Forest Ecology and Management 502 (2021) 119649

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Spatial optimization for reducing wind exposure of forest stands at the property level

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ARTICLE INFO

Keywords:
Forest planning
Mixed-integer programming
Storm damage
Decision support system

ABSTRACT

Storms constitute one of the major natural disturbances in Sweden and its associated damages appear to be in an upward trend during the last 35 years in Europe. In addition, storm damages are expected to increase in the future due to the shortening of the soil frost period during the winter caused by climate change. Here we present a new optimization model to be used in forest planning for decreasing the wind exposure for storms over time through the minimization of vulnerable edges between neighbouring stands in a forest property. Three different cases were investigated where height differences of 5, 10 and 15 m between neighbouring stands were used to identify vulnerable edges in the property. The model, which accounts for the higher sensitivity of spruce compared to other tree species, was formulated as a mixed integer programming problem and solved using a branch and bound algorithm in a case study for a forest property in southern Sweden. In the case study, we investigated the trade-off between minimizing the length of vulnerable stand edges and the net present value from wood production. Our results show that it is possible to decrease vulnerable edge length with relatively moderate declines in the maximum achievable net present value, resulting in a clustering of dominant heights of neighbouring stands. Larger decreases in vulnerable edge length led to larger decreases in net present value, and an increased area proportion of forest older than 80 years. This model can easily be adapted to other planning problems in which edge effects are important.

1. Introduction

Forests are subject to a wide range of natural disturbances over their lifetime. In Europe, natural disturbances have accounted for large economic losses during the last 150 years (Schelhaas et al., 2003). Storms alone were responsible for half of this damage, resulting in approximately 17.5 million m^3 of annual timber losses (Schelhaas et al., 2003), with an upward trend during the last 35 years in Europe (Senf & Seidl 2021). In Sweden, storms have harmed more than 100 million m^3 of timber during the last century (Nilsson et al., 2004). In 2005, 75 million m^3 were felled by only one storm in southern Sweden (Holmberg, 2005). In addition, the damage caused by storms is expected to increase in the future due to global warming and the shortening of the soil frost period during the winter because of warmer temperatures (Schlyter et al. 2006; Lindner et al. 2010; Gregow et al. 2011).

Common factors that have a large influence on the forests' sensitivity to storms include tree properties, forest stand characteristics, silvicultural practices and the spatial layout of management activities (Persson 1975; Peltola et al. 1999; Blennow & Sallnäs 2004; Zeng et al. 2007; Hanewinkel et al. 2011; Albrecht et al. 2012; Gardiner et al. 2013; Dhubháin & Farrelly 2018; Venäläinen et al. 2020). Concerning tree properties, tree species can affect the disposition of forest stands to be damaged in the long term (Albrecht et al. 2012). Conifers, in general, are susceptible to storm damage since they keep the needles during late autumn and winter when most storms occur (Schmidt et al. 2010; Gardiner et al. 2013) and spruce in particular, due to the deficiency of rooting depth (Quine & Gardiner 2007). Apart from tree species, tree height also plays a fundamental role, where the damage probability increases greatly with larger heights. In previous studies, forest stands have been classified as 'windstorm sensitive' if dominant heights were over 10 m (Zeng et al. 2007) or 15 m (Lagergren et al., 2012). In addition, forest management activities such as final fellings or thinnings can increase wind exposure and cause a sudden and temporal loss of stability in the forest (Zeng et al. 2006; Wallentin & Nilsson 2014). Forest stands located close to gaps or recently harvested stands, where wind speeds tend to increase and the remaining forest has less stability, are more

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https://doi.org/10.1016/j.foreco.2021.119649
Received 15 June 2021; Received in revised form 19 August 2021; Accepted 22 August 2021
Available online 23 September 2021

susceptible to suffer damages from strong wind gusts (Zeng et al., 2004).

One way to decrease the risk of storm damage is to formulate optimization problems that integrate the risk of storm damage in the forest planning process (e.g. Meilby et al. 2001; Zeng et al. 2007; Heinonen et al. 2009; Hanewinkel et al. 2010; Ross & Tóth 2016; Zubizarreta-Gerendiain et al. 2017). Forest planning problems that have considered the risk of storm damage have in many cases used heuristic methods for solving the resulting optimization models-(e.g. Lockwood & Moore 1993; Meilby et al. 2001; Zeng et al. 2007). Zeng et al. (2007) investigated how the spatial distribution of clearcuts and the economic gains from the forest were affected by the aggregation of new clearcuts and the avoidance of harvestings close to 'windstorm sensitive' stands. In their study, three heuristic approaches, simulated annealing, tabu search and genetic algorithms were tested. Heinonen et al. (2009) and Zubizarreta-Gerendiain et al. (2017) also focused on minimizing the risk at stand level by using simulated annealing. However, one of the main drawbacks of heuristic methods is that these are not able to find, in most cases, the optimal solution to the planning problem presented.

An alternative to solving planning problems with heuristic techniques is to use exact solution techniques, such as integer programming (IP) with a branch and bound algorithm (Williams, 1985). IP has been used in many forest scheduling problems (e.g. Goycoolea et al. 2005; Constantino et al. 2008) and numerous decision support systems for forest planning are currently based on these kinds of solution methods, e.g. the Heureka system developed and used in Sweden (Wikström et al. 2011). Exact methods have, for example, been implemented as an alternative to heuristics when considering spatial relationships such as edge effects into long-term forest planning for biodiversity purposes. Among others, Öhman & Wikström (2008) investigated how to maximize the NPV over time and at the same time support the spatial clustering of old forest areas to preserve biodiversity by using a mixed integer programming approach. In addition, other spatial problems such as maximum final felling area restrictions, the ecological assemblage of habitats or the production of new forest edges connected to final fellings and their impacts on wildlife habitats have been solved by using exact methods (e.g. Goycoolea et al. 2005; Öhman et al. 2011; Ross & Tóth 2016). Nevertheless, there are so far few model formulations to handle the risk for storm damage solvable with exact solution methods in acceptable solution times and for large forest properties.

The objective of this study is to present and evaluate a model for considering the risk of storm damage in long-term forest planning. The model minimizes the length of forest stand edges that are affected from edge effects from neighbouring stands (forest stands next to each other with common edges) to decrease the risk of storm damage over time and within a forest property. The model can be used in decision support systems using exact solution methods for solving the optimization problem. The planning problem was solved by optimising the spatio-temporal arrangement of forest management activities over the planning horizon within a forest property in southern Sweden. In contrast to previous studies, we have used a longer planning horizon (70 years), a larger study area (538 stands) and a exact method to solve the specified model.

