Farming Futures in a Changing Climate

Spatial shifts in agricultural suitability across British Columbia under multiple climate change scenarios

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The study documented in this report is part of a larger research project, *The Social Implications of Agri-genomics* (www.ufv.ca/agrigenomics), which is being led by the Food and Agriculture Institute at the University of the Fraser Valley and Royal Roads University.

This study was done in partnership with i-Open Technologies, which supported the research by providing the Agrilyze platform (www.agrilyze.ca). Agrilyze is a spatial data platform designed specifically for agricultural data, and it was used to organize, manage, and visualize the data in this study. The outcomes of the modelling work reveal future agricultural land suitability in British Columbia under different climate change scenarios, and these outcomes were imported and displayed as spatial data layers in Agrilyze.

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1.Summary

This study assesses the future suitability of agricultural land for field-grown crops in the province of British Columbia, Canada, under different climate change scenarios. The research focuses on crops that are economically and dietarily important in the province, specifically: cabbage, cauliflower, lettuce, strawberry, kale, broccoli, and celery. The analysis involves a spatial modelling approach, using data on historical crop planting and production of the crops, high-resolution climate projections (as per the Intergovernmental Panel on Climate Change's SSP2, SSP3, SSP5 scenarios), land capability classifications, and regional economic indicators. Machine learning models were developed to evaluate land suitability across the province from the current year to the end of the 21st century.

The analysis reveals spatial shifts in future agricultural suitability, with cabbage, cauliflower, and lettuce expanding their potential production ranges northward due to warmer conditions (particularly in high-emissions scenarios). In contrast, the modelling of strawberry, kale, and broccoli suitability produced more nuanced results, with expansion occurring in moderate warming scenarios but losses in suitable crop production land in the latter half of the 21st century under high warming scenarios. Finally, celery is projected to experience a consistent decline in suitable agricultural land across all scenarios, but this may be due to how data limitations on current cultivation in the province impact the reliability of the model.

This work developed a method for integrating geospatial, climatic, and economic data to generate spatially explicit agricultural predictions across a relatively large geographic area, and the outcomes of the work can be applied by agricultural policymakers and planners throughout British Columbia. For instance, the models identify areas currently underutilized for agriculture (such as in the northern and central parts of the province), which may become viable for crop production as climate change progresses. Insights from this modelling exercise can be used to guide strategic land use planning, investment prioritization, and climate adaptation strategies.

While not all socio-economic or ecological considerations were included in the model, this work provides a robust, data-driven approach for decision-support in agri-food system planning and policymaking. The model is flexible and scalable, and it can be used to examine other crops and regions, as well as be further developed to include more variables and factors. Researchers and practitioners are encouraged to adapt and apply the models in regions across Canada and beyond for enhanced decision-support in agricultural planning and policy in the face of a changing climate.

2. Introduction

2.1 Background and purpose

Agri-food systems across the world are facing a complex and increasingly severe multitude of pressures, including climate change, global trade disruptions, and technological innovations. These pressures reshape where and how food is produced, processed, and distributed. The combination of changes in growing conditions, a need for strengthening local food systems, and technological opportunities for growing food in previously unsuitable locations presents critical considerations for local and regional governments in their efforts to identify and implement ways of developing resilient and sustainable food systems.

Climate change is a highly influential factor in the reshaping of food systems (Perez *et al.*, 2015; Drolet, 2011). In British Columbia, Canada, a changing climate is altering growing conditions through shifts in temperature, precipitation patterns, and the frequency of extreme weather events, making different regions more or less suitable for growing certain crops (Government of British Columbia, 2025). For example, coastal regions in British Columbia are expected to face increased rainfall intensity and frequency, while the province's interior is projected to experience reduced precipitation and prolonged drought conditions (Young, 2024). These types of changes result in new conditions for growing crops by (in some cases) decreasing local/regional suitability for currently common agricultural products, which in turn disrupts agricultural economies and landscapes.

Along with climate change, increased disruptions in global trade are exposing vulnerabilities in the food system. British Columbia is heavily reliant on imported food, particularly from the United States (Schmoeker et al., 2016; Ostry et al., 2011), which creates risks of supply chain instability. For example, based on 2022 data, it is estimated that 62% of British Columbia's supply of lettuce and chicory was from California, with Arizona being the province's second top supplier of these crops (Food Flows Canada, 2025). Concerns about such reliance on transboundary supply chains have spurred interest in re-localizing agricultural production and food processing to increase food system resilience and security (Ostry et al., 2011, Dhillon et al. 2020).

Along with environmental and economic pressures, agricultural systems are being reshaped by a suite of emerging technologies that are part of the so-called fourth agricultural revolution (Rose et al., 2021). Innovations such as controlled environment agriculture (CEA), agri-genomics, and alternative protein production offer both challenges and opportunities for developing sustainable and resilient agriculture systems in British Columbia and beyond (Glaros et al., 2024; Ghezeljeh et al., 2022; Powell et al., 2023). These technologies can decouple food production from traditional environmental constraints such as soil quality, water availability, and growing days, which enables localized and climate-resilient systems (Newman et al., 2023); however, social, economic, environmental, and technical barriers to their implementation exist (Smyth, 2017; Powell et al., 2023; Glaros et al., 2024).

For example, the high energy demand of CEA may increase product prices or disincentivize farmers from investing. Additionally, due to the energy demand, CEA may generate more greenhouse gas emissions than conventional agriculture, despite the latter's reliance on long supply chains and transportation distances (Crawford, 2023; Newell et al., 2021).

Understanding both the shifting geography of agricultural suitability in the face of climate change and the potential for implementing new food production technologies to adapt to a changing climate is essential for guiding future land use planning and agri-food policy. In British Columbia, few comprehensive analyses have been done to understand and predict the shifting agricultural landscape. This type of work is required to stimulate thinking on how best to increase domestic production, through both rethinking where crops are grown and considering how to enhance food production via emerging food production technologies. Integrating agri-food supply chains, crop production, and climate data into holistic assessments of crop performance can inform British Columbia's agricultural and food security policy priorities.

This study uses machine learning and geospatial techniques to model the effects of climate variables (i.e., temperature, precipitation, and growing season length) on the production of a selection of vegetable crops that are at high of supply disruptions in British Columbia. The aims of the modelling exercise are: (1) to identify how climate change is impacting agricultural productivity, and (2) to forecast which regions are likely to face increasing risk or new growing opportunities under future climate scenarios. The outcomes of this research can be used to inform climate adaptation strategies, as well as support the strategic deployment of agri-technologies by identifying the areas where climate-resilient food production methods are most urgently needed. Accordingly, the study contributes to efforts to enhance the resilience of British Columbia's agri-food systems to ensure that they remain productive, adaptive, and secure in the face of accelerating climate change and global economic uncertainties.

2.2 Agriculture and climate change models

Studies that project crop suitability and production potential under climate scenarios typically use regional and global datasets alongside spatial analysis and scenario simulations (e.g., Mehrabi, 2023). Such research includes models that predict how climate variables (e.g., temperature, precipitation, and growing season dynamics) may alter the spatial distribution and yield of specific crops. For instance, Hannah et al. (2020) conducted a global assessment of how warming trends may expand or reduce areas suitable for staple crops like corn, soy, and wheat. Similarly, Perez et al. (2015) and Gasser et al. (2016) used climate data to forecast yield changes in barley, oats, and corn in British Columbia across different greenhouse gas emissions scenarios, identifying both losses of suitable agricultural land and new growing opportunities depending on the crop and region.

Recent studies have used the Intergovernmental Panel on Climate Change's (IPCC) Shared Socioeconomic Pathways (SSP) scenario framework to assess the potential impacts of climate change on agriculture in British Columbia. For example, Ball (2023) used the Coupled Model Intercomparison Project Phase 6 (CMIP6) climate models and the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios to predict the production of spring-planted canola in the Peace River region and southern British Columbia over a time period that extends to 2040. The study indicates that agricultural yields will decrease under these scenarios.

Hewer and Gough (2021) developed a predictive model for grape production in British Columbia's Okanagan Valley using global climate model data that projects to 2100. Their findings suggest that future warming trends may create opportunities to cultivate new grape varieties that can be used to create high-quality wine. In a similar study, Beech and Hewer's (2021) research on rising temperatures in the Fraser Valley throughout the 21st century revealed a need to introduce new grape varieties suited to warmer conditions. They also suggested refocusing agriculture on existing cool-climate grape varieties in places that are higher north of the Fraser Valley and/or higher in elevation (i.e., places where the optimal growing conditions will be in the future).

These types of modelling studies provide valuable insights for supporting crop diversification and agricultural land use planning and policies, as they can be used to identify areas where agricultural expansion may be viable and where production may no longer be sustainable. However, while these studies provide useful regional insights, there remains a need for comprehensive, provincial-scale assessments for in-demand crops considering new technologies for food production. Accordingly, this study models the spatial effects of climate change on high-demand, import-dependent crops across British Columbia. The study applies machine learning in a modelling exercise that combines climate projections with geospatial agricultural production data. The outcomes of this work can be used to identify localized vulnerabilities and emerging opportunities at a provincial scale, supporting data-driven decisions for agricultural adaptation, land use planning, and targeted agri-tech interventions.

