Distribution and intensification of pig production in China 2007–2017

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Keywords: pig production systems, agricultural intensification, livestock geography, China

Supplementary material for this article is available online

Abstract
Driven by population growth and rising incomes, the demand for animal source foods in low and middle-income countries is increasing rapidly. Pork is one of the most commonly consumed animal-based food, with the highest demand being in China due to its largest population and changing dietary habits linked to increasing wealth. Here, we show the changes in pig production systems in terms of farms capacity, productivity and production at the national and provincial levels by analyzing several censuses of China. In addition, we used a downscaling methodology to provide a recent and highly detailed map of the distribution of pigs in China. Between 2007 and 2017, pork production in China increased by 26.6%, up to 55 million tons and the number of large-scale farms with a yearly production of over 10 000 heads increased by 145%. Much of the production has changed from extensive backyard subsistence farming to intensive corporate farming. Moreover, the pig distribution has shifted from watercourse-intense southeast to northeast and southwest of China due to environmental policy in 2015. These policy-driven transitions primarily aimed to increase pig production efficiency and reduce environmental impacts and resulted in a profound transformation of geographic production patterns.

Implications
Our data describe the geographical and system shifts of pig production in China, linked to productivity improvements and changes in farm size. This analysis will be beneficial decision making on relocation of pig farm and on a better prevention of environmental impact and disease risk related to pig farming.

1. Introduction
China has the largest pig population (412 million in 2020, FAO) and annual production of pork (55 million tons, FAO). Pork consumption in China represents 46% of the global pork production (FAO, Gale et al 2012), and is expected to grow in the coming decades (Ortega et al 2009). China’s rapid annual GDP growth (average annual growth of 9.5% from 1979 to 2018, World Bank) and industrialization have prompted more and more rural populations to migrate to urban areas (Rae and Zhang 2009). Between 2007 and 2017, the proportion of Chinese urban population has increased of 13.6%, from 44.9% in 2007 to 58.5% in 2017 (China, n.d). Increased wealth is generally associated with dietary changes through increased annual per capita consumption of animal protein (Gilbert et al 2015), leading to a rapid increase of pork production which is expected to continue in the future according to FAO projections (FAO et al 2017).

Until 2007, China was mostly self-sufficient in pork production, but since then the need for pork imports has increased to meet the growing domestic demand (Zhang et al 2017). Between 2007 and 2017, China mainland’s pork imports increased substantially, from 49 thousand tons to 2.5 million tons (FAOSTAT). In terms of domestic production, the pig industry has undergone a vast transition toward intensification of production (Heng-wei et al 2011). In 2007, the epidemic of swine disease (Porcine
reproductive and respiratory syndrome, PRRS) and the surge in grain prices (McOrist et al 2011) have led to a temporary decline in the pig population. However, the longer-term trend of increasing stock and production caught up in the following years. A previous study has shown that the proportion of the traditional backyard model (1–50 head) has declined sharply from approximately 94% to 25% of pig farms in the period 1985–2013 (Pan et al 2019). Correspondingly, pig producers (>500 head) have entered a period of rapidly growth and have dominated Chinese pig production since 2007 (Qiao et al 2016), representing an ever increasing share of commercial pork. The rapid development also leads to an increasing impact of the livestock sector on the environment, through water and air pollution (Chakravorty et al 2007), and on the epidemiological risk of several infectious diseases affecting different production sectors, such as avian influenza in poultry production, PRRS, swine influenza and African swine fever (ASF) in pig production.

Spatially detailed data on the geographical distribution and temporal trends of the livestock sector help to document the potential past and future impact and to promote the sustainable development of the livestock sector. Ma et al (2020) used a pig density map from 2006 (Wint and Robinson 2007) as a major predictor to analyze ASF risk in China. To our knowledge, the most recent maps were published by Gilbert et al (2018) and Li et al (2021) for global pig distribution in 2010 and pig distribution in Western China in 2015, respectively. For more detailed studies of intensification processes in space and time, we need updated datasets with high spatial accuracy.

In this paper, we use census data available at different administrative levels to analyze the evolution of the pig production system between 2007 and 2017 at the provincial scale. We describe the pig farming intensification in China with the pig population, number of intensive farms and productivity measures. Finally, with a downscaling methodology that harmonizes and standardizes the census data, we provide a recent and accurate distribution of pigs in China to map the recent changes at a local scale. The digital layer of the pig distribution at 1 km resolution for the year 2017 is available in the Supplementary Material.