2. Materials and methods

2.1. Modelling framework

The approach for including consideration to wind damage is included in a long-term forest planning problem consisting of selecting forest management activities for every stand in a landscape over time so that the amount of forest stand edges with large height differences between neighbouring stands and dominated by spruce is minimized. The aim was to create a smoother landscape in terms of tree heights between neighbouring stands over the planning horizon. The objective of minimizing the length of edges with large height differences between neighbouring stands is subject to a demand for a net present value and to an even flow timber harvest constraint. As can be seen in the formulation below, the problem formulation is built on the concept of a treatment schedule, which is a sequence of forest management activities over the planning horizon for one single forest stand. Consequently, this problem formulation is building on a model I type formulation (Johnson & Scheurman 1977).

2.2. Model formulation

The mathematical formulation for this forest planning problem is as follows:

$$MinY_1 = \sum_{i=1}^{I} \sum_{l=1}^{L_i} b_{il} \sum_{p=1}^{P} Z_{ilp} \quad (1)$$

Subject to the following constraints:

$$\sum_{j=1}^{J_l} h_{ljp} x_{lj} - \sum_{j=1}^{J_i} h_{ijp} x_{ij} \le d + MZ_{ilp} \forall p \in P, \forall il \in Y, \forall i \in S \quad (2)$$

$$Z_{ilp} = \{0,1\} \quad \forall il \in Y, \forall i \in S, \forall p \in P \quad (3)$$

$$\sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J_i} v_{ij(p+1)} x_{ij} a_i \ge (1-\mu) \sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J_i} v_{ijp} x_{ij} a_i \quad \forall p \in P-1 \quad (4)$$

$$\sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J_i} v_{ij(p+1)} x_{ij} a_i \le (1+\mu) \sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J_i} v_{ijp} x_{ij} a_i \quad \forall p \in P-1 \quad (5)$$

$$\sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J_i} a_i n_{ij} x_{ij} \ge \beta^* MaxNPV \quad (6)$$

$$\sum\nolimits_{j=1}^{J_i} x_{ij} = 1 \quad \forall i \in I \quad (7)$$

$$x_{ij} = \{0,1\} \quad \forall i \in I, \forall j \in Ji \quad (8)$$

where

i specifies a stand contained in set *I,*

l specifies a stand neighbour to *i* contained in set L_i,

j specifies a treatment schedule contained in set J_i,

p specifies a period contained in set *P,*

I the set of stands,

Y the set of neighbour stands,

S the set of stands with Norway spruce as dominant species,

L_i the set of neighbours to stand i,

J_i the set of treatment schedules for stand i,

J_l the set of treatment schedules for stand l,

x_{ij} the binary decision variable that ensures that stand *i* is designated the value 1 if treatment schedule *j* is assigned to stand *i*,

Z_{ilp} the indicator variable that alternatively takes the value of 1 if the common edge between stand *i* and *l* makes up a vulnerable edge in period *p,* otherwise 0. If vulnerable or not is dependent on *d* and if the stand is dominated by Norway spruce or not.

d the maximum accepted height difference between two neighbouring stands in order to not consider the common edge between two stands as vulnerable,

v_{ijp} the volume harvested per hectare for stand i and treatment schedule j in period p,

h_{ijp} the height for stand *i* and treatment schedule *j* in period *p*,

h_{ljp} the height for stand *l* and treatment schedule *j* in period *p*,

b_{il} the common edge length between stand i and stand l,

n_{ij} the net present value per hectare for a treatment schedule j and stand i,

M a large number greater than the maximum possible height of a forest stand,

a_i the stand area,

β indicates the percentage of MaxNPV that is demanded,

μ indicates the maximum and minimum harvest deviation allowed between period *p* and $p+1$,

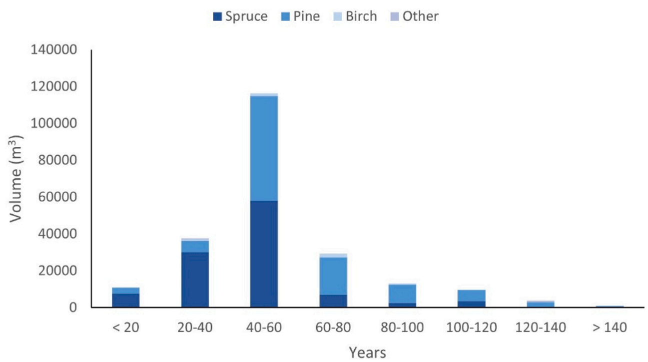

Fig. 1. Initial volume distribution by age class.

MaxNPV is a parameter obtained from maximizing the net present value subject to even-flow harvest constraints (see Appendix A for the mathematical formulation of how *MaxNPV* was calculated).

Eq. (1) minimizes the edge length between neighbouring stands in the forest property if the height difference between them is larger than parameter d. Eqs. (2) and (3) ensure that the indicator variable, Z_{ilp}, takes the value of 1 if the difference in height between two neighbouring stands is larger than the specified value of parameter d and value 0 otherwise. It also ensures that only forest stands dominated by Norway spruce are selected to minimize their vulnerable edges if the conditions in Eqs. (2) and (3) are fulfilled. There is one Eq. (2) for every stand and neighbour, i.e., if one stand has four neighbours there are four Eq. (2) in every period. Eqs. (4) and (5) ensure that the demand for even flow timber harvest is fulfilled. Eq. (6) ensures that we meet the net present value demand. Eqs. (7) and (8) ensure that only one treatment schedule is assigned to each treatment unit.

2.3. Case study

The proposed model was evaluated for a case study area consisting of 538 forest stands encompassing different types of measurements from trees, soil, and site characteristics for each stand such as the productive area, proportion of species or site index, among others. The forest property is located in Småland, Southern Sweden (56°37′N, 15°30′E) and the data was collected during the year 2019. The average stand size is approximately 3.5 ha and in total 1917 ha of productive forest (forest with a mean annual increment greater than 1 $m^3ha^{-1}year^{-1}$) were included in the study. The species distribution was dominated by pine with 48% of the total volume and by spruce with 45% (Fig. 1). In addition, 95% of the forest property area was managed for timber production and 5% of the productive forest was set aside for nature conservation purposes. The forest planning horizon for this study was 70 years divided into 14 five-year periods.