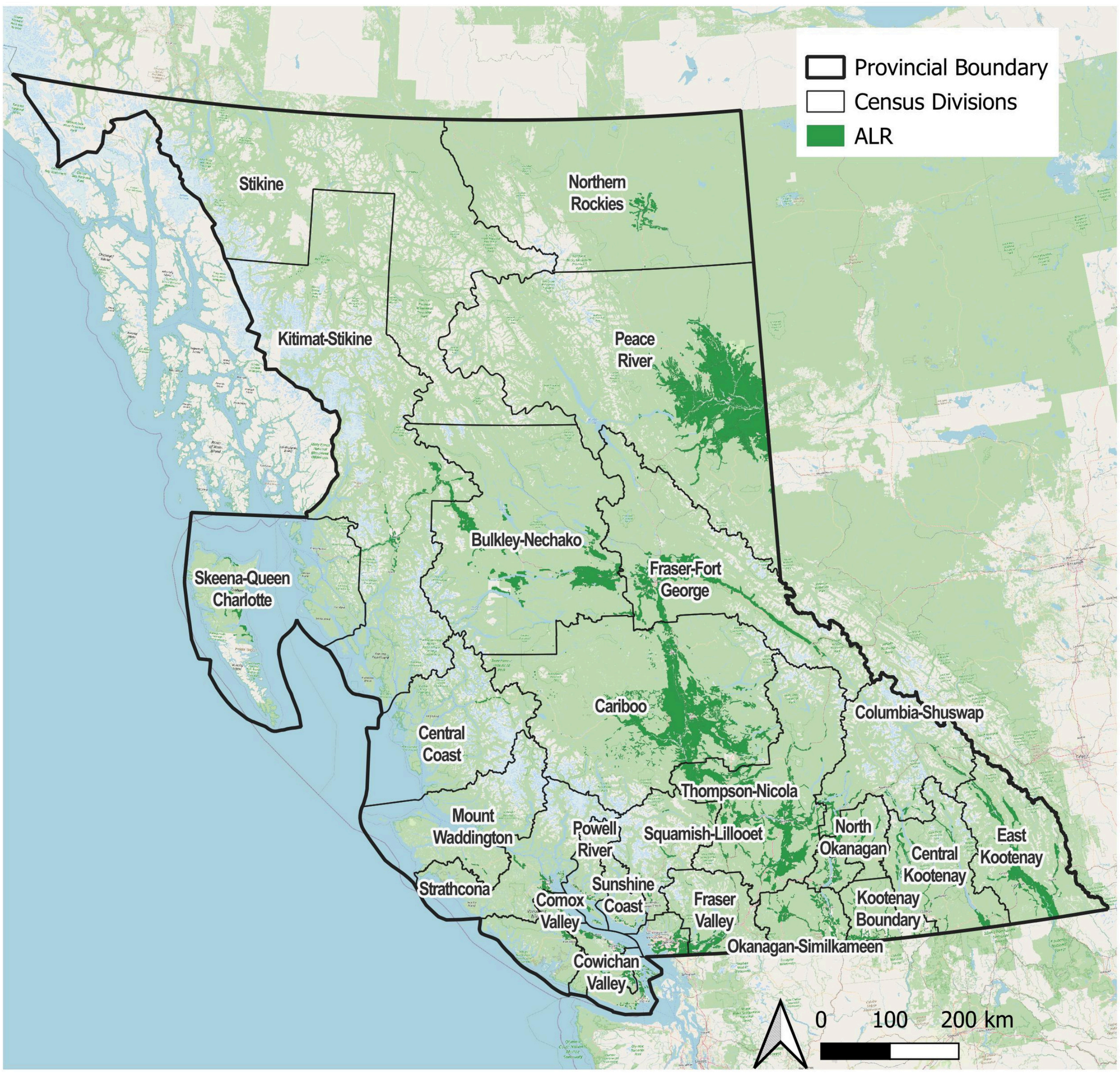
3. Methods

The study began by identifying a selection of horticultural crops in British Columbia that are both imported in high volumes from the United States (i.e., goods that are vulnerable to supply chain disruptions) and are potentially suitable for indoor CEA. Then, using machine learning and geographic information systems (GIS) techniques, the future suitability of agricultural lands in British Columbia for growing the selected crops was modelled under different climate scenarios. The models were developed and trained using current data on climate conditions and agricultural yields. Then, the models were applied to explore how future climate scenarios may affect agricultural suitability across the province.

3.1 Study area and crop selection

The study focuses on British Columbia's Agricultural Land Reserve (ALR), which consists of areas legally designated to support farming and to preserve land for agricultural use in the province (Figure 1). The majority of farming in British Columbia occurs within the ALR; thus, it provides an appropriate and useful geographic focus for this study on agricultural suitability in the province. The ALR was established to include lands that are favourable for agriculture based on biophysical characteristics (e.g., climate, soil) and land-use type (i.e., spaces that have not been urbanized or irreversibly developed) for the purposes of supporting high agricultural productivity and a wide range of agricultural activities (Provincial Agricultural Land Commission, 2025).

Figure 1. ALR areas within census divisions across BC (see Provincial Agricultural Land Commission, 2024)



The study focuses on a series of crops that were selected based on three criteria:

1) economic importance (in terms of both domestic consumption and international trade)
2) potential for CEA and vertical farming
3) nutritional value

Data were sourced from provincial government reports on crop production and value, which reported on Statistics Canada figures related to total area used for farming the crops, crop production volumes, and market value for the different crops. Data on crop imports and exports were collected from Statistics Canada's trade database, and national food availability statistics were reviewed to determine the economic importance of these crops. Each crop was ranked among all crops produced in British Columbia in terms of production, import volume, and overall market demand, as per Equation 1:

Equation 1.

[Demand Pressure] = ([Disposition Rank] × [Import Rank]) / [Production Rank]

In Equation 1, disposition rank is a normalized value that ranges from 0 to 1, and it captures the total amount of a crop that is consumed in and exported from British Columbia. The normalization process produces a value that represents the degree of disposition for a crop relative to the degree of disposition of all other crops in the province. A higher rank indicates greater overall usage and economic activity of a crop in terms of domestic consumption and product exports.

Import rank refers to crop imports into British Columbia, and it is a normalized value that represents the import volume of a crop relative to the total import volume of crops. Similarly, production rank is a normalized value that represents the production volume of a crop in British Columbia, relative to all other produced crops in the province. A higher production rank value results in a lower demand pressure value, as it suggests that domestic production is occurring at levels that can meet much of the domestic demand.

Equation 1 was used to identify crops with high demand pressures, that is, those that are heavily consumed and imported while also being under-produced locally. These crops were deemed to be important in terms of assessing opportunities for expanding domestic production and improving local/domestic food systems. Such opportunities were considered both in terms of conventional land-based agriculture and CEA. With respect to the latter, a review of scientific literature was conducted to ensure that the crops selected for this analysis can be cultivated using CEA methods. Nutritional data were also reviewed to focus on crops that contribute to health and dietary outcomes. Seven crops were selected for the modelling and analysis: lettuce, broccoli, cauliflower, celery, kale, cabbage, and strawberries.

3.2 Data collection

The study employed a spatial approach, and it used a combination of climate, economic, and agricultural data. The climate data were obtained from Environment and Climate Change Canada, and the data capture variables including average annual temperature, total annual precipitation, and growing season length. These data are based on CMIP6 climate projections, and data were collected for three of IPCC's SSP scenarios: SSP2, SSP3, and SSP5. The scenarios represent various degrees of greenhouse gas emissions production and global warming, with the three scenarios capturing a range from lower (i.e., SSP2) to higher (i.e., SSP5) levels of warming.

ALR boundary spatial data were sourced from the Agricultural Land Commission, and these data included the land capability classification for agriculture used for the ALR, which ranks land from Class 1 (highest quality) to Class 7 (lowest quality). Additionally, Agriculture and Agri-Food Canada's (AAFC) Annual Crop Inventory maps and Statistics Canada's 2021 Census of Agriculture data were used to identify where each of the seven case study crops is currently being grown within ALR boundaries.

The model included average land/property values, and these data were sourced from Statistics Canada's 2021 Census. These data were included in the model to account for economic considerations related to how farms located in areas with high property values and cost-of-living typically need to produce high-value crops to maintain the economic viability of the farms. In contrast, regions with lower property values are able to produce lower-value crops on large tracts of land, as lower property prices make this economically feasible.

3.3 Data processing

Spatial data were projected in QGIS (version 3.34) using the EPSG:3005 – NAD83 / BC Albers projected coordinate system. Data were prepared in polygon shapefile format and compiled as a GeoPackage. Table 1 provides a list of the data layers and sources included in the GeoPackage.

