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1 **Templates for multifunctional landscape design**

2

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10

11

12 **Abstract**

13 *Context* – In climate-smart landscapes people manage land use for integrating sustainable production,
14 climate change adaptation and mitigation. The spatial dimension of this multifunctionality remains to
15 be formalised to increase effectiveness of nature-based solutions.

16 *Objectives* – We aimed to systematically analyse effects of fragmentation on multifunctionality and
17 their interactions with land-use intensity responses.

18 *Methods* – We generated virtual landscapes to model interactions among six ecosystem services (ES)
19 of different spatial sensitivities. We simulated land-use patterns on topographies from plains to
20 mountains. Four land-use intensity treatments departed from hypothesised optimal composition for
21 biodiversity and ES with > 30% intensive, < 30% extensive or protected and > 40% intermediate
22 intensity use. For each composition we generated landscapes with differing fragmentation.

23 *Results* – Pixel- and landscape-level multifunctionality emerge from sensitivities of the six ES to
24 landscape composition, fragmentation and their interactions. In heterogeneous landscapes of
25 intermediate land-use intensity extensive grasslands and spatial complementarity supported multiple
26 ES provision. Increasing land use intensity decreased multifunctionality by reducing all ES. However,
27 greater fragmentation mitigated some of these effects because its benefits to nitrogen retention and
28 pollination exceeded losses for recreation, especially in finer-grained landscapes. The five regulating
29 ES were synergistic and showed trade-offs with recreation. Although interactions were most sensitive
30 to intensity given its dominant effects on individual ES, fragmentation mediated interaction strength.

31 *Conclusions* – Virtual simulations allow a systematic understanding of how interactions between land-
32 use intensity and fragmentation modulate multifunctionality. This constitutes an essential step to
33 designing templates for climate smart-landscapes tailored to regional geographies, land-use allocation
34 and ES priorities.

35

36 **Keywords** : nature-based solutions, neutral landscape, multifunctionality, ecosystem service trade-off

37

38

39 **Introduction**

40 Managing and restoring ecosystems can support climate adaptation by mitigating and buffering the
41 detrimental impacts of climate change, and providing options for material and non-material benefits
42 to livelihoods (Colloff et al. 2020; Lavorel et al. 2015), considered as ‘nature-based solutions’ (Cohen-
43 Shacham et al. 2019; Seddon et al. 2020). The conservation and restoration of native woody vegetation
44 (Case et al. 2020; Valdés et al. 2020) or of extensive grasslands (Bardgett et al. 2021; Lavorel et al.
45 2015) are such solutions. Much of the literature and practice has focused on nature-based solutions
46 targeting a single contribution of nature to people (Chausson et al. 2020), yet land use decisions are
47 made by negotiating trade-offs between multiple objectives (Ellis et al. 2019; Meyfroidt et al. 2018).
48 Failing to consider this underpins several recognised impediments to the effectiveness of nature-based
49 solutions, including lack of system-wide and cross-scale effects (Fedele et al. 2020; Seddon et al. 2020).
50 Integrating multiple goals for climate adaptation must therefore be addressed under a
51 ‘multifunctionality’ framing (Lavorel et al. 2020; Mastrangelo et al. 2014). Landscapes are relevant and
52 indispensable entities for integrating biodiversity dynamics and biophysical functioning that underpin
53 the ecosystem service synergies and trade-offs which shape such multifunctionality (Lavorel et al.
54 2015; Lavorel et al. 2020) and thereby landscape sustainability (Wu 2021).

55 In climate-smart landscapes people manage and reconfigure land use for integrating multiple goals of
56 climate mitigation, sustainable production and livelihoods (Harvey et al. 2014; Scherr et al. 2012).
57 Climate-smart landscapes have been implemented in developing regions (Harvey et al. 2014; Sarker et
58 al. 2019) and increasingly in Europe (Fusco et al. 2020) and Australasia (Gosnell et al. 2019; Heeb et al.
59 2019). However the spatial dimension of the required multifunctionality has received insufficient
60 attention (Bowditch et al. 2020; Prestele and Verburg 2020). While spatial configuration, for instance
61 fragmentation, is not expected to have substantial impacts on carbon sequestration which tends to be
62 proportional to area, it has essential effects on many regulating contributions that underpin
63 sustainable production like pollination, pest control or regulation of water quality (Arroyo-Rodríguez
64 et al. 2020, Jeanneret et al. 2021, Tscharncke et al. 2021), and on non-material contributions to
65 people’s lives (Wartmann et al. 2021).

