TESE DE DOUTORAMENTO

STUDY OF GROWTH-ENVIRONMENT RELATIONSHIPS AND OPTIMISATION OF MANAGEMENT INCLUDING CLIMATIC UNCERTAINTY OF RADIATA PINE STANDS IN GALICIA

Miguel Ángel González Rodríguez

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Study of growth-environment relationships and optimisation of management including climatic uncertainty of radiata pine stands in Galicia

D. Miguel Ángel González Rodríguez

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Dr. Ulises Diéguez Aranda, Profesor titular do Departamento de Enxeñaría Agroforestal da Universidade de Santiago de Compostela

Dr. Felipe Crecente Campo, CERNA Ingeniería y Asesoría Medioambiental SL

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To my family, for taking me to the forest.

To 蓉蓉, for making a distant land seem so near.

In the forest, there was a crooked tree and a straight tree. Every day, the straight tree would say to the crooked tree, “Look at me...I’m tall, and I’m straight, and I’m handsome. Look at you...you’re all crooked and bent over. No one wants to look at you." And they grew up in that forest together. And then one day the loggers came, and they saw the crooked tree and the straight tree, and they said, “Just cut the straight trees and leave the rest." So the loggers turned all the straight trees into lumber and toothpicks and paper. And the crooked tree is still there, growing stronger and stranger every day.

Tom Waits

List of articles

This thesis summarises three articles, denoted by Roman numerals (I-III) hereunder, whose central objective was to assess the potential impact of climate change on radiata pine forests' productivity in the northwest of Spain and evaluate how this impact will influence the profitability of plantations under climate change. The accepted manuscripts of each of the articles are provided in the Appendix A. Besides of these three main articles, the work carried out in this thesis also gave place to another article focused on Scots pine productivity, which is mentioned under the heading "**Other articles**".

Main articles of the thesis

I (Study I) González-Rodríguez, M. A., & Diéguez-Aranda, U. (2020). Exploring the use of learning techniques for relating the site index of radiata pine stands with climate, soil and physiography. Forest Ecology and Management, 458, 117803. `https://doi.org/10.1016/j.foreco.2019.117803`

II (Study II) González-Rodríguez, M. A., & Diéguez-Aranda, U. (2021). Delimiting the spatio-temporal uncertainty of climate-sensitive forest productivity projections using Support Vector Regression. Ecological Indicators, 128, 107820. `https://doi.org/10.1016/j.ecolind.2021.107820`

III (Study III) González-Rodríguez, M. A., Vázquez-Méndez, M. E., & Diéguez-Aranda, U. (2021). Forecasting variations in profitability and silviculture under climate change of radiata pine plantations through differentiable optimisation. Forests, 12(7). https://doi.org/10.3390/f12070899

Other articles

- González-Rodríguez, M. Á., & Diéguez-Aranda, U. (2021). Rule-based vs parametric approaches for developing climate-sensitive site index models: a case study for Scots pine stands in northwestern Spain. Annals of Forest Science, 78(1), 23. https://doi.org/10.1007/s13595-021-01047-2

Author contribution

In the above articles, the authors' responsibilities were, according to the CRediT (Contributor Roles Taxonomy) framework:

- **Miguel Ángel González Rodríguez**: Conceptualization, Formal Analysis, Funding Acquisition, Project Administration, Software, Writing – Review & Editing, Investigation, Methodology, Validation, Visualization, Writing – Original Draft Preparation.

- **Ulises Diéguez Aranda**: Conceptualization, Formal Analysis, Funding Acquisition, Project Administration, Software, Writing – Review & Editing, Resources, Supervision.

- **Miguel Ernesto Vázquez Méndez (Study III)**: Conceptualization, Methodology, Writing – Review & Editing, Supervision.

Main articles' impact

Study	Journal	Category	JIF 2020
I	*Forest Ecology and Management*	Forestry	3.558 (Q1)
II	*Ecological Indicators*	Environmental sciences	4.958 (Q1)
III	*Forests*	Forestry	2.633 (Q1)

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The accepted manuscript of Study I is presented in the Appendix A under a CC BY NC ND 4.0 license and under the terms established by Elsevier sharing and hosting policies for accepted manuscripts.

The accepted manuscript of Studies II and III are presented in the Appendix A under a CC BY 4.0 license.

Abstract

Climate change is intended to impact forest dynamics significantly in the following decades. To proactively adapt forest management to these expected alterations, new methodologies for handling the uncertainties regarding forest growth under varying environmental conditions become necessary. The purpose of this thesis was to forecast the impact of climate change on radiata pine plantations in the northwest of Spain in terms of productivity, profitability, and silvicultural treatments. In Study I, several statistical techniques were used for predicting the site index (*SI*) of radiata pine stands using environmental predictors extracted from available raster maps. A non-linear technique, Multivariate Adaptive Regression Splines (MARS), was suggested as the best modelling alternative, explaining up to 52% of the *SI* variability. In Study II, the Support Vector Regression technique was used to predict *SI* and delimit the validity area of predictions based on the radial basis kernel. The resulting model had high predictive performance, provided robust predictions under varied climatic conditions, and included a relatively small number of predictors. Moreover, the model was able to identify areas where climatic conditions were very different from the observed and consequently regularised predictions for those areas. In Study III, silviculture under climate change was optimised for maximising the soil expectation value of a set of radiata pine plantations. The future forest productivity projections, produced by the model developed in Study II, forecasted an overall reduction in *SI* under climate change, mainly driven by increased temperatures and continentality. Consequently, the economic simulations forecasted a drop in profitability under climate change that was more intense for more pessimistic scenarios (RCP 6.0). However, the climatic projections were very varied over the set of used climate models, which led to a great dispersion in productivity and profitability predictions. From the perspective of silviculture, the most notable forecasted variation is the expected increase in optimum rotation lengths.

Keywords: climate change, site index, radiata pine, machine learning, stand growth modelling, differentiable optimisation, stand-level management, risk modelling, extrapolation

Resumo en galego

1. Introdución e obxectivos

O cambio climático supón un conxunto de alteracións da dinámica atmosférica con relevantes impactos sobre os sistemas naturais. As masas forestais, debido á súa importancia como sumidoiros naturais de carbono, son protagonistas esenciais das políticas de mitigación e adaptación ó cambio climático. Nas últimas décadas, a investigación forestal apunta ó desenvolvemento de novas metodoloxías para a xestión forestal sostible adaptada ao cambio climático. Entre os principais eixos desta tendencia de investigación están a predición de crecementos e a estimación da rendibilidade económica das masas forestais baixo diferentes escenarios posibles de cambio climático.

A previsión do crecemento forestal é unha preocupación técnica crucial para a planificación dos investimentos e a xestión forestal. O enfoque máis frecuente para esta previsión é o uso de modelos empíricos, cuxa principal vantaxe é a súa simplicidade. Porén, este enfoque conta cunha desvantaxe moi importante: ao non ser sensibles ás condicións ambientais, non poden ser empregados para proxectar crecementos do arborado nun contexto de cambio climático. A metodoloxía máis habitual nas últimas décadas para afrontar esta desvantaxe é o desenvolvemento de relacións entorno-produtividade. Isto consiste no axuste dun modelo de regresión que permita estimar un determinado indicador de produtividade forestal, derivado dun modelo de crecemento empírico, con variables ambientais, coma as climáticas. No caso das masas forestais regulares, o indicador de produtividade máis frecuente neste senso é o índice de sitio. As técnicas estatísticas empregadas para levar a cabo esta regresión tenden ser métodos supervisados de "aprendizaxe de máquina" con selección automática de variables, coma "stepwise", redes neuronais artificiais ou "Random Forest".

No contexto español, diferentes modelos de crecemento foron desenvolvidos nos últimos anos para diferentes especies, entre as cales, unha das máis relevantes, especialmente no noroeste da península, é o piñeiro radiata (*Pinus radiata* D. Don). Trátase da oitava especie arbórea máis estendida en España na actualidade, sendo a conífera máis cortada no sector madeireiro (5M m^3 de madeira en 2018). A pesar da importancia rexional da especie, os actuais modelos de crecemento dispoñibles non son sensibles ao clima, polo que non se poden empregar para predicir baixo cambio climático. No Artigo I desta teste realizouse unha primeira aproximación ao problema da predición do índice de sitio masas de piñeiro radiata en Galicia en función de variables ambientais. Malia o éxito relativo das investigacións previas sobre os modelos de entorno-produtividade, existe unha certa controversia acerca da robustez das predicións. Por exemplo, moitos modelos amosan problemas sistemáticos coma a regresión á media. Ademais, debido a que os modelos son habitualmente validados con datos estatisticamente similares aos empregados no axuste, existe unha gran incerteza acerca de como estes modelos manexan as extrapolacións. É dicir, é posible de que moitos modelos entorno-produtividade desenvolvidos estean a cometer erros significativos cando fan predicións para condicións ambientais moi diferentes das observadas, coma é o caso cando se fan proxeccións baixo escenarios futuros de cambio climático. No Artigo II desenvolveuse un método para predicir o índice de sitio de masas de piñeiro radiata tendo en conta a incerteza derivada da extrapolación, permitindo delimitar zonas nos mapas resultantes onde estas predicións eran fiables.

A predición de produtividade adaptada ó clima, por si mesma, non é suficiente para valorar correctamente os potenciais impactos do cambio climático sobre os bosques, xa que tamén é necesario estimar as consecuencias económicas das alteracións. Esta estimación económica pasa por predicir as tanto os custos da xestión forestal coma as potenciais extraccións de produtos forestais comerciais derivados das actuacións silvícolas. Estas actuacións deben estar deseñadas de acordo coa produtividade forestal estimada, a cal é sensible ao escenario climático considerado. É dicir, a silvicultura debe estar "optimizada" para satisfacer un determinado obxectivo económico tendo en conta as potenciais condicións ambientais no futuro. Tradicionalmente, esta optimización da silvicultura, tanto a nivel rodal como a nivel monte, ten sido aplicada empregando ou ben métodos de programación dinámica ou métodos de busca directa. Porén, estudos recentes apuntan aos métodos diferenciables como a alternativa máis rápida (en termos de computación) e capaz de proporcionar boas solucións empregando variables de decisión continuas, sempre e cando a función obxectivo sexa "suave". No Artigo III, realizáronse unha serie de simulacións silvícolas de rodais de piñeiro radiata en Galicia baixo diferentes escenarios climáticos empregando optimización diferenciable.

Obxectivos

Esta tese engloba tres artigos cuxo obxectivo xeral era a avaliación do impacto do cambio climático na produtividade e rendibilidade dos piñeiros radiata no noroeste de España. Os obxectivos específicos da tese foron:

- desenvolver modelos para predicir a produtividade dos piñeiros radiata en función dos motores ambientais, como o clima, o solo e a fisiografía (Artigo I);
- propoñer un método para avaliar a fiabilidade das predicións de produtividade do bosque de piñeiros radiata que permita realizar extrapolacións en futuros escenarios de cambio climático (Artigo II);
- avaliar o impacto da futura produtividade do piñeiro radiata baixo o cambio climático sobre a rendibilidade financeira e o risco das plantacións (Artigo III).

2. Materiais e métodos

Datos

A principal fonte de datos de produtividade forestal (índice de sitio) empregada nesta tese foi unha rede de parcelas de investigación establecida pola Unidade de Xestión Ambiental e Forestal Sostible (UXAFORES) da Universidade de Santiago de Compostela. No Artigo I, utilizouse todo o conxunto de 489 combinacións parcela-inventario para modelar o índice de sitio. No estudo II, só se empregou a primeira medición de cada parcela de investigación, sumando 165 observacións. Finalmente, no estudo III, un subconxunto de 128 parcelas utilizouse como suxeito para simulacións silvícolas e económicas. Os datos de preditores ambientais (fisiografía, solo, clima) empregados na tese procederon das seguintes fontes cartográficas: modelo dixital de elevacións do Instituto

Xeográfico Nacional de España, mapas de solos do European Soil Data Center, e variables climáticas dos proxectos Spain02 e Worldclim

Métodos 1: Modelos de aprendizaxe lineal para predicir o índice de sitio (Artigo I)

No Artigo I, No Artigo I, empregáronse diferentes técnicas de aprendizaxe estatística para predicir o índice de sitio en función de 43 potenciais preditores ambientais extraídos de cartografía ráster. Entre as técnicas empregadas, axustadas empregando a linguaxe de programación R, incluíronse varias estritamente lineais (LASSO, Elastic Net, PLS, stepwise, IFSR e LAR) e unha capaz de modelar relacións non lineais (MARS). De xeito xeral, a selección de variables foi levada a cabo por eliminación recursiva baseada no R^2 con validación cruzada. A avaliación final dos modelos baseouse en métricas de validación bootstrap e na visualización dos residuos e das predicións.