An agricultural land parcel data layer was sourced from AAFC's Annual Crop Inventory. Parcel polygons were labeled as "suitable" (value = 1) for a particular crop if they exist in the ALR and in regions where a crop has been grown, as per the 2021 Census. Parcels located in the ALR but not being used for crop production were labeled as "not currently used" (value = 0). Additionally, parcels with land capability classes of 5, 6, or 7 were also given a value of 0, as these lands are not suitable for growing any of the case study crops.

A series of spatial joins was done to add climate data, dwelling values, and land capability information to the land parcel data attributes. The land parcel data were then exported as a CSV file, which was used for the modelling exercise.

Table 1. Overview of the datasets stored in the GeoPackage database for suitability models with associated descriptions, and sources.

Dataset	Description	Source
Climate	Predicted annual temperature, precipitation, and growing season length up to 2100, across scenarios SSP2, SSP3, and SSP5.	Environment and Climate Change Canada
Agriculture	Land capability classes for agriculture ranked by Environment and Climate Change Canada, as well as annual crop inventory data to show where crops are currently grown and ALR to specify the boundaries of lands reserved for agriculture.	BC Ministry of Environment, Agriculture and Agri-Food Canada, and Agricultural Land Commission
Economic	Market pressures indicated by average dwelling values per census area.	Statistics Canada

3.4 Modelling

The crop suitability models were built in Python using Scikit-learn. The study compared the fit of four machine learning modelling techniques, namely artificial neural networks, support vector machines, random forests, and gradient boosting. These models are capable of identifying complex patterns in data and are well suited for spatial prediction exercises (Fawagreh et al., 2014; Jun, 2021; Natekin and Knoll, 2013; Zhou, 2021). A grid search method was used to fine-tune the models and improve their accuracy (Jiménez et al., 2008).

Input variables for the model included normalized climate indicators, average dwelling value, and categorical land capability classes. The climate data were normalized using the minimum and maximum values for the entire dataset of all years and all SSP scenarios (SSP2, SSP3, and SSP5). A single minimum value and a single maximum value were identified for each climate variable from the full range of data, and using these values to normalize the data ensured consistency among the model training and future projection phases.

The models were trained using data on the current conditions, namely data from 2021 and for SSP2. The models were then applied to climate projections from 2022 to 2100 under SSP2, SSP3, and SSP5. This process allows for an exploration of how temperature, precipitation, and growing season changes may influence agricultural land suitability in the future.

3.5 Model validation

Model performance was assessed using two methods: success rate (i.e., measuring model accuracy on the training data) and predictive rate (i.e., assessing model performance on different validation data). The data were split 70/30 (i.e., 70% training and 30% validation) into training and validation sets. Accuracy was measured as the proportion of correctly classified land parcels, and it was calculated by dividing the correctly predicted suitable and unsuitable parcels by the total number of parcels (Owusu-Adjei et al., 2023). Accuracy evaluation metrics assess the proportion of correct predictions over total predictions, with values closer to 1 indicating stronger model performance.

The receiver operating characteristic (ROC) curve was used to evaluate how well each model distinguishes between suitable and unsuitable land across different thresholds (Bradley, 1997; Fawcett, 2006). The ROC curve plots the true positive rate against the false positive rate, providing insight into the trade-offs between sensitivity and specificity. The area under the ROC Curve (ROC-AUC) serves as a measure of models' performance. Values above 0.5 and closer to 1 indicate a stronger model performance (Melo, 2013).

Monte Carlo simulations were used to test the stability of the models (Raychaudhuri, 2008). The process of splitting the data (70% training and 30% validation) was repeated to evaluate it 1,000 times using different random splits. Monte Carlo simulations assess risk and uncertainty in highly complex, difficult-to-predict models with potential for random variable influence. They do so by running many iterations of the model using random values and averaging the various iterations (Rubinstein and Kroese 2016).

Accuracy and ROC-AUC scores were recorded for each model iteration. A z-test and 95% confidence intervals for both accuracy and ROC-AUC metrics were used to assess the consistency of model simulation results. The models were considered to be robust and not strongly affected by changes in how the data were split if the accuracy and AUC values fell within a narrow range across simulations.

4. Results

4.1 Agricultural suitability maps

Figures 2 to 8 display the outputs of the modelling exercise, specifically the agriculture suitability maps for current (2021) conditions and for future (2100) conditions under the three different climate scenarios (SSP2, SSP3, and SSP5). For example, Figure 2a shows the current suitability of lands for broccoli cultivation, and Figures 2b, 2c, and 2d show projected suitability for broccoli cultivation in 2100 as per SSP2, SSP3, and SSP5 scenarios. The figures also include graphs of projected changes in total areas of high-suitability agricultural land for each crop over an 80-year period (i.e., 2021 to 2100). Agricultural land suitability is measured using score values that range between 0 and 1, and lands with scores ≥ 0.75 are considered to be highly suitable for the production of a particular crop.

Figure 2 shows that several regions that currently have suitable areas for broccoli production (e.g., North Okanagan, Squamish-Lillooet, Fraser Valley, and Capital Region District) are likely to experience a decline in these areas and agricultural suitability by 2100. Conversely, areas within the Thompson-Nicola and Cariboo regions are projected to become more suitable, particularly in SSP2 and SSP3 futures. Under the high-emissions scenario (i.e., SSP5), new opportunities and suitable lands for broccoli cultivation appear in northern areas by 2100, such as in the Peace River region. These projections indicate that a potential northward shift in broccoli agriculture may occur in response to a changing climate.

Similar to broccoli, northward shifts in agricultural suitability were also observed for crops such as cabbage, cauliflower, lettuce, strawberry, and (to a lesser degree) kale (Figures 3 to 7). The projected agricultural suitability changes for celery presented a different pattern than what was seen with the other crops (Figure 8). Large areas in the Peace River region and smaller areas in the Fraser Valley and Capital Region District are identified as suitable for celery cultivation in the current conditions scenario. However, under all future climate scenarios, the model projects that the amount of suitable land for celery agriculture will decline substantially and be entirely gone by the middle of the century.

The time series graphs in (Figures 2 to 8) show that, with the exception of celery, all crops are projected to gain high-suitability lands (i.e., score ≥ 0.75) under the SSP2 and SSP3 scenarios. Under the SSP5 scenario, cabbage, cauliflower, and lettuce are expected to have an even more substantial increase in suitable agricultural lands than what is projected for the SSP2 and SSP3 scenarios. In contrast, broccoli, kale, and strawberries are projected to reach their peaks in the SSP5 scenario in terms of total area of high-suitability land in the mid- to late-century, and these peaks are followed by steady declines occurring from the peak period to 2100. Celery exhibits a different trend than what is observed with the other crops, as its peak occurs in 2021with declines to zero by mid-century seen in three climate scenarios.

Figure 2. Agricultural suitability for broccoli in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.

