The Economics of Ecosystem and Biodiversity (TEEB): Promoting a Sustainable Agriculture and Food Sector

Implementation in China

Data and Methodology Report for the Heilongjiang "Soybean Expansion" policy study

【Deliverable 2.3】

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Table of Contents

Introduction

"The Economics of Ecosystems and Biodiversity: Promoting a Sustainable Agriculture and Food Sector" project's second application in China[1] focuses on the national soybean expansion policy and chooses Heilongjiang Province as the study area to model and forecast the natural, economic and social impacts of the differences in land use brought about different soybean expansion policies (hereafter "the Heilongjiang study").

This report is the second in a series of reports of the Heilongjiang study. The first, the scoping and scenario setting report, includes a comparison of alternative future development scenarios, driven by agriculture policy priorities, climate change, demographic change, and urbanization, that will be assessed by the TEEBAgriFood evaluation framework (detail in section 1).

This report presents an outline of the processes and methodologies that will be used by the research team to measure and value the dependencies and impacts of the implementation of the soybean expansion policies in the province. It builds on a stakeholder consultation mission to Heilongjiang province from 8-10 May 2023, which is to validate the scenario setting of the Heilongjiang study, verify key parameters, and help compile data and information to build up the models.

1. Scenario-setting

Heilongjiang Province, located in Northeast China, has a total area of 473,000 km^2, ranking 6^{th} in the country. The regional gross domestic product (GDP) in 2020 was 1,369.85 billion CNY, with the proportion of the primary industry accounting for 25.1%, much higher than the national average (7.7%). Heilongjiang is the core area of a black soil region in China and an important part of the world's black soil resources. Arable land in Heilongjiang covers 15,940,850 ha, accounting 33.87% of the province's total land area.

For many years, Heilongjiang's total grain production and the production of the three major grain crops (maize, rice and soybeans) rank first in the country. In 2020, the soybean planting area was 4,832,000 ha, accounted for one third of the total planting area in the province, far exceeding the national average and other provinces. For the past decade, the planting area and production of soybeans in Heilongjiang have accounted for over 40% of the national total, reaching 50% in some years, making it an important soybean production base in China.

[1] The research has been made possible with the funds and support from the European Union through the European Union Partnership Instrument (EUPI), and continuous guidance from United Nations Environment Programme (UNEP) TEEB Office.

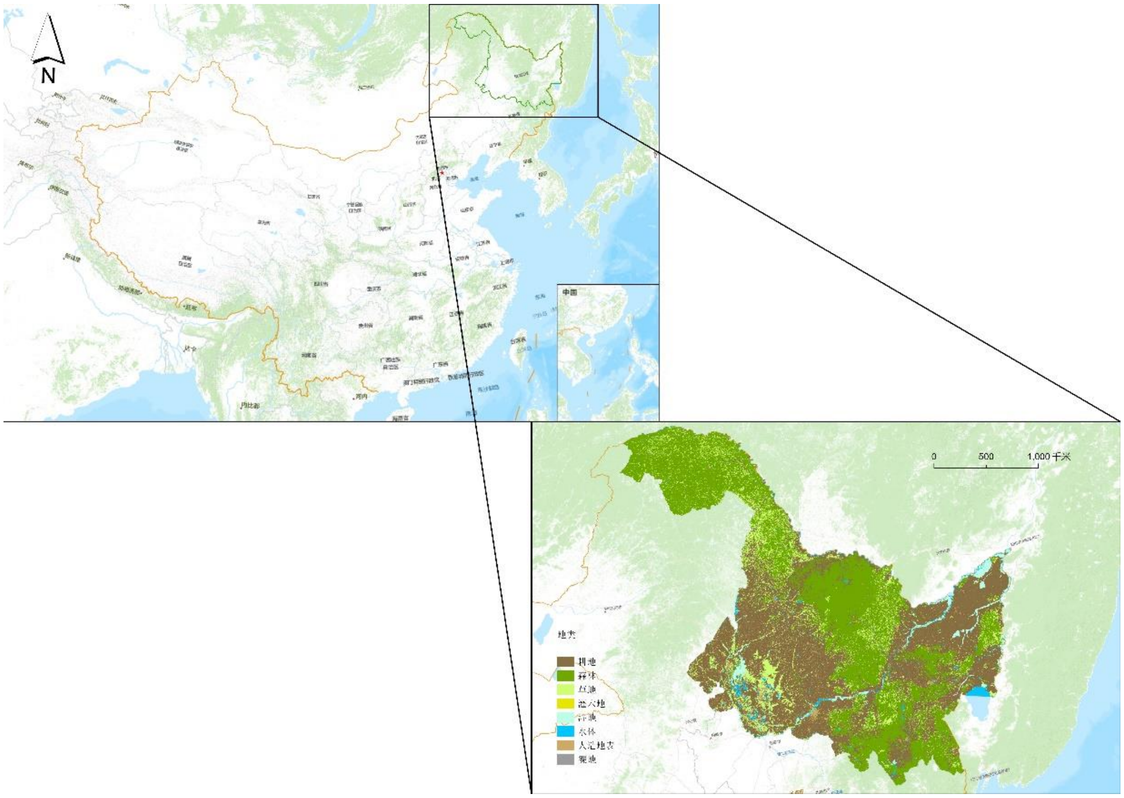

Figure 1 Geographic location of Heilongjiang Province

China's demand for soybeans continues to increase. From 2010 to 2020, soybean demand increased from 70.20 million tons to 119.92 million tons (an increase of 71%). The majority of the growth was supplemented by imports. In recent years, the uncertainty of soybean supply such as climate change and geopolitics has increased. In order to cope with the increase in domestic soybean demand and enhance the resilience of the food systems, the Chinese government is seeking solutions such as moderately expanding soybean planting in suitable regions. According to stakeholder consultation and related government documents, the soybean expansion practice in Heilongjiang will be conducted through "paddy to soy" and "maize to soy" programs.

The scenario analysis attempts to depict the differences in the natural, economic and social costs and benefits of implementing different soybean expansion strategies in Heilongjiang (i.e., business as usual, soybean priority and grain priority, see below for elaborations), throughout the three key time points for national development plans (i.e. 2025, 2035, and 2050). The study also integrates climate change (RCP4.5 and RCP 8.5) and other socio-economic drivers into modelling, such as future trends driven by soybean breeding improvement, specialized cultivation, reducing pesticide and fertilizer use, and promoting conservation tillage.

In total, the Heilongjiang study considers six scenarios formed by the intersection of three soybean expansion pathways and two climate change scenarios at three time points as shown in table 1.

Table 1 Scenario setting

Scenario 1	Scenario 2	Scenario 3
RCP4.5 + BAU	RCP4.5 + Soybean priority	RCP4.5 + Grain priority
Scenario 4	Scenario 5	Scenario 6
RCP8.5 + BAU	RCP8.5 + Soybean priority	RCP8.5 + Grain priority

Business as usual (BAU) represents a situation that is very likely to happen under the current policy orientation and planning, that is, moderately expanding soybean cultivation on the existing planting mode and basis. The setting of parameters of the BAU scenario is as follows (Table 2).