66 Overall, mechanistic understanding is limited in studies of patterns of interactions among ecosystem
67 services (Dade et al. 2019): systematic approaches to drivers of multifunctionality are urgently needed
68 (Spake et al. 2017). Moreover, the pattern-oriented approach is heavily constrained by available data,
69 and the lack of mechanistic understanding treats the influence of each land use as additive, when it is
70 well understood that trade-offs and synergies make these effects non-additive. Landscape
71 composition - the proportions of different land uses, is a key determinant of biodiversity, ecosystem
72 functioning and services, and of their trade-offs (Arroyo-Rodríguez et al. 2020; Garibaldi et al. 2021;

73 Turkelboom et al. 2018). Additionally landscape spatial configuration influences individual ecosystem
74 services (Qiu 2019) and their interactions (Cordingley et al. 2015; Qiu et al. 2021; Richards et al. 2018;
75 Rieb and Bennett 2020). Climate adaptation actions and their consequences for biodiversity,
76 ecosystem services and human well-being differ between landscapes where productive land uses and
77 nature conservation coexist (land sharing) versus being spatially segregated (land sparing) (Burton et
78 al. 2019; Finch et al. 2021; Fischer et al. 2018; Verkerk et al. 2018). However, the effects of landscape
79 configuration on multifunctionality are not systematically understood due to lack of mechanistic
80 approaches. This knowledge gap severely impedes the ability to prioritise land use interventions (Jones
81 et al. 2013; Spake et al. 2019) and is a research priority (Wu 2021).

82 Multifunctionality emerges from interactions between individual ecosystem services. Conceptual
83 (Mitchell et al. 2015b; Seppelt et al. 2016), empirical (Arroyo-Rodríguez et al. 2020; Hertzog et al. 2019;
84 Sirami et al. 2019; Valdés et al. 2020) and very few studies combining both approaches (Plas et al. 2019;
85 Qiu et al. 2021; Rieb and Bennett 2020; Thomas et al. 2020) show that all ecosystem services (ES)
86 respond to some degree to landscape pattern (composition and configuration) given its influence on
87 ecological and social processes (Duarte et al. 2020). How landscape pattern affects ES pairwise
88 interactions and ES multifunctionality is more complex to understand.

89 Studies have explored the effects of landscape scenarios for ES by either manipulating current pattern
90 (Cordingley et al. 2015; Richards et al. 2018) or simulating multiple fragmentation levels (Thomas et al.
91 2020). Virtual landscape simulations which manipulate composition and configuration in controlled
92 designs take this further as a powerful method for understanding how their combination effects
93 ecosystem services (Langhammer et al. 2019). Without virtual landscapes, the analytical range of
94 investigations is limited by real world landscapes. With virtual landscapes, topography and land use
95 composition and configuration can be systematically varied within bounds realistic to actual
96 landscapes.

97 In this research we develop a virtual landscape modelling approach to advance mechanistic
98 understanding of how land-use spatial patterns support climate-smart landscapes. We asked: which
99 combinations of land use composition and spatial configuration support the multifunctionality
100 required for climate-smart landscapes? Specifically, we aimed to reveal the effects of configuration
101 (e.g. level of fragmentation) on multifunctionality and their interactions with well-documented effects
102 of composition, that is the representation of different land uses, and especially functionally critical
103 uses like intensive agriculture and native forest. We demonstrate how a landscape modelling
104 environment developed to formally explore effects of landscape pattern on ES interactions and
105 multifunctionality can generate the lacking generic, quantitative understanding of effects of landscape
106 composition and configuration on ES interactions and multifunctionality. For this, we used virtual

107 landscapes to identify patterns and mechanisms of interactions among climate-adaptation relevant
108 ecosystem services of different spatial sensitivities, depending on landscape composition and
109 configuration. Our results demonstrate the usefulness of such simulations for exploring interactive
110 effects of land use composition and pattern and their mechanisms. We discuss how virtual landscape
111 experiments can advance the understanding and management of interactions between land use
112 intensity and fragmentation, and thereby advance land sustainability science.