Métodos 2: Modelos de regularización baseados en distancias para avaliar a incerteza da extrapolación (Artigo II)

No Artigo II, empregouse a técnica de regresión por vectores de soporte con kernel de base radial para axustar un modelo de predición de índice de sitio de piñeiro radiata en función de variables climáticas. Algunhas das vantaxes desta técnica fronte a outras foron: 1) a modelización de relacións reposta-preditores non lineais complexas, 2) a modelización de interaccións entre preditores, e 3) a aplicación dunha regularización baseada en distancias. O modelo foi axustado empregando a linguaxe R. A selección de variables, a calibración de hiperparámetros e a avaliación do modelo baseáronse na maximización do R^2 en validación cruzada.

O enfoque da regularización baseada en distancias, regulada polo hiperparámetro σ, consistiu na regresión das predicións á media observada do índice de sitio en función da súa distancia euclidiana aos vectores de soporte (as observacións do conxunto de datos máis determinantes para a predición). Esta característica implicou que o modelo puido empregarse para identificar predicións para as que condicións climáticas foron moi diferentes do observado no conxunto de datos de axuste. A calibración desta regularización (σ) permitiu analizar o balance entre especificidade e xeneralidade do modelo. A proxección espacial desta idea permitiu delimitar áreas xeográficas de Galicia onde as condicións climáticas son moi diferentes das observadas nos datos de axuste e que, polo tanto, son susceptibles de xerar maiores erros preditivos ao facer extrapolacións. O análise realizado no Artigo II baseouse na comparación das superficies regularizadas e do rendemento preditivo ao longo do rango de calibración de σ par o escenario climático presente e para doce escenarios diferentes de cambio climático.

Métodos 3: Avaliación financeira das plantacións de piñeiro radiata baixo cambio climático (Artigo III)

No Artigo III, utilizouse un enfoque de optimización diferencial para prever a máxima rendibilidade e os tratamentos silvícolas óptimos para un conxunto de 128 mouteiras de piñeiro radiata baixo diferentes escenarios de cambio climático. O crecemento das masas foi simulado empregando modelos dinámicos, basados no enfoque do estado-espazo, desenvolvidos nos últimos anos para esta especie en Galicia. Os tratamentos silvícolas (claras e corta final) foron simulados empregando a intensidade (peso en número de pés por hectárea) a relación de extracción (relación entre dimensións das árbores extraídas en as árbores antes da corta) e a idade (anos). A produtividade forestal foi incluída empregando o modelo de vectores de soporte axustado no Artigo II tanto para clima presente como para un total de 22 escenarios diferentes de cambio climático (once modelos de clima para dous Representative concetration Pathways, 4.5 e 6.0). As constantes económicas necesarias para facer a simulación financeira, como os prezos da madeira en pé, e os custos de plantación e mantemento foron proporcionados pola empresa CERNA Ingeniería y Asesoría Medioambiental SL. A función obxectivo da optimización foi o Valor Agardado do Solo (VAS). A optimización levouse a cabo mediante un algoritmo de programación cuadrática secuencial en linguaxe R para o conxunto de 128 mouteiras, 22 escenarios de clima, tres tasas de desconto (1%, 3%, e 5%) e programas silvícolas de 0, 1 e 2 claras. Unha vez realizadas as simulacións, comparáronse as variacións en produtividade en rendibilidade medias entre as condicións climáticas presentes e futuras, así como a dispersión das proxeccións para os diferentes escenarios de cambio climático.

3. Resultados e discusión

Predición do índice do sitio

Entre os modelos axustados no Artigo I, a intensidade da selección de variables foi variada. Algunhas técnicas produciron modelos máis sinxelos e interpretables, coma LASSO, PLS e MARS, mentres que outras, coma LAR e Elastic Net, conduciron a modelos con moitos preditores. En canto ó rendemento aparente, o mellor modelo foi MARS, explicando o 52% da variabilidade do índice de sitio. O rendemento en validación deste modelo foi lixeiramente menor que outras técnicas, conducindo a unha maior relación de sobreaxuste. Porén, tendo en conta tanto o rendemento dos modelos coma a busca da parmisonia, o modelo MARS foi considerado a mellor alternativa para modelar o índice de sitio en función de variables ambientais. Ademais, a variabilidade das predicións xeradas co modelo foi moi semellante á observada, mentres que noutras alternativas (LASSO, PLS) esta variabilidade foi moito menor, denotando unha forte regresión á media. O modelo de vectores de soporte con base radial desenvolvido no Artigo II incluíu soamente catro preditores bioclimáticos: temperatura media anual, rango diurno medio, ratio de isotermalidade e temperatura media do mes mási frío. En canto ó rendemento aparente, este modelo explicou o 56% da variabilidade do índice de sitio cun erro relativo do 10%. En xeral, o rendemento dos modelos axustados nos Artigos I e II estivo dentro do rango doutros modelos desenvolvidos para outras especies noutras rexións, polo que se considerou que os resultados da predición do índice de sitio foron satisfactorios. Sen embargo, as diferencias entre rendemento aparente e de validación destes modelos suxiren a necesidade de recoller datos complementarios para avaliar en profundidade a robustez das predicións. A maior idoneidade dos modelos MARS e SVR en comparación coas técnicas lineais empregadas revelou que a inclusión de formas non lineais é necesaria para predicir o índice de sitio en función de variables ambientais de xeito eficiente. Neste senso, SVR destacou especialmente por, a diferencia de MARS, ser capaz de modelar interaccións entre preditores. Ambas técnicas produciron predicións de índice de sitio, para o conxunto de datos de axuste, que non estaban regresadas á media observada, como si aconteceu co modelo LASSO do Artigo I. A interpretación ecolóxica dos modelos desenvolvidos semellou coherente. Tanto no caso de MARS coma no caso do modelo SVR. En relación a MARS, os parámetros das tres variables de orientación incluídas no modelo mostraron un efecto positivo da orientación oeste no índice de sitio, que pode deberse ao significativo efecto orográfico que ten lugar no territorio. As variables relacionadas coa calor/enerxía tiveron un impacto positivo no índice do sitio, o que é coherente coas necesidades térmicas e fotosintéticas para o crecemento das árbores. Aínda que en estudos previos se atopou unha influencia positiva das precipitacións anuais no índice de sitio do piñeiro radiata, nesta investigación atopouse o contrario, tendo p termo dereito desta esta variable (por encima de 1176 mm) un coeficiente negativo. A principal explicación diso é que, unha vez alcanzado o punto de corte de 1176 mm de precipitacións anuais, o aumento das precipitacións non contribúe de xeito significativo á calidade de estación, mais a alta correlación existente entre precipitacións e altitude pode levar a correlacións positivas artificiais entre as precipitacións e as variables asociadas a estrés por xeadas. A temperatura media do mes máis frío tivo un termo esquerdo negativo e un dereito positivo, definindo un mínimo aproximadamente ao medio do seu rango. Isto pódese explicar a través do efecto de "refrescado", que foi amplamente estudado para outras especies de piñeiros. Así, o termo esquerdo representou sitios onde as temperaturas invernais son demasiado baixas para o crecemento das árbores, pero o suficientemente cálidas como para unha taxa de respiración significativa que poida provocar estrés no balance de carbono. Os catro preditores incluídos no modelo SVR son variables relacionadas coa temperatura. Malia que a ausencia de preditores de precipitación no modelo pode parecer contraria a algúns estudos previos, outros estudos xa apuntaron a que a produtividade do piñeiro radiata non era sensible ás precipitacións nas zonas atlánticas de España. A relación entre os catro preditores e o índice de sitio foi pouco uniforme, o que revela o predominio de relación non lineais e interaccións entre preditores. De xeito similar ao observado no modelo MARS do Artigo I, a temperatura media do mes máis frío posuíu unha influencia negativa no índice de sitio, o que podería explicarse a través do estrés no balance de carbono debido á intensa respiración ocasionada por temperaturas invernais elevadas.

Extrapolación da produtividade forestal

No Artigo I, observouse que LASSO e PLS produciron predicións moi regresadas á media. Aínda que o modelo MARS non posuíu este problema para as predicións no conxunto de datos observados, o seu mecanismo de extrapolación lineal resulta pouco conveniente para facer predicións baixo escenarios ambientais moi diferentes do observado. Este inconvenientes foi aparentemente superado polo modelo SVR de base radial desenvolvido no Artigo II. O mapa de índice de sitio predito por este modelo para o clima presente amosou estatísticos semellantes ás observadas mais cun rango de variación lixeiramente superior, o que significa que o modelo permitiu extrapolar fóra do rango observado, en contraste con outros modelos de aprendizaxe desenvolvidos noutros estudos previos. Non obstante, nos mapas de índice de sitio predito para clima futuro con σ óptimo (= 0,69), a variabilidade das predicións foi, en xeral, moi baixa. Por exemplo, co modelo de clima GFDL-CM3 os valores de índice de sitio oscilaron entre 18,9 e 19,9 para RCP 8.5. Isto revelou que a intensidade da regularización era moi variable en diferentes escenarios climáticos, o que era consistente coas diferenzas existentes entre as proxeccións climáticas e as condicións incluídas polo conxunto de datos de axuste. Para o caso do clima actual, a superficie regularizada estimada usando σ óptimo foi aproximadamente o 60% do territorio. A maioría destas zonas altamente regularizadas concentráronse na zona costeira atlántica (moi temperada e húmida) e nas serras montañosas do sueste (con forte influencia mediterránea e / ou alpina), o que é coherente coas diferenzas climáticas coñecidas entre esas áreas e a extensión comprendida polas mesuradas. parcelas de investigación (clima Csb). Este feito pode demostrar a coherencia climática do enfoque de regularización baseado en distancias para delimitar áreas homoxéneas en termos de posibles erros de extrapolación. En canto ao clima futuro, as predicións empregando σ óptimo para RCP 8.5 foron máis regularizadas que as do escenario RCP 2.6, dando conta da dinámica diverxente do clima futuro con respecto ás concentracións actuais de gases de efecto invernadoiro. Por exemplo, o modelo de clima GFDL-CM3 produciu as superficies regularizadas de ata o 99,1% do territorio para RCP 2,6 e o 99,8% para RCP 8,5. En xeral, a elevada proporción de áreas regularizadas revelou que as condicións climáticas existentes na maioría dos territorios (e tamén en escenarios futuros) poden ser demasiado diferentes ás observadas no conxunto de datos de axuste para ser obxecto de predicións fiables de índices de sitio. Con todo, a recalibración de σ premitiu mitigar a alta especificidade deste modelo. A redución do valor de σ conduciu a unha caída do rendemento preditivo xunto cunha redución das superficies regularizadas e a conseguinte mellora na capacidade de xeneralización do modelo. Por exemplo, para $\sigma = 0{,}21$, as superficies regularizadas para clima presente reducíronse do 60% ao 36%, mentres que, no caso dos mapas climáticos futuros, alcanzou un valor mínimo do 48% (para o modelo MPI-ESM-LR baixo RCP 2.6). En resumo, a estratexia de regularización baseada na distancia do modelo SVR permitiu facer predicións robustas e proporcionou un criterio eficaz para delimitar a área de validez do modelo, descartando todas as áreas con condicións climáticas moi diferentes do conxunto de datos de axuste e para as cales os erros preditivos poderían ser demasiado incertos.

