual mean temperatures, respectively.

3.2.3 Beef and Mutton

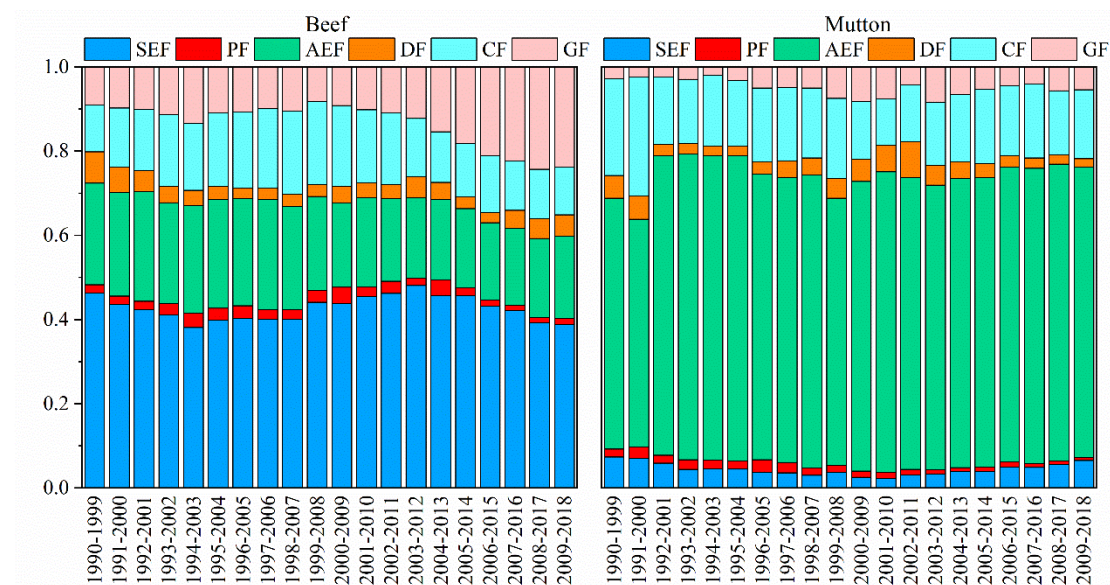


Fig. 7 Factor importance variation tendency on beef and mutton consumption (SEF: Socioeconomic factors; PF: Price factors; AEF: Agro-environmental factors; DF: Demographic factors; CF: Cultural factors; GF: Globalization factors). Supporting data is provided in Supplementary Table S5 and Table S6.

Compared with pork and poultry consumption, the quantity of beef and mutton consumption is lower (FAO, 2021). In previous studies, beef and mutton were usually uniformly regarded as ruminant meat (Milford et al., 2019), but the main drivers of beef and mutton consumption are substantially different (Fig. 7). Beef consumption is driven more by socioeconomic factors, especially GDP, while mutton consumption is driven by agro-environmental factors. For beef consumption, the urbanization rate is

a positive driver for per capita annual beef consumption; i.e., a 10% urban population share rise contributes to a 3.1 kg per capita annual beef consumption increase. It is noteworthy that, in beef consumption, the importance of the globalization factors shows a clear uptrend, but a similar tendency is not observed in mutton consumption. Per capita agricultural land plays an important role in beef consumption; i.e., a hectare per capita agricultural area rise contributes to a responding +3.4 kg beef per capita annual consumption change. For mutton consumption, per capita agricultural land, annual mean temperature, and rainfall all exert important influences (Table S6).

3.3 Marginal effect of meat consumption drivers

Fig. 8 depicts the change of meat consumption in response to the change of a specific feature (PDPs, introduced in Section 2.4). The top 6 most important variables in meat consumption (Table S2) were chosen to show their influences on meat consumption. For ease of interpretation, the grey line in Fig. 8 was produced using locally estimated scatterplot smoothing. The results show that when per capita GDP reaches 40 thousand PPPGKD (Purchasing-Power-Parity-adjusted Geary–Khamis Dollar), the quantity of per capita annual consumption remains stable. Education is a positive factor for meat consumption, but when the share of the population with at least secondary education reaches approximately 60%, the per capita meat annual consumption decreases slightly. The elderly population share and per capita agricultural land are positive factors for meat consumption. Initially, per capita annual meat consumption increases with the growth of the elderly population share, and then remains stable when that share reaches approximately 10%. Meat consumption increases with the growth of per capita agricultural land. Urbanization is another important factor, and meat consumption increases substantially after the urban population share reaches 80%. Excessive high or low temperatures both have negative impacts on meat consumption, which is in consistent with our analysis in Section 3.2.1.