113

114 **Methods**

115 **Virtual landscape creation**

116 We systematically considered virtual topographies for landscapes ranging from plains to mountains,
117 upon which land use patterns were simulated. Our *in silico* experiment consisted in a factorial
118 combination of landscape composition and fragmentation across three topographies. The virtual
119 landscapes were created in Python using the NumPy (Harris et al. 2020), SciPy (Virtanen et al. 2020),
120 scikit-(van der Walt et al. 2014), NetworkX (Hagberg et al. 2008), NLMpy (Etherington et al. 2015),
121 GDAL (GDAL/OGR contributors 2021), and RichDEM (Barnes 2016a) packages.

122

123 Topography

124 Each landscape had dimensions of 2000 × 2000 cells with 25 m grain and therefore 50 × 50 km extent.
125 The topography of each landscape was initialised with a randomly directed slope with an elevation
126 range of 0-200 m. Further topographic complexity was then added using the Perlin noise approach
127 (Musgrave et al. 1989) to parameterise three types of topography: plains, hills, and mountains
128 (Supplementary Table 1) each of which was replicated 10 times. Topographic depressions were then
129 filled (Barnes 2016b) to calculate slope (Horn 1981) and to identify river channels based on D8 drainage
130 (O'Callaghan and Mark 1984) that drained at least 3.75 km².

131

132 Land cover

133 To produce land cover distributions each landscape was first divided into patches by randomly
134 selecting 5000 cells and then creating patches as discrete Voronoi polygons around the selected cells.
135 The mean elevation and slope of each patch was calculated to determine the suitability of each patch
136 for six land cover types (Table 1) based on New Zealand patterns from an analysis of the national land
137 cover data base LCBD5 (Manaaki Whenua Landcare Research 2020). Proceeding in turn from the most

138 topographically limited to least topographically limited land cover type, several suitable patches were
139 randomly selected to act as seed patches. The distribution of land cover was then grown from these
140 seed patches using an Eden growth process (Eden 1961) that randomly selected a suitable patch that
141 neighboured an existing land cover patch. If no neighbouring patches were suitable, a new seed patch
142 would be randomly selected. This land cover growth process continued until a land cover had reached
143 its specified maximum proportion of the landscape. Any patches that were not attributed to a land
144 cover type were classified as bare ground.

145 Knowledge syntheses have hypothesised optimal landscape compositions for biodiversity and
146 therefore ES with no more than 30% intensive, no less than 30% extensive or protected (including 10%
147 to 20% high quality habitat) and 40% intermediate intensity use (Arroyo-Rodríguez et al. 2020;
148 Garibaldi et al. 2021; Smith et al. 2013). Intensive land use refers to cropping and intensively managed
149 grasslands where resources and disturbance regimes are strongly modified by human inputs (Blüthgen
150 et al. 2012), while intermediate intensity land uses comprise more moderate inputs as in extensively
151 managed grasslands with a significant perennial grass component (McIntyre and Lavorel 2007). To
152 examine the effects of changing land cover proportions, four different land cover treatments were
153 specified (Table 1). Consistent with this ‘optimal’ template, we set reference land use at 30% intensive
154 (intensive grassland and crops-horticulture), 40% extensive (extensively managed grasslands and
155 exotic forestry) and 30% native (shrubland and forest), referred to as ‘intermediate – even’ henceforth.
156 We then deviated from this baseline by modifying the proportion of land under intensive use to either
157 10% in ‘extensive’ landscapes (reflecting the dominance of extensive grassland) or 40% in
158 ‘intermediate – intensive’ landscapes (to reflect the modest increase in intensive agriculture as
159 compared to the baseline), keeping the relative contributions of intensive grassland and crops-
160 horticulture constant. For this, consistent with recent intensification in New Zealand and other
161 livestock farming regions (Levers et al. 2016; MacLeod and Moller 2006; McIntyre and Lavorel 2007),
162 we converted extensive grassland to intensive land use while keeping semi-natural cover at 30% (20%
163 native forest, 10% shrubland) and total forest cover at 30% (20% native, 10% exotic). The fourth
164 scenario pictured upper-end intensification with 60% intensive use, reduction of semi-natural
165 vegetation to a total of 10% and total forest to 15% (intensive henceforth). These land cover scenarios
166 were within actual variability in crop, intensive grassland and native forest cover in New Zealand
167 catchments. For example, the intermediate - even treatment was similar to the Hurunui or the
168 Rangitikei Districts; the Masterton and Selwyn Districts were reflected in the intermediate – intensive
169 treatment. The extensive treatment was similar to the Mackenzie District, while the intensive
170 treatment captured patterns in intensive dairy production regions like the Hauraki and Manuwatu
171 Districts.