Table 2 Soybean production data under the BAU scenario

Year	Cultivated area (10000 ha)	Yield (t/ha)	Fertilizer efficiency (%)	Pesticide efficiency (%)	No-till rate (%)	Production (10000 t)
2022	493.17	1.93	40.2	40.6	0	951.82
2025	504.31	2.51	45	45	20	1265.81
2035	537.71	2.70	50	50	50	1451.82
2050	537.71	2.90	50	50	70	1559.36

2022 data sourced from https://www.hlj.gov.cn/hlj/c107856/202212/c00_31502977.shtm

Soybean priority (SP) scenario is a mode of expanding soybean planting area further on the BAU. The setting of parameters of the SP scenario is shown in Table 3.

Table 3 Soybean production data under the Soybean priority scenario

Year	Cultivated area (10,000 ha)	Yield (t/ha)	Fertilizer efficiency (%)	Pesticide efficiency (%)	No-till rate (%)	Production (10,000 t)
2022	493.17	1.93	40.2	40.6	0	951.82
2025	Y	2.51	45	45	20	TBM
2035	1093.17+X	2.70	50	50	50	TBM
2050	1093.17+X	2.90	50	50	70	TBM

X represents the converted area of water-intensive rice cultivation to soybean cultivation in groundwater overexploited areas (to be determined in later research), while Y represents the soybean planting area in 2025 calculated based on the soybean planting area growth trend from 2021 to 2035. Total production in 2025, 2035, and 2050 are to be modelled (TBM).

Grain priority (GP) scenario means not expanding soybean cultivation and maintaining the existing planting structure to ensure the planting mode of staple grains. Soybean yield, fertilizer utilization rate, pesticide utilization rate, and no-tillage adoption rate will all be maintained at the current levels. Therefore, the soybean planting area in 2025, 2035, and 2050 will be maintained at the 2022 level of 4.93 million hectares, with a yield of 1.93 t/ha and a production of 9.52 million tons. The utilization rate of fertilizers and pesticides will be 40.2% and 40.6%, respectively, and the no-tillage adoption rate will be 0.

2. Content of analysis

Planting soybeans, maize, and paddy rice require different labour and agricultural inputs, which result in varying crop output and economic benefits. The environmental impacts of the planting process are also different. Therefore, the impact of the differences in land uses brought about by different soybean expansion practices is multidimensional. The content of analysis is categorized into natural capital, produced capital, human capital, and social capital, as shown in Table 4.

Table 4 Contents of analysis

Capital	Benefit	Cost
Natural	Ecosystem services: recreation enabling, water provisioning, water purification, soil retention, pollination, carbon sequestration	Pollutant emissions: air pollutants (ammonia nitrogen, nitrogen oxide, nitric oxide, nitrogen dioxide, methane, pesticides), water pollutants (chemical oxygen demand, nitrate, phosphate, pesticides), solid waste (unused straw, animal excrement), and greenhouse gases over the entire life cycle[2]
Produced	Crop and livestock production	Input of agricultural materials (energy, fuel, fertilizers, pesticides, etc.)
Human	Quantity of labour, skills training	Health impacts: occupational exposure, exposure to air pollution, exposure to downstream water bodies, and exposure to consumption of agricultural products.
Social	Female empowerment, social mechanisms (agricultural cooperatives)	/

Through such design, the study aims to provide comprehensive information and reference for the implementation of soybean expansion policies in Heilongjiang Province and the country, and support the formulation and improvement of sustainable agriculture policies.

3. Data collection

Since October 2022, the project implementation team has been consulting with different stakeholders at national, provincial and local levels, via online exchanges and on-site visits, to collect information and data needed for the study. Online open sources are also used to acquire spatial and census data, which include land cover type, basic geographic information data, socio-economic data and climate projection data[3]. Data required for modelling, including its sources are listed in Table 5.

Table 5 Multi-source data for land-use land-cover change modelling

[2] The study includes all greenhouse gases mentioned in the fifth report of the Intergovernmental Panel on Climate Change (IPCC), including carbon dioxide, methane, and nitrous oxide.
[3] Rainfall and temperature data under RCP4.5 and RCP8.5 scenarios are from the climate projection of China based on the RegCM4.6 (2007-2099).

Data type	Indicator	Year	Data resolution	Data source
Land use data	land use	2000-2020	30m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
Socio-economic driver	Administrative boundaries			
	GDP	2015	1000m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
	Population	2015	100m	WorldPop (www.worldpop.org/)
	Distance from administrative center	2015	30m	National Catalogue Service for Geographic Information (www.webmap.cn)
	Distance from major roads	2015	30m	National Catalogue Service for Geographic Information (www.webmap.cn)
	Distance to highway and railroad	2015	30m	National Catalogue Service for Geographic Information (www.webmap.cn)
Natural driver	Digital elevation model (DEM)	2015	30m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
	Slope	2015	30m	Based on DEM
	Slope direction	2015	30m	Based on DEM
	Soil type	1995	1000m	FAO (www.fao.org/)
	Distance from water system	2015	30m	National Catalogue Service for Geographic Information (www.webmap.cn)
	Temperature	2015	1000m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
	Rainfall	2015	1000m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
Future climate scenario	Temperature	2020-2035	0.25°	National Tibetan Plateau Data Center (data.tpdc.ac.cn)
	Rainfall	2020-2035	0.25°	National Tibetan Plateau Data Center (data.tpdc.ac.cn)

Data on the inputs and outputs of cultivation of soybean, maize and rice in Heilongjiang was collected through face-to-face interviews with representative farms, cooperatives and households in May 2023. The interviews revolved around following aspects – i) arable land conditions and farming practices, ii) inputs and expenditures, iii) products and sales, iv) institution support, and v) attitude towards soybean expansion.

4. Land-use land-cover (LULC) change modelling

The scenario analysis will encompass the spatially-explicit modeling, which will be built upon a predictive land-use/land-cover (LULC) change modeling that integrates existing biophysical data and future predictions to offer landscape assessment and spatial land-use forecast. Multi-source data is needed to provide a more complete picture of the contribution of the various elements to land-use change. Data required for the scenario analysis is listed in Table 2.

4.1 Land use simulation

The simulation of land use patterns is based on a geographic cellular automata (CA) background. The land use grid of the study area will be transformed into individual raster grids of 30m*30m units, and the main class of each grid is selected for the assignment. This process divides the study area into a number of cells that function as the most basic unit of the CA process. In the simulation process, these cells each correspond to a certain land-use type. The historical trend of land-use change, land suitability, and related policy and economic factors constitute the rules, which together determine the possibility of land use type conversion in each cell.

Natural conditions are the basis of land cover and land use distribution and play a dominant role, while human factors such as social, economic, technological, and policy factors have a decisive influence on spatial and temporal changes in land use. The simulation of land-use change by using cellular automata not only takes into account the influence of natural factors such as soil conditions, climate conditions, and geomorphological conditions, but also the influence of human factors such as policy, and at the same time consider the historical trend of land-use change, and carry out a dynamic simulation to obtain the future land use situation.

The purpose of geographic CA is to assist in land-use policymaking. However, most existing CA models have focused too much on the enhancement of simulation techniques and the correction of transformation rules, and relatively little has considered how simulation techniques can be used to deepen the understanding of the underlying drivers of land use. Therefore, existing CA models come up short in exploring the causes of land-use change and simulating patch-level changes in multiple land-use types in a spatial and temporal dynamic manner, especially for natural land types such as woodlands and grasslands.