2. Methods and materials

2.1. Data—administrative censuses
Two different spatial databases were assembled. The first database aims to identify and integrate the highest resolution data available on pig populations in 2017. We collected the province data from the China Statistical Yearbook (National Bureau of Statistics of China or NBSC, 2008, 2018), and searched for more detailed city and county level data on the website of each province. Of the 31 provincial units in mainland, 11 have data at the county level, 13 have data at the city level and 7 only have data at the provincial level (table A1). The pig data were linked to a map of provincial administrative boundaries obtained from the Department of Resources and Environment Remote Sensing database of China (2016). These databases allowed us to construct a multi-level map with the most detailed data available on the pig population.

The second spatial database aims to integrate province-level data on stock, production and farms in the period 2007–2017. We used data from the China Statistical Yearbook (NBSC, 2008, 2018) and integrated these in a Geographic Information System (GIS) database. In addition, farm size data at the provincial level were taken from the China Animal Husbandry and Veterinary Year books (CAHVYE, 2008, 2018) and integrated into the GIS database. We categorized farms according to the pig output heads per year: small-scale (<500 slaughtered pigs/year), medium-scale (500 to 9999 slaughtered pigs/year) and large-scale (>10 000 slaughtered pigs/year). This classification is used to show the change in farm size distribution between the years 2007 and 2017 at the provincial level.

2.2. Data—spatial predictor variables
Finally, several spatial predictor variables are used to downscale the pig stock distribution data. The predictor variables in the Gridded Livestock of the World dataset (Gilbert et al 2018) were used and are described in table 1 (exhaustive and detailed list in table A3). The spatial predictors include: five types of vegetation used for animal feed (crop, forest cover, length of growing period, green-up data and indicator of living green vegetation); two types of topography (Slope and Elevation) aim for get the geographical location of pig farm; two types of anthropogenic (Worldpop, TTCity) account for access to market. Two types of climatic (precipitation, day land surface temperature from MODIS) was for observing the pig farm distribution with influence of water. Those spatial predictors are available for China at a spatial resolution of 0.008 333 3 decimal degrees (approximately 1 km at the equator).

2.3. Downscaling and gap-filling procedure
The downscaling and gap-filling procedures of the latest version of the Gridded Livestock of the World database are described in the paper (Gilbert et al 2018) and are only briefly recalled here. The pig distribution is available in two representations, termed dasymetric (DA) and areal-weighted (AW). The AW model distributes the animals in a census polygon uniformly, and the density of animals in each pixel
Table 1. List of input spatial dataset used to build the pig density map.

| Type          | Variable                                                                 | Source                                                                 | Year    | Abbreviation |
|---------------|---------------------------------------------------------------------------|------------------------------------------------------------------------|---------|--------------|
| Anthropogenic | Human population density (consensus model between Worldpop, Landscan and GPW4) | Tatem (2017) Dobson et al (2000)                                       | 2015    | Worldpop     |
|               | Travel time to major cities (>50,000 people)                              | Weiss et al (2018)                                                    | 2015    | TTCity       |
| Topography    | Slope(GTOPO30): degrees slope from the global digital elevation model (DEM) | Earth Resources Observation And Science (EROS) Center (2017)            |         | SLP          |
|               | Elevation (GTOPO30)                                                      | Earth Resources Observation And Science (EROS) Center (2017)            |         | DEM          |
| Vegetation    | Green-up data (cycle 1)                                                  | Zhang et al (2003)                                                    | 2001    | Greenb1      |
|               | 10 Fourier-derived variables from Normalized Difference Vegetation Index from MODIS^b | Scharlemann et al (2008)                                              | 2001–2005 | NVDI        |
|               | Crop cover                                                               | Fritz et al (2015)                                                    | 2005    | Crop         |
|               | Forest cover                                                             | Hansen et al (2013)                                                   | 2012    | Forest       |
|               | Length of growing period^c                                               | Jones and Thornton (2009)                                             | 2000    | LGP          |
| Climatic      | Precipitation                                                            | Fick and Hijmans (2017)                                               | 2013    | PRECIP       |
|               | Day land surface temperature from MODIS                                   | Scharlemann et al (2008)                                             | 2001–2005 | Modis5_Dls   |

^a The start of the first greening after 1 January is considered the first greening cycle.
^b Annual mean, annual minimum, annual maximum, amplitude and phase of annual cycle, amplitude and phase of bi-annual cycle, amplitude and phase of tri-annual cycle, variance in annual, bi-annual, and tri-annual cycles.
^c The average number of days which meet favorable climatic conditions: the average air temperature exceeds 6 °C and the ratio of actual to potential evapo-transpiration exceeds 0.35.