The simulation of treatment schedules including future forest conditions was done using the Heureka PlanWise system (version 2.17.2.0) (Wikström et al. 2011). PlanWise simulates the development of the tree layer based on empirical single-tree models and height functions in time steps of five years. The regression models used to simulate the development of the forest are based on the National Forest Inventory, the HUGIN young stand survey and scientific trials (Wikberg 2004; Fahlvik et al. 2014). PlanWise offers the user the possibility to select different management systems (even-aged, uneven-aged, and unmanaged) and modify the settings for silvicultural practices including regeneration, cleaning, thinning, final felling and fertilization, among others. The settings for final fellings follow the Swedish Forestry Act (SFS 1979).

In the case study, a set of potential treatment schedules based on four different management strategies was generated for every forest stand. The four management strategies were the following:

- Default management strategy defined in PlanWise (production), but the final felling age was delayed by 0 – 20 years;
- As production, but the final felling age was delayed by 20 – 45 years;
- As production, but the final felling age was delayed by 45 – 70 years;
- No management.

The forest areas in the stand register that were identified to have high nature conservation values were designated to the “No management” strategy. The identification of these areas was done based on different forest conditions such as volume of dead wood or proportion of deciduous trees. All four strategies were applied to the rest of the stands in the forest property. The maximum final felling delay allowed for more flexibility when selecting the best treatment schedule alternative in the optimization. A discount rate of 2.5% was chosen for the calculations of discounted costs and revenues of harvest and silvicultural practices. The calculations were done in Swedish crowns (SEK) and the results presented in Euros (EUR), where 10 SEK = 1 EUR. For the forest development simulation, on average twelve potential treatment schedules were generated for each stand over 14 five-year periods.

The mixed integer programming problem was formulated using Heureka’s optimization module utilizing Zimpl (Koch 2005) and Gurobi 8.1 as a solver using a branch and bound algorithm approach. The total number of variables and constraints was between 41,000 and 58,000. The computer used had a 2.40 GHz Intel® Core™ i9-9980HK processor. A relative mip gap of 0.01% was used meaning that once the solver found an integer solution within 0.01% of optimal this solution was declared optimal. The final mip gap was below 0.01 for all cases and alternatives. The stated planning problem was solved for three different cases with d values of: 5, 10 and 15 m. In this study, stand *i1* was considered to create an edge effect into stand *i2* if the height difference between stands *i1* and *i2* was more than the specified value of d (see equation (2)). d is the maximum height difference value, in meters, allowed between two stands under which no edge effect is considered to occur. The choice of larger values of d implied the identification of less vulnerable edges compared to smaller and more restrictive values such as 5 m. To analyse the trade-off between NPV and the total vulnerable edge length (VEL), the optimization problem was solved 9 times for each d value with the following increasing NPV demand alternatives in % (equation (6)): 70, 80, 90, 95, 96, 97, 98, 99 and 100, and with even-flow harvest constraints. The NPV demand alternatives are hereafter denoted NPV70, NPV80 and so forth. The maximum NPV corresponds to NPV100 (see Appendix A). The even-flow harvest constraints (equation (4) and (5)) permitted a maximum harvest increase or decrease of 20% from period to period. This was done to investigate the impact of both net present value and even-flow harvest constraints on the total vulnerable edge length in the forest property.

To determine if the optimization model was able to create a landscape with similar heights between neighbouring stands we used the Global Moran I (GMI) correlation coefficient to assess whether or not the resulting dominant heights within the forest property had a clustered, random or dispersed pattern (Getis & Ord 1992). The GMI statistical test gives a measure of spatial autocorrelation for the entire forest property. This meant that if a clustered pattern was identified, forest stands located next to each other in the forest property tended to have similar dominant height values which would, in turn, meet the objective of the optimization model. The GMI value was calculated every two periods, namely eight times during the planning horizon (periods 0, 2, 4, 6, 8, 10, 12 and 14) to assess the development of the spatial autocorrelation for all d cases. In these estimations, only forest stands with common edges were used in the calculations. Case $d = 10$ was chosen for the calculations since in previous studies forest stands with dominant heights of at least 10 m were identified as “windstorm sensitive” e.g. Zeng et al. 2007.

3. Results

The model was solved for three different d cases and nine different

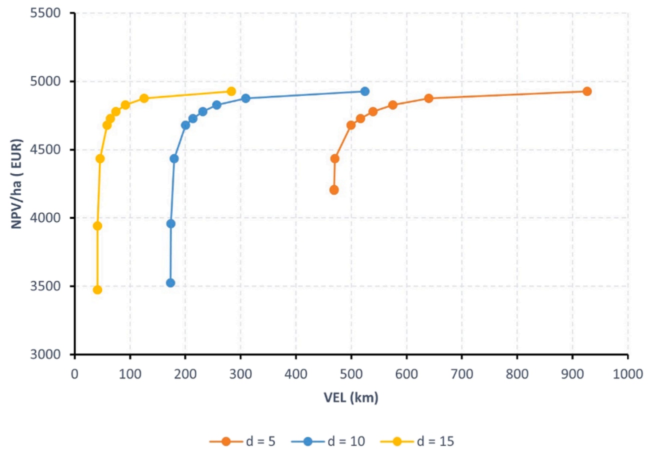

Fig. 2. Trade-off curve between net present value (NPV) and total vulnerable edge length (VEL) over the planning horizon for the investigated cases ($d = 5$, $d = 10$, $d = 15$). The points on each curve from the right to the left NPV100, NPV99, NPV98, NPV97, NPV96, NPV95, NPV90, NPV80 and NPV70. In curve $d = 5$, NPV80 and NPV70 have similar values and overlap in the figure.

NPV demand alternatives. An even flow harvest constraint was applied for all cases and alternatives and the solution times are presented in Appendix C. Table C.2.

The total VEL over the planning horizon varied between 41 and 927 km among the different d cases and NPV demand alternatives (Fig. 2). Small declines on the maximum NPV, 1–5%, were able to produce large decreases of VEL for all cases. A decrease of 1% of the NPV demand from the maximum NPV resulted in a decrease of 31, 41 and 56% for d cases 5, 10 and 15, respectively. In addition, a decrease of 5% in NPV demand resulted in a lowering of VEL by 46, 62, and 79% for d values of 5, 10 and 15. Further declines, down to NPV90 and below, occured simultaneously with an abrupt decline in the NPV. For case $d = 10$, NPV99 and NPV90 resulted in a reduction of the maximum VEL of 41 and 65%, respectively, compared to NPV100 (Fig. 2). However, for this case only small vulnerable edge declines of $<$6.5 km were achieved when reducing the NPV demand further from NPV90 down to NPV70. The largest reduction of VEL was achieved in case $d = 15$ where the edge decreased by 85% for NPV70 compared with NPV100.