Among the existing models, the Transformation Analysis Strategy (TAS) is too complex and has low flexibility, with too much emphasis on the mining algorithm. Pattern analysis strategy (PAS) is not based on land-use change over time and lacks the temporal concept, therefore does not carry the capacity to excavate the driving mechanisms of land-use change. In this study, the FLUS model is used to simulate land use, consider different future greenhouse gas emission targets, and characterize climate change with rainfall and temperature changes.

The FLUS model was established by integrating Artificial Neural Networks (ANN) algorithm and Roulette wheel selection mechanism based on System Dynamics (SD) model and meta-cellular automata (CA) model, which can be used to simulate land-use change scenarios under the effect of various natural, social and economic drivers. The main body of the model is divided into two parts, the ANN-based Probability of Occurrence Estimation (ANN) module, and the Self-Adaptive Inertia and Competition mechanism (SICA) module. The ANN module is a biological neural network-inspired machine learning model, which is a nonlinear dynamical system and can achieve a better approximation of nonlinear functions with self-learning, self-organizing, and self-adaptive features, and can effectively integrate different data types to achieve parallel processing of multivariate and complex information. Therefore, it can synergistically integrate multiple types of driving data (natural, social, and economic) and simulate the probability of suitability distribution of each land type under a predefined scenario to establish the correlation between different land types and driving factors. At the same time, the FLUS model innovatively introduces an adaptive inertia competition mechanism based on roulette selection based on the traditional CA model to deal with the uncertainty and relative complexity of changes in multiple land types under the synergistic effects of nature, society, and economy, to achieve a more accurate simulation of land-use change.

4.2 Climate scenarios

Different future GHG emission targets are considered to characterize climate change in terms of rainfall and temperature changes. The future climate data are based on projections made under RCP4.5 and RCP8.5 using the RegCM4.6 model emission scenarios. Downscaling is performed to fit the scale of the study before specific use.

The RCP4.5 emission scenario is a radiative forcing value of 4.5 W m^{-2} corresponding to GHG in 2100 while RCP8.5 refers to a radiative forcing value of 8.5 W m^{-2} corresponding to GHG concentrations in 2100. The RCP4.5 emission scenario is an optimistic emission scenario representing an intermediate mitigation scenario - GHG emissions peak at mid-century and then begin to decline. The RCP8.5 emissions scenario is a pessimistic emissions scenario representing a "business-as-usual" approach-a future climate scenario caused by continued increases in GHG emissions during this century. The RCP4.5 GHG emissions trends are consistent with China's national conditions. The RCP8.5 GHG emission trends are consistent with rapid global economic development。

Therefore, this study projected the precipitation and temperature in the study area in 2025, 2035, and 2050 under these two climate scenarios, respectively. The raw resolution of the above climate projection data is 0.25° × 0.25° for the data. This coarse resolution prediction data was first downscaled using the bilinear interpolation method, which is a simple method to improve the horizontal resolution, and it retains the original field characteristics of the input at a higher level. Then, the regional statistics of the precipitation and temperature data under the two emission scenarios after downscaling are determined to obtain the spatial raster data of precipitation and temperature in the respective years.

4.3 Policy scenarios

The three policy scenarios are business as usual (BAU), soybean priority (SP), and grain priority (GP). The land use capacity is projected based on CA-Markov, and the land use structure data of 2015-2020 and 2005-2020 are used to obtain the land use data of Heilongjiang in the three-time points. The year 2005-2020 is used to simulate the long-term changes, while 2015-2020 is used to simulate the short-term changes.

Table 6 Restriction matrix under BAU scenario

	Built land	Farmland	Grassland	Forest	Garden	Bare land	Waterbody

Built land	1	1	1	0	0	0	1
Farmland	1	1	1	1	0	1	1
Grassland	1	1	1	1	1	1	1
Forest	0	1	0	1	1	0	0
Garden	1	1	1	1	1	1	1
Bare land	1	1	1	1	1	1	0
Waterbody	1	0	1	0	1	1	1

5. Ecosystem service assessment

The ecosystem services we will be analyzing are crop and livestock provisioning, recreation enabling, waterflow regulation, water purification, soil erosion control, pollination, and carbon storage and sequestration.

5.1 Crop provisioning service

As part of the biomass provisioning services, crop provisioning service is a final ecosystem service that measures the ecosystem contributions to the growth of cultivated plants that are harvested by economic units for various uses such as the production of food, fiber, fodder, and energy.

Here, the land rental price method will be used to measure the ecosystem contributions to the growth of grains (rice, wheat, and maize), oilseed rape, medicinal herb, vegetable, tea, and fruit.

In the case of annual and perennial crops, ecosystem contribution is provided by the land, which is combined with other inputs, such as labor, capital, seeds, etc., to produce the final product, the crop. The contribution of each input can be estimated by a production function, where the output (Y) is a function of inputs (labor, L), (capital, K), (land, W), and (other factors, Z). The production function is expressed as:

$$Y = F(L, K, W, Z) \qquad (1)$$

If all factors, including land, were priced in a competitive market, their prices would be equal to their marginal value products. In the case of land, taking its rental price per hectare as P_W, this condition is written in mathematical terms as:

$$P_Y \frac{\partial Y}{\partial W} = P_W \qquad (2)$$

The same applies to all other inputs. In addition, if production takes place in an economy that satisfies certain competitive equilibrium conditions, then the production function also satisfies the following conditions:

$$Y = \frac{\partial Y}{\partial L} L + \frac{\partial Y}{\partial K} K + \frac{\partial Y}{\partial W} W + \frac{\partial Y}{\partial Z} Z \qquad (3)$$

in which case, combining (2) and (3) gives:

$$P_Y Y = P_L L + P_K K + P_w W + P_z Z \qquad (4)$$

In this case, the contribution of the land as an Ecosystem Service is the equivalent of the payment received for the production of the crop. The beneficiary is the economic owner of the land. If only part of the land is leased, the remaining part can be estimated based on the leased land (offering adjustment for quality differences, e.g., soil fertility). The key advantage of this method is that rental data often differ across regions (e.g., more fertile land can command higher rental prices) so that valuation results are spatially heterogeneous. In the case when spatial heterogeneity of the rental price is not sufficient, the contribution of land may also be calculated, using the resource rent method, by deducing its residual from the value of the crops when payments to all other factors, including paid and unpaid labor, capital equipment that is rented or owned (in which case depreciation), and material costs, have been subtracted.

5.2 Water flow regulation

Water is an irreplaceable natural resource for industrial and agricultural production, economic development, and environmental improvement. The provision of fresh water is one of the ecosystem services that provide multiple social benefits to humans. The water production capacity of ecosystems is dependent on the dynamic hydrological cycle within the system and is influenced by climate, soils, vegetation, topography, and land-use structure to show variability. In recent years, the uncertainty of water supply due to climate change has seriously threatened the security and stability of the ecosystem, affecting changes in the natural landscape and the layout of regional population and socio-economic development. The unreasonable overuse of scarce water resources has exacerbated desertification, with some rivers breaking, wetlands disappearing and groundwater levels dropping year by year.