The goodness of fit (GOF) metrics of the predictions are all established through cross-validation, i.e. by measuring the correlation between observed and predicted animal numbers in polygons that were not used to train the RF model. The datasets are divided into training and validation sets according to sub-national census polygons, using datasets from 70% of the polygons for model training and 30% for model accuracy assessment. The 30% of the data set is used to estimate the GOF measures: the coefficient correlation and the root-mean-square error (RMSE) between the predicted and observed values. The first measure of GOF, the correlation coefficient $R^2$, allows to evaluate the linear correlation between the observed and the predicted variables, in other terms measure the proportionality between the two variables, while the RMSE allow to measure the absolute differences between the predictions and observations.

2.4. Productivity measure

In order to describe the geographical distribution of the pig productivity, we used the province-level data on stock and production to estimate pig production output-input ratios per province, expressed in ton/head/year. The output-input ratio is calculated for each province as below:

$$O_{I\text{ratio}} = \frac{P}{N}$$  \hspace{1cm} (1)

is the average number of animals per pixel (i.e. the surface of a pixel is about 1 km$^2$) of suitable land in the census unit. This representation allows to visualize the available census data, but does not provide information of the livestock distribution at local scale. However, AW representation is free of the influence of the spatial predictors. In contrast, in the DA representation, different animal densities are assigned to different pixels within a given census polygon according to the random forest (RF) models. The DA representation allows estimating the animal densities at higher resolution which is crucial for further studies such as transmission disease models or environmental impacts assessments. We detail below the modeling procedure of the DA model (figure A1).

The first step is to collect and harmonize data from different data censuses. We gathered data from the 1050 counties from 11 provinces in the 2017 published in the statistical yearbooks (table A1). The second step is to train a RF model (ranger package in R) using available pig population data and covariates, and then applying the model to make predictions at the pixel level (1 km resolution). Finally, after creating the initial prediction map out of the model, province-level totals were adjusted to match the pig stock totals at the province-level spatial database for the year 2017. This ensure that aggregated pig densities at the province level correspond to the numbers in the China Statistical Yearbook (NBSC, 2018).
where the P is the meat production in tons and N is the number of pigs at the end of year.

Due to the high variety of climate zones and cropping systems found in China, the analysis of the province-level statistics was carried out by regions, according to the agricultural regions defined by Liu and Li (2018) (figure 1): (1) North China (NC), (2) Middle and lower Yangtze River Basin (MLYR), (3) Northeast (NE), (4) Northwest (NW), (5) Southeast (SE), (6) Southwest (SW) and (7) Others (NA).

In the western part of China (NW and SW regions), livestock are mainly fed by grazing on rangelands (Verburg and Van Keulen 1999). Grasslands cover huge areas of temperate and cold semi-arid to arid zones through the Tibetan plateau to the Asian steppe (Li et al. 2008). Herding communities are generally ‘minority nationalities’, including Mongolians, Kazakhs, Kyrgyz and Tibetans. The NC region is located in the northern plain, where pigs are mainly fed corn. The human population density of this region is the highest in the whole country and there is a great demand for meat. The eastern and southeastern China (MLYR and SE regions) are characterized by arable land where pigs are raised in mixed or landless farming systems.

3. Results

3.1. Changes in pig distribution

Pig population is highly concentrated in the East part of China while Western part display very low densities except in the North of Xinjiang (XJ, province names are identified on the map figure 1 and table A2) province. In 2017, the MLYR region is the region with the highest pork production (29% of Chinese total production). NC region ranks second in pork production (24%), followed by the SW, SE, NE regions and the region with the lowest pork production is the NW region (figure A3). The main pork production regions, namely MLYR, NC and SW regions produced 73% of pork in 2017. In the SW region (20% of national production), Sichuan (SC) and Chongqing (CQ) provinces account for the largest portion (11%) of pork production and are the key contributors in this region.

Overall, the pork production growth rate was positive between 2007 and 2017 in all regions without impacting the ranking of agricultural regions (figure A3; agricultural regions are defined in figure 1). Although the NE region had low pork production (9.5%) in 2017, its growth rate was the
Figure 2. (a) Pork production by region throughout the study period (2007–2017) in million tons. (b) The number of pig farm (>500) in 2017 and growth rate between 2007 and 2017.

highest of all regions (36%). Meanwhile, MYLR had the highest national pork production (29%), but the growth rate (24%) was lower than the average (27%). The NC region ranks second in terms of growth rate (36%) and contribution to national pork production.

At the provincial level, pig population distribution has changed from 2007 to 2017 (figure 3(a)), with an increased concentration in the East part of China except for eastern coastal provinces (figure 2(a)). The highest growth rates of pig population occur in Xinjiang (XJ), Xizang (XZ) and Qinghai (QH) with respectively 117%, 47% and 39% of population growth over the study period (figure A4). However, these three provinces represent only 1% of the total population in 2017. The highest increases in absolute population occur in Yunnan (YN), Shandong (SD) and Hubei (HU) provinces with respectively 23.3%,
14.5% and 12.6% of population growth rate. These three provinces, located in SW, NC, MLYR of China, represent 20% of the total population.