O impacto potencial do cambio climático sobre a produtividade e a rendibilidade

Os modelos de clima futuro considerados no Artigo III prediciron, de media, un incremento dos preditores climáticos excepto dun, a isotermalidade. O maior cambio foi o da temperatura media do mes máis frío, que aumentou un 40% con respecto ás condicións anteriores. As predicións de índice de sitio, feitas co modelo desenvolvido no Artigo II, conduciron a unha redución da produtividade baixo cambio climático, dende 20,8 m de media observada en clima presente ata 17,3 m de media para RCP 6.0. Consecuentemente, as simulacións económicas con estas produtividades reflectiron unha notable redución do VAS, con perdas relativas de rendibilidade do 15% -64% para RCP 4.5 e 22% -89% para RCP 6.0, fortemente dependentes da taxa de desconto. Esta perda observada de produtividade e rendibilidade estivo en consonancia cos resultados doutros estudos previos sobre masas de piñeiros de Europa. A elevada variabilidade nas proxeccións dos modelos de clima futuro conduciu a unha notable dispersión nas predicións tanto de produtividade como de rendibilidade. Como consecuencia desta dispersión, existiron escenarios con perdas de rendibilidade moito maiores, de ata o 47% -142% para RCP 4.5 e do 55% -156% para RCP 6.0. Esta dispersión suxiriu a necesidade de avaliar e comprender en maior profundidade os modelos de clima empregados para facer as proxeccións en futuros estudos.

Silvicultura óptima baixo cambio climático

No que se refire aos programas silvícolas simulados no Artigo III, os número óptimo de claras foi unha en case todas as simulacións. As intensidades e relacións de extracción das claras foron pouco sensibles tanto ao clima como ás taxas de desconto. As principais diferenzas nos programas silvícolas entre escenarios climáticos foron as idades de execución das claras e da corta final. Baixo cambio climático, especialmente no caso do RCP 6.0, o descenso de produtividade conduciu a un incremento da duración das quendas óptimas. Con respecto ás simulacións de silvicultura insensible ao clima, a aplicación de programas optimizados para clima presente a escenarios de clima futuro conduciu a perdas de rendibilidade (dun 2% -19% do VAS para RCP 4.5, e do 3%-39% para RCP 6.0) dependentes da taxa de desconto. Isto último reflectiu a potencial utilidade da optimización silvícola sensible ao clima para mitigar as perdas de rendibilidade ocasionadas polo cambio climático. Porén, ao depender da taxa de desconto, este efecto mitigador estivo fortemente condicionado pola apreciación do valor do tempo.

4. Conclusións

No Artigo I, empregáronse varias técnicas estatísticas para predicir o índice de sitio (*SI*) de rodais de piñeiro radiata empregando preditores ambientais extraídos de mapas ráster. Unha técnica non lineal, Multivariate Adaptive Regression Splines (MARS), suxeriuse como a mellor alternativa de modelado, explicando ata o 52% da variabilidade do *SI*.

No Artigo II, a técnica de regresión por vectores de soporte foi empregada para predecir o *SI* e delimitar o área de validez das predicións con base no kernel de base radial. O modelo resultante tiña un alto rendemento preditivo, proporcionou predicións robustas en condicións climáticas variadas e incluíu unha cantidade relativamente pequena de preditores. Ademais, o modelo foi capaz de identificar as áreas onde as condicións climáticas eran moi diferentes ás observadas e, polo tanto, regularizaron as predicións para esas áreas.

No Artigo III, a silvicultura baixo o cambio climático optimizouse para maximizar o Valor Agardado do Solo dun conxunto de plantacións de piñeiro radiata. As proxeccións de produtividade forestal futura, producidas polo modelo desenvolvido no Artigo II, prognosticaron unha redución global do *SI* baixo o cambio climático, principalmente impulsada por un aumento das temperaturas e da continentalidade que foi máis intenso para escenarios máis pesimistas (RCP 6.0). Non obstante, as proxeccións climáticas foron moi variadas ao longo do conxunto de modelos climáticos usados, o que levou a unha gran dispersión nas previsións de produtividade e rendibilidade. Desde a perspectiva da silvicultura, a variación prevista máis notable é o aumento esperado na duración da quenda óptima.

Contents

1 Introduction and objectives

1.1 Introduction

1.1.1 Climate change and forests

Climate change encompasses a range of variations in climatic characteristics attributed, directly or indirectly, to human activity, regardless of the natural climate variability (UNFCCC, 1992). The sources of these variations are human activities that entail greenhouse gas emissions, thus impacting global atmosphere composition, such as the use of fossil fuels, intensive agriculture, and deforestation. Many recent studies have highlighted the alarming increasing trend in global temperatures caused by anthropogenic greenhouse gases emissions. The 5th Assessment Report of the Intergovernmental Panel on Climate Change (Allen et al., 2014) estimated an atmospheric and oceanic temperature increase since 1950 of 0.85 °C on average, which is unprecedented in recent millennia. Moreover, the existing climatic simulations for the rest of the 21^{st} century (Taylor et al., 2012) forecast more pronounced oncoming variations, which will be intensely dependent on the success of climate change mitigation policies.

The recent consequences of climate change on natural systems have already become noticeable. Among these impacts, the increase of sea level (up to 0.2m on average since 1900) and the reduction of ice surfaces (e.g. ∼0.4% of yearly reduction in Arctic sea-ice since 1980) are the most extensively reported (Allen et al., 2014). In addition, the early effects of climate change on flora (Hellmann et al., 2008; De Boeck et al., 2019), animals (Bradshaw and Holzapfel, 2010) and human health (Haines, 2004) are also under study. Moreover, climate change might also have relevant consequences on the economy, as several studies (Tol, 2009; Du et al., 2017) have alerted about the increase of financial and social risks derived from global warming, especially if mitigation policies are not carefully implemented.

Forest ecosystems play a crucial role in the global warming process, as they are important reservoirs of carbon dioxide (Moomaw et al., 2020). For this reason, climate change mitigation strategies tend to focus on avoiding deforestation (Shukla et al., 1990) and promoting protective forest management practices (Anderson et al., 2011) that reduce emissions and improve carbon sequestration. However, regardless of the impact of human activities on forests, climate change is intended to shift forest dynamics in the following decades (Bontemps and Bouriaud, 2014). Productivity and species suitability areas are expected to change significantly, with very varied results across different regions (Lindner et al., 2008; Bussotti et al., 2015; Thurm et al., 2018). These changes might compromise the ability of forest ecosystems for producing goods and services, which might lead to socioeconomic conflicts, such as scarcity in timber supply chains (Brecka et al., 2018) and food and energy shortages in rural communities (Sonwa et al., 2012). Because of these risks, scientific research in the field of climate-aware forest modelling has become an essential cornerstone for the development of forest management strategies that provide climate change adaptation and reduce the potential negative impacts of global warming (Maracchi et al., 2005).

1.1.2 Predicting forest productivity in a changing environment

Forecasting forest growth is a primary technical concern for the planning of forest investments and management. Over the years, forest research has addressed this technical necessity by resorting to a broad spectrum of different modelling approaches, among which empirical models are the most recurring alternative (Pretzsch, 2009, p. 33). Their prevalence over other approaches, such as process-based models, is mainly due to their simplicity and ease of use, especially in input requirements. This advantage is of particular importance when models have to be frequently used for practical forest management by non-technical users, as it is the case of the small-scale forestry context in the NW of Spain (Robak et al., 2012).

However, over the last decades, climate change has brought the major disadvantage of empirical models to light: their lack of *climate-sensitiveness*. Admittedly, the primary scientific concern for using these approaches is the lack of directly modelled relationships between growth and environmental conditions. As empirical models are essentially built upon observed past growth measurements, they rely on the assumption that future growth will be similar to past growth. In other words, empirical models assume that forest productivity is constant and, consequently, that the environmental conditions that determine tree growth, such as climate, cannot change (Vanclay and Skovsgaard, 1997). Though in terms of usability, the simplification implied by environmental constancy was precisely one of the major advantages of empirical models, the contemporary perspective of future climatic variations is turning these approaches into a less adequate alternative (Kahle et al., 2008). Considering the expected significant consequences of climate change on forest ecosystems (Kirilenko and Sedjo, 2007; Lindner et al., 2008), the assumption of environmental constancy, and hence the use of traditional empirical growth models, may prove unfeasible in the following decades.

For this reason, as the weaknesses of empirical models are being noted, new research trends in climate-sensitive growth modelling are required for proactively adapting to shifts in forest productivity caused by climate change (Bontemps et al., 2009; Bontemps and Bouriaud, 2014). Among these trends, the most usual approach, from the perspective of empirical growth modelling, is the development of growth-environment relationships (Fontes et al., 2010). This approach consists, in summary, in connecting site conditions (i.e., climate, soil and physiography) with productivity indicators or parameters derived from previous empirical growth models. The most frequent among these productivity indicators, especially in the context of even-aged forestry, is the *site index* (Skovsgaard and Vanclay, 2008), which represents the dominant height (mean height of the dominant trees) of the forest stand at a certain *reference age*. The connection between growth and environment is then addressed through predictive modelling by relying on regression techniques for relating historic climatic variables (typically, year-on-year means) with observed forest variables at specific ages (e.g. dominant height) basing on forest inventory data. The resulting modelled relationships between growth and environmental variables, once combined with future climate projections, allow to extrapolate future forest growth (Hibbard et al., 2011), hence overcoming the assumption of constant productivity.

Concerning the predictive techniques for modelling growth as a function of climate, the task frequently involves the challenge of a particularly complex multivariate analysis. Under the most frequent setup, the applied predictive techniques tend to be non-spatial, though geostatistical approaches, such as kriging, have also provided good results (Nothdurft et al., 2012). In this regard, Watt et al. (2021) recently found non-spatial alternatives the best in terms of performance. Regardless of the approach, the chosen techniques for this task should provide some variable selection criterion for reducing the dimensionality of the problem and hence build parsimonious models that avoid overfitting. Additionally, the model structure should be as simple as possible to be interpretable and allow the relationships between growth and predictors to be evaluated in terms of ecological coherence. Considering these requirements, many studies regarding this matter have relied on supervised *statistical learning* or *machine learning* techniques, which can provide powerful algorithms for automatic variable selection and parameter calibration. So far, the methodologies used for this range from simple parametric or semi-parametric techniques such as stepwise regression (Codilan et al., 2015) and Generalized Additive Models (Shen et al., 2015), to non-parametric non-linear approaches, such as Neural Networks (Aertsen et al., 2010; Hlásny et al., 2017), also including rule-based models, such as Random Forest (Weiskittel et al., 2011) or Boosted Trees (Aertsen et al., 2010).

Over the years, several growth-environment models, specifically targeting the site index, have been developed for different tree species and regions based on the described approach. The first model that could be inserted in this setup was developed by Hunter and Gibson (1984) for the site index of radiata pine in New Zealand. Other more recent examples are the models developed by Fontes et al. (2003) for Douglas fir in Portugal, Wang et al. (2004) and Monserud et al. (2006) for lodgepole pine in Canada, Seynave et al. (2005) for Norway spruce in France, or Benavides et al. (2009) for Scots pine in Spain. Concerning the recent advances in the Spanish forestry research context, various empirical stand growth models have been developed for different tree species of the northwest of Spain (Diéguez-Aranda et al., 2006; Gómez-García et al., 2014; Arias-Rodil et al., 2016). The focus of these research advances has been partially put on the radiata pine (*Pinus radiata* D. Don), as it is one of the most important commercial species in this region. Radiata pine, despite its relatively limited natural range on the Californian coast, is one of the most popular tree species for commercial plantations worldwide, with a strong presence in Spain, South Africa, Australia, New Zealand and Chile since the 19^{th} century (Burdon et al., 2017). It is the 8^{th} most spread tree species in Spain, with a particular prevalence in the northwest, with a planted surface of pure stands that amount to 264K ha and a growing stock of 52M m^3 (MAGRAMA, 2018). In recent years, it has become an important species for the logging sector, being the most logged conifer of Spain in 2018 (5M m^3 of timber logged). However, despite the regional importance of this species, the existing growth models for radiata pine in the northwest of Spain (Sánchez et al., 2003; Castedo-Dorado et al., 2007, 2009) still rely on the observed site index as the only indicator of productivity, without implementing any growth-climate connection. Consequently, these models cannot be effectively used for simulating radiata pine forest growth given the environmental variability caused by climate change. A first approach to the problem of predicting the site index of radiata pine stands in the northwest of Spain as a function of environmental predictors was carried out in Study I. In this study, several cartographic sources of environmental predictors, as well as several statistical techniques of linear modelling barely used in forestry, were tested.