The InVEST Water Yield model estimates the relative contributions of water from different parts of a landscape, offering insight into how changes in land-use patterns affect annual surface water yield and hydropower production. The model runs on a gridded map. It estimates the quantity and value of water used for hydropower production from each sub-watershed in the study area. It has three components, which run sequentially. First, it determines the amount of water running off each pixel as the precipitation minus the fraction of the water that undergoes evapotranspiration. The model does not differentiate between surface, subsurface, and baseflow, but assumes that all water yield from a pixel reaches the point of interest via one of these pathways. This model then sums and averages water yield to the sub-watershed level. The pixel-scale calculations allow us to represent the heterogeneity of key driving factors in water yield such as soil type, precipitation, vegetation type, etc. Based on the physical amount of water yield, we estimate the economic value by multiple the local water price. The equations show as below:

$$S_i^{WY} = P_i - QF_i - AET_i$$

$$E_i^{WY} = V_i * S^{WY}$$

For each pixel i, where S_i^{WY} refers to the supply of WY, P_i is precipitation, QF_i is the quick flow estimated through the Soil conservation service – curved number (SCS-CN) approach, AET_i is the actual evapotranspiration, V_i is the local water price.

Table 7 Data requirement of the InVEST water provisioning model

Data	Type	Description
Land use/land cover	Raster	Map of land use/land cover codes
Watersheds	Vector/ polygon	Map of the boundaries of the watershed(s) over which to aggregate the model results
Average annual precipitation (mm)	Raster	Map of average annual precipitation
Average annual reference evapotranspiration (mm)	Raster	Map of evapotranspiration values
Water prices (monetary)	/	
Root Restricting Layer Depth(mm)	Raster	Map of root restricting layer depth, the soil depth at which root penetration is strongly inhibited because of physical or chemical characteristics
Plant Available Water Content	Raster	Map of plant available water content, the fraction of water that can be stored in the soil profile that is available to plants
Area of Interest	Vector/ polygon	A map of areas over which to aggregate and summarize the final results
Biophysical Table	CSV	A table mapping each LULC code to biophysical properties of the corresponding LULC class
Z Parameter	/	The seasonality factor, representing hydrogeological characteristics and the seasonal distribution of precipitation

5.3 Water purification

Water purification in ecosystems refers to the process and ability of ecosystems to retain water over a given time and space scale. Water quality purification is a fundamental service provided by ecosystems. The material-energy cycle of ecosystems has processing and purifying effect on the quality of the water environment. And when the level of impact goes beyond the ecosystem's ability to clean itself, the decline in water quality will have a direct impact on human well-being and health.

Land-use change, particularly the shift to agricultural land, has dramatically altered natural nutrient cycles. The overuse of pesticides and fertilizers and the discharge of irrigation and industrial effluents directly lead to a decline in water quality and the enrichment of nutrients such as nitrogen, phosphorus, and potassium in water, causing ecological problems such as water pollution, damage to aquatic life, and salinisation of land.

One way to reduce non-point source pollution is to reduce the number of anthropogenic inputs (i.e. fertilizer management). When this option fails, ecosystems can provide a purification service by retaining or degrading pollutants before they enter the stream. For instance, vegetation can remove pollutants by storing them in tissue or releasing them back to the environment in another form. Soils can also store and trap some soluble pollutants. Wetlands can slow flow long enough for pollutants to be taken up by vegetation. Riparian vegetation is particularly important in this regard, often serving as the last barrier before pollutants enter a stream.

Land-use planners from government agencies to environmental groups need information regarding the contribution of ecosystems to mitigating water pollution. Specifically, they require spatial information on nutrient export and areas with the highest filtration. The nutrient delivery and retention model provides this information for non-point source pollutants. The model was designed for nutrients (nitrogen and phosphorous) given that data are available on the loading rates and filtration rates of the pollutant of interest.

The model uses a simple mass balance approach, describing the movement of a mass of nutrients through space. Unlike more sophisticated nutrient models, the model does not represent the details of the nutrient cycle but rather represents the long-term, steady-state flow of nutrients through empirical relationships. Sources of nutrients across the landscape also called nutrient loads, are determined based on a land use/land cover (LULC) map and associated loading rates. Nutrient loads can then be divided into sediment-bound and dissolved parts, which will be transported through surface and subsurface flow, respectively, stopping when they reach a stream. In a second step, delivery factors are computed for each pixel based on the properties of pixels belonging to the same flow path (in particular their slope and retention efficiency of the land use). At the watershed/sub-watershed outlet, the nutrient export is computed as the sum of the pixel-level contributions. The equations are shown as below:

$$ALV_i = HSS_i \cdot pol_i$$

ALV_i is the adjusted load value of pixel i. pol_i is the output coefficient of pixel i, and HSS_i is the hydrological sensitivity score of the calculation method of pixel i:

$$\mathrm{HSS_i} = \frac{\lambda_\mathrm{i}}{\overline{\lambda_\mathrm{w}}}$$

λ_i is the runoff coefficient at pixel i , while $\overline{\lambda_\mathrm{w}}$ is the average runoff coefficient index.

$$\lambda_x = \log\left(\sum_u \gamma_u\right)$$

$\sum_u \gamma_u$ represents a spatially varying pixel of runoff potential, which is the ability to deliver nutrients downstream. This raster can be defined as the is the total water yield into pixel x, which can be calculated using the quick flow index from the InVEST Seasonal Water Yield model.

$$E_i^{WP} = \left(v_N + v_p\right) * S_i^{WP}$$

where v_N and v_p are the treatment costs of nitrogen and phosphorus. $S_i^{WP}$is the amount of water retained (as was calculated in the water flow regulation model in section 4.4).

Table 8 Data requirement of the InVEST water purification model

Data	Type	Description
Land use/land cover	Raster	Map of land use/land cover codes
Nutrient Runoff Proxy	Raster	Map of runoff potential, the capacity to transport nutrients downstream
Watersheds	Vector/ polygon	Map of the boundaries of the watershed(s) over which to aggregate the model results
Wastewater treatment cost of nitrogen and phosphorus	/	
Digital Elevation Model	Raster	Map of elevation above sea level
Area of Interest	Vector/ polygon	A map of areas over which to aggregate and summarize the final results
Biophysical Table	CSV	A table mapping each LULC code to biophysical properties of the corresponding LULC class
Threshold Flow Accumulation	/	The number of upslope pixels that must flow into a pixel before it is classified as a stream
Borselli K Parameter	/	Default value:2

5.4 Soil erosion control

Erosion and overland sediment retention are natural processes that govern the sediment concentration in streams. Sediment dynamics at the catchment scale are mainly determined by climate (in particular rain intensity), soil properties, topography, and vegetation; and anthropogenic factors such as agricultural activities or dam construction and operation. Main sediment sources include overland erosion (soil particles detached and transported by rain and overland flow), gullies (channels that concentrate flow), bank erosion, and mass erosion (or landslides). Sinks include on-slope, floodplain or instream deposition, and reservoir retention. Conversion of land use and changes in land management practices may dramatically modify the amount of sediment running off a catchment. The magnitude of this effect is primarily governed by: i) the main sediment sources (land-use change will have a smaller effect in catchments where sediments are not primarily coming from overland flow); and ii) the spatial distribution of sediment sources and sinks (for example, land-use change will have a smaller effect if the sediment sources are buffered by vegetation).