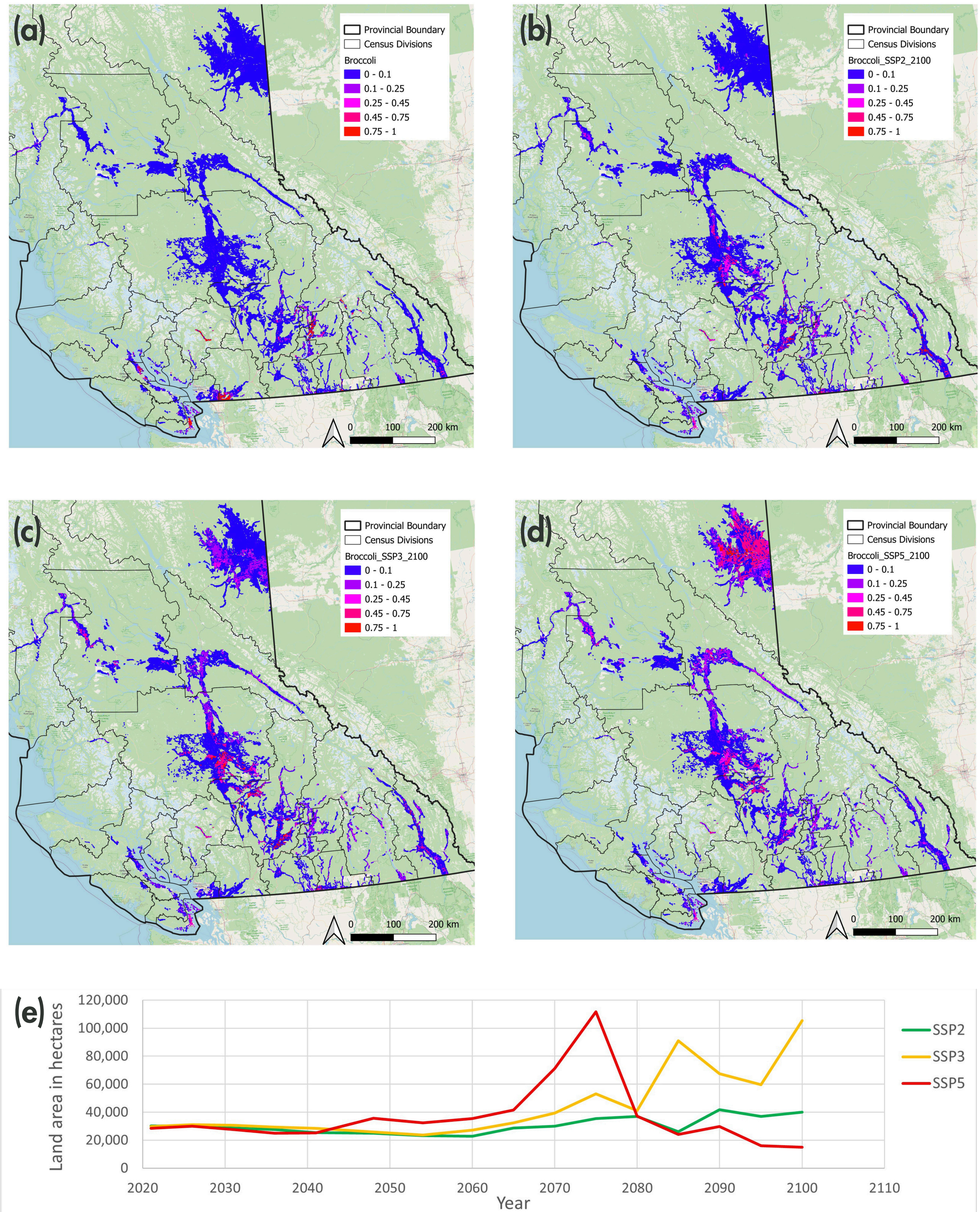


Figure 3. Agricultural suitability for cabbage in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.

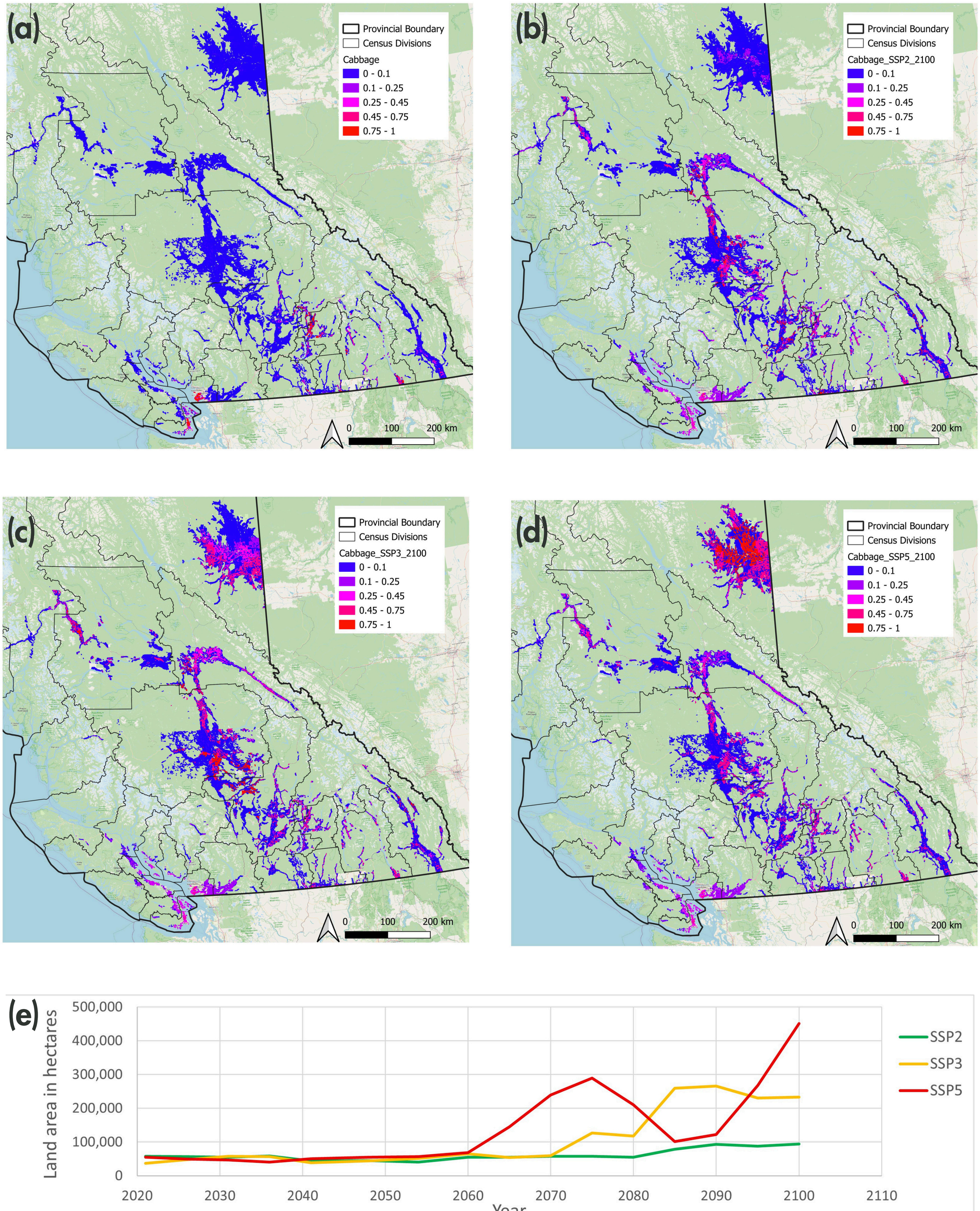


Figure 4. Agricultural suitability for cauliflower in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.

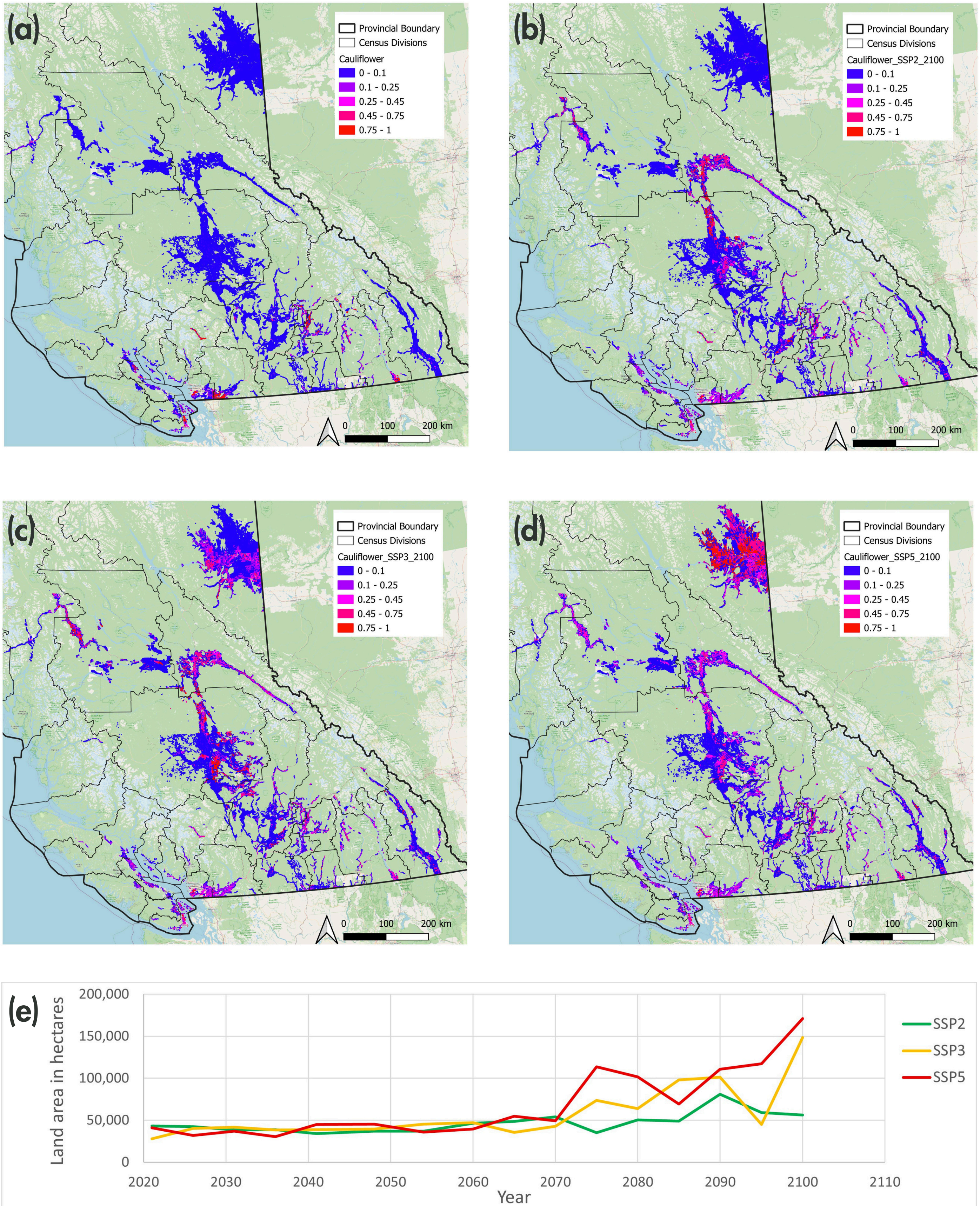


Figure 5. Agricultural suitability for lettuce in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.