Despite the relative success of previous research on growth-environment relationships modelling, the use of these regression techniques has also raised controversy, especially concerning model interpretability and robustness. On the one hand, the structural complexity of many of these models, often labelled as “black boxes", makes them hard to interpret in terms of ecological coherence (Aertsen et al., 2010). On the other hand, concerning robustness, some of the used techniques (e.g., random forest) have shown significant performance issues, especially in validation metrics and some systematic drawbacks, such as regression to the mean (Sabatia and Burkhart, 2014; González-Rodríguez and Diéguez-Aranda, 2021). Though the latter downsides have been previously studied, other issues regarding the predictive robustness of growth-environment models are still unclear. In this regard, one of the major problems could be the lack of understanding of how these models handle extrapolations. Growth-environment regressions are frequently used as a basis for producing cartographic outputs, i.e., for “mapping" forest productivity over broad territories and future climate scenarios (Monserud et al., 2006; Jiang et al., 2015; Parresol et al., 2017). This can imply a certain degree of extrapolation, as predicting forest productivity for new areas or climatic scenarios means that models are taking as input environmental conditions that were not present in the dataset used for training. The most common approaches for evaluating model robustness in previous studies are cross-validation or validation *per se*. Under both alternatives, model performance is estimated using the same dataset used for training or some supplementary sample statistically similar to the latter. Consequently, the performance of these models regarding extrapolation errors, i.e., errors resulting from predicting over strictly unseen environmental conditions, remains unevaluated to the date. This lack of knowledge has important implications concerning the reliability of cartographic outputs of forest productivity, as it is not clear if the performance metrics reported when fitting the models are truly generalisable for the application conditions. This might be especially concerning when predictions encompass extensive geographic areas or use long-term climatic projections. Effectively addressing this uncertainty might be a necessary research step for developing climate change-adapted forest management in the following decades (Lindner et al., 2014).

A method for predicting forest productivity considering the uncertainty derived from extrapolation was developed in Study II. This approach aimed at producing robust predictions of site index radiata pine stands in the northwest of Spain under future climate change scenarios and a cartographic delimitation of the areas where these predictions were reliable.

1.1.3 Optimisation of forest management under uncertain productivity

Forest management encompasses all the necessary silvicultural practices and economic flows for meeting the manager's objectives (Bettinger et al., 2017a). The silvicultural practices are intended to modify the forest characteristics to improve its current or future value regarding those objectives. They can be translated into economic figures as inputs (costs) when they imply an investment or outputs (revenues) when they imply the extraction of marketable forest products. Forest management *per se* usually refers to the management of areas large enough for including a significant variability of forest and land characteristics (i.e. tree species, ages or sizes). In contrast, "stand-level management" is a particular instance that refers to the silvicultural actions that are applied to a single forest unit, which is internally homogeneous both in terms of biotic and abiotic attributes.

In the last decades, the most commonly applied forest management approach, especially in the context of commercial timber-oriented forestry, is Rotation Forest Management (FAO, 2010) or RFM. This approach consists of the management of even-aged forests that are periodically cut and regenerated, being the length of the interval between cuts known as "rotation". Under the RFM setup, the main silvicultural treatments are the final cut (or clearcut, when all the trees are cut simultaneously) and the thinnings, which are partial removals with the objective of either generating revenues or facilitating the growth of the standing trees.

The application of silvicultural treatments implies a decision process in which actions and investments have to be calibrated and planned in time and space to maximise the management objective. In the context of RFM, this decision process is mainly focused on the timing of clearcutting (rotation length) and the timing and characteristics of thinnings (Pukkala and Miina, 1997). However, the impact of a specific silvicultural programme on the objective does not depend exclusively on treatments but also on natural forest dynamics, such as growth and mortality. Consequently, silvicultural planning should take into account the potential variability of environmental factors through time that might affect the utility of the applied treatments and, in the case of forests with commercial objectives, the production of marketable goods (Pasalodos-Tato et al., 2013). This fact makes predictive models of forest productivity, such as the ones developed in Study I and Study II, an essential tool in the decision process for estimating future forest growth and plan silviculture consequently.

Despite the recent research advances in the field of future forest productivity modelling, connecting productivity predictions with their economic and silvicultural repercussions is still an uncertain task. The two most relevant reasons for this uncertainty might be:

1. if future productivity is significantly different to past or current productivity, forest management should adapt to these productivity changes and provide a silvicultural schedule optimised for future conditions; and

2. if productivity predictions are based on a set of alternative future climate scenarios, then the economic simulations derived from these predictions should be considered as a whole and its internal variability should be part of the financial analysis.

Taking these constraints into account, several recent studies have evaluated financial risks associated with uncertain future productivity basing on optimisation at stand-level (Roessiger et al., 2011; Pukkala and Kellomäki, 2012) and forest-level or portfolio-level (Hahn et al., 2014; Mei et al., 2019). These studies consist, in summary, of the numerical optimisation of a financial indicator (e.g. the *soil expectation value*), which depends on decision variables associated with silviculture and investments under varying economic and climatic conditions.

Previous research on stand-level management optimisation has maily resorted to either dynamic programming or direct search methods (Pasalodos-Tato, 2010). The principal advantage of dynamic programming is that it ensures convergence to the global maximum, although at the cost of losing information due to the need for discretising decision and state variables (Valsta, 1990). Direct search methods, on the other hand, may work with continuous decision variables and provide reasonably good solutions faster, but do not ensure the convergence towards the global maximum (Valsta, 1993). To overcome the disadvantages of dynamic programming and after analysing the mathematical properties of the model functions they used, which resulted to be smooth enough, Arias-Rodil et al. (2017a) proposed the use of differential optimisation methods. This new approach implements continuous decision variables and provides good solutions even faster than direct search methods. Concerning forest management optimisation under uncertain future productivity, the most common approach resorts to risk metrics derived from a covariance analysis between risk factors (i.e., productivity shifts) and profitability. Considering the high number of simulations that this task might imply (the objective function is evaluated exhaustively for estimating covariances) the use of computationally efficient methods, such as differential optimisation, becomes especially convenient.

In Study III, a series of simulations of the development of forest plantations in the northwest of Spain was carried out considering different climate change scenarios. Stand-level differential optimisation was used for finding the silvicultural programmes that maximised economic profitability for the climatic conditions considered. The risk associated with variability in financial simulations due to climate variations across scenarios was estimated using a common risk metric (*expected shortfall*). The simulations carried out also allowed for the comparison between optimum silviculture under current and future climatic conditions.

1.2 Objectives

This thesis encompasses three studies whose major goal was the assessment of the impact of climate change on productivity and profitability of radiata pine stands in the northwest of Spain. In Study I, different machine learning techniques are used for predicting productivity (site index) of radiata pine stands as a function of a set of physiographic, edaphic and climatic variables. In Study II, a distance-based regularisation model is used for predicting site index under future climatic scenarios and evaluating the extrapolability of these predictions. The latter are used as inputs in Study III, in which a series of economic and silvicultural simulations of radiata pine plantations under different climate change scenarios are performed.

The specific goals of this thesis were:

1. to develop models for predicting productivity of radiata pine stands as a function of environmental drivers, such as climate, soil and physiography (Study I);

2. to propose a method for evaluating the reliability of radiata pine forest productivity predictions that allows for making extrapolations under future climate change scenarios (Study II);

3. to asssess the impact of future radiata pine productivity under climate change on the financial profitability and risk of plantations (Study III).

2 Materials and Methods

2.1 Data

2.1.1 Site index data

The main source of forest data used in this thesis was a network of research plots established by the Sustainable Environmental and Forest Management Unit (UXAFORES) of the University of Santiago de Compostela. This network includes 113 measurements carried out in 1995-1996, 76 measurements in 1997-1998, 52 measurements in 1999-2000, 66 measurements in 2004-2005, 147 measurements from 2009 to 2013, and finally, 35 measurements in 2016. The research plots correspond to pure, even-aged stands of radiata pine located essentially in the province of Lugo, in the region of Galicia . The measured variables in each plot were the diameter at breast height (*dbh*) of all the trees, the total height of a sample and core samples from dominant trees for counting the growth rings. The stand variables were calculated from this data, being the dominant height (H) defined as the mean height of the 100 trees per hectare with the largest *dbh*.

For each plot measurement, the site index was estimated by projecting the observed dominant height at the measurement age (t_1) to the reference age of the species (20 years) using the Generalized Algebraic Difference transition function developed by Diéguez-Aranda et al. (2005) for this region.

In Study I, the whole set of 489 plot-inventory combinations was used for modelling the site index. In Study II, only the first measurement of each research plot was used, amounting to 165 plots overall. Finally, in Study III, a subset of 128 plots was used as subject for financial simulations.

2.1.2 Environmental predictors data

The primary sources of environmental variables used for predicting site index in this thesis were previously published raster maps developed through different spatial modelling techniques.

In Study I, physiographic, edaphic and climatic predictors were considered. The physiographic predictors were derived from the digital elevation model (DEM) with a resolution of 200 m developed by the National Geographical Institute of Spain (MDT200 <2009> CC-BY 4.0 ign.es). From this DEM, several variables were computed/extracted, including altitude, slope, the Topographic Position Index, the Terrain Ruggedness Index and trigonometric transformations of aspect azimuth. The soil variables were extracted from the raster maps developed by th European Soil Data Center (Panagos et al., 2012; Ballabio et al., 2016) with a resolution of 500 m. These variables included textural percentages, bulk density, and the available water capacity (*awc*) as described by Veihmeyer and Hendrickson (1927). Finally, the climatic variables were obtained from the Spain02 v5 dataset (Herrera et al., 2012, 2016) with 10 km of spatial resolution and monthly temporal resolution encompassing the period 1951-2015. From this dataset, the first set of basic climatic variables were extracted (e.g., mean annual temperature) from which the second set of derived variables were computed, including several biophysical indices such as the Potential evapotranspiration (Thornthwaite, 1933) and the summer aridity index of Martonne (Martonne, 1942). The total amount of predictors used in this study was 43.

In Study II, only climatic predictors were considered. The source of these predictors was the Worldclim 2 bioclimatic dataset (Fick and Hijmans, 2017). This dataset consists of 19 raster maps of bioclimatic indicators with 1 km of spatial resolution, which corresponds to historical averages for 1970-2000.

The predictions of future forest productivity carried out in Study II and Study III were based on the future climate projections of the Worldclim 1.4 project (Hijmans et al., 2005) for the Global Climate Models (GCMs) included in Coupled Model Intercomparison Project Phase 5 (Taylor et al., 2012) and several Representative Concentration Pathways (RCPs).

2.2 Methods

2.2.1 Linear learning models for predicting site index (Study I)

In Study I, different linear machine learning techniques were used for predicting site index as a function of the 43 potential environmental explainers. For fitting these models, different libraries of the R language (R Core Team, 2021) were used. Among them, six methods perform strictly linear regressions (stepwise, LASSO and Elastic Net, Least Angle Regression, Infinitesimal Forward Stagewise, and Partial Least Squares) while the Multivariate Adaptive Regression Splines is able to model non-linear forms. All the used techniques provide an automatic variable selection procedure.