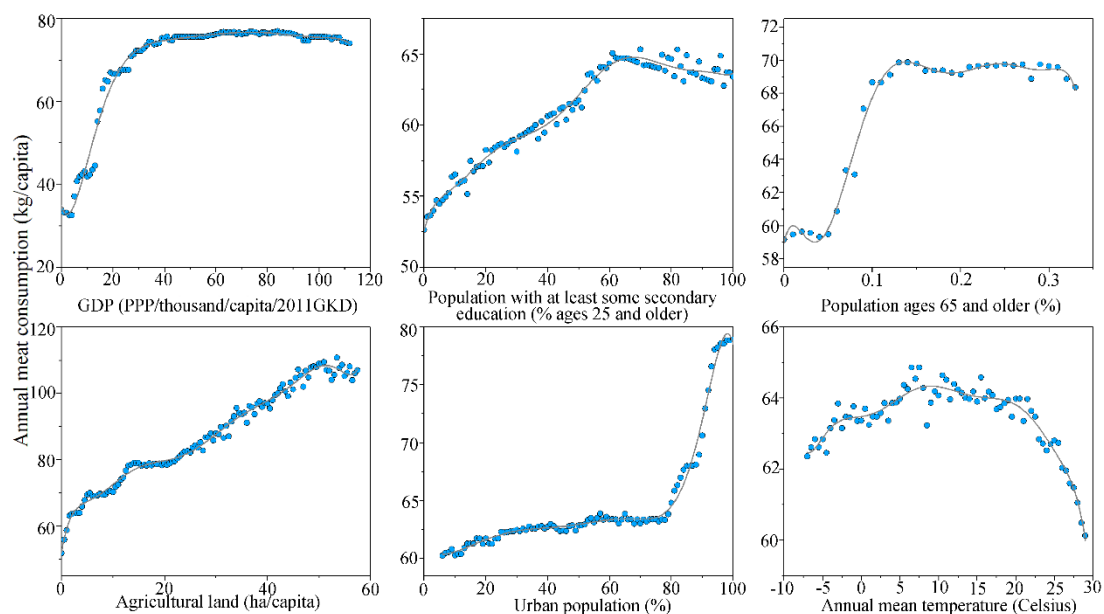


Fig. 8 Partial dependence plots of per capita annual meat consumption on drivers

3.4 Predictive power test

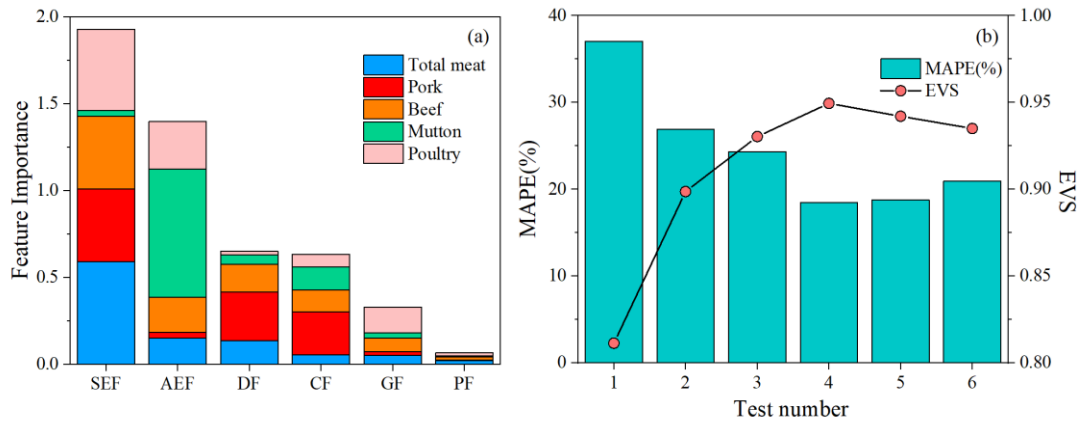


Fig. 9 Factor importance and predictive power test. (a) The feature accumulated importance from the total meat, pork, beef, mutton, and poultry sectors (SEF: Socioeconomic factors; AEF: Agro-environmental factors; DF: Demographic factors; CF: Cultural factors; GF: Globalization factors; and PF: Price factors). (b) Estimation indicators for the predictive power test with different factors: Test 1 was derived from only socioeconomic factors; Test 2 was derived from socioeconomic and agro-environmental factors; Test 3 was derived from socioeconomic, agro-environmental and demographic factors; Test 4 was derived from socioeconomic, agro-environmental, demographic and cultural factors; Test 5 was derived from socioeconomic, agro-environmental, demographic, cultural and globalization factors; and Test 6 was derived from all factors.

Table 3 Evaluation indicators for model predictive power tests.