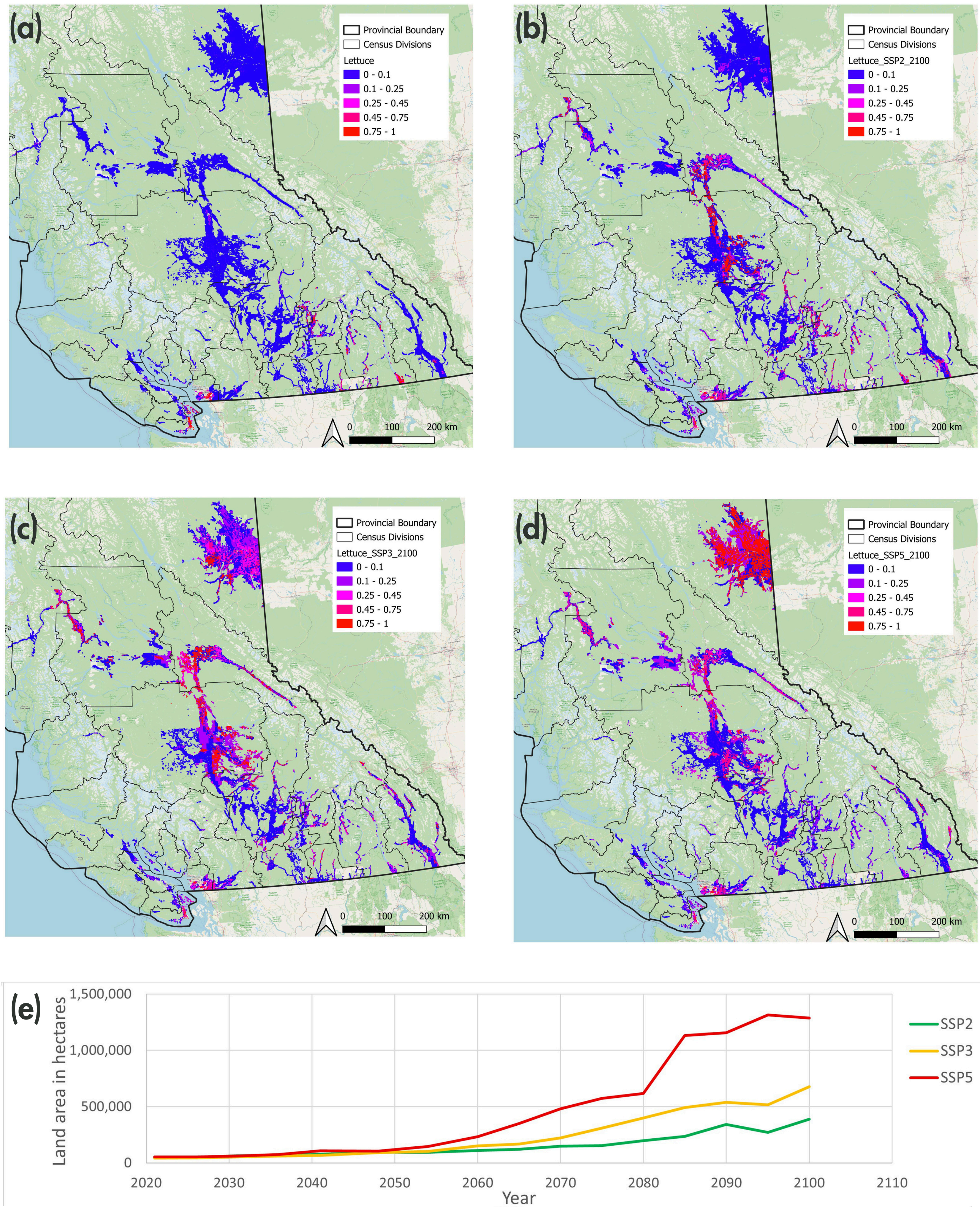


Figure 6. Agricultural suitability for strawberry in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100

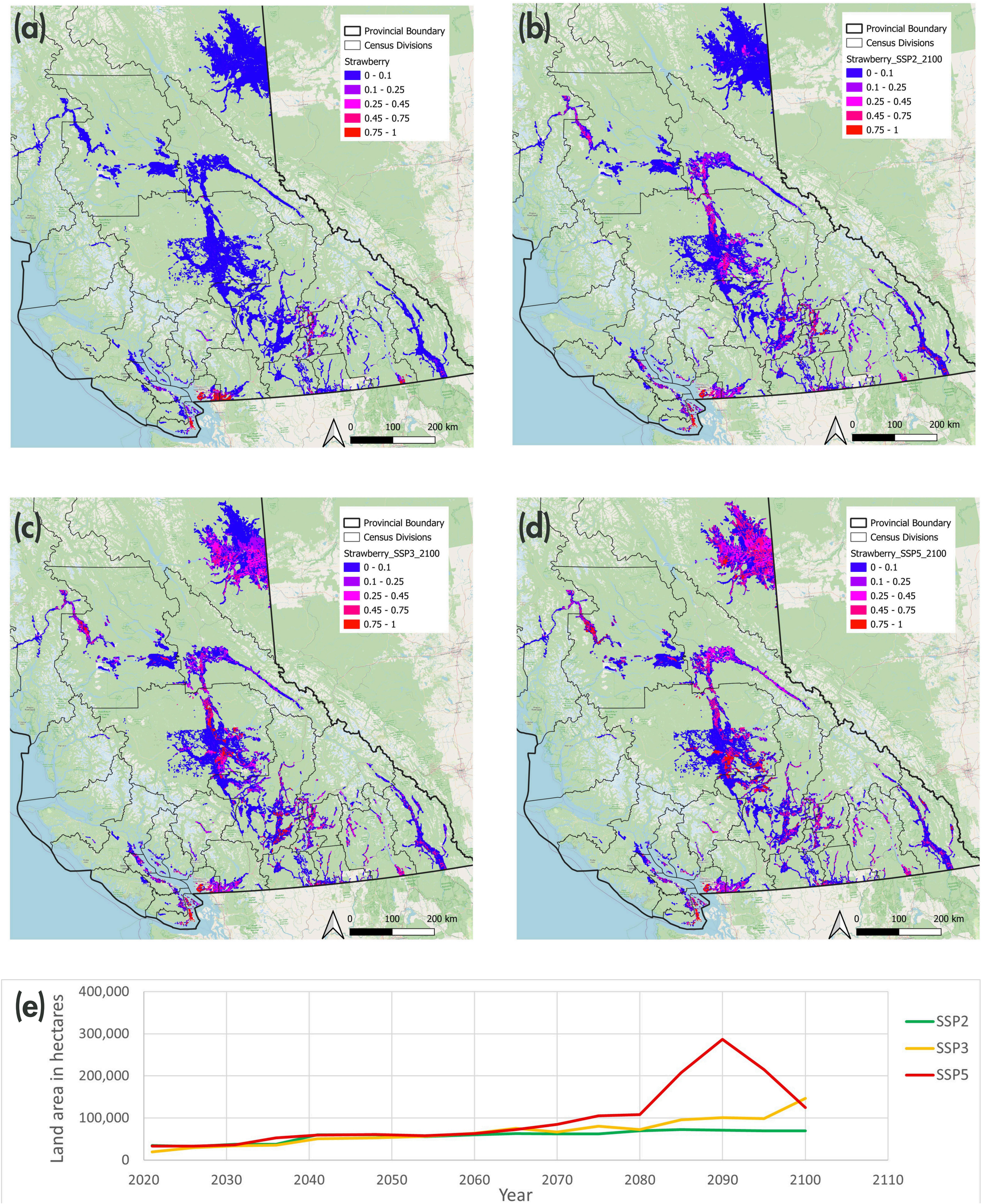


Figure 7. Agricultural suitability for kale in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.