Once the models were fitted, model selection was based on bootstrap validation performance, using the 632+ rule (Efron and Tibshirani, 1997) implemented with the R package *boot* (Canty and Ripley, 2017). The models were also evaluated in terms of parsimony, multicollinearity and heteroscedasticity.

Stepwise regression is a commonly used technique in forestry for multivariate linear modelling with automatic variable selection which has been previously used for site index prediction (Codilan et al., 2015). Variable selection is performed through an iterative process by introducing or removing one predictor in each iteration (forward or backward fitting). The best combination of predictors is evaluated using a loss function that penalises the number of model parameters basing on a penalty constant k (when $k = 2$, it corresponds to the Akaike Information Criterion). In Study I, k was calibrated using repeated 10-fold cross-validation.

Partial Least Squares (PLS, Wold, 1966) is a linear regression technique that maps predictors into orthogonal components called Latent Variables (LVs). Unlike Principal Component Regression, PLS defines LVs based on their correlation with the response variable, thus ensuring that the first components are the best explainers. In Study I, the a PLS model was fitted using the R package *plsr* (Mevik et al., 2018). Variable selection was carried out through a recursive feature elimination procedure based on the Variable Importance on the Projection (VIP, Wold et al., 1993). Two different models were produced basing on two criteria for defining the optimum number of predictors (PLS1 and PLS2). The selected number of LVs was the one that accounted for the 99.9999% of the total predictors' variability

LASSO and Elastic Net (Tibshirani, 1991; Zou and Hastie, 2005) are linear regularisation techniques that apply a penalty on model parameters that is added to the prediction error in order to produce “flat" models and avoid overfitting. LASSO applies an L1 penalty (sum of absolute values of model parameters) while Elastic Net applies an additional L2 norm (sum of squares). Variable selection is implicit in both methods as model parameters can be automatically set to zero. In Study I, both regressions were fitted using the R package *elasticnet* (Zou and Hastie, 2018). The penalties and shrinkage intensities were calibrated using 10-fold cross-validation.

Least Angle and Infinitesimal Forward Stagewise regressions (LAR, Efron et al., 2004; and IFSR, Hastie et al., 2007) perform a forward shrinkage path (from the null model to the Ordinary Least Squares, OLS, model) by increasing the values of the model parameters recursively. In LAR, the parameter increment at each step is proportional to the OLS estimates while in IFSR the increment is a predefined constant. In this study, both models were fitted by using the R package *lars* (Hastie and Efron, 2013) and the shrinkage intensity was calibrated using 10-fold cross-validation.

Multivariate Adaptive Regression Splines (MARS, Friedman, 1991) builds a linear equation able to model non-linear relationships between response and predictors. For doing so, it transforms the predictors into new variables called “terms" using a hinge function. The hinge function, essentially, splits each predictor into two parts ($left$ and *right* terms) at a certain cut point (for models with one cut point). Then, the transformed terms are added to the model as linear predictors and variable selection is performed basing on generalised cross-validation. In Study I, a MARS model was fitted using the R package *mda* (Hastie et al., 2017). The penalty parameter in the generalised cross-validation was calibrated through a repeated 10-fold cross-validation procedure.

2.2.2 Distance-based regularisation models for evaluating extrapolation uncertainty (Study II)

In Study II, Support Vector Regression (SVR) (Vapnik et al., 1997) was used for performing distance-based regularisation modelling of radiata pine site index as a function of climate. The distance-based approach was implemented using the radial basis kernel transformation, which allows to model non-linear response-predictor relationships and interactions between predictors. For the sake of comparison, other kernels, such as the linear and polynomials, were also evaluated.

SVR techniques have been barely used in previous forest research, especially in the field of climate-sensitive forest growth modelling. In summary, the currently most frequent SVR implementation, known as $\varepsilon-$SVR under *dual formula*, is a Lagrangian optimisation problem where L2 regularisation is applied and only a subset of observations is used as basis for computing new predictions. These observations are the "support vectors", which are selected basing on their contribution to predictive residuals (i.e., samples for which predictions have high errors). Once that the support vectors are defined, their independent variables are combined for producing new response predictions. The main model hyperparameters under this approach are ε, the error threshold for defining support vectors, C, the cost parameter that controls L2 regularisation and σ, the kernel parameter that controls distance-based regularisation. The SVR models were fitted using the R library *kernlab* (Karatzoglou et al., 2004) and hyperparameters were calibrated using repeated 10-fold cross-validation. Variable selection was carried out through recursive elimination based on the repercussion of each predictor on model performance. The optimum number of predictors was defined as the first corresponding to a drop in validation R^2 higher than 5%.

Distance-based regularisation approach

The general formula for making new predictions with SVR using the radial basis kernel is:

$$\hat{y} = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \exp\left(-\sigma \|x_i - x\|^2\right) + b, \tag{1}$$

being α_i and α_i^* Lagrange multipliers $\in [0, C]$, l is the number of observations in the training dataset, σ is the dispersion parameter that controls the impact of the Euclidean norm $\|x_i - x\|^2$ on model flatness, x_i is the vector of predictors of the i-th observation in the training dataset, x is the vector of predictors of the new observation for which predictions are made, and b the independent parameter that tends to match the response's observational mean.

The L2 regularisation controlled by C globally constraints the maximum variability of predictions. In contrast, the σ hyperparameter in distance-based kernels, such as the radial basis, controls how predictions are being constrained based on Euclidean norms between support vectors and new data. If the new data provided is substantially different from the observed in the training dataset (i.e., the support vectors), distance-based regularisation will consequently shrink predictions towards the null model (i.e., the observational mean). A high value of σ would produce highly regularised predictions (with low variability), while a low value of σ would produce very varied predictions. Thus, calibrating the intensity of this regularisation (i.e., calibrating σ) represents a trade-off between model specificity and generality. On the one hand, a strongly regularised model will be more “adapted" to the training dataset and consequently have high performance but a very narrow range of application. On the other hand, a lightly regularised model will lead to a broader range of application at the expense of producing worse performance metrics. In terms of spatial modelling, this trade-off means that accurate predictions will only be available for areas whose predictors (e.g., climate variables) are very similar to the observed in the training dataset, but if broader and more varied territories are considered then a higher predictive error is expected. This idea is also applicable to temporal modelling: a high predictive performance is only expectable under future climate scenarios that are similar to observed climate whereas predictions for very diverging scenarios will have higher errors.

Regularisation analysis

The fitted SVR model with radial basis kernel, SVR_{RB}, was used for generating raster maps of site index predictions for the Galician territory considering past climate (1970-2000) and six future climate scenarios (GFDL-CM3, HadGEM2-ES and MPI-ESM-LR models for the Representative Concentration Pathways 2.6 and 8.5).

As the radial basis regularisation flattens predictions over the territory based on their dissimilarity with the training dataset (in predictor space), model predictions under unseen climatic conditions are systematically regressed to the mean. As a consequence, identifying highly regularised predictions allows for mapping the areas where the fitted model, basing on the current regularisation setup (σ), is not able to make predictions. Derived from this, the uncertainty analysis of this study was focused on detecting and delimiting highly regularised areas. The major difficulty for performing this delimitation is to be able to discriminate highly regularised values from actual average predictions. The approach for solving this was to identify non-regularised values in two stages: 1) firstly, by extracting predictions differing more than 5% from the observational *SI* mean (20.8 m) and 2) secondly, by repeating the “extraction" procedure after performing a smoothing operation of the raster pixels using a 3x3 moving window. Then, the extracted values in this way were classified as non-regularised. After translating the reclassified raster pixels into spatial polygons, an estimation of regularised and non-regularised surfaces for all the *SI* raster maps generated was obtained. For improving visualisation, the edges of the resulting regularisation surfaces were smoothed using the R package *smoothr* (Strimas-Mackey, 2020).

As σ_{CV} is calibrated for maximising predictive performance exclusively, a σ reduction analysis was carried for discussing the ability of the radial basis model for predicting *SI* along the specificity-generality trade-off. This consisted on reducing the value of σ iteratively, from σ_{CV} to the 10^{th} percentile of the Euclidean norms range, and carrying out a performance test (both apparent and cross-validated) and a delimitation of regularised areas (for current climate) at each iteration. The result from this was a path representing the variation of regularised surfaces and R^2 along the calibration range of σ.

2.2.3 Financial assessment of radiata pine plantations under climate change (Study III)

In Study III, a differential optimisation approach was used for forecasting the maximum profitability and the optimum silvicultural treatments for a set of 128 radiata pine stands under different climate change scenarios.

Optimisation approach

Forest stand management was optimised following a similar methodology to that used by Arias-Rodil et al. (2017a) in the NW of Spain. The approach consists, essentially, of: i) time-dependent transition functions that describe the natural dynamics of the forest (growth and mortality), ii) control functions that quantify the impact of silvicultural treatments on the stand, iii) output functions that estimate the timber outcomes from harvesting, and iv) an economic model that translates timber production into incomes and computes a financial objective function.

The natural dynamics of the forest were simulated using the “state-space" approach (first used in forestry by García, 1994), being the forest state variables the dominant height (mean height of dominant trees in the stand, in meters), $H(t)$, number of stems per hectare, $N(t)$, and stand basal area (total area of stem sections at 1.3 m, in m^2/ha), $G(t)$. The evolution of these state variables was simulated using the equations developed for radiata pine in this region by Diéguez-Aranda et al. (2005) and Castedo-Dorado et al. (2007). Forest productivity is implemented in these equations using the site index, which mainly conditions the growth in dominant height and the initial value of the basal area.

The control variables used for simulating silvicultural treatments were: the clearcut timing (years), the thinning timing, the thinning intensity (I, proportion of stems removed) and the thinning removal relation (R, ratio between the proportion of stand basal area removed and the proportion of stems removed). R was kept in the interval $(0,1]$ for ensuring that the dominant height is not affected by treatments (i.e., only thinnings from below were simulated). Thus, being n_t the number of thinnings, the vector of control variables in a silvicultural programme is $\mathbf{u} = (I_1, R_1, t_1, \dots, I_{n_t}, R_{n_t}, t_{n_t}, t_{n_t+1}) \in \mathbb{R}^{3n_t+1}$, where t_{n_t+1} is the clearcut timing.

The main output function for estimating timber outcomes from harvesting was a merchantable timber volume equation developed in a previous study (Arias-Rodil et al., 2017b). This equation estimates the volume for different timber products basing on a limit log diameter and using the three state variables as inputs.

The economic objective function considered for optimisation was the soil expectation value (SEV, Bettinger et al., 2017b):

$$\mathrm{SEV}(\mathbf{u}) = \frac{R(\mathbf{u}) - C}{(1+r)^{t_{n_t+1}} - 1}, \tag{2}$$

where $R(\mathbf{u})$ and C are the discounted revenues and costs, and r is the interest rate. The revenues were computed as the discounted product of stumpage prices and timber outcomes from harvesting.

Input parameters and simulations

Forest productivity was forecasted for a set of climate change scenarios using the Support Vector Regression *SI* model developed in Study II. Specifically, these scenarios were the downscaled projections in the

Worldclim project (Hijmans et al., 2005) for the period 2041-2060 of a set of 11 Global Climate Models (GCMs) included in the Coupled Model Intercomparison Project Phase 5 (Taylor et al., 2012) for the Representative Concentration Pathways (RCPs) 4.5 and 6.0. Thus, 22 predictions of *SI* were considered for each of the 128 forest stand locations.

The necessary silvicultural and economic parameters for simulating costs and revenues were provided by the Spanish forest consultancy company CERNA SL. The considered interest rates for discounting revenues were 1%, 3% and 5%. The proposed management programme comprised the initial plantation, scrub clearance, and low pruning. The initial plantation density was 950 stems/ha. The simulations were carried for programmes of one and two thinnings. The constraints silvicultural decision variables were set as (minimum-maximum): 15%-45% for intensity (I), 0.35-1 for removal relation (R), and 10-60 years for timing, with a minimal interval of five years between cuttings. The timber product considered were chip and pulpwood, sawlog and rotary veneer. The thinning stumpage prices were estimated by depreciating the clearcut stumpage prices proportionally to the thinning variables, such that

$$p_i^j = \frac{p_j}{a^{(2-R_i)(1-I_i)}},$$

where p_i^j is the price of the j-th timber product at the i-th thinning and $a > 1$ is the stumpage price depreciation parameter.