Increases in sediment yield are observed in many places in the world, dramatically affecting water quality and reservoir management. The sediment retention service provided by natural landscapes is of great interest to water managers. Understanding where the sediments are produced and delivered allows managers to design improved strategies for reducing sediment loads. Changes in sediment load can have impacts on downstream irrigation, water treatment, recreation, and reservoir performance. Outputs from the sediment model include the sediment load delivered to the stream at an annual time scale, as well as the amount of sediment eroded in the catchment and retained by vegetation and topographic features.

The sediment delivery module is a spatially-explicit model working at the spatial resolution of the input digital elevation model (DEM) raster. For each pixel, the model first computes the amount of annual soil loss from that pixel, then computes the sediment delivery ratio (SDR), which is the proportion of soil loss actually reaching the stream. Once sediment reaches the stream, we assume that it ends up at the catchment outlet, thus no in-stream processes are modeled.

Ecological factors in the ecosystem (e.g. vegetation cover) enhance the prevention of soil erosion and prevent soil runoff into rivers, helping to maintain the soil's ability to filter pollutants and regulate water quality. Calculated by the classical modified universal soil loss equation.

$$S_i^{SC} = R_i * K_i * L_i * S_{i^*}(1 - C_i * P_i)$$

R is rainfall erosivity, K is soil erodibility, L is a slope length-gradient factor (unitless), C is a cover-management factor (unitless), and Pi is a support practice factor.

$$E_i^{SC} = S^{SC} * (m_N * v_N + m_P * v_P + m_K * v_K)$$

The economic value of soil retention services can be calculated by multiplying the local fertilizers.

Table 9 Data requirement of the InVEST soil conservation model

Data	Type	Description
Land use/land cover	Raster	Map of land use/land cover codes
Watersheds	Vector/ polygon	Map of the boundaries of the watershed(s) over which to aggregate the model results
Erosivity(MJ·mm/(h·ha·year))	Raster	Map of rainfall erosivity, reflecting the intensity and duration of rainfall in the area of interest
Soil Erodibility(t·h·ha/(ha·MJ·year))	Raster	Map of soil erodibility, the susceptibility of soil particles to detachment and transport by rainfall and runoff
Digital Elevation Model(m)	Raster	Map of elevation above sea level
Area of Interest	Vector/ polygon	A map of areas over which to aggregate and summarize the final results
Biophysical Table	CSV	A table mapping each LULC code to biophysical properties of the corresponding LULC class
Threshold Flow Accumulation	/	The number of upslope pixels that must flow into a pixel before it is classified as a stream
Borselli K Parameter	/	Default value:2
Borselli ICo Parameter	/	Default value:0.5
Maximum SDR Value	/	Default value:0.8

Maximum L Value	/	The maximum allowed value of the slope length parameter in the LS factor

5.5 Pollination

Seventy-five percent of globally important crops are partially or completely dependent on animal pollination. Crop pollination by bees and other animals is a potentially valuable ecosystem service in many landscapes of mixed agricultural and natural habitats. Pollination can increase the yield, quality, and stability of fruit and seed crops as diverse as tomato, canola, watermelon, coffee, sunflower, almond, and cacao. Despite these numbers, it is important to realize that not all crops need animal pollination. Some crop plants are wind-pollinated (e.g., staple grains such as rice, corn, wheat) or self-pollinated (e.g., lentils and other beans), needing no animal pollinators to successfully produce fruits or seeds.

A wide range of animals can be important pollinators (e.g., birds, bats, moths, and flies), but bees are the most important group for most crops. As a result, the InVEST Pollination model focuses on the resource needs and flight behaviors of wild bees. Many people think of honeybees, managed in artificial hives when they think of pollinators, but wild bees also contribute to crop pollination. In fact, for several important crops (e.g., blueberries), native species are more efficient and effective pollinators than honeybees. These native bees, in addition to feral honeybees living in the wild, can benefit crops without the active management of captive hives. This is the pollination service associated with habitat conservation. For bees to persist on a landscape, they need two things: suitable places to nest, and sufficient food (provided by flowers) near their nesting sites. If provided these resources, pollinators are available to fly to nearby crops and pollinate them as they collect nectar and pollen.

The model translates land cover into an index of suitability (0-1) for bees to create a pollinator source map. Higher scores indicate sources of greater relative bee abundance. To calculate the index, the model assumes that bees require two types of limited resources to persist on a landscape - nesting substrates and floral resources. Given an input of land cover that describes the landscape, various suitability values of each LULC class are assigned based on their ability to provide these resources.

The Pollination model then uses the nest supply index to estimate the pollinators visiting crop fields. It assumes the supply from nearby parcels contributes more than those farther away. Additionally, this model incorporates the potential use of managed bees into a yield index. With information on the location of crops and their dependence on pollinators, the model uses a simple yield function to project how wild pollinator abundance in agricultural areas and the use of managed bees contribute to an index of crop yields.

The abundance indices for peak-pollinating bees were calculated as follows.

$$P_{x\beta} = N_j \cdot \frac{\Sigma_{m-1}^{M} F_{jm} e^{\frac{-D_{mx}}{\alpha_\beta}}}{\Sigma_{m-1}^{M} e^{\frac{-D_{mx}}{\alpha_\beta}}}$$

$P_{x\beta}$ is an index of species richness for raster cell x and species β. N_j is the nesting fitness of type j in the LULC plot, F_j is the relative number of floral volunteers produced at LULC type j, Dmx is the Euclidean distance between cells m and x, and α_β is the expected foraging distance of pollinators.

Table 10 Data requirement of the InVEST pollination model

Data	Type	Description
Land use/land cover	Raster	Map of land use/land cover codes
Watersheds	Vector/ polygon	Map of the boundaries of the watershed(s) over which to aggregate the model results
Guild Table	CSV	A table mapping each pollinator species or guild of interest to its pollination-related parameters
Area of Interest	Vector/ polygon	A map of areas over which to aggregate and summarize the final results
Biophysical Table	CSV	A table mapping each LULC code to biophysical properties of the corresponding LULC class

5.6 Changes in soil carbon storage due to conservation tillage

Ecosystems regulate the Earth's climate by adding and removing greenhouse gases such as carbon dioxide from the atmosphere. The total amount of carbon stored in forests, grasslands, peat bogs, and other terrestrial ecosystems far exceeds that of the atmosphere. Ecosystems release this carbon stored in wood, other biomass, and soil as carbon dioxide into the atmosphere, which in turn causes changes in the climate.

In addition to storing carbon, many systems continue to accumulate carbon in plants and soils over time, thereby 'sequestering' additional carbon. Significant amounts of carbon dioxide can be released through fire, disease, or vegetation conversion (e.g., land use and land cover changes). The way we manage terrestrial ecosystems is therefore critical to regulating our climate.

Managing carbon storage at the landscape scale requires information on the spatial distribution and amount of carbon stored, how much carbon has been stored or lost over time, and how land use affects carbon storage and storage over a time period. The InVEST model uses LULC maps as well as the amount of timber harvested, the rate of degradation of harvested products, and the carbon stocks of four carbon pools (above-ground biomass, below-ground biomass, soil, dead organic matter) to estimate the amount of carbon currently stored in the landscape or sequestered over time. With the market or social value of the stored carbon and its annual rate of change, as well as discount rate data, the value of ecosystem carbon sequestration services to society can be estimated.