Conversely, some provinces have drastically reduced their pig industry. The provinces with the highest rate of decline are located on the East coast of China, with growth rates of $-48\%$, $-29\%$ and $-10\%$ for Zhejiang (ZJ), Fujian (FJ) and Shanghai (SH) (figures 2(a) and A4). In the West part of China, Sichuan province (SC) has undergone high decrease of pig number ($-17.4\%$) while it represents 10% of the total pig population. The lowest pig population occurs in NW region (5.5% of the total population), including Xinjiang (XJ), Xizang (XZ), Qinghai (QH), Gansu (GS) provinces, but the growth rate was positive (2.5%, figure 2(a)). Although Xinjiang (XJ) province had very low pig population (0.8%) in 2017, it had the highest growth rate (150%). The largest decrease in pig population has been observed in the south-eastern corner of the country (SE region). In Zhejiang (ZJ) and Fujian (FJ) provinces pig population shrank by 48% and 29% respectively.

The figure 3(a) shows the observed pig distribution (AW representation) for 2017. Thanks to the RF model, we down-scale the census data collected for Chinese provinces, counties and cities. The model has a correlation coefficient of 0.87 and the RMSE is 0.347 on log-transformed pig densities (table A4). Pig density distribution is highly correlated with the population density as this spatial covariate show the highest importance in the RF modeling (figure A2). Then, the most important spatial covariates are human population distribution, crop cover, time travel to cities and to ports, indicating the importance of infrastructure and agricultural characteristics for the development of pig production in China.

To observe local changes, the 2017 pig distribution map (figure 3(b)) is compared to the pig distribution map (Gilbert et al 2018) produced for the year 2010 at 10 km resolution. The GLW map is relevant for analyzing recent changes in pig distribution because we used the same downscaling model, but we will indicate some differences. First, our RF model is trained only on Chinese data census, and Gilbert et al (2018) trained their model on the entire continent of Asia. Secondly, we use data at finer scales (county census data). These differences result in a better fit of our model compared to the GLW model which performs predictions with a correlation coefficient of
about 0.62, 0.75 and 0.79 for polygons of less than 100 km$^2$, 100–5000 km$^2$ and more than 5000 km$^2$ respectively (see table A4 for the GOF measures of our model). Finally, the differences between 2010 and 2017 pig density maps are displayed in figure 3(c) and show significant local changes within provinces: in the NC region, there are local hotspots of pig decline balanced by hotspots of increase, which lead to a small increase at the regional and provincial levels. While we also observe a continuous spatial decrease of pigs for Sichuan (SC), Shanghai (SH) and Zhejiang (ZJ) provinces which is consistent with the provincial data census.

### 3.2. Changes in production systems structure toward large-scale farms

Figure 4 shows that the number large-scale farms increased by 145% between 2007 and 2017, the number of medium-scale farms increased by 60% and the number of small-scaled farms decreased by 54%. Looking at a more detailed distribution (figure A5), the farm size category with the highest growth is farm above 50 000 pigs which have increased from 50 in 2007 to 407 farms in 2017. Despite the increase in intensive farming, large-scale farms represents 15% of pigs while small-scale farms represents 47% of pigs in 2017. On the study period, large-scale and medium-scale farms (>500 heads) are increasingly concentrated in MLYR and NC regions with a growth rate of 96% and 47% respectively (figure 2(b)). The NE, SE and SW regions had similar pig farming scales, but the SW region (176%) had a higher growth rate. The NW region, including Inner Mongolia (NM), Gansu (GS), Xinjiang (XJ) provinces, did not have many large and medium scale farms in 2017, but the growth rate of large and medium scale farms (151%) is high. SE region has the lowest growth rate (21.5%) of large and medium scale farms.

At the same time, output-input ratio which is a feature of the productivity of production systems increased with the development of intensive pig farming (figure A6). Pig productivity increased in all provinces except Tianjin and Xinjiang between 2007 and 2017 (figure 5), with an overall significantly positive trend ($p < 0.01$). Provinces with the highest rate of intensive farm present the highest output-input ratio (figure A7). In general, Eastern China has higher productivity levels than Western China. The main pig production regions MLYR and NC increased their productivity with output-input ratios growth of 21% and 26% respectively. However, this growth is lower than productivity growth in NE (39%) and SW (31%) regions. Finally, the Western part of China display the lowest productivity rates with low intensive farm rate. Nevertheless, these regions have very extreme temperatures that can affect productivity because the optimal temperature for fattening pigs is $18 \, ^\circ C–22 \, ^\circ C$.