Evaluation indicators	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
MAPE (%)	37.04	26.89	24.29	18.43	18.73	20.93
RMSE	13.08	9.64	8.42	7.24	7.31	7.57
R ²	0.80	0.89	0.93	0.94	0.94	0.93
EVS	0.81	0.90	0.93	0.95	0.94	0.93

Figure 9a shows the accumulated importance of factors based on our model and driver analysis. Socioeconomic factors are the most important driver, followed by agro-environmental, demographic, and cultural factors. To test the explanatory power of those factors and predictive power, tests with different factors were organized. Data from 1990 to 2015 were used as training samples and data from 2016, 2017 and 2018 were used as predicting samples and validation data. A detailed description of each test is provided in Fig. 9. The evaluation indicators are yearly averages calculated from

the difference between observed values and prediction values of the total meat, pork, mutton and poultry sectors in 2016, 2017 and 2018 samples. Test 4 (training and predicting with socioeconomic, agro-environmental, demographic and cultural factors) shows the best performance among total 6 tests (Fig. 9b and Table 3). These results indicate that based on socioeconomic, agro-environmental, demographic and cultural factors, the meat consumption could be simulated well (Fig. 9b). The prediction performance becomes worse when globalization and price factors are added to the model (Table 3). Besides, the accumulated importance of globalization and price factors is also much lower than other factors (Fig. 9a).

4. Discussion

4.1 Drivers of meat consumption

The present analysis indicates that the socioeconomic and agro-environmental factors generally are the most important drivers for total meat, pork, beef, mutton, and poultry consumption (Fig. 9a) in. For total meat consumption, the importance of socioeconomic factors decreases slightly during 1990-2018. This decrease could reflect the substantial decrease of socioeconomic factors in poultry consumption (Fig. 6). Except the case of poultry consumption, the importance of socioeconomic factors remains stable (Fig. 6; Fig. 7). Agro-environmental factors are much more important drivers of mutton consumption than other factors (Fig. 7). This supports the hypothesis that mutton consumption is mainly determined by domestic production capacity (Miller 2020). As for other types of meat consumption, the importance of agro-environmental factors generally remains stable (Fig. 6; Fig. 7).

The influence of globalization factors increases on beef and poultry, but remains stable on pork and mutton consumption (Fig. 6; Fig. 7). This suggests a stronger influence of international trade on beef and poultry consumption. The effects of demographic factors substantially increase only on pork consumption, and does so only recently (Fig. 6). Demographic factors however encompasses diverse elements, for example, the fact that young consumers are more receptive to vegetarian lifestyles (Pfeiler and Egloff, 2018a), but are likely to consume more meat than their elderly counterparts (Aston et al., 2013; Pfeiler and Egloff, 2018b). A younger population share can also be correlated with economic conditions (wealthy countries having a smaller fraction of young consumers; Gagnon et al. 2021). The overall importance of cultural factors remains stable across meat sources, although the influence of cultural factors has strongly declined since about 2003-2010 (Fig. 6).

Price factors do not show strong impacts on any kind of meat consumption. Multiple possible reasons may be considered for the lack of price factors effects. Current studies in microeconomics have found that there usually is a sensitivity threshold on price (Terui and Dahana 2006). Consumption would not likely decrease substantially with increasing prices unless price exceeds such a threshold (S. Han et al. 2001). Combining with the comparatively stable price on food at annual level for recent years (FAO, 2021), the increasing food price is possibly below the threshold to

influence consumer's food choice.

According to historical trends and our prediction tests (Fig. 5 and Fig. 9), the socioeconomic, agro-environmental, demographic, and cultural factors show comparatively stable influence on meat consumption and thus could simulate meat consumption well. Therefore, the future meat demand perhaps can be projected based on these factors.

4.2 Inverted U-shaped relationship

Several previous studies reported an "inverted U-shaped relationship", in which meat consumption would decrease with increasing per capita GDP (Bodirsky et al., 2015; Vranken et al., 2014). However, our results show that per capita annual meat consumption would remain stable rather decrease after per capita GDP reaches certain level (Fig. 7). Other recent studies, such as Parlasca and Qaim (2022), also support our observation.

To verify our results, we fit the relationship between the quantity of meat consumption and per capita GDP with the same method used in previous studies (Bodirsky et al., 2015; Vranken et al., 2014). However, we found that an inverted U-shaped relationship only occurred when a quadratic function was used for fitting (Supplementary Fig. S5), which means that an inverted U-shaped relationship between per capita GDP and meat consumption is questionable and needs further investigation.