As all the implemented functions were smooth (C^∞ class), the approach was compatible with the use of differentiable methods. The chosen method for this purpose was Sequential Quadratic Programming (SQP), implemented in the R package *nloptr* (Johnson, 2011).

The optimisations were executed for the 128 locations, considering two types of management programs (one and two thinnings), 22 *SI* predictions under climate change (eleven GCMs and two RCPs), and three interest rates, leading to a total of 16896 optimization problems. For each stand location, the risk associated with the dispersion in *SI* predictions was quantified by computing the *expected shortfall* (ES, Artzner et al., 1997), defined as the 2.5 percentile of the SEV distribution for every stand location ($ES_{2.5}$). To assess the potential sensitiveness of SEV to favourable future climate scenarios, the symmetric of $ES_{2.5}$, $ES_{97.5}$, was also computed.

For analysing the optimisation results, the SEV estimated for current productivity, SEV_{CP}, was compared with the mean SEV for climate change scenarios ($\overline{SEV_{CC}}$), $ES_{2.5}$ and $ES_{97.5}$. In addition, the economic effect of not adapting silviculture to climate change was also analysed by applying the optimum silvicultural programmes for current productivity to RCP 4.5 and RCP 6.0 scenarios (“climate-insensitive" silviculture).

3 Results and Discussion

3.1 Site index prediction

Concerning model calibration, among the fitted models for predicting site index in Study I, the intensity of variable selection was varied. For the LASSO and Elastic Net models, the intensity of regularization was high in the first case ($s = 0.1927$) and low in the second one ($s = 0.9333$), producing a significant difference in the number of selected predictors between both techniques (12 and 40, respectively). However, the Elastic Net model was clearly balanced towards the linear penalty, having an optimal $\lambda_{ratio} = 0.05$. The LAR and the ISFR approaches produced quite similar models, having both reduced regularization factors ($s = 0.1313$ and $s = 0.0808$, respectively), which nevertheless did not imply a significantly steep variable selection (respectively, 34 and 37 predictors). The two criteria proposed for the selection of the PLS1 and PLS2 alternatives led to models of 35 and 16 predictors and 32 and 16 LVs, respectively. With regard to the MARS, an optimal penalty of $k = 7$ produced a model of 13 predictors and 18 terms, which means that among the selected predictors, five of them ($slope$, TRI, $sin(\theta)$, $sin(\theta\prime)$ and $mmin$) had both their terms included in the definitive model form, while the remaining eight predictors had only one significant term. Overall, the amount of predictors of these models was significantly high in comparison to other site index-environment models found in the literature. For instance, six predictors were selected by Aertsen et al. (2010) for relating environment and site index, while seven predictors were selected by Weiskittel et al. (2011), and up to twelve, including interactions, by Seynave et al. (2005). However, it is important to remark that, in this research, a significantly higher amount of potential predictors was considered, in comparison with the cited previous studies. The relative intensity of variable selection (number of discarded predictors / total number of predictors) of the models fitted in these studies, ranged from 79% (Weiskittel et al., 2011) to 29% (Seynave et al., 2005), with an approximated mean of 50%. Across the eight models fitted in this paper, the relative intensity of the variable selection ranged from 7% to 72%. Hence, the LASSO, MARS and PLS2 models had relative intensities of variable selection (72%, 70% and 63% respectively) higher than the mean value observed in the cited previous studies. By contrast, the rest of the fitted models performed a not very effective variable selection in comparison to previous research experiences.

The one-dimensional analysis of multicollinearity for these models showed that, for Elastic Net, PLS1, LAR and IFSR models, most of the predictors had Leamer's values lower than the minimum threshold of 0.1 recommended by Imdadullah and Aslam (2016). The same analysis for the PLS2 model revealed that seven of the 16 selected predictors had Leamer's values lower than the threshold (*gsdd*, *gsp*, *map*, *pe*, *pei*, *prgsdd*, *tei*). In the case of the MARS model, three predictors, $sin\theta$, $sin\theta'$, $cos\theta'$, had Leamer's values equal to zero, which is unavoidable considering the existing linear relationship between them ($sin\theta' = 1 - cos\theta'$, $cos\theta' = cos(\theta + \alpha) = cos\theta cos\alpha - sin\theta sin\alpha$, being $\alpha = \pi/4 - max[0, 2\pi\,\mathrm{sgn}(\theta + \pi/4 - 2\pi)]$). Finally, in the LASSO model, no collinear predictors were found. The high multicollinearity found for some models revealed that these approaches were unable to automatically filter highly correlated predictors during the variable selection process. LASSO, PLS2 and MARS models provided simpler and more interpretable functional forms, with the number of predictors ranging from 12 to 16, which, in the case of MARS and, especially, LASSO, did not show a significant presence of multicollinearity in comparison with the rest of the alternatives. Though the significant multicollinearity found for the PLS2 model predictors might be a drawback for the use of this model for *SI* prediction, the following points should be considered:

i collinearity between predictors is an undesirable feature which may lead to instability in the parameter estimates (Belsley et al., 1980) for models based on Ordinary Least Squares,

ii a high level of multicollinearity may always be expected in environmental modelling, being climate, soil and physiography tightly connected factors (Dormann et al., 2013), and

iii the cross-validation procedure carried out ensures a reasonable level of robusticity for the models and parameter estimates based on the selected predictors.

Concerning hyperparameters of the SVR models fitted in Study II, the values of ε tended to be close to the lower bound of its variation range (minimum of 0.05 in fourth degree polynomial model) which consequently led to a high proportion of support vectors, whose number varied from 123 to 157. The optimum C values close to the maximum (the most frequent value was 9), which implied a low global regularisation intensity. The resulting σ hyperparameter from the cross-validation procedure (σ_{CV}) was 0.69, which is slightly higher than the mean value of the Euclidean norms range. The number of predictors included in these models ranged from three (linear model) to five (polynomials), being four the number of predictors in the radial basis model. These predictors we, in decreasing order of variable importance score: *bio*2 (importance score = 0.273), *bio*3 (0.245), *bio*1 (0.241) and *bio*6 (0.2402). In comparison with other published site index models, and especially compared to the models developed in Study I, SVR techniques seemed to be more effective at performing variable selection and providing more parsimonious models. The number of support vectors in these models was notably high, accounting for 75%-95% of the total number of observations. Admittedly, a high number of support vectors implies that the model is balanced towards a *high bias-low variance* fitting strategy (James et al., 2013) which, in this case, might be an indicator of overfitting. Even so, the cross-validation procedure carried out should be an effective backing for ensuring a reasonable level of robusticity. However, clearing this matter would require further research for validating model predictions with a supplementary dataset.

Concerning model performance, among the *SI* models fitted in Study I, the best metrics (NRMSE and ME_{adj}) were found in the MARS model (0.100 and 0.523), closely followed by stepwise (0.103 and 0.501), PLS1 (0.102 and 0.496), LAR (0.102 and 0.495) and IFSR (0.103 and 0.484). Nearly these same models had the best bootstrap performance scores, except for stepwise and MARS. The best $\mathrm{ME}_{adj;632+}$ was reached by PLS1 model (0.415), followed by LAR (0.403) and IFSR (0.397). From the perspective of NRMSE_{632+}, the best models were also PLS1 and LAR (with identical values = 0.110). Concerning the *relative overfitting rate*, the highest value was found in MARS (0.322), whereas the stepwise model was in second place (0.213). The latter is coherent with the significant decrease in $\mathrm{ME}_{adj;632+}$ in both models, compared to their apparent errors (from 0.523 to 0.319 in MARS and from 0.501 to 0.377 in stepwise). Basing on this rate the more robust model was PLS2 ($R = 0.099$), followed by LASSO, while PLS1, LAR and ISFR had average values (from 0.129 to 0.155). The performance of the Elastic Net model was modest, having a low apparent accuracy ($\mathrm{ME}_{adj} = 0.336$) and a noticeable *relative overfitting rate* (equal to 0.134).

Regarding the SVR models fitted in Study II, their cross-validation statistics ran parallel to their apparent performance, being in both cases the radial basis model (SVR_{RB}) the best in terms of R^2 (0.56) and NRMSE (0.098). Interestingly, this model also included a lesser amount of bioclimatic predictors (*bio*1, *bio*2, *bio*3, and *bio*6) than other models (e.g., the third-degree polynomial) and had also a lesser proportion of support vectors, which proves the efficiency of this kernel for this specific modelling task.

Overall, all the models fitted in Studies I and II explained from $\sim$20% to $\sim$56% of the total variability of the observed site index. These values are close to the ones obtained in previous studies (e.g., 24%-27%in Monserud et al., 2006; 27%-41% in Wang et al., 2004; 20%-52% in Aertsen et al., 2010; 24%-64% in Seynave et al., 2005) for other species and regions. Though the best validation performance metrics in Sutdy I where PLS1, LAR and IFSR, these models also included an excesive amount of highly multicollinear predictors. Thus, considering the seek for model parsimony, LASSO, PLS2 and MARS models might be a better alternative for site index prediction than the more complex ones. However, the analysis of residuals showed that LASSO and PLS2 models had a much narrower range of predicted values than the observed, revealing a slight trend to the observational mean, which is more severe in the case of LASSO. By contrast, the predictions of the MARS model had a similar variation range than the observed site index values. It reveals that the LASSO and PLS2 fitted models might be artificially increasing their accuracy and robustness by resorting to a certain *regression* towards the mean. This fact, which was also found in other site index predictive models (Hamel et al., 2004; Weiskittel et al., 2011; Sabatia and Burkhart, 2014), may be responsible for the reduced *relative overfitting rates* produced by both models in comparison to MARS. Besides, the LASSO and PLS2 models showed greater errors occurring in the lowest and intermediate sections of the predicted values, while the MARS model provided much more regularly distributed residuals, with no noticeable trace of heteroscedasticity. This all suggests that the non-linear forms implemented by MARS are more effective than the purely linear ones in describing the underlying relationships between site index and environmental variables. As a consequence, the MARS model fitted might be a better candidate for site index prediction than the linear approaches.

Concerning the interpretation of the MARS model, the described relationships between site index and environmental predictors seem to be ecologically coherent. The parameters of the three aspect variables included in the model ($\sin\theta$, $\cos\theta\prime$ and $\sin\theta\prime$) showed a positive effect of the west orientation on site index, which can be due to the significant orographic effect that takes place in the Galician territory (Martinez Cortizas et al., 1999), with a decreasing gradient of relative humidity in the west-east direction. The heat/energy-related variables *gsd* and *gsdd* had both a positive impact on site index, which is coherent with the thermal and photosynthetic needs for tree growth (Monserud et al., 2006). A special comment should be made about the role of *map* in the fitted MARS model. Though Hunter and Gibson (1984) found a positive influence of the annual rainfall on the site index of radiata pine stands, in this research the opposite was found, having the *map* right term a negative coefficient. Indeed, this seems to be in contradiction with the overall trend in the data, shown by the positive correlation between *SI* and *map*. The major explanation for this is that, once the cut point of 1176 mm of annual rainfall is reached, additional increase in precipitation does not contribute significantly to site quality, but instead the high existing correlation between *map* and *altitude* may lead to positive artificial correlations between *map* and frost stress variables, thus leading to a negative influence of *map* on *SI*. The predictor *smt* had a negative influence on site index, which accounts for the sensitiveness of summer growth to hydric stress. In this regard, *ci*, which involves not only hydric stress but also frost stress, similarly had a negative influence on site index. The variables *cti* and *mtcm* performed a similar role in the MARS model, both having a left negative section and a right positive one, hence defining a minimum at approximately the middle of their range. This can be explained through the *chilling effect*, which has been widely studied for other pine species (Garber, 1983; Valkonen et al., 1990; Wu et al., 2001). Thus, the left terms of *cti* and *mtcm* may represent sites where winter temperatures are too low for tree growth but warm enough for a significant respiration rate that could lead to stress on carbon balance (Smith et al., 2013, p. 116). Once the minimum (cut point) is surpassed, both predictors contribute to tree growth, acting as energy-related variables such as *gsd* and *gsdd*.