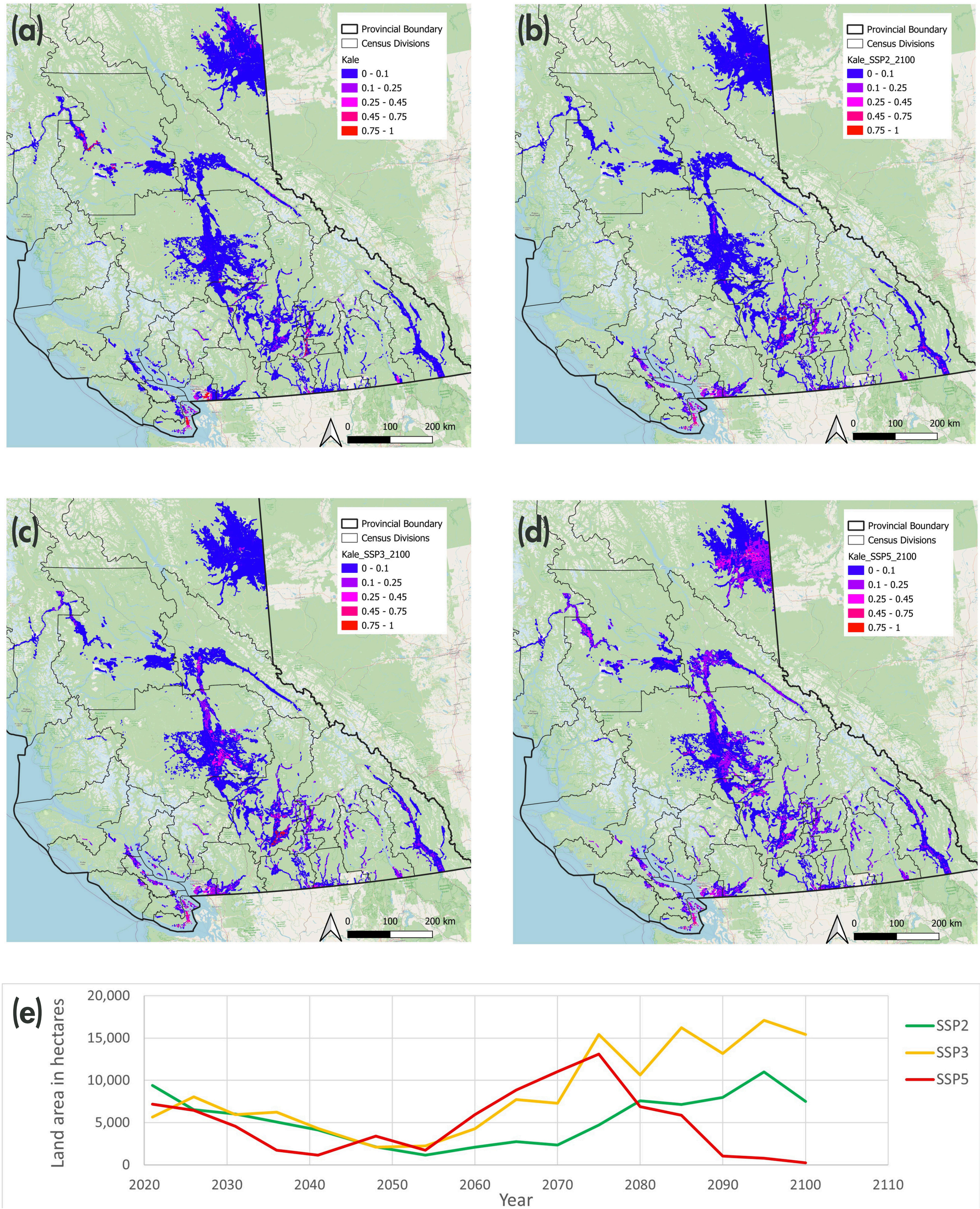
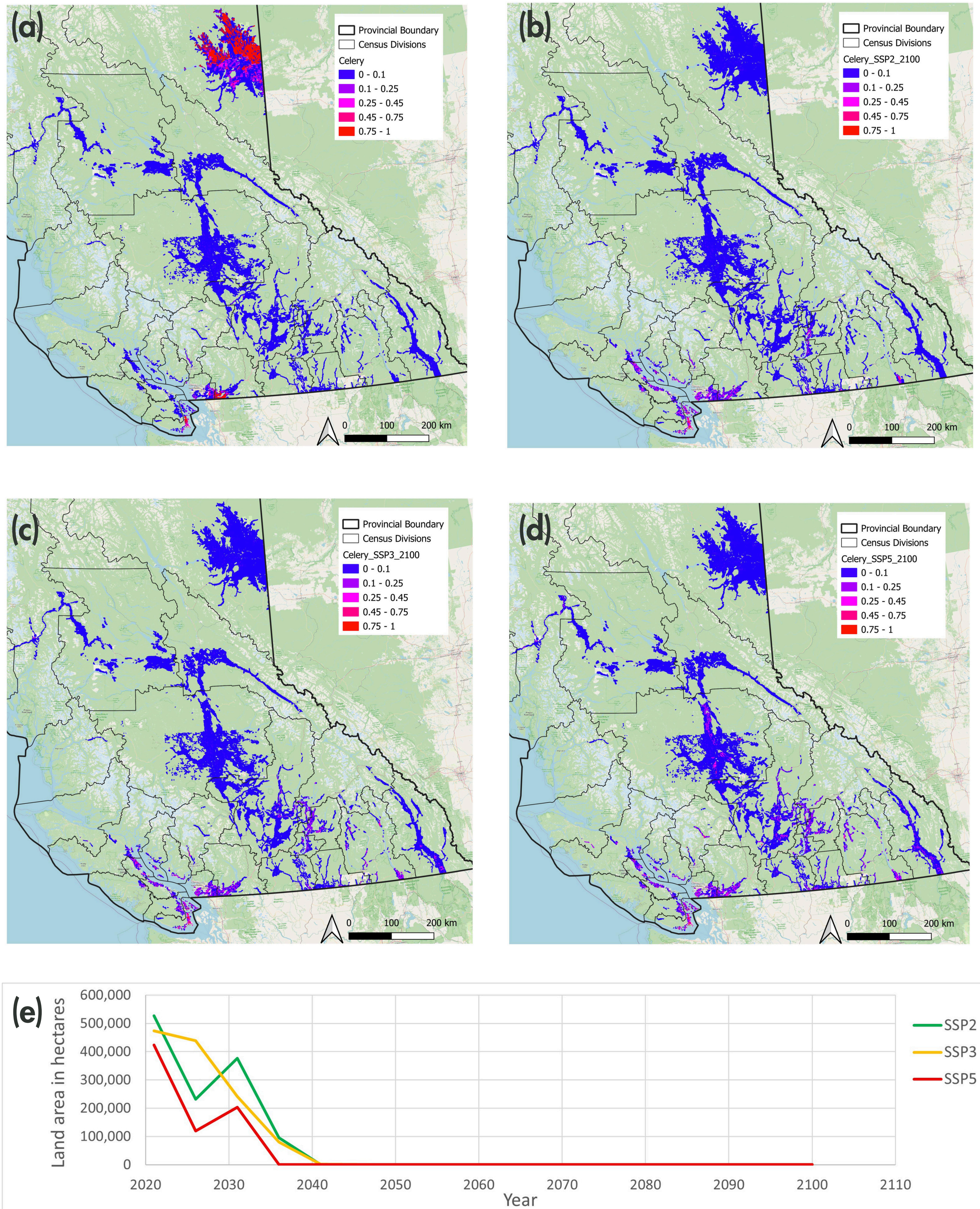


Figure 8. Agricultural suitability for celery in (a) 2021 and in 2100 for (b) SSP2, (c) SSP3, and (d) SSP5, and (e) total high-suitability land (score ≥ 0.75) from 2021 to 2100.



4.2 Model performance and selection

The performances of the four machine learning models (i.e., random forest, gradient boosting, support vector machine, and artificial neural networks) were assessed using accuracy and ROC-AUC as evaluation metrics. Table 2 provides a summary of the results for both the training set (in the SR column) and the testing set (in the PR column). Among the seven crops analyzed, the random forest and gradient boosting models consistently delivered the strongest performance, with AUC values of 0.97 or higher and testing accuracies of 0.95 or higher. The support vector machine and artificial neural network models demonstrated noticeably weaker performance, particularly for crops such as broccoli, cauliflower, kale, and strawberry, where testing accuracy frequently fell below 0.9. For example, in the case of broccoli, the random forest and gradient boosting models respectively achieved testing accuracies of 0.95 and 0.96 and AUC values of (for both) 0.98, whereas the support vector machine and artificial neural network models both had accuracy values of 0.88 and AUCs of (respectively) 0.93 and 0.92.

Table 2. Model performance metrics, Accuracy (Acc.) and ROC-AUC (AUC) for crop suitability classification across seven crops. Results are shown for both training (SR) and testing (PR) datasets for RF, GB, SVM, and ANN models.