4.3 Machine learning methods choice

Machine learning methods have many advantages such as no requirements on specific data form (Arteaga-Pérez et al., 2013). Further, ML-generated models do not require prior choice of values for model parameters, and are powerful in solving nonlinearity in complex system questions (Uzun et al., 2017; Zhao et al., 2021). Some complexity in meat consumption that were ignored by conventional empirical methods were revealed by data-driven ML methods (De Clercq et al. 2020; Zhao et al., 2021; Q. Han et al. 2022). However, ML methods are sometimes criticized as "black boxes", because the internal logic of ML methods is more difficult to understand than traditional empirical methods (Lei et al., 2019; Jia and Cui, 2022; Lipton, 2018). To overcome these difficulties of ML methods, employing interpretable approaches to identify the influence of each driver on meat consumption is a possible way (De Clercq et al. 2020).

4.4 Prospects of machine learning methods on meat consumption research

The models developed in the present work are driven by more variables than previous studies such as in Komarek et al. (2021) and Bijl et al. (2017). Such models may generate more accurate simulations, and may overcome shortcomings of conventional empirical models. For example, Kwasny et al. (2022) generated their results from a systematic literature review methodology, which is time-consuming and

relies on the quality of previous studies and expert judgements. Besides, other studies with conventional regression methods, such as York and Gossard (2004) and Milford et al. (2019), showed lower accuracy on simulation results than ML-based ones. Therefore, ML-based models show a comparatively higher and more robust global meat consumption simulation power (less than 15% relative errors in most countries in the world; Fig. 10). High relative error however generally occurs in low-income countries. The first explanation is that the available data is comparatively more limited in low-income countries than in high-income countries (FAO, 2021). Another possibility may be that the observed consumption value in those low-income countries is usually low (FAO, 2021), so once the simulation value deviates from observations, the relative error could be strongly increased.

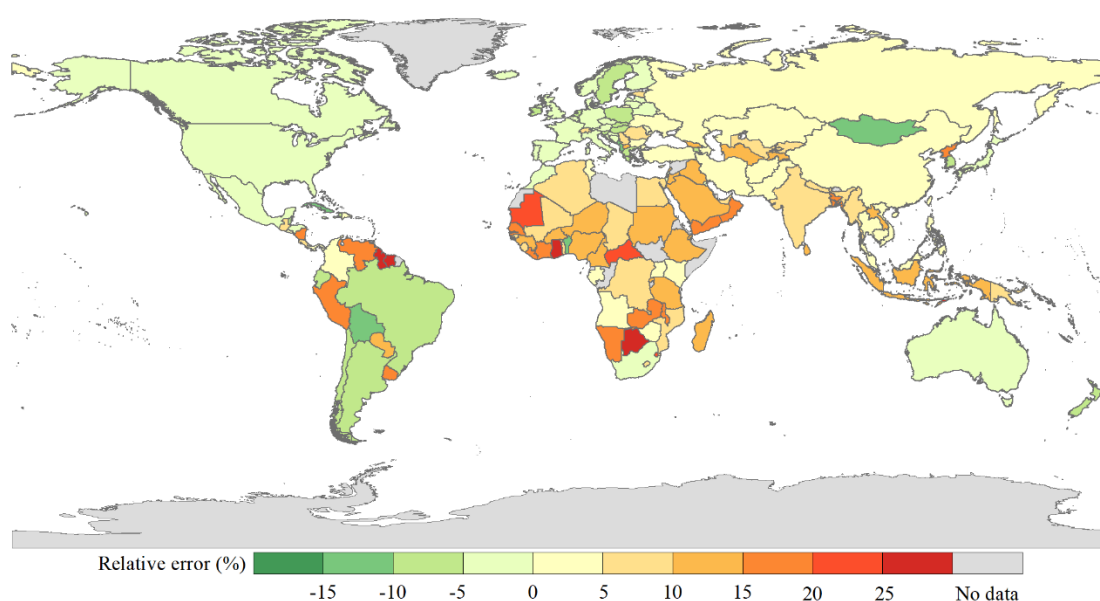


Fig. 10 Mean relative error (average of relative error of 2016, 2017 and 2018) between per capita meat consumption prediction and observed values.

Long-term meat consumption projections are necessary for the policies toward dietary transition (Komarek et al., 2021). These may be generated by our modelling approach, assuming the availability of data on drivers of meat consumption. The combination of our models with socioeconomic drivers data sources, such as those from Shared Socioeconomic Pathways (SSPs) scenarios developed by O'Neill et al. (2017), could provide reliable long-term meat consumption projections, and thus, scientific references for policymaking and further research.

Declarations and COI

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Ethics approval:

All authors: Junwen Jia, Fang Wu, Hao Yu, Jieming Chou, Qinmei Han, Xuefeng Cui

1. This material has not been published in whole or in part elsewhere;
2. The manuscript is not currently being considered for publication in another journal;
3. All authors have been personally and actively involved in substantive work leading to the manuscript and will hold themselves jointly and individually responsible for its content.

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