The effectiveness of non-linear vs linear models outlined by the results in Studies I and II is even more clear when SVR_{RB} is included in the comparison. This SVR model produced better performance metrics with a relatively reduced number of predictors. The most relevant advantages of this approach over MARS could be: 1) as radial basis functions are universal approximators, SVR_{RB} can model more complex non-linear response-predictor relationships and 2) this kernel can also model interactions between predictors, which is not possible for 1^{st} degree MARS. Moreover, *SI* predictions from SVR_{RB} for the observed plot locations were also varied enough for ensuring that model performance was not inflated by a systematic regression to the mean, as it happened, for instance, for the LASSO model developed in Study I.

The four predictors included in the radial basis model are temperature-related variables. The absence of rainfall-related predictors in the model may seem contrary to previous studies about radiata pine's productivity (Hunter and Gibson, 1984). However, Romanyà and Vallejo (2004) already found that *SI* for this species was not significantly sensitive to precipitation in the Atlantic areas of Spain. The analysis of the correlation image revealed, overall, a sparse and non-uniform relationship between predictors and estimated site index. This is an expected result from the used interpretation method when substantial non-linear response-predictors relationships occur (Üstün et al., 2007). In the case of *bio*1, the main hypothesis is that this irregular role might be due to the ambiguous relationship between this variable and other temperature variables responsible for stress factors with diverging effects on growth (i.e., frost stress or heat stress variables). The predictors *bio*2 and, to a lesser extent, *bio*6 showed a somewhat clear monotone trend in correlations with sorted support vectors (increasing and decreasing with estimated site index, respectively). In contrast, *bio*3 had its maximum near the center of the 1,2,...,N_{sv} range; showing negative correlation values towards the extremes of this range. Interestingly, the negative role of *bio*6 in high quality sites is consistent with the results in Study I (negative influence of $mtcm$ on *SI*). In that case, the main hypothesis was that this could be due to the *chilling effect*, meaning that very warm winter temperatures may lead to stress on carbon balance (Smith et al., 2013, p. 116) due to high respiration rates, which has been observed in other pine species (Garber, 1983; Valkonen et al., 1990; Wu et al., 2001). The performance of *bio*2 as main driver of productivity for high *SI* values could be analogous to the role of *bio*6, implying that high diurnal ranges could reduce the stress on carbon balance related to nightly respiration, specially during the warmest months. Though the importance of night respiration on forest growth has been acknowledged in many physiological studies (Ryan, 1991; Ryan et al., 1997), there is a lack of reference to this topic in studies regarding *SI* modelling. The main drawback of this interpretation could be the unexplained noise of heat stress variables (i.e., maximum temperatures in summer), necessarily correlated with *bio*6, that should affect growth negatively. However, this finding might be a specific feature of the geographic extent of this study, where the humid and temperate climatic conditions (mainly Csb climate, with Csa, Cfa and Cfb local variants, according to the Köppen-Geiger classification updated by Kottek et al., 2006) may make the high temperatures and drought-related factors in warm seasons a not usual constraint for growth. The role of *bio*3 is related to the role of *bio*2 (*bio*3 is actually derived from *bio*2), as it is reflected in the correlation image for low ranges of $\widehat{SI}$. In the alternative case, for high values of predicted *SI*, the negative influence of *bio*3 on growth may be associated with the effect of continentality (*bio*7, another Worldclim variable used for computing *bio*3), which was found an important restriction for pine growth in central Spain in a previous study (Büntgen et al., 2013).

In summary, the models developed in Studies I and II were able to effectively predict radiata pine *SI* using predictors extracted from cartography, having the non-linear approaches, especially SVR, a better performance overall. However, the relatively intense overfitting observed for these models suggests that it will be necessary to conduct further research for a deeper evaluation of their robusticity. Moreover, the characteristics of the raster cartography used as source of environmental predictors, especially the resolution, are also important constraints to the performance and usability of these models (Bontemps and Bouriaud, 2014) that should be more deeply evaluated in the future.

3.2 Forest productivity extrapolation

In Study I, it was observed that LASSO and PLS2 produced predictions highly regressed to the mean. This was mainly a consequence of the poor extrapolation properties of linear models highlighted during the cross-validation procedure. To prevent very extreme predictions (i.e., too high or too low predicted *SI* for the validation subset) the model adopts the strategy of shrinking slope parameters and consequently reducing the dispersion of the outputs. Though this was observed in Study I for linear models, previous studies have reported similar issues for other techniques, such as rule-based models (Sabatia and Burkhart, 2014; González-Rodríguez and Diéguez-Aranda, 2021). In this sense, a special mention should be made concerning the random forest approach and other "mean models", whose predictions are strictly limited to the bounds of the observed data, hence preventing their adequate use for extrapolation. All the aforementioned inconveniences for extrapolating *SI* were seemingly overcome by the radial basis SVR model developed in Study II.

The map of site index predicted by this model for current climate using σ_{CV} yielded similar statistics than the observed *SI*, though it had a slightly higher variation range. This feature is interesting as it means that the model allowed for extrapolating outside of the observed range, in contrast to rule-based models (Weiskittel et al., 2011; Sabatia and Burkhart, 2014; Barrio-Anta et al., 2020), whose predictions were constrained to the observed range or varied in a much lesser extent. Because of this, support vector regression might be considered a preferable technique to rule-based methods in many circumstances, especially when extrapolations are necessary. However, in future climate maps for σ_{CV}, the variability of predictions was, overall, very low. For instance, GFDL-CM3 yielded values that ranged from 18.9 to 19.9 for the concentration pathway 8.5. This revealed that the intensity of regularisation was very variable across different climatic scenarios, which was consistent with the existing differences between climatic projections and the conditions encompassed by the training dataset. For the case of current climate, the regularised surface estimated using σ_{CV} was approximately 60% of the territory. Most of these highly regularised areas were mostly concentrated in the Atlantic coastal zone (very temperate and humid) and the southeastern mountainous ranges (with strong mediterranean and/or alpine influence), which is consistent with the known climatic differences between those areas and the extent encompassed by the measured research plots (Csb climate, predominantly). This fact might prove the climatic coherency of the distance-based regularisation approach for delimiting homogeneous areas in terms of potential extrapolation errors.

Concerning future climate, predictions using σ_{CV} for RCP 8.5 were more regularised than those for the RCP 2.6 scenario, accounting for the diverging dynamic of future climate with respect to present concentrations of greenhouse gases. GFDL-CM3 produced the most extensive regularised surfaces, accounting for 99.1% of the territory for RCP 2.6 and 99.8% for RCP 8.5. HadGEM2-ES provided very similar but slightly smaller regularised areas than GFDL-CM3. MPI-ESM-LR, on the contrary, produced significantly less regularised maps, especially for RCP 2.6 ($\sim$27% of the territory was not regularised). The high proportion of regularised areas estimated for these, revealed that, overall, the existing climatic conditions in most of the territories (and also over future scenarios) might be too different from the observed in the training dataset for being subject of reliable site index predictions.

However, the high specificity of this model, optimum in terms of cross-validation performance (σ_{CV}), was effectively mitigated by reducing σ. The σ reduction path showed a monotone drop of both apparent and cross-validated performance along the path, together with a reduction in regularised surfaces, and the consequent improval in model generalisation power, until approximately $\sigma = 0.21$. Under this value of σ, the regularised surfaces for all the climate conditions considered are reduced significantly. For current climate, the proportion of regularised territory dropped from 60% to 36%, while, for the case of future climate maps, it reached a minimum value of 48% (for the MPI-ESM-LR model under RCP 2.6). However, the other two future climate models were not that sensitive to the σ reduction, being its values of regularised surfaces always above 80% of the territory. Concerning the predictive performance of the model based on $\sigma = 0.21$, the apparent R^2 dropped from 0.56 to 0.47, while the cross-validation R^2 dropped from 0.38 to 0.34.

The outcome of this specificity-generality trade-off strongly depended on the chosen value of σ. As there is not a particularly objective approach for doing this calibration, it should be determined by the specific goals of the modeller. In this sense, the simplest criterion for calibrating σ could be to try to maximise the validity area of the model (i.e., to minimise the regularised areas) subject to meet a minimum performance requirement. Another alternative could be to maximise the validity area (and, hence, the dispersion of predictions) subject to keep the predictive range within reasonable bounds (for instance, by restricting predictions to maximum and minimum values registered in previous studies). Further research will be necessary for evaluating the practicality of these criteria.

In summary, the distance-based regularisation strategy implemented in the SVR model allowed to make robust *SI* predictions and provided an effective criterion for delimiting the actual validity area of the model, discarding all the areas with very different climatic conditions from the training dataset, and for which predictive errors could be too uncertain. This might be a useful method for understanding and controlling the limitations of *SI* predictive models, especially when extrapolations for new territories or climatic scenarios are needed.

3.3 The potential impact of climate change on productivity and profitability

The future climate models considered in Study III forecasted, on average, an increase in the four *SI* climatic predictors except for the isotermality, which experienced a slight decrease. The most notable shift in climatic variables was the mean temperature of the coldest month, which increased $\sim 40\%$ with respect to previous conditions. However, these forecasts varied notably over climate models, being the mean temperature of the coldest month the most sparse for both RCPs (relative dispersion $\sim$15%). The forest productivity predictions derived from these climatic projections using the approach developed in Study II revealed a decreasing trend in mean *SI* under climate change. The mean *SI* reduced from 20.8 m (observed productivity) to 18.8 m (RCP 4.5) and 17.3 m (RCP 6.0). Moreover, the variability of these predictions increased notably, with *SI* ranges (min.-max.) of 7.9-32.1 m for RCP 4.5 and 7.1-29.4 m for RCP 6.0 that contrast the observed range of 12.8-27.7 m.

Regarding the economic the simulations of Study III, in most of the locations $\overline{\mathrm{SEV}_{CC}} < \mathrm{SEV}_{CP}$, in other words, simulations under climate change led to a drop in profitability in comparison with the scenario of current productivity. The average relative decrease in profitability from current productivity to climate change scenarios varied in the ranges 15%-64% for RCP 4.5 and 22%-89% for RCP 6.0. These wide ranges of variation were mostly driven by interest rates, being the highest decreases in profitability associated with with high values of r. Increases in SEV from current productivity to climate change (i.e., where $\overline{\mathrm{SEV}_{CC}} > \mathrm{SEV}_{CP}$) were scarce and mostly found in some locations with current low-average productivity. Altogether, a descending trend in SEV was noticed in the direction current productivity-RCP 4.5-RCP 6.0. A slightly decreasing trend was also found in $\mathrm{ES}_{2.5}$ between RCP 4.5 and RCP 6.0. The estimated relative decreases of profitability based on $\mathrm{ES}_{2.5}$, from current productivity to climate change scenarios, were of 47%-142% (also varying with r) for RCP 4.5 and 55%-156% for RCP 6.0. In contrast, $\mathrm{ES}_{97.5}$ revealed an increase in SEV under climate change scenarios, with relative values of up to 40% for RCP 4.5 and 47% for RCP 6.0.