Model	Random Forest				Gradient Boosting				Support Vector Machine				Artificial Neural Networks			
	SR		PR		SR		PR		SR		PR		SR		PR	
Crop	Acc.	AUC	Acc.	AUC	Acc.	AUC	Acc.	AUC	Acc.	AUC	Acc.	AUC	Acc.	AUC	Acc.	AUC
Broccoli	0.98	0.99	0.95	0.98	0.98	0.99	0.96	0.98	0.88	0.94	0.88	0.93	0.88	0.93	0.88	0.92
Cabbage	0.98	0.99	0.97	0.99	0.99	0.99	0.97	0.99	0.96	0.99	0.93	0.98	0.95	0.98	0.92	0.97
Kale	0.99	0.99	0.98	0.99	0.99	0.99	0.98	0.99	0.93	0.97	0.93	0.97	0.89	0.95	0.89	0.95
Celery	0.99	0.99	0.97	0.98	0.99	0.99	0.97	0.98	0.92	0.95	0.88	0.95	0.92	0.96	0.9	0.95
Cauliflower	0.98	0.99	0.96	0.98	0.98	0.99	0.96	0.98	0.88	0.94	0.84	0.94	0.89	0.94	0.83	0.93
Lettuce	0.99	0.99	0.98	0.99	0.99	0.99	0.98	0.99	0.94	0.98	0.93	0.97	0.94	0.98	0.95	0.98
Strawberry	0.98	0.99	0.95	0.97	0.97	0.99	0.95	0.97	0.91	0.95	0.89	0.94	0.91	0.95	0.88	0.95

The Monte Carlo simulations on the different crop-model combinations showed that the random forest and gradient boosting models consistently outperformed support vector machine and artificial neural network models across all crops in terms of averages for both accuracy and AUC. The support vector machine and artificial neural network models achieved an average accuracy score below 0.9 for some crops (i.e., broccoli, celery, cauliflower, and strawberry), whereas the random forest and gradient boosting models achieved accuracies of 0.94 or higher for all seven crops in all 1,000 iterations of the Monte Carlo simulation process.

The agricultural suitability maps presented in this report were developed using the results of the random forest and gradient boosting models, as these models consistently demonstrated high robustness, accuracy, and reliability. An ensemble approach was applied by averaging the agricultural suitability values generated by both models. The support vector machine and artificial neural network models ultimately were not used in the development of the agricultural suitability maps due to their comparatively lower accuracy and AUC values.

5. Discussion

This research demonstrates the value of spatial prediction models for supporting climate adaptation planning and policy in the agricultural sector. Applying the model to British Columbia revealed how agriculture for different field crops may benefit from an increase in suitable cultivation areas or experience challenges due to a loss of suitable spaces, depending on the world's future climate trajectory (i.e., lower versus higher greenhouse gas emissions). Outcomes from the model indicate shifts in land suitability for agriculture will occur across British Columbia throughout the 21st century, with a northward shift in suitable lands seen for most of the crops examined in this study.

Some crops are projected to benefit from climate change-related increases in temperature, precipitation, and growing season length, and these increases are projected to expand suitable agricultural land for the cultivation of these crops. In particular, models of cabbage, cauliflower, and lettuce agriculture show a general trend of gaining more suitable land throughout the century, with the most substantial gains seen with the SSP5 scenario. These crops thrive under warmer conditions, and the expansion of suitable lands is the result of a northward shift of favourable agro-climatic zones. In related research, Pearson et al. (2015) reported that a temperature increase of up to +3°C could accelerate the lettuce growing period by approximately 20%. Similarly, studies by Rahman et al. (2007) and Wurr et al. (2004) found that rising temperatures to an optimum degree under climate change scenarios can significantly reduce the maturity period after curd initiation for winter cauliflower. These findings align with the results of this study, namely the results that indicate warming temperatures in various places (particularly northern places) across British Columbia will result in an expansion of suitable areas for cultivating cauliflower.

The northward shift in suitable agricultural land presents a significant opportunity for farmers in the northern regions of the province. The models employed in this study were trained on agricultural data on the locations where crops are currently grown and using present-day climate data to characterize what makes for favourable conditions for successful crop cultivation. As these conditions shift geographically due to climate change, the models predict that regions with larger ALR areas that are not currently used for agricultural production (e.g., parts of the Cariboo, Fraser-Fort George, and Peace River regions) may become suitable for crop cultivation in the coming decades. Such changes present opportunities for establishing new farms and attracting new farmers to the industry.

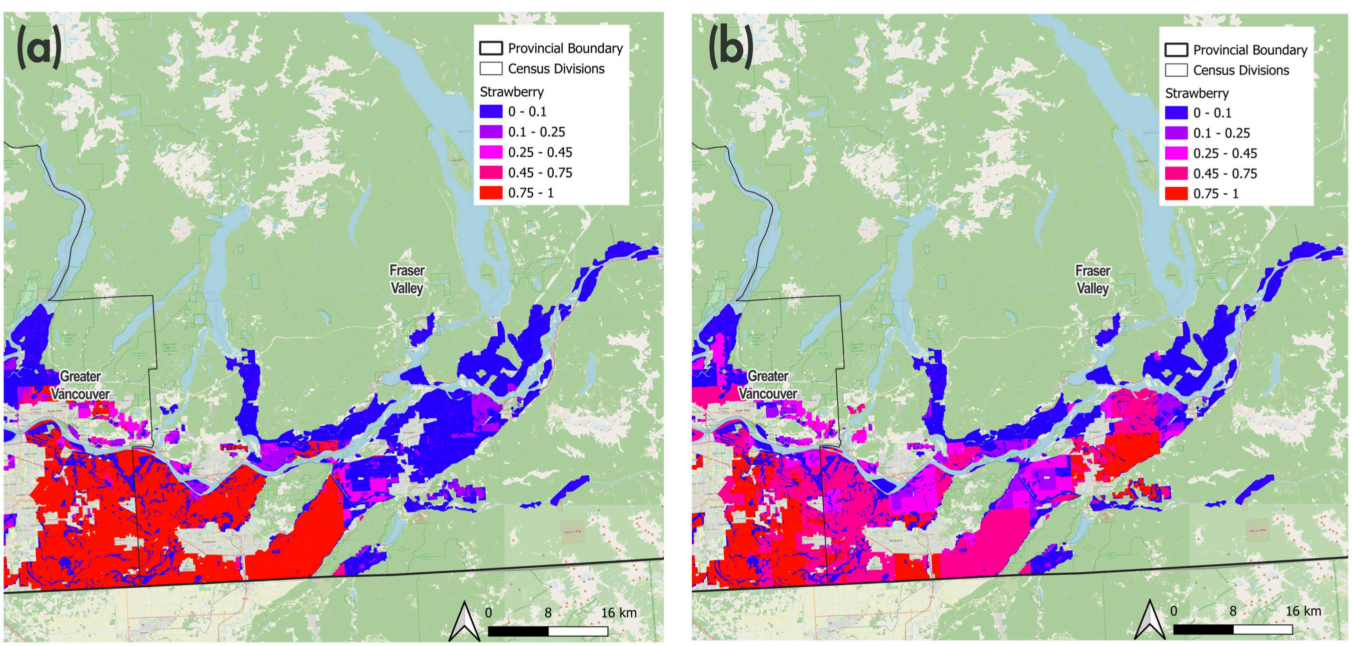
Similar to the models of cabbage, cauliflower, and lettuce agriculture land suitability, the models of broccoli, kale, and strawberry agriculture also show gains in suitable land under the SSP2 and SSP3 scenarios, driven by warming and extended growing seasons. However, being cool-season crops, the high-emissions scenario (i.e., SSP5) projects that total area of suitable land for these crops may peak by mid- or late-century before declining significantly toward the end of the century. Such reductions in a high-emissions climate future are predicted to occur due to increases in heat stress and changes in precipitation patterns that compromise conditions for optimal growth. For instance, broccoli is a cool-season crop that performs best under moderate temperatures (Siomos et al., 2022), and while it can adapt to moderate warming and elevated CO_2 levels, broccoli agricultural productivity declines under extreme warming conditions such as those projected in SSP5 (Pineda et al., 2024). Similarly, both strawberries and kale are cooler-climate crops (Husaini & Xu, 2016; Kornecki & Balkcom, 2020). The optimal temperature for strawberry is around 20 °C (Kimura 2008), while temperature above 30 °C decreases leaf growth and leads to lower yields (Menzel 2024). Although expansions in suitable agriculture land are initially observed in the first half of the century for the SSP5 scenario, the continued temperature rise and climatic variability in the scenario eventually result in a continued loss of suitable spaces by 2100, particularly in southern and lower-elevation regions.

Celery is the only crop that exhibited a complete loss of suitable agricultural land across all climate scenarios. These model outcomes may be due to the optimal conditions for the crop being cooler and temperate conditions (Li et al., 2022), which are projected to decrease across the province in a changing climate. This being said, these findings may also be due to data limitations and issues related to model accuracy. According to the 2021 Census of Agriculture, celery is grown in only 8 hectares in British Columbia, with one-fourth of this space located in the cooler region of Peace River. The models in this study were trained on these limited data, which perhaps resulted in agricultural suitability for celery being narrowly associated with the climatic conditions of these specific cooler locations. As warming continues, the regional climates in which celery is currently farmed in the province may no longer exist in British Columbia, leading the models to predict a complete loss of agricultural suitability for celery under future climate scenarios.