The harvest volume from final fellings was larger for higher NPV demands compared to lower NPV demands during the first half of the planning horizon (Fig. 3, Appendix B.1.). In contrast to this, the harvested volume during the second half of the planning horizon varied more among NPV alternatives. NPV80 and NPV70 presented the lowest harvested volumes throughout the whole planning horizon. On the other hand, the total volume harvested from thinnings was quite similar for NPV100, NPV95 and NPV90 during the first 45 years (first 9 periods) (Fig. 3). However, in the last 25 years (periods 10 to 14) of the planning horizon the differences became larger and in comparison to NPV100, the harvested volume from final fellings and thinnings was 16 and 26% lower for NPV95 and NPV90, respectively. NPV80 and NPV70 showed considerably lower harvested volumes after 70 years ending up being 20 and 35% lower than NPV100, respectively.

The amount of forest area older than 80 years increased progressively over the planning horizon for case $d = 10$ with decreasing NPV demand (Fig. 4). NPV100 presented in total 6% of the total forest area above this age. NPV95 and NPV90 showed a considerable gain of forest over 80 years old with 11 and 19% of the total area respectively, compared to NPV100. In addition, NPV80 and NPV70 presented the largest increases with more than 33 and 40% respectively.

The initial period, common for all cases and NPV demand alternatives, for which the GMI was calculated showed a GMI value of 0.079 (p-value < 0.01; z-score: 3.00) (Appendix C) suggesting a strong clustered pattern. This meant that, for the initial period, neighbouring forest stands tended to have similar dominant height values. In the NPV95 alternative, all the investigated periods presented clustered patterns with$<$1% likelihood (p-value < 0.01) suggesting that the patterns had $<$1% probability of being the result of a random chance. For this alternative, the GMI value increased considerably over time up to period 8, when it started decreasing again for all three cases (Fig. 6, Appendix C.1.). Including the model demand in the optimization resulted in clustered patterns over time for all cases and NPV demand alternatives, compared to alternative NPV100 which didn't include this demand (Fig. 5, Appendix B.2.). In contrast, for the NPV100 alternative, the GMI value hardly changed over time meaning that different values of d didn't generate large differences on the index over the planning horizon. This alternative developed regular random patterns even if some occasional clustered patterns ocurred in the middle of the planning horizon.

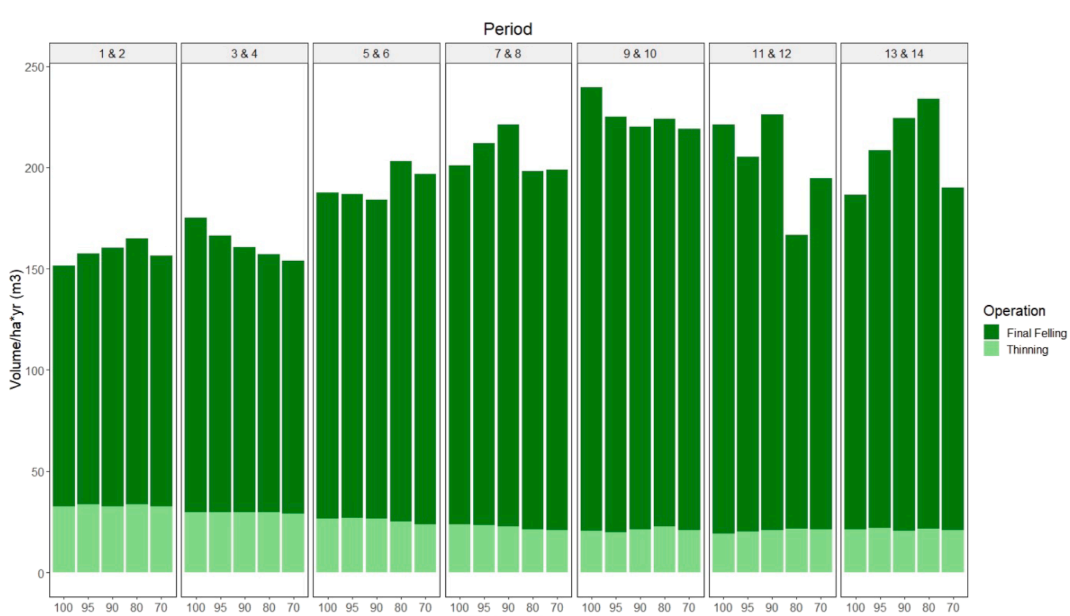

Fig. 3. Harvest profile for case $d = 10$ and NPV alternatives NPV100, NPV95, NPV90, NPV80 and NPV70. The harvest profile was calculated for all periods grouped two by two where each group represents a ten-year period.