The decreasing trend in profitability under climate change was caused by a drop in average productivity over climate scenarios which was mainly driven by an increase of temperatures and continentality. Considering that the sharpest increase among these climatic drivers was the mean temperature of the coldest month, it is logical to state that this variable was responsible for an important proportion of the observed variations in productivity from current to future climate. The negative role of this variable on the *SI* was already observed both in the MARS model (as $mtcm$) in Study I and in the SVR model developed in Study II (see Subsection 3.1). Though there is a certain concurrence on the potential effects of climate change on tropical and boreal forests productivity (negative and positive effects, respectively, according to Salafsky, 1994; Van and Kooten, 1990; Feeley et al., 2007), the economic impacts of future climate on temperate forests is still an unclear matter. For instance, according to Alig et al. (2002), future forest profitability may be reduced in the southwest of the USA, while Susaeta et al. (2016) predict an increase in productivity in the southeast (Florida). The results of Study III might run parallel to the findings made by Hanewinkel et al. (2013), which state that, overall, temperate European forests may suffer a severe loss in profitability due to climate change. Specifically, Hanewinkel et al. (2013) projected a retreat of pine forests in the northwest of Spain for an expansion of *Eucalyptus* spp. and Mediterranean oaks. Routa et al. (2019) and Serrano-León et al. (2021) also predicted a decline in profitability in European pine forests under unfavourable climatic scenarios (e.g., RCP 8.5).

Regarding the observed dispersion in profitability estimations, the comparison between SEV_{CP} and $\overline{\mathrm{SEV}_{CC}}$ should be taken cautiously given the observed diverging trend between $\mathrm{ES}_{2.5}$ and $\mathrm{ES}_{97.5}$. This trend implies that the dispersion of forest productivity predictions along the different GCMs is high enough to forecast increments and reductions in future profitability alternatively. This fact was already noted by AL-Rahahleh et al. (2018) when analysing the potential impacts of RCP 4.5 and 8.5 projections on forest growth in Finland. A more detailed assessment of the observed dispersion between GCMs would require a deeper understanding of the mechanisms within the models and downscaled climatic predictions. As ALRahahleh et al. (2018) concluded, the use of a varied set of different GCMs is necessary for realistically representing the underlying uncertainties of forest productivity under future climate. Nevertheless, even considering the yielded dispersion in future financial indicators, the results point out a clear declining trend of average profitability across climatic scenarios (e.g., a decrease of $\sim 22\%$ for RCP 4.5 and $\sim 29\%$ for RCP 6.0, with $r = 0.03$). Considering that the results yielded by both RCPs are notably different (being RCP 6.0, overall, more pessimistic), their implications in terms of financial risks are also distinct. In this regard, despite the existing uncertainty regarding future greenhouse gases emission scenarios, some studies have performed likelihood analyses for assessing the probabilities associated with the different radiative forcing pathways. For instance, Capellán-Pérez et al. (2016) used an integrated assessment model for estimating the probability of surpassing the different RCPs by 2100. In their study, Capellán-Pérez et al. (2016) report a probability of 92% of surpassing RCP 4.5 and a probability of 42% of surpassing RCP 6.0, being the most likely scenario an intermediate point between both pathways (notably closer to RCP 6.0). Considering these probabilities, a weighted mean of the estimated $\overline{\mathrm{SEV}_{CC}}$ values for both RCPs would produce an expected loss of $\sim 28\%$ from current profitability with an interest rate of 3%. The most probable value of ES2.5 in this context would imply a risk of profitability loss of $\sim 82\%$, for the same interest rate.

In summary, the *SI* model developed in Study II and the optimisation approach implemented in Study III forecast a reduction in productivity and profitability of radiata pine plantations under climate change in Galicia. The driver of these reductions is the increase in temperatures, especially the mean temperatures of the coldest month, and continentality. However, these predictions were strongly varied over the different climate models used, which means that both increases and decreases in productivity and productivity could be expected alternatively. More research will be necessary to clear the uncertainty regarding the observed strong differences between GCMs. Finally, the relative impact of climate change on profitability was also strongly dependent on the interest rates, which highlights the necessity for correctly calibrating the time value appreciation and quantifying its risk-driven components for analysing forest investments under climate change.

3.4 Optimum silviculture under climate change

Concerning the silvicultural programmes simulated in Study III, the optimum number of thinnnings was one ($n_t = 1$) in all the optimisation scenarios. However, the differences in SEV between optimum silvicultural programmes of one and two thinnings were very slight, being the mean difference equal to 180€/ha. Climatic scenarios had a noticeable influence on the optimum rotation length, which tended to reach higher values under climate change (RCP 6.0 $>$ RCP 4.5, in most of cases) in comparison to current productivity. In other words, optimum silviculture under climate change will consist of longer rotations. Considering the estimated reduction in future mean *SI* under climate change scenarios, this result seems consistent with the negative rotation length-growth rate correlation observed in previous studies (Palahí and Pukkala, 2003). As expected, the rotation lengths also showed a negative correlation with r.

The thinning intensities and removal relations were scarcely influenced by climatic scenarios and, overall, experimented low variability. Concerning the first thinning (or the only thinning when $n_t = 1$), the results of most of NLPs yielded values very close to the lower bounds of these decision variables, implying low intensities ($I_1 \sim 0.15$) and thinning from below ($R_1 \sim 0.35$). The optimum intensities of the second thinning (for those NLP with $n_t = 2$) had a broader variation range, with some of the NLPs reaching $I_2 \sim 0.45$. Similarly to the rotation length, the optimum thinning timings suffered a noticeable variation across optimisation scenarios, specially influenced by r. The mean timing for the first thinning was, overall, 19 years and the mean timing of the second thinning was 31 years. In contrast to some previous studies (Pukkala, 2018), thinning intensities and removal relations were not strongly sensitive to interest rates, as they experienced narrow variations across scenarios.

The simulations under climate-insensitive silviculture led, overall, to a noticeable reduction in profitability. This reduction showed a very high variability, which was mainly conditioned by the interest rate, being the worst cases of profitability loss located in scenarios where $r = 5\%$. These climate-insensitive simulations yielded a mean relative drop in SEV of $2\% - 19\%$ (increasing with r) for RCP 4.5 and $3\% - 39\%$ for RCP 6.0 with respect to silviculture optimised for future climate. The estimated decreases in comparison with the SEV under current productivity were $11\% - 64\%$ (with a maximum of 120%) for RCP 4.5 and $22\% - 150\%$ for RCP 6.0.

Overall, the optimisation of timing decision variables (i.e. thinning timing and rotation length) was decisive for maximising the SEV across climatic scenarios and interest rates. Even though the greatest variations in SEV were mainly driven by productivity and r, the comparison between optimal and climate-insensitive simulations revealed that silviculture can significantly alleviate part of the profitability losses due to unfavourable climate change conditions. However, the magnitude of this alleviation was strongly dependent on the interest rate (e.g., the drops in SEV were $3\% - 39\%$ for RCP 6.0 when applying suboptimal programmes, depending on r). This seems reasonable considering that the major differences between optimal and climate-insensitive programmes were timing variables, whose repercussion on the SEV is coinstrained by r. Consequently, the potential damping effect of silvicultural optimisation on profitability losses under climate change might essentially depend on the forest manager's appreciation of time-dependent risks. If this appreciation leads to high interest rates, optimising silviculture considering climate change scenarios might be decisive for mitigating economic losses due to unfavourable productivity conditions.

4 Conclusions

In Study I, several statistical techniques were used for predicting site index (*SI*) of radiata pine stands using environmental predictors extracted from available raster maps. The resulting models explained up to 52% of the *SI* variability and included a very varied number of predictors. A non-linear technique, Multivariate Adaptive Regression Splines (MARS), was suggested as the best modelling alternative, as it provided good performance metrics and a relatively simple and interpretable model (13 predictors). Moreover, the model did not show any systematic trend to regress predictions to the observed mean, in contrast to other used techniques, such as LASSO and Partial Least Squares.

In Study II, the Support Vector Regression technique was used for predicting *SI* and delimiting the validity area of predictions basing on the radial basis kernel. The resulting model had high predictive performance, explaining up to 56% of the *SI* variability, provided robust predictions under varied climatic conditions, and included a relatively small amount of predictors. The growth-climate relationships represented in this model were found ecologically reasonable. Moreover, the distance-based regularisation strategy implemented in the model allowed to identify areas were climatic conditions were very different from the observed and consequently regularised predictions for those areas. The calibration of the regularisation intensity allowed to increase the delimited validity areas at the expense of losing performance, which resulted a useful criterion for assessing the uncertainty derived from extrapolation.

In Study III, silviculture under climate change was optimised, using a differentiable method, for maximising the soil expectation value of a set of radiata pine plantations. The future forest productivity projections, produced by the model developed in Study II, forecasted an overall reduction in *SI* under climate change, mainly driven by an increase in temperatures and continentality. As a consequence, the economic simulations forecasted a drop in profitability under climate change that was more intense for more pessimistic scenarios (RCP 6.0). For RCP 4.5, the loss in soil expectation value under climate change, with respect to current climate, was 2%-19%, while for RCP 6.0 was 3%-39%. However, the climatic projections were very varied over the set of used climate models, which led to a great dispersion in productivity and profitability predictions. Under the worst scenarios, the expected shorfalls for RCP 6.0 forecasted a loss of 55%-156% in profitability. From the perspective of optimum silviculture under climate change, the most notable variation is the expected increase in timing variables (thinnings timing and rotation length). The main economic consequence of this increase was a great sensitiveness to interest rates, which makes the time value appreciation a key factor to consider for the estimation of profitability under climate change.

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A Published studies

A.1 Study I

González-Rodríguez, M. A., & Diéguez-Aranda, U. (2020). Exploring the use of learning techniques for relating the site index of radiata pine stands with climate, soil and physiography. Forest Ecology and Management, 458, 117803. https://doi.org/10.1016/j.foreco.2019.117803

González-Rodríguez, M.A. [1,2], Diéguez-Aranda, U. [2]

[1]CERNA Ingeniería y Asesoría Medioambental S.L.P., R/ Illas Cíes nº 52-54-56, Ground floor, 27003 Lugo, Spain

[2]Unidade de Xestión Forestal Sostible, Departamento de Enxeñaría Agroforestal, Universidade de Santiago de Compostela. Escola Politécnica Superior de Enxeñaría, R/ Benigno Ledo, Campus Terra, 27002 Lugo, Spain

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Ulises Diéguez Aranda: Conceptualization, Formal Analysis, Funding Acquisition, Project Administration, Software, Writing – Review & Editing, Resources, Supervision.

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A.2 Study II

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González-Rodríguez, M.A. [1,2], Diéguez-Aranda, U. [2]

[1]CERNA Ingeniería y Asesoría Medioambental S.L.P., R/ Illas Cíes nº 52-54-56, Ground floor, 27003 Lugo, Spain [2]Unidade de Xestión Forestal Sostible, Departamento de Enxeñaría Agroforestal,

Universidade de Santiago de Compostela. Escola Politécnica Superior de Enxeñaría, R/ Benigno Ledo, Campus Terra, 27002 Lugo, Spain

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Ulises Diéguez Aranda: Conceptualization, Formal Analysis, Funding Acquisition, Project Administration, Software, Writing – Review & Editing, Resources, Supervision.

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A PUBLISHED STUDIES

A.3 Study III

González-Rodríguez, M. A., Vázquez-Méndez, M. E., & Diéguez-Aranda, U. (2021). Forecasting variations in profitability and silviculture under climate change of radiata pine plantations through differentiable optimisation. Forests, 12(7).
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González-Rodríguez, M.A. [1,2], Vázquez-Méndez, M.E. [3], Diéguez-Aranda, U. [2]

[1]CERNA Ingeniería y Asesoría Medioambental S.L.P., R/ Illas Cíes nº 52-54-56, Ground floor, 27003 Lugo, Spain

[2]Unidade de Xestión Forestal Sostible, Departamento de Enxeñaría Agroforestal, Universidade de Santiago de Compostela. Escola Politécnica Superior de Enxeñaría, R/ Benigno Ledo, Campus Terra, 27002 Lugo, Spain

[3]Departamento de Matemática Aplicada, Instituto de Matemáticas, Universidade de Santiago de Compostela. Escola Politécnica Superior de Enxeñaría, R/ Benigno Ledo, Campus Terra, 27002 Lugo, Spain

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Ulises Diéguez Aranda: Conceptualization, Formal Analysis, Funding Acquisition, Project Administration, Software, Writing – Review & Editing, Resources, Supervision.

Miguel Ernesto Vázquez Méndez (Study III): Conceptualization, Methodology, Writing – Review & Editing, Supervision.