### 4. Discussion

This study provides a better understanding of pig distribution and pork production in China between 2007 and 2017. Qiao et al (2016) and Zhang et al (2017) have shown a shift from extensive to intensive farms, but mapping the evolution of pig density in China (figures 3(b) and (c)) is a new aspect. In addition, we provide the most recent map of pig

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**Figure 4.** Rate of change in the number of farms according to their size: large (>10 000 head), medium (500–9999 head), small (<500 head), between 2007 and 2017. Red stand for positive, blue stand for negative.
distribution in China at a higher resolution than previous studies (Gilbert et al 2018). These new aspects would allow several research studies to be conducted to assist in the development of environmental policies and in controlling the spread of epidemics.

Pig farming usually coincides with areas of high grain production which are located on plains in the NE, NC, and MLYR regions. The NC and MLYR regions have large areas of fertilized croplands and are the most productive regions. Also, these two regions have a large market for consumption and convenient transportation that can import feed from abroad easily. Further west, the Sichuan (SC) province is another hotspot for pig farming, which has a large demand for pork and fertile soils for grain production.

The pig population map (figure 3) shows a decreasing trend of pig farming in Zhejiang (ZJ) and Fujian (FJ) provinces located in the watercourse-intense SE region (East coast of China). Meanwhile, the pig population in the Yunnan (YN) province (SW region) and Heilongjiang (HLJ) province (NE region) has increased significantly. Pollution of the local environment and watercourses are major impacts related to pig farming in the densely populated southeastern region (Liu and Li 2018). As response to the high pollution levels, the Chinese government issued an environmental policy limiting livestock production close to watercourses in several heavily affected provinces, including parts of the SE region. The policy was enacted in 2015 (Bai et al 2019) and may have contributed to the observed reduction in pig production in the Zhejiang (ZJ) and Fujian (FJ) provinces. Concurrently, the government has been encouraging large pig farms in the NE and SW regions (Bai et al 2019). This has led to investments in large high-technology farms in these regions, and also reflect the regions’ rapid increases in productivity (figure 5).

The environmental policy serves to reduce the pollution burden in densely populated parts of China while promoting economies in the more rural southwest and northeast regions. Pig farming has traditionally been most common in the densely populated regions, due to the proximity of markets and grain production. The feed is the largest expense of the pig production in China, accounting for 57% of total costs (Gale 2017). A common feed ration for pigs is about 60% maize and 15% soybean meal (Gale et al 2012). Base on the abundant feed resources in the Northeast, the pig industry has achieved higher economic benefits with lower feed costs.

The farm size data point to a trend of increasing farm sizes and intensification in many parts of the country, most notably in Yunnan (YN) and Guizhou (GZ) in the southwest and in Inner Mongolia (NM) in the northwest. Northern China has large areas of grassland with plenty of land for pig breeding and manure disposal. This general trend of pig production intensification is associated with the shift of pig farming away from heavily developed area to the SW,
NW and NE regions. More and more larger farms are cropping up in these parts of China. As the larger-scale farms replace the small-scale farms, more specialists with expertise in pig farming management and technology are required (Zhang et al 2017). Small-scale farms, including backyard production, find it increasingly hard to compete due to low productivity and difficulty to attract younger workers. Formerly, small-scale farmers had access to many cheap land and self-sufficient feed production, while also supplying manure for crops. Then pig production began to shift to an industrialized system in the 1980s in China. The first feed company in China was established in 1979. In 2017, China had produced 220 million tons of feed, including 98 million tons of pig feed, compared to 1 million ton in 1980 (data from Ministry of Agriculture and Rural Affairs of the People’s Republic of China website). This accelerated the structural change and commercialization of the pig industry. Meanwhile, increases in labor wages and declining birth rates reversed the labor-abundance, and traditional household pork production could not meet the country’s growing demand for pork. Therefore, the number of commercialized pig farm is rising rapidly with the gradual withdrawal of small-scale farm. The ongoing structural change have resulted in small-scale farm being the majority (38 million farms in 2017) but commercialized farm account for the bulk of pig production. The trend toward industrialized production systems was crowed after 2018. Indeed, many pig farmers gave up raising pig because of the outbreak of ASF, especially in small-scaled farmers. The small scaled farm (<500 head/year) decreased from 38 million in 2017 to 23 million in 2019. And the share of intensive pig farm increased by 18% between 2017 and 2019 (Zhu et al 2020).