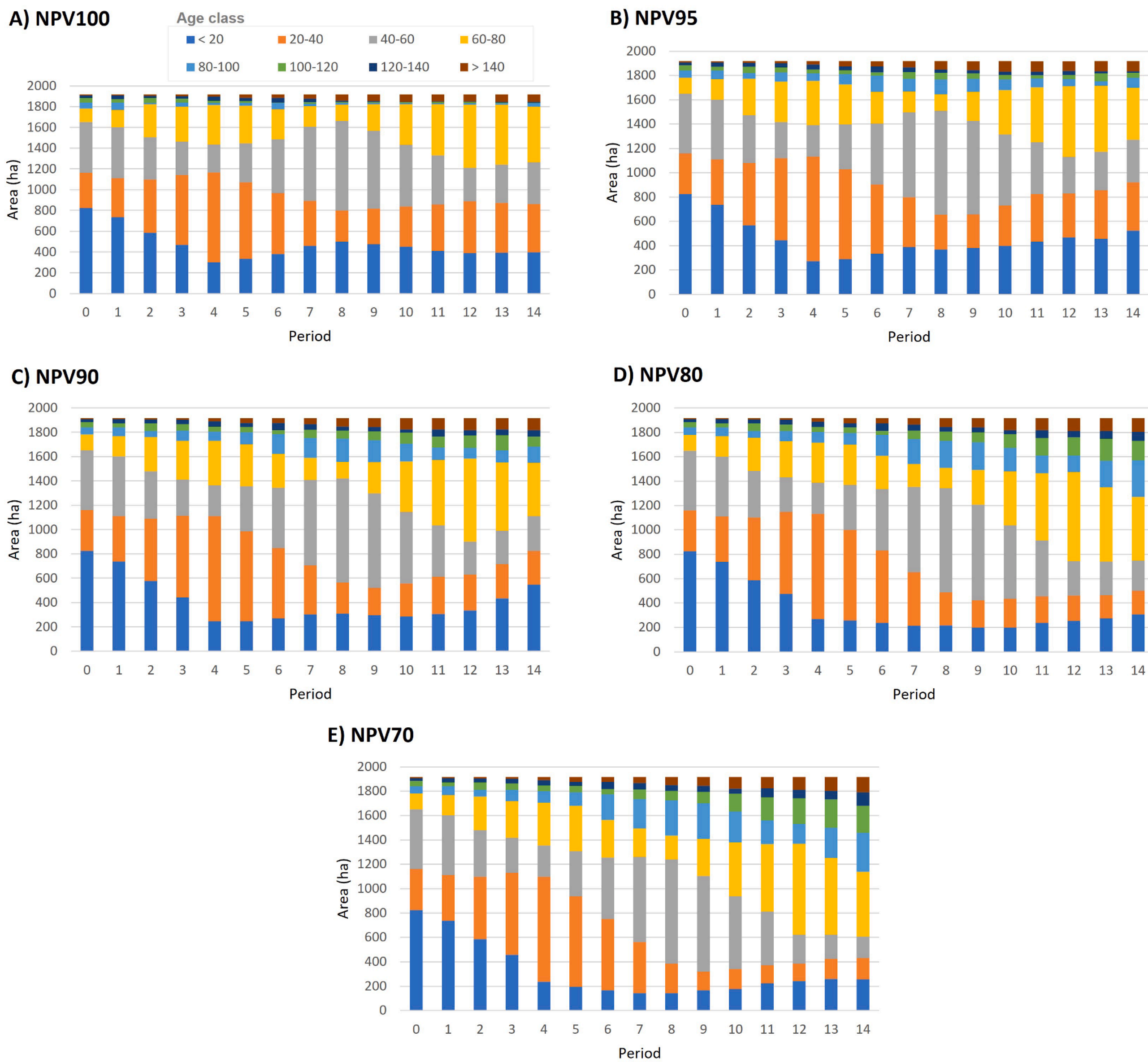

Fig. 4. Area distribution by age class and per period. For case $d = 10$ A) NPV100, B) NPV95, C) NPV90, D) NPV80 and E) NPV70.

4. Discussion

Nowadays, numerous optimization approaches provide the possibility to consider spatial relationships at large scales in order to solve complex problems with several simultaneous objectives. Here we presented a model to reduce height differences between neighbouring stands over time to reduce the overall wind exposure by using mixed integer programming together with a traditional branch and bound algoritm as exact solution technique.

The proposed model demonstrated a large potential to minimize the number of vulnerable edges affected from edge effects over time and within the forest property. However, large reductions on the VEL were only achieved for already relatively moderate declines of NPV regardless of which d value was used. The wind exposure of forest stands at the property level decreased over time when the height differences between stands with common edges was minimized. The resulting forest landscape was smoother regarding dominant heights at the end of the planning horizon and goes in line with results obtained from similar studies where, in turn, heuristic methods were applied (Zeng et al. 2007; Heinonen et al. 2009; Zubizarreta-Gerendiain et al. 2017).

The results indicate that the choice of the maximum height difference allowed between neighbouring stands to consider a forest stand edge vulnerable or not had a substantial impact on the identification of vulnerable edges in the property and their minimization. Applying larger values of maximum height differences between stands decreased the total VEL identified to a great extent. Despite this, the GMI values obtained for the largest d value investigated, $d = 15$, also showed strong clustered patterns with high values as well as for cases $d = 5$ and $d = 10$. Apart from this, the reduction of the VEL of the property influenced the spatiotemporal distribution of final fellings where the model was prone to delay and cluster some of them. This result is in line with the finding that was previously observed by Zeng et al (2007) where the