Carbon storage on a land parcel largely depends on the sizes of four carbon pools: aboveground biomass, belowground biomass, soil, and dead organic matter. The InVEST Carbon Storage and Sequestration model aggregates the amount of carbon stored in these pools according to land use maps and classifications provided by the user. Aboveground biomass comprises all living plant material above the soil (e.g., bark, trunks, branches, leaves). Belowground biomass encompasses the living root systems of aboveground biomass. Soil organic matter is the organic component of soil and represents the largest terrestrial carbon pool. Dead organic matter includes litter as well as lying and standing deadwood.

Using maps of LULC classes and the amount of carbon stored in carbon pools, this model estimates the net amount of carbon stored in a land parcel over time and the market value of the carbon sequestered in the remaining stock. Limitations of the model include an oversimplified carbon cycle, an assumed linear change in carbon sequestration over time, and potentially inaccurate discounting rates. Biophysical conditions important for carbon sequestration such as photosynthesis rates and the presence of active soil organisms are also not included in the model.

The InVEST model calculates carbon stocks for different periods and different land types based on the data of different land-use types and their corresponding carbon density of four major carbon pools: aboveground biomass, belowground biomass, soil, and dead organic matter.

$$C_z = C_{above} + C_{below} + C_{dead} + C_{soil}$$

$$E_i^{CF} = S^{CF} * v_i$$

Where C_z is the total carbon stock, C_{above} is the aboveground carbon stock, C_{below} is the belowground carbon stock, C_{dead} is the dead organic matter carbon stock, and C_{soil} is the soil carbon stock. Each carbon stock is obtained by multiplying carbon density with the area.

Table 11 Data requirement of the InVEST carbon storage and sequestration model

Data	Type	Description
Land use/land cover	Raster	Current and future maps of land use/land cover codes
Carbon Pools	CSV	A table that maps each LULC code to carbon pool data for that LULC type
Area of Interest	Vector/ polygon	A map of areas over which to aggregate and summarize the final results
Carbon price	/	

The interference of tillage practices on soil carbon has been recognized as an influence on Soil Organic Carbon (SOC). Non-tillage provides better physical protection of soil aggregate organic carbon by reducing soil disturbance, thus reducing SOC decomposition. Straw returning to field accelerates the formation of large aggregates and increases SOC retention by providing more organic matter. Compared with conventional tillage, higher soil moisture and lower soil temperature under non-tillage conditions will slow down the degradation rate of organic residues and promote soil carbon sequestration. Therefore, the soil carbon sequestration effect of no-tillage and straw returning combined measures is higher than that of single measures, but there is an "anti-synergistic effect". In other words, the carbon sequestration amount of soil when no tillage and straw returning were used together was lower than the sum of carbon sequestration amount when they were used separately. Referring to the literature, the combined effect of non-tillage and straw returning on soil carbon sink is calculated as follows:

$$C = C_1 + C_2 - \alpha \times \sum[S \times (\Delta SOC_1 + \Delta SOC_2)] \quad (1)$$

Where C_1 and C_2 represent soil carbon sequestration with non-tillage and with straw returning (tC), respectively. α is the anti-synergy effect coefficient. S is for conservation tillage area (using both non-tillage and straw-returning) in the study (hm^2). $\Delta SOC_1 and\, \Delta SOC_2$ are the annual carbon sequestration rate of no-tillage (relative to ploughing) and straw returning (relative to straw not returning) [t C/(hm^2·a)], respectively.

$$C_1 = S_1 \times \Delta SOC_1 \quad (2)$$

$$C_2 = S_2 \times \Delta SOC_2 \quad (3)$$

Where S_1 and S_2 are the area for non-tillage and straw-returning in the study (hm^2), respectively. $\Delta SOC_1 and\, \Delta SOC_2$ are the annual carbon sequestration rate of no-tillage (relative to ploughing) and straw returning (relative to straw not returning) [t C/(hm2·a)], respectively.

According to the literature, the values for different parameters in the study area are as follows:

Table 12 The values of different parameters for conservation tillage

Parameter	ΔSOC_1	ΔSOC_2	α
Unit	t C/(hm^2·a)	t C/(hm^2·a)	
Value	0.39	0.53	0.26

6. Analysis of residual emissions

The types of pollutants in this section include air pollutants (ammonia nitrogen, nitrous oxide, methane), water pollutants (chemical oxygen demand, ammonia nitrogen, total nitrogen, total phosphorus), solid waste (unused straw), and greenhouse gases (carbon dioxide, methane, nitrous oxide and other greenhouse gases deputed in IPCC 5 report). Methods to be used for accounting specific substance masses of the different pollutants are as follows.

Water pollutants (chemical oxygen demand, ammonia nitrogen, total nitrogen, total phosphorus): the coefficient method will be used to account for the physical mass of water pollutant emissions based on the emission coefficients taken from the literature and *Handbook of Agricultural Pollution Source Production and Emission Coefficients* published by the Ministry of Ecology and Environment of the People's Republic of China in 2021, within the listed amount of pollutants in plantation investigated.

Atmospheric pollutants (ammonia nitrogen, nitrous oxide, methane): The coefficient method will be used to account for the material quantities of emissions of atmospheric pollutants based on the emission coefficients of different types of planting types reported in the literature and the number of different types of planting investigated. The emission coefficient is mostly taken from the literature and *Handbook of Agricultural Pollution Source Production and Emission Coefficients*, same as the water pollutants.

Solid waste (unused straw): questionnaire method will be used to investigate the quantities of unused straw.

Greenhouse gases: the life cycle assessment method will be used to account for life cycle greenhouse gas emissions across the value chain.

The different pollutant types will be converted into standard air or water pollutant substance equivalents, and then the economic value of the pollutants will be accounted for in accordance with the provisions of the *Heiilongjiang Environmental Protection Tax Standard*, quantifying the environmental cost of the pollutants.

7. **Analysis of changes in human capital**

The scope of human capital includes the quantity and quality of the workforce, the skills training of the workforce, the health of the workforce, and the health impact of agricultural products on consumers.

7.1 Quantity of workforces

The quantity of labor is proxied by the number of people participating in agricultural production, while its value is reflected by the wage levels. The specific accounting methods for the value corresponding to the quantity and quality of labor in the system are as follows:

$$\mathrm{L} = \sum_{i=1}^{n} (P_i \times T_i)$$

Where L is the value of the labor force, i is the i^{th} labor force, P_i is the wage level of the i^{th} labor force and T_i is the hours worked by the i^{th} labor force. The workforces needed in different farming categories in the future is projected based on the scale of different farming categories in different scenarios and current workforces in different farming categories collected in the survey. It is assumed that in the future the work forces in different farming categories would increase proportionally with the farming scale. The salary of the workforces is also assumed to increase in accordance with the country.

7.2 Skills training of workforces

As the value of workforce skills training is difficult to quantify, it is described using a combination of qualitative and quantitative methods, with a survey to obtain information on the type, frequency, length, and level of training received by the workforces.

The change of skills training of the workforce will be projected based on the current skills training of workforces collected in the survey as well as the change of workforce depicted in 6.1 in different scenarios. It is assumed that the training of workforces will increase in a linear manner and all workforces will get proper training until 2050.