Although the intensification of the pig farming improves the economy, there are major concerns about the risk of disease spread and environmental impacts. The concentration of production in several provinces raises questions about export needs between provinces. We estimate that about 25 provinces have a deficit in relation to their consumption in 2017, which represents a shortfall of about 28 million tons of pork to be imported into these provinces (table A5 in appendix). The transport of live pigs from NE or SW regions to the south where most of the pork is consumed, increases the risk of disease spreading. It has been shown for the avian influenza A (H7N9) (Zhou et al 2015) and the ASF (Gao et al 2021). As we know, an outbreak of ASF occurred in the northeast in August 2018 and quickly spread across the country (Ma et al 2020). By November 2019, 160 pig farms were infected with African swine fever and 1.2 million heads of pigs had to be culled (Hu and Ge 2020). At this time the national pig population had shrunk by 27.5% and pork production had decreased by 21.3%. Although live pig shipments dropped from 68% in 2017 to 33% in 2019 after ASF (Zhu et al 2020), it was still a high risk of disease transmission.

Also, without appropriate technology to manage manure, the increase in large farms in the SW and NW regions, where grasslands are fragile, will threaten the local ecology due to soil degradation and air and water pollution. According to Wang et al (2006) one pig produces 5.3 kg of waste daily, which contains large amounts of heavy metals (copper, zinc, iron, other trace element additives) and pharmaceutical residues. Long-term application of livestock fecal waste to agricultural lands may lead to excessive accumulation of heavy metal elements in the soil degrading agricultural product quality and compromising food safety (Bai et al 2018, Pan et al 2019). Some recently built scale pig farms are short of facilities to manage manure which are often simply washed into watercourses (Bai et al 2019). Therefore, assessing environmental impacts and adopting beneficial management practices require livestock and environmental data at the local scale (Zhang et al 2019). While environmental impacts have been measured at the provincial scale in China (Sun and Wu 2013, Gan and Hu 2016), the recent higher spatial resolution pig map presented here would improve the reliability of these studies.

5. Conclusion

Our objective was to analyze recent changes in pig production systems in China by mapping the pig population and quantifying farm capacity and productivity. Pig production is currently undergoing a remarkable evolution from small-scale to intensive operations, resulting in increased productivity but also increased environmental risks such as epidemiological risks (ASF). At the same time, faced with the challenge of limited natural resources and rising labor costs, the distribution of pigs has shifted from the watercourse-intense southeast to the northeast and southwest of China. Higher production efficiency and a favorable environment promoted this profound transformation of geographical patterns. Our results indicate that the ongoing changes could help improve the cost problem and environmental pollution (especially, water pollution in southeastern China).

Finally, we also produced a recent and very detailed map of the distribution of pigs in China by downscaling aggregated data from different census sources. These results are made available to the scientific community and the public for use in a wide
range of applications from epidemiological studies to environmental and agricultural policies.

Data availability statement

Pig data are publicly available in the National Bureau of Statistics and Provincial Bureau of Statistics. Chinese National Bureau of Statistics website is at the following link: www.stats.gov.cn/english/. Pig farm data are available in the China animal husbandry and veterinary yearbook.

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgment

We acknowledge the China Science Council for the scholarship (201807650002) to QZ. We also acknowledge the support provided to MCD by the UKRI GCRF One Health Poultry Hub (Grant no. BB/S011269/1), 1 of 12 interdisciplinary research hubs funded under the UK government’s Grand Challenge Research Fund Interdisciplinary Research Hub initiative.

Ethics

Not applicable.
Appendix

Table A1. Data sources.

| Data level | Year     | Source of the data |
|------------|----------|--------------------|
| Province   | 2007, 2017 | China statistical yearbooks published in 2008 and 2018; Hebei provincial statistical yearbook (PSY) published in 2018; Anhui PSY published in 2018; Liaoning PSY published in 2018; Shandong PSY published in 2018; Hubei PSY published in 2018; Guangdong PSY published in 2018; Hainan PSY published in 2018; Sichuan PSY published in 2018; Xizang statistical yearbook published in 2018; Shaanxi PSY published in 2018; Qinghai PSY published in 2018; Jiangxi PSY published in 2017; Guizhou PSY published in 2017; |
| City       | 2017     | Heilongjiang PSY published in 2018; Zhejiang PSY published in 2018; Henan PSY published in 2018; Yunnan PSY published in 2018; Ningxia statistical yearbook published in 2018; Xinjiang statistical yearbook published in 2018; Hunan PSY published in 2017; Gansu PSY published in 2017; |
| County     | 2017     | Shanxi PSY published in 2018; Inner Mongolia statistical yearbook published in 2018; Jilin PSY published in 2018; Heilongjiang PSY published in 2018; Zhejiang PSY published in 2018; Henan PSY published in 2018; Yunnan PSY published in 2018; Ningxia statistical yearbook published in 2018; Xinjiang statistical yearbook published in 2018; Hunan PSY published in 2017; Gansu PSY published in 2017; |