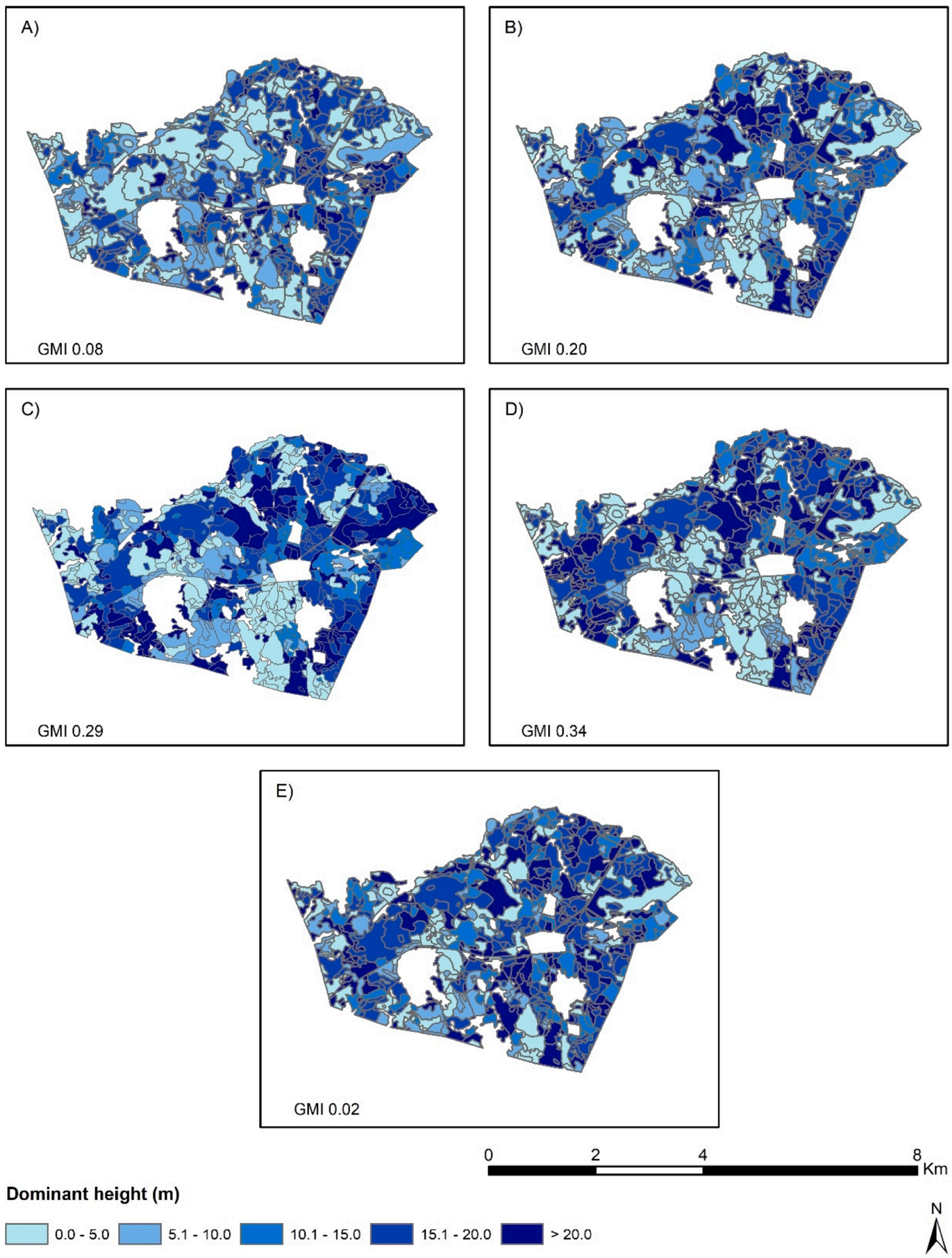

Fig. 5. Distribution of dominant heights and the Global Moran Index value in the initial period 0 (A) and in the final period 14 for NPV95; case $d = 5$ (B), case $d = 10$ (C), case $d = 15$ (D) and for NPV100 and case $d = 10$ (E). NPV100 for the three different d cases displayed similar values and therefore only $d = 10$ was presented in the figure.

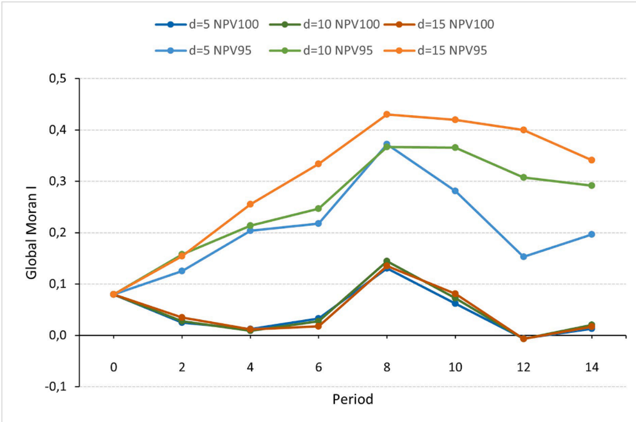

Fig. 6. Global Moran I autocorrelation analyses for cases $d = 5$, $d = 10$ and $d = 15$, and NPV demand alternatives NPV100 and NPV95. In alternative NPV95, all GMI values were statistically significant with $p < 0.01$. In alternative NPV100, periods 8 and 10 were statistically significant with $p < 0.05$ and a random pattern was present in the rest of the periods.

minimization of the occurrence of forest edges identified as vulnerable lead to the clustering of final fellings areas. In addition, the delay of final fellings led to an increase in the amount of forest area over 80 years old which ended up being up to 40% of the whole property when decreasing largely the NPV demand down to NPV70 and for case $d = 10$.

The resulting trade-off curve showed nine different combinations of NPV demand alternatives and their corresponding VEL. It was possible to decrease the amount of VEL rapidly for NPV demand alternatives down to NPV95, and after this point substantial NPV decreases were needed to continue reducing the VEL. This finding can provide adequate support and flexibility to different types of decision makers according to their risk aversion. Decision-makers who are more risk-averse should choose solutions that are further to the right of the trade-off curve.

On the other hand, NPV100 alternative also presented sporadical clustered patterns in the forest property without applying any demand to minimize the VEL. These clustered patterns appeared at periods 8 and 10 and could possibly be explained by the initial state of the forest which already displayed a clustered pattern and after an entire rotation period similar structures to the initial one may be developed. Nevertheless, in our study the production of more even landscapes regarding dominant heights led to a particularly high increase in the proportion of forest over 80 years old in the property for NPV80 and NPV70. This suggests that when NPV demands are considerably reduced the need to harvest disappears to a large extent and the harvest levels decrease leaving older forest stands in the landscape. Nonetheless, this had nearly no impact on the average final felling age for any case or NPV demand alternative. One reason that could explain this is that in alternatives NPV70 and NPV80 a larger proportion of forest is left uncut resulting in two different situations. First, the average stand age of the property gets gradually older, and second, the remaining logged forest for these alternatives continues to be harvested at similar ages compared to NPV95, for example.

When dealing with different types of risks or natural disturbances, the use of operations research techniques is convenient as they provide the possibility of integrating spatial considerations into forest planning. Previous planning problems dealing with the risk of storm damage have mostly been solved utilising different heuristic techniques (Meilby et al. 2001; Zeng et al. 2007; Zubizarreta-Gerendiain et al. 2017) and only a few using exact methods (e.g. Ross & Tóth 2016). The latter ones have been more often implemented when taking into account ecological and biodiversity conservation goals (e.g. Bettinger et al. 2003; Öhman & Wikström 2008) and seldom when considering the risk of storm damage in the forest planning process. Some of the most common heuristic techniques applied in planning problems have been simulated annealing, tabu search and genetic algorithms. However, these cannot ensure that the optimal solution is found. This study has successfully implemented exact methods using a branch and bound algorithm, which in turn makes this model easier to use by forest companies or forest owners as many decision support systems (DSS) are built on exact methods.

Although the model can easily be adapted to other planning problems if adequate input data is available and by changing the decision variable, it does not include all aspects of relevance to storm damage. For example, specific considerations connected to forest management activities that could cause a loss of stability in the forest, such as thinnings or other management activities involving the removal of timber, were not included. For this reason, the addition of constraints to limit these activities, to some extent, to prevent from increasing the probability of damage to older stands could be considered. Moreover, and as long as it is not in conflict with nature conservation objectives, restrictions can be added to minimize the creation of forest areas that could be more susceptible to strong wind gusts i.e., old forest stands or stands with great heights. On the other hand, priorities could be set to reduce the VEL of forest stands depending on their location in the property and in relation to the winds' prevailing direction. Forest stands located upwind, from where the wind is coming, are more exposed to strong winds and therefore have a higher risk of suffering wind damage. Hence, these could be prioritized over the rest.

5. Conclusion

Overall, the model performance was successful and the VEL were reduced substantially over time with only small NPV declines. The trade-off curve exemplified the risk degree for all alternatives and cases being a good means for forest owners or managers to support decisions based on their risk aversion.

Funding

The research was partly funded by the Swedish Agency for Innovation Systems (Grant number: 2019–02248, Project title: The National Forest Data Lab).

CRediT authorship contribution statement

Teresa López-Andújar Fustel: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Jeannette Eggers:** Conceptualization, Methodology, Writing – original draft, Supervision. **Tomas Lämås:** Conceptualization, Methodology, Writing – original draft, Supervision. **Karin Öhman:** Conceptualization, Methodology, Writing – original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank Sveaskog for providing the forest dataset used in this study.