7.3 Health implications

7.3.1 Occupational exposure

Occupational exposure is defined as the contact between agents (environmental elements with harmful substances) and targets. In our case, agents include air, water, and soil that contain potentially harmful substances resulting from agri-chemical inputs into the soil and disseminated into the environment. Agents encompass all range of agricultural practitioners such as farmers and employees in conventional cultivation that work strictly in an agricultural setting. Therefore, we have selected soil exposure as the primary route of contact in the assessment process. The source of the harmful substances contains agricultural chemicals, mainly insecticide, being applied in the farming process. Contact may take place at any exposure surface including mouth, skin, and eyes over an extended working period and at an exposure frequency.

Lifetime theoretical maximum contributions (LTMCs) of the chemicals are computed from human major exposure routes at maximum legal exposures, which include occupational (i.e. farmland) soil, water, and air. The worldwide average human life expectancy is assumed to be 70 years, and the lifetime exposure to pesticides is considered only for working adults. The LTMC computed from occupational soil exposure is expressed in the following equations and includes ingestion, inhalation, and dermal contact.

$$LTMC_{ingestion} = RGV \times CF \times EF \times (IR \times ED)$$

$\mathrm{LTMC}_{ingestion}$: LTMC calculated from occupational ingestion (kg)

RGV: Chemical concentration value in the soil (mg/kg), which can be obtained from the use of pesticides and fertilizers and their corresponding coefficients going to the soil.

IR: Ingestion rate of soil for adults (1.0 × 10.4 kg/day or 0.1 mg/day) (ATSDR, 2005)

EF: Exposure frequency (days/yr, to be calculated based on field survey)

ED: Exposure duration (24 yr) (USEPA, 2002)

CF: Conversion factor (1.0 × 10^{-6} kg/mg)

$$LTMC_{inhalation} = \frac{RGV \times CF \times EF}{PEF} \times (IhR \times ED)$$

LTMC$_{inhalation}$: LTMC calculated from soil dust inhalation (kg)

$RGV, CF, and\ EF$: inherited from previous equation

PEF: Particulate emission factor (1.32 × 109 m^3/kg) (USEPA, 1996)

IhR: Inhalation rate for adults (20.0 m^3/day) (USEPA, 1986)

$$LTMC_{dermal} = RGV \times AF \times CF \times EF \times (SF \times SA \times ED)$$

LTMC$_{dermal}$: LTMC calculated from soil dermal contact (kg)

$RGV, CF, and\ EF$: inherited from previous equations

SF: Skin adherence factor for adults (7.0 × 10^{-8} kg/cm^{-2}) (ATSDR, 2005)

SA: Exposed skin area for adults (4656 cm^2) (USEPA, 1997)

AF: Bioavailability factor (or dermal absorption factor) (0.1 unit less) (ATSDR, 2005)

Thus, the LTMCs computed from the soil exposure from previous equations are combined as follows to yield the total soil LTMC$_{soil}$.

$$LTMC_{soil} = LTMC_{ingestion} + LTMC_{inhalation} + LTMC_{dermal}$$

The occupational exposure in different scenarios is simulated based on the current pesticide use in different crops categories, future crop's structure, and pesticide decrease rate in different scenarios settings. The human health of occupational exposure in different scenarios will be calculated according to the equations in this section.

To quantify the human health impacts of maximum legal exposure to pesticides, the health risk characterization factor (DALYs) was employed to convert the LTMC into the human health damage metric: DALYs per million populations. The human health damage factor (DALYs per incidence) is based on cancer and noncancer damage resulting from human exposure to pesticides via ingestion of soil, water, and foods that include carcinogens and noncarcinogens. Health damage, incidence rate, and toxic effect of chemicals were derived from lognormal dose-response curves (Huijbregts et al., 2005) while other studies (Pennington et al., 2002; Crettaz et al., 2002) applied linear dose-response curves when below the effect dose affecting 10% of the individuals (ED10). Cancer and noncancer incidences for selected pesticides are weighted according to their respective severity and expressed by a loss of (healthy) lifetime expressed in DALYs (Fantke and Jolliet, 2016; Huijbregts et al., 2005; Li, 2018). Aggregated cancer and noncancer health damage for the pesticides in human major exposure routes were derived using the following health risk characterization factor equation:

$$\mathrm{CF} = \sum_{i=1}^{n} (LTMC_{soil} \times P \times (DRSF_{cancer} \times DF_{cancer} + DRSF_{non-cancer} \times DF_{non-cancer}))$$

CF： Health risk characterization factor (DALYs per million population, or DALYs)

$LTMC_{soil}$： LTMC calculated from soil exposure

P： Population (1.0×10^6, million)。

$DRSF_{cancer}$ and $DRSF_{non-cancer}$: Dose-response slope factors (Fantke and Jolliet, 2016) for cancer and noncancer (incidence/kg; DRSFs of pesticides in this study were taken from Rosenbaum et al., 2015)

DF_{cancer}: Damage factor for cancer (11.5 DALYs per incidence) (Fantke and Jolliet, 2016) (Huijbregts et al., 2005)

$DF_{non-cancer}$: Damage factor for noncancer (2.7 DALYs per incidence) (Fantke and Jolliet, 2016) (Huijbregts et al., 2005)

7.3.2 Air exposure

Air exposure because of pesticide and fertilizer use is calculated based on the use of pesticides and fertilizers (collected in the survey data) and their corresponding coefficients going to the air (acquired from the literature). All the pollutants entering into air are classified based on their chemical composition. And the health impact because of air exposure is calculated based on those chemicals. The health impact will be calculated using the Impact 2002+ method integrated in Simapro Software and expressed in DALY.

The health impact in different scenarios is also projected based on the pesticides and fertilizers used in different scenarios. The Impact 2002+ method integrated into Simapro Software will be employed to calculate the health impact from are exposure, known as the health Risk characterization factor (CF, DALYs per million population, or DALYs).

7.3.3 Water exposure downstream

Water exposure because of pesticide and fertilizer use is calculated based on the use of pesticides and fertilizers (collected in the survey data) and their corresponding coefficients going to the water (acquired from the literature). All the pollutants entering into water bodies are classified based on their chemical composition. And the health impact because of water exposure is calculated based on those chemicals. The health impact will be calculated using the Impact 2002+ method integrated in Simapro Software and expressed in DALY.

The health impact in different scenarios is also projected based on the pesticides and fertilizers used in different scenarios. The Impact 2002+ method integrated into Simapro Software will be employed to calculate the health impact from water exposure downstream, known as the health Risk characterization factor (CF, DALYs per million population, or DALYs).

7.3.4 Consumption of agricultural products

The health effects related to the consumption of agricultural products are accounted for according to the residues of pesticides and other harmful substances in the product, as described below.

The lifetime theoretical maximum contributions (LTMC) computed from the agricultural foods' exposure is expressed in the equation below, and only ingestion was considered. The consumption rates of the most commonly consumed agricultural foods were estimated. The agricultural foods' consumption rates were estimated by taking average values of residents in China.

$$\mathrm{LTMC}_{food} = \sum_{i=1}^{n} (MRL_i \times CoF \times ED \times CR_i)$$

LTMC_{food}: LTMC calculated from agricultural foods (kg)

MRL_i: Pesticide agricultural food maximum residue level in food i (mg/kg)

CoF: Conversion factor (1.0×10^{-6} kg/mg).