Notes: The data from statistical yearbook in 2018 is 2017’s data. The 2017 city data of Jiangxi and Guizhou are extrapolated from 2016 data; The 2017 county data of Hunan and Gansu are extrapolated from 2016 data.
Table A2. List of provinces and their corresponding abbreviations and regions.

| Province code | Province name | Abbreviation | Region |
|---------------|---------------|--------------|--------|
| 11            | Beijing       | BJ           | NC     |
| 12            | Tianjin       | TJ           | NC     |
| 13            | Hebei         | HB           | NC     |
| 14            | Shanxi        | SX           | NC     |
| 15            | Nei Mongol    | NM           | NW     |
| 21            | Liaoning      | LN           | NE     |
| 22            | Jilin         | JL           | NE     |
| 23            | Heilongjiang  | HLJ          | NE     |
| 31            | Shanghai      | SH           | MLYR   |
| 32            | Jiangsu       | JS           | MLYR   |
| 33            | Zhejiang      | ZJ           | MLYR   |
| 34            | Anhui         | AH           | MLYR   |
| 35            | Fujian        | FJ           | SE     |
| 36            | Jiangxi       | JX           | MLYR   |
| 37            | Shandong      | SD           | NC     |
| 41            | Henan         | HN           | NC     |
| 42            | Hubei         | HU           | MLYR   |
| 43            | Hunan         | Hnx          | MLYR   |
| 44            | Guangdong     | GD           | SE     |
| 45            | Guangxi       | GX           | SE     |
| 46            | Hainan        | Hn           | SE     |
| 50            | Chongqing     | CQ           | SW     |
| 51            | Sichuan       | SC           | SW     |
| 52            | Guizhou       | GZ           | SW     |
| 53            | Yunnan        | YN           | SW     |
| 54            | Xizang        | XZ           | SW     |
| 61            | Shaanxi       | SHAX         | NW     |
| 62            | Gansu         | GS           | NW     |
| 63            | Qinghai       | QH           | NW     |
| 64            | Ningxia Hui   | NX           | NW     |
| 65            | Xinjiang Uygur| XJ           | NW     |
| 71            | Taiwan        |              |        |
| 81            | Hong kong     |              |        |
| 82            | Macao         |              |        |
Table A3. List of predictors with their abbreviations and units.

| Predictor abbreviations | Description | Units |
|-------------------------|-------------|-------|
| Modis5_dLSTa0           | daytime Land Surface Temperature (dLST) mean | °K |
| Modis5_dLSTa1           | dLST annual amplitude | °K |
| Modis5_dLSTa2           | dLST bi-annual amplitude | °K |
| Modis5_dLSTa3           | dLST tri-annual amplitude | °K |
| Modis5_dLSTmn           | Minimum dLST | °K |
| Modis5_dLSTmx           | Maximum dLST | °K |
| Modis5_dLSTp1           | dLST phase of annual cycle | Months |
| Modis5_dLSTp2           | dLST phase of bi-annual cycle | Months |
| Modis5_dLSTp3           | dLST phase of tri-annual cycle | Months |
| Modis5_dLSTvr           | dLST variance | °K² |
| Modis5_NDVIa0           | Normalised Difference Vegetation Index (NDVI) mean | No units |
| Modis5_NDVIa1           | NDVI annual amplitude | No units |
| Modis5_NDVIa2           | NDVI bi-annual amplitude | No units |
| Modis5_NDVIa3           | NDVI tri-annual amplitude | No units |
| Modis5_NDVImn           | Minimum NDVI | No units |
| Modis5_NDVImx           | Maximum NDVI | No units |
| Modis5_NDVIp1           | NDVI phase of annual cycle | Months |
| Modis5_NDVIp2           | NDVI phase of bi-annual cycle | Months |
| Modis5_NDVIp3           | NDVI phase of tri-annual cycle | Months |
| Modis5_NDVIvr           | NDVI variance | No units |
| SLP                     | Degrees slope | Degree |
| PRECIP                  | Precipitation | mm |
| DEM                     | Elevation | m |
| FOREST                  | Forest cover | % |
| CROP                    | Crop cover | % |
| Worldpop_Lg             | Log10(human population density) | log10 (cap km²) |
| TTCity1_Lg              | Travel time to cities with 5000 000 <x< 50 000 000 inhabitants | Minutes |
| TTCity2_Lg              | Travel time to cities with 1000 000 <x< 5000 000 | Minutes |
| TTCity11_Lg             | Travel time to cities with 50 000 <x< 50 000 000 inhabitants | Minutes |
| TTPort1_Lg              | Travel time to large ports | Minutes |
| TTPort2_Lg              | Travel time to medium ports | Minutes |
| TTPort12_Lg             | Travel time to large and medium ports | Minutes |