Appendix A

Mathematical formulation for the Maximum Net Present Value (MaxNPV).

$$MaxNPV = \sum_{i}^{I} a_i \sum_{j}^{J} d_{ij} x_{ij} \tag{A.1}$$

Subject to:

$$\sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ij(p+1)} x_{ij} a_i \geq (1-\mu) \sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ijp} x_{ij} a_i \forall p \in P-1 \tag{A.2}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ij(p+1)} x_{ij} a_i \leq (1+\mu) \sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ijp} x_{ij} a_i \forall p \in P-1 \tag{A.3}$$

$$\sum_{j=1}^{J_i} x_{ij} = 1 \forall i \in I \tag{A.4}$$

$$x_{ij} = \{0,1\} \forall i \in I, \forall j \in Ji \tag{A.5}$$

where:
x_{ij} is the binary decision variable that ensures that stand i is designated the value 1 if treatment schedule j is assigned to stand i,
v_{ijp} is the volume harvested for stand i and treatment schedule j in period p,
μ indicates the maximum and minimum harvest deviation allowed between period p and $p+1$.
a_i is the area in hectares of stand i,
d_{ij} is the NPV per hectare of stand i and treatment schedule j from period 1 to infinity,
Equation (A.1) is the objective function, i.e. summarizes the net present value of all stands and their corresponding treatment schedules. Equations (A.2) and (A.3) ensure that the maximum fluctuation of timber harvest per period is fulfilled. Equations (A.4) and (A.5) ensure that only one treatment schedule is assigned to each treatment unit.

Appendix B

See Figs. B1 and B2

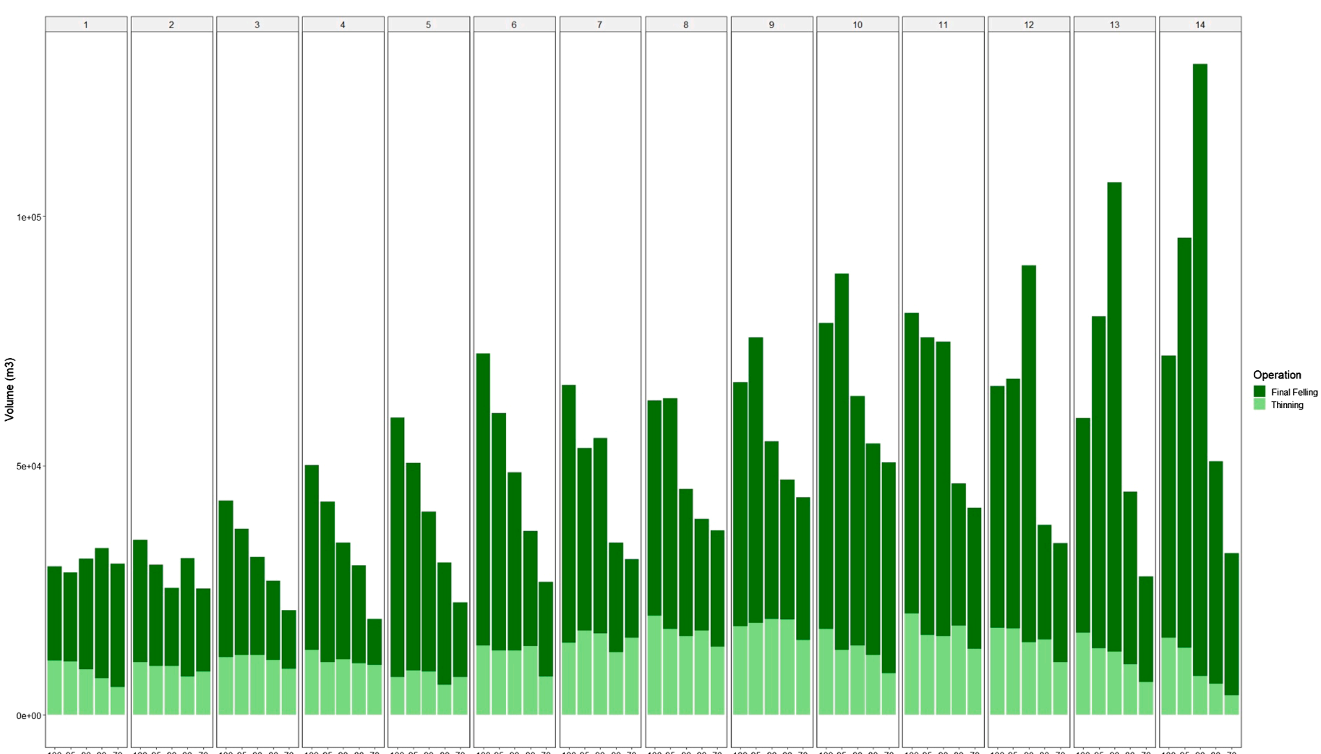

Fig. B1. Harvest profile. Estimations for case $d = 10$ and all periods in the planning horizon (five-year periods). NPV100, NPV95, NPV90, NPV80 and NPV70 were included.