Under moderate warming conditions (SSP2), regions in southwest British Columbia, including the Fraser Valley, Greater Vancouver, and the Capital Region District, are projected to remain suitable for crop production. Additionally, areas in central British Columbia that are currently limited by shorter growing seasons and cooler temperatures are expected to become increasingly viable for new crops and agricultural opportunities in a moderate warming future. However, under more severe climate change scenarios (i.e., SSP3 and SSP5), a pronounced northward shift in agricultural suitability is observed, where current agriculturally active regions in southern areas face reductions in suitable lands for crops that are currently grown in these places. These potential shifts in agricultural land suitability patterns have important implications for long-term planning and policy in terms of considering how to design and implement strategies and policies for land-use transitions in regions that are not currently used for intensive agriculture but have the potential to be highly productive. For instance, the Peace River, Cariboo, and Thompson-Nicola regions currently have limited agricultural activity for the crops examined in this study; however, the models project that increases in agricultural land suitability for these crops may occur in the next decades, particularly in higher greenhouse gas emissions scenarios like SSP3 and SSP5.

Within the upcoming decade, areas located near and adjacent to current production areas (which may currently be agriculturally limited by climate conditions) are projected to become more favourable for some crops in the next few years as climate conditions shift. For example, suitable lands for strawberries in the SSP2 scenario will shift from the southwestern part of the Fraser Valley to the northeastern part of the ALR lands within the same region in less than a decade (see Figure 9).

Figure 9. Example of shifts in suitability of lands for strawberry in a short period from 2021 (a) to 2029 (b) in SSP2



Importantly, while the models account for key climate and land quality conditions, they do not capture all constraints on agricultural expansion. Proximity to markets, labour availability, infrastructure access, agri-tech adoption policies, and many other socioeconomic and cultural factors influence whether these newly suitable lands are realistically used for crop production. In addition, while this work focuses on the effects of climate change on conditions for agricultural sustainability, it also provides insights into broader questions about agri-tech, nutritional composition, and supply vulnerability. These considerations were not included in the model as variables; however, they were used to identify the crops used in the agricultural suitability analyses.

The case study crops were (in part) selected based on their potential to be grown via CEA. Accordingly, the outcomes from this modelling exercise can be used to inform policies and programs for incentivizing CEA, particularly in areas that are anticipated to experience reductions in suitable agricultural land. As noted by Newman et al. (2023) and Glaros et al. (2024), CEA can enhance food system resilience in that it allows for the production of crops in facilities that are protected from climate change and extreme weather events. In regions that currently have high agricultural activity but are projected to see losses in suitable land (e.g., the Fraser Valley), CEA offers a strategy for (at least in part) supporting the continuation of the local/regional agricultural industries, and strategies for incentivizing the growth of CEA operations potentially could be designed to specifically target these regions.

It is important to recognize that this research is limited in that it focuses on only seven crops. The crops were selected for this analysis due to being vulnerable to trans-boundary supply chain disruptions and having the potential to be cultivated indoors using CEA. However, these crops are not necessarily the most economically important for certain regions in British Columbia, such as blueberries and cranberries in the Fraser Valley or tree fruits in the Okanagan. The model can be adapted and applied to other crops in different regions to support their agricultural planning and policy using different selection criteria depending on the local agricultural priorities and needs (e.g., economic value to the local agriculture industry, cultural significance, etc.).

6. Implications for Agricultural Planning and Policy

Modelling the potential future agricultural suitability under different climate scenarios provides a forward-looking basis for aligning agricultural expansion and transition strategies in the face of new climate realities. The findings suggest that while current agriculturally-active regions in southern British Columbia are likely to remain viable under a moderate warming scenario (i.e., SSP2), more severe warming scenarios (i.e., SSP3 and SSP5) likely will decrease agricultural suitability in the south of the province due to increased temperature stress and/or shifting precipitation patterns. At the same time, longer growing seasons and warmer temperatures may offer new opportunities for cultivation in currently underutilized regions, such as parts of the Peace River, Cariboo, and Thompson-Nicola.

The following recommendations for agricultural policy and land-use planning are based on the findings of this study:

- **Support farmers and deliver farming programs in newly suitable agricultural areas.** In regions projected to gain agricultural suitability (e.g., Cariboo, Peace River, Fraser-Fort George), it is recommended to support farmers through education and training programs such as workshops and online courses, technical assistance and consultations, and on-farm research and demonstration projects. These efforts should promote climate adaptation strategies that involve shifts toward crops suited to the changing climate and new climatic conditions. Such efforts will help farmers build capacity for transitioning to new production opportunities.

- **Promote agri-tech adoption and provide agri-tech incentives to farmers in vulnerable areas losing land suitability.** In areas facing declining agricultural suitability (e.g., Fraser Valley, Capital Region), it is recommended to create targeted policies and funding programs that support farmers to adopt agri-technologies such as vertical farming, digital agriculture, and agri-genomic tools. Such policies will help to enable continued productivity on otherwise vulnerable lands. Training programs, technical support, and demonstration projects will be critical for successfully facilitating the adoption of these technologies.

- **Invest in community and regional infrastructure in newly suitable agricultural areas.** Planning and funding infrastructure in regions that are anticipated to become viable for agriculture is critical to ensure long-term sustainability. This may include building food hubs, cold storage facilities, transportation and improved market access, and digital infrastructure (e.g., broadband Internet). Early investment in communities located in emerging agriculturally-suitable regions will accelerate the transition of these regions from being potentially suitable for farming to being highly productive and agriculturally-active areas.

- **Develop community agri-tech innovation ecosystems in regions with declining agricultural suitability.** Innovation hubs, incubators, and accelerator development programs focused on agri-tech development and deployment should be established in southern regions expected to lose agricultural viability. These hubs and programs can encourage the development and dissemination of agri-tech solutions for climate adaptation. In addition, the hubs and programs would support the development of new employment pathways, as well as offer ways for affected communities to remain economically healthy despite losing conventional farming potential.

7. Conclusion and Future Work

This study demonstrated how machine learning models and spatial analyses can be applied to assess and identify future agricultural land suitability for crops across British Columbia in the face of climate change. The results revealed both risks and opportunities for future farming in the province. Under moderate warming (i.e., SSP2), many southern regions remain viable for crop production, while central and northern areas of the province see new opportunities for agriculture. Under more severe climate change scenarios (i.e., SSP3 and SSP5), increased temperature stress and changes in precipitation may reduce the agricultural suitability in currently productive and active areas, while also improving agricultural opportunities in regions such as the Peace Region and Cariboo.

The findings of this study underscore the urgency of proactive agricultural planning and investment. Climate change will not impact all regions equally, and the adaptive capacity of agricultural systems will depend on how well land use strategies, infrastructure planning, and technology adoption are aligned with these shifting agro-climatic realities. This work lays the foundation for an evidence-based approach to agricultural planning under climate uncertainty, that is, one that can inform policy, guide investment, and support producers in making informed decisions about the future of farming in British Columbia.

The integration of this modelling framework into decision-support systems can enhance planning for resilient food systems in British Columbia. However, it is important to recognize that the model used in this study is primarily built using climate, land quality, and property value data, while many other factors shape agricultural landscapes and food production systems (e.g., such as water availability, labour, market access, policy frameworks, and farm-level decision-making). Expanding the models to comprehensively incorporate socio-economic considerations such as agri-tech adoption rates, labour dynamics, proximity to processing and retail markets, and land use policy constraints would offer a more comprehensive picture of future agricultural viability. Scenario planning that includes these additional variables can support nuanced, region-specific strategies for sustainable expansion, climate adaptation, and agri-food innovation.

It is also important to note that although agri-tech cultivation potential, nutritional composition, and supply vulnerability were included in the study as crop selection criteria, these considerations were not incorporated into the model as variables. Future modelling studies can use a more comprehensive approach that includes these variables (following Mehrabi, 2023). For example, Mason D'Croz et al. (2019) modelled global fruit and vegetable availability under climate stress, revealing potential nutritional shortfalls in vulnerable regions. These models reveal the cascading effects that localized climate impacts can have on global food systems, particularly when trade dependencies are high.

Another important area for future research is the evaluation of individual variable importance in influencing crop suitability outcomes. While this study used robust classification algorithms to predict suitability, it did not assess the relative contribution of each input factor (e.g., temperature, precipitation, land capability, or economic indicators) to model predictions. Understanding which variables are most influential in shaping agricultural land suitability outcomes can provide insights into the driving forces of agricultural change, which can be used to support targeted policy interventions. Future studies could employ model-agnostic techniques to quantify variable importance across multiple algorithms, thereby enhancing the interpretability and applicability of the modelling framework.

Land use change and agri-food planning are inherently complex phenomena. Future research should use this agricultural suitability assessment as a foundation for work that also considers tradeoffs associated with land use. For example, this study does not examine ecological indicators (e.g., biodiversity, carbon sequestration potential) within suitability models. Thus, if and where newly suitable lands for agriculture are present, tradeoffs may occur across land use changes and environmental performance (e.g., if land clearing for agriculture generates substantial greenhouse gas emissions) (see Hannah et al., 2020).

Finally, future research should apply the model to a wider variety of crops. Such work could use selection criteria such as identifying economically and culturally important crops for various agricultural regions across British Columbia. Creating a broader portfolio of crops to model agricultural suitability in the province will provide decision-makers and policymakers (at both provincial and local levels) with a greater breadth of information from which to make agri-food planning decisions.

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