Table A4. Table of GOF measures. Area is the range of the size of polygons, $R^2$ is the correlation coefficient, RMSE is the root mean standard error and $N$ is the number of samples per category of polygons size.

| Area (km²) | $R^2$ | RMSE | $N$ |
|------------|-------|------|-----|
| <100       | 0.712 | 0.547| 167 |
| 100–5000   | 0.786 | 0.340| 2347|
| >5000      | 0.914 | 0.249| 322 |
| All        | 0.867 | 0.347| 2836|
Table A5. Pork production and pork consumption per province in 2017.

| Year | Province name | Human population | Pork production (tons) | Pork consumption (tons) |
|------|---------------|------------------|------------------------|------------------------|
| 2017 | Beijing       | 21 707 000       | 192 182                | 274 765                |
| 2017 | Tianjin       | 15 570 000       | 225 863                | 246 845                |
| 2017 | Hebei         | 75 195 200       | 2914 699               | 935 487                |
| 2017 | Shanxi        | 37 020 000       | 626 691                | 352 392                |
| 2017 | Nei Mongol    | 25 290 000       | 735 239                | 427 079                |
| 2017 | Liaoning      | 43 690 000       | 2209 000               | 806 804                |
| 2017 | Jilin         | 27 170 000       | 1361 432               | 425 883                |
| 2017 | Heilongjiang  | 37 887 000       | 1593 079               | 585 228                |
| 2017 | Shanghai      | 24 180 000       | 145 700                | 473 342                |
| 2017 | Jiangsu       | 80 293 000       | 2143 000               | 1575 047                |
| 2017 | Zhejiang      | 56 570 000       | 833 100                | 1236 086                |
| 2017 | Anhui         | 62 550 000       | 2426 800               | 1157 899                |
| 2017 | Fujian        | 39 110 000       | 1283 711               | 1011 515                |
| 2017 | Jiangxi       | 46 220 000       | 2494 900               | 968 846                |
| 2017 | Shandong      | 10 005 8300      | 4274 410               | 1322 806                |
| 2017 | Henan         | 95 591 300       | 4669 000               | 1057 834                |
| 2017 | Hubei         | 59 020 000       | 3392 871               | 1220 853                |
| 2017 | Hunan         | 68 601 500       | 4496 000               | 1864 981                |
| 2017 | Guangdong     | 11 169 0000      | 2779 635               | 3242 145                |
| 2017 | Guangxi       | 48 850 000       | 2549 670               | 1354 684                |
| 2017 | Hainan        | 9260 000         | 444 000                | 233 014                 |
| 2017 | Chongqing     | 30 751 600       | 1299 700               | 1041 662                |
| 2017 | Sichuan       | 83 020 000       | 4722 302               | 2998 929                |
| 2017 | Guizhou       | 35 800 000       | 1601 000               | 989 916                |
| 2017 | Yunnan        | 48 005 000       | 3201 609               | 1272 243                |
| 2017 | Xizang        | 3370 000         | 11 400                 | 27 239                 |
| 2017 | Shaanxi       | 38 350 000       | 858 342                | 398 688                 |
| 2017 | Gansu         | 26 260 000       | 498 820                | 302 023                 |
| 2017 | Qinghai       | 5980 000         | 86 700                 | 68 123                 |
| 2017 | Ningxia Hui   | 68 820 000       | 89 079                 | 43 224                 |
| 2017 | Xinjiang Uygur| 24 450 000       | 358 024                | 100 363                 |

Figure A1. Overall workflow of GLW modeling. https://doi.org/10.1371/journal.pone.0096084.g001.
Figure A2. Covariates importance of the GLW model for China.

Figure A3. Pork production by region throughout the study period (2007–2017) in million tons. Regions: Middle and lower Yangtze River Basin (MLYR), North China (NC), Northeast (NE), Northwest (NW), Southeast (SE), Southwest (SW) and Others (NA).
Figure A4. Evolution of pig population in eight provinces. The provinces selected for the figures are the provinces with the highest changes rates throughout the study period 2007–2017 (percent difference). The abbreviations of provinces are in the figure 1.

Figure A5. Distribution of pig farms size for 2007 (red) and 2017 (blue). Farm size is the number of animal per farm.
Figure A6. Growth of national productivity in function of the rate of intensive farms on the study period. The rate of intensive farms is the number of farms with more than 500 pigs per year divided by the total number of farms.

Figure A7. Productivity in function of the rate of intensive farms by province for 2017 (logarithmic scale). The rate of intensive farms is the number of farms with more than 500 pigs per year divided by the total number of farms.
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