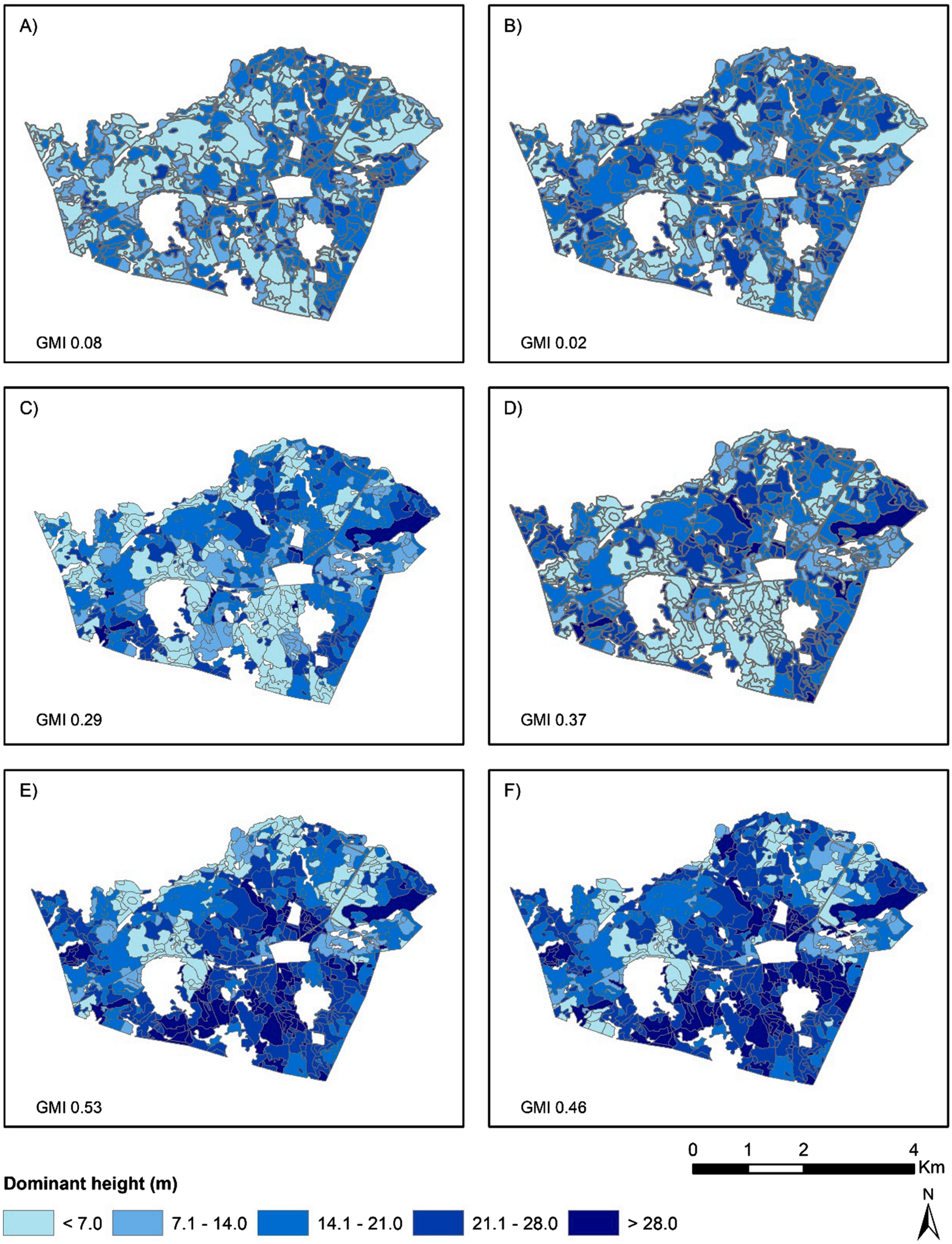

Fig. B2. Dominant height distribution for case $d = 10$ and different NPV alternatives in A) the initial period 0; B) NPV100 and period 14; C) NPV95 and period 14; D) NPV90 and period 14; E) NPV80 and period 14; F) NPV70 and period 14.

Appendix C

See Tables C1 and C2

Table C1
Global Moran I statistical test calculations. The Global Moran I (GMI) value, p-value and z-score are presented for all cases, alternatives NPV100 and NPV95 and every two periods. (i) common period for all cases and NPV alternatives.

d Case	NPV Alternative	Period	GMI Value	p-value	z-score
5	100	0 (i)	0,079449	0,002634	3,007464
	100	2	0,024985	0,320689	0,993042
	100	4	0,012430	0,597095	0,528583
	100	6	0,032960	0,197848	1,287707
	100	8	0,130594	0,000001	4,898667
	100	10	0,062023	0,018116	2,363230
	100	12	−0,006510	0,863589	−0,171807
	100	14	0,012773	0,588117	0,541567
5	95	2	0,124938	0,000003	4,690196
	95	4	0,203941	0,000000	7,611725
	95	6	0,217457	0,000000	8,111431
	95	8	0,372095	0,000000	13,829924
	95	10	0,280861	0,000000	10,456064
	95	12	0,153039	0,000000	5,728877
	95	14	0,196420	0,000000	7,333770
10	100	2	0,027498	0,277491	1,085973
	100	4	0,008960	0,688938	0,400296
	100	6	0,027388	0,279396	1,081677
	100	8	0,144124	0,000000	5,399025
	100	10	0,072414	0,006004	2,747562
	100	12	−0,007186	0,843979	−0,196807
	100	14	0,020451	0,409012	0,825633
10	95	2	0,157379	0,000000	5,890312
	95	4	0,213806	0,000000	7,976411
	95	6	0,246881	0,000000	9,199224
	95	8	0,367011	0,000000	13,641735
	95	10	0,365361	0,000000	13,581718
	95	12	0,307339	0,000000	11,436457
	95	14	0,291464	0,000000	10,848762
15	100	2	0,034542	0,178150	1,346472
	100	4	0,011694	0,616096	0,501391
	100	6	0,017700	0,469400	0,723456
	100	8	0,134968	0,000000	5,060457
	100	10	0,081092	0,002151	3,068533
	100	12	−0,006717	0,857563	−0,179477
	100	14	0,017074	0,483485	0,700708
15	95	2	0,154467	0,000000	5,782022
	95	4	0,254940	0,000000	9,496632
	95	6	0,333894	0,000000	12,416754
	95	8	0,429820	0,000000	15,965173
	95	10	0,419705	0,000000	15,592241
	95	12	0,399973	0,000000	14,863943
	95	14	0,341067	0,000000	12,683807

Table C2
Processing time. The solution times and vulnerable edge length (VEL) for the studied *d* cases ($d = 5$, $d = 10$, $d = 15$) and NPV alternatives (NPV100, NPV99, NPV98, NPV97, NPV96, NPV95, NPV90, NPV80 and NPV70) is presented.

d Case	NPV Alternative	VEL (%)	Solution Time (s)
5	NPV100	0.0	667
	NPV99	−31.1	663
	NPV98	−38.1	1012
	NPV97	−42.0	614
	NPV96	−44.4	1907
	NPV95	−46.2	560
	NPV90	−49.4	916
	NPV80	−49.6	2485
	NPV70	−49.6	530
10	NPV100	0.0	6761
	NPV99	−41.1	368
	NPV98	−51.1	259
	NPV97	−55.8	255

(continued on next page)

Table C2 (*continued*)

d Case	NPV Alternative	VEL (%)	Solution Time (s)
	NPV96	−59.2	255
	NPV95	−61.8	139
	NPV90	−65.7	51
	NPV80	−66.9	93
	NPV70	−66.9	43
15	NPV100	0.0	2290
	NPV99	−55.6	567
	NPV98	−67.7	114
	NPV97	−73.7	406
	NPV96	−77.3	246
	NPV95	−79.4	351
	NPV90	−83.8	12,300
	NPV80	−85.5	61
	NPV70	−85.5	48

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