ED: Exposure duration (70 yr)

CR_i: Consumption rate for agricultural food i (kg/year)

To quantify the human health impacts of maximum legal exposure to pesticides, the health risk characterization factor (DALYs) was employed to convert the LTMC into the human health damage metric: DALYs per million populations. The human health damage factor (DALYs per incidence) is based on cancer and noncancer damage resulting from human exposure to pesticides via ingestion of soil, water, and foods that include carcinogens and noncarcinogens. Health damage, incidence rate, and toxic effect of chemicals were derived from lognormal dose-response curves (Huijbregts et al., 2005) while other studies (Pennington et al., 2002; Crettaz et al., 2002) applied linear dose-response curves when below the effect dose affecting 10% of the individuals (ED10). Cancer and noncancer incidences for selected pesticides are weighted according to their respective severity and expressed by a loss of (healthy) lifetime expressed in DALYs (Fantke and Jolliet, 2016; Huijbregts et al., 2005; Li, 2018). Aggregated cancer and noncancer health damage for the pesticides in human major exposure routes were derived using the following health risk characterization factor equation:

$$\mathrm{CF} = \sum_{i=1}^{n} (LTMC_{food} \times P \times (DRSF_{cancer} \times DF_{cancer} + DRSF_{non-cancer} \times DF_{non-cancer}))$$

CF: Health risk characterization factor (DALYs per million population, or DALYs)

$LTMC_{food}$: LTMC computed from the food intake

P: Population (1.0×10^{6}, or million)

$DRSF_{cancer}$ and $DRSF_{non-cancer}$: Dose-response slope factors (Fantke and Jolliet, 2016) for cancer and noncancer (incidence/kg; DRSFs of pesticides in this study were taken from Rosenbaum et al., 2015)

DF_{cancer}: Damage factor for cancer (11.5 DALYs per incidence) (Fantke and Jolliet, 2016) (Huijbregts et al., 2005)

$DF_{non-cancer}$: Damage factor for noncancer (2.7 DALYs per incidence) (Fantke and Jolliet, 2016) (Huijbregts et al., 2005)

7.3.5 Health economic value loss accounting

The economic value loss because of different sorts of health impact is calculated according to the equation below.

$$Loss_{health} = CF \times 10^{-6} \times VSL$$

$Loss_{health}$: Economic value loss because of health impact

CF: Health risk characterization factor (DALYs per million population, or DALYs)

VSL: Value of statistical life

8. Analysis of changes in social capital

The scope of accounting for social capital includes "the networks, norms, values, and understandings that facilitate cooperation within and between groups" (TEEBAgriFood). This study qualitatively analyzes the benefits of social capital from the perspectives of female empowerment and social mechanisms (agricultural cooperatives).

8.1 Women empowerment

Women empowerment data mainly include the quantity of female workers in the agri-food system and their salary. Based on the women empowerment data in the current agri-food system in Heilongjiang collected in the survey and the expected agri-food system development in different scenarios, we can project the quantity and distribution of women’s workforces in different sectors and their salaries.

8.2 Social institutions

Social institutions mainly refer to the rural cooperatives for farming in the region. Based on the data of different categories of farming and corresponding rural cooperatives, we project that the number of cooperatives of different farming categories would increase in a linear pattern, and all farming entities would join rural cooperatives until 2050. Also joining rural cooperatives would bring economic benefits to the entities. It is assumed that a net increase of 150yuan/mu in farming profit could be achieved for households/entities within the cooperative system.

9. Technical framework of the study

The following figure shows the main content and the process of the analysis, as well as the proposed methods to be used.

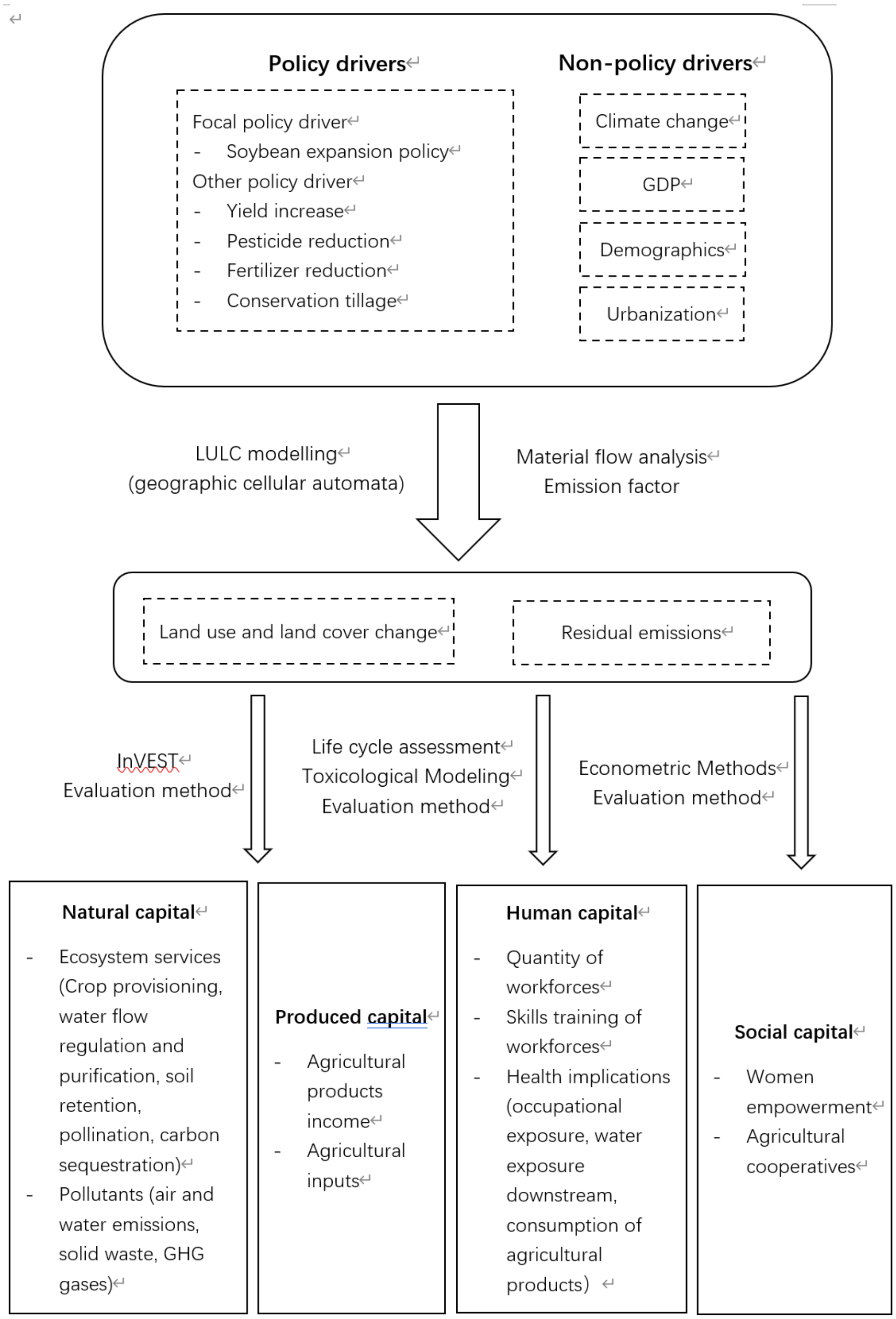

Figure 2 Technical framework of the study

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