172 We then varied land use configuration to produce landscapes with differing degrees of fragmentation,
 173 expecting that in landscapes with suboptimal composition decreased fragmentation of extensive,
 174 native vegetation enables multifunctionality under greater proportions of intensive use (Tschardt et
 175 al. 2012). To examine the effects of fragmentation, each land cover was grown from 5, 10, 50, 100,
 176 500, and 1000 seed patches – increasing the number of seed patches increased the fragmentation of
 177 the resulting land cover distributions. A factorial combination of six levels of seed patches and four
 178 different land cover proportions produced 24 different land covers for each of the 10 replications of
 179 the three topography types, a total of 240 simulated landscapes.

180

181 **Table 1** - Parameterisation for the six land cover types across composition treatments. Each landscape
 182 had a topographic limit for suitability set as a function of both elevation and slope. The maximum
 183 landscape proportion for each land cover type was varied across four different treatments.

184

Land cover	Patch maximum elevation	Patch maximum slope	Maximum proportion of landscape for composition treatments			
			Extensive	Intermediate - even	Intermediate - intensive	Intensive
Crops- horticulture	500	10	0.001	0.01	0.04	0.06
Intensive grass	1000	20	0.099	0.29	0.36	0.54
Extensive grass	2000	90	0.5	0.3	0.2	0.2
Shrubland	1750	90	0.1	0.1	0.1	0.05
Exotic forest	1250	50	0.1	0.1	0.1	0.1
Native forest	1250	90	0.2	0.2	0.2	0.05

185

186

187 **Ecosystem service models**

188 We modelled six ecosystem services essential to nature-based climate adaptation and mitigation by
 189 climate-smart landscapes. Pollination, erosion and water quality regulation underpin sustainable,
 190 healthy and climate-resilient food production. Carbon sequestration and greenhouse gas mitigation

191 are essential for the climate mitigation dimension. Landscape attractiveness for recreation
 192 ('recreation' henceforth) was selected as a critical component of health, rural quality of life and of
 193 income from tourism, two important components of rural livelihoods. These ecosystem services also
 194 capture the diversity of spatial relationships of ecosystem services (Duarte et al. 2020). Spatially
 195 insensitive (e.g. carbon stocks), proximity-based (e.g. pollination, landscape aesthetic value) and flow-
 196 based (e.g. regulation of erosion or water quality) ecological processes underpin ES supply. These
 197 combine with functions of social access and value delivery (Lavorel et al. 2020): non-spatial (e.g.
 198 climate mitigation), proximity- (e.g. pollination, recreation) or topographical flow-dependence (e.g.
 199 water quality regulation), and size thresholds. We modelled supply capacity for ES representing this
 200 range of sensitivities, parameterised with New Zealand data (Table 2).

201

202 **Table 2** – Ecosystem service models used and parameterisation. Constitutional sensitivities of ES
 203 models to different spatial components are indicated as dots. Terrain: models with a function of slope
 204 or topographic features like ridges; Gravity: models with a downhill flow component; Patch size:
 205 models with an explicit function of patch size; Distance: models with an explicit function of distance to
 206 certain land covers (the open dot for nitrogen retention and distance represents inherent spatial
 207 relationships between pollutant sources and regulating vegetation, which are not directly coded in the
 208 model as opposed to the pollination model). Colouring of model parameters for the 6 land cover types
 209 indicate low (red tones) to high (green tones) effects of respective ES supply potential.

Landcover	Carbon stocks	GHG emissions	Erosion	Nitrogen retention		Pollination	Recreation
Model	Look-up	Look-up	NZUSLE	InVEST		Schulp et al. 2014	ROS
Terrain			•	•			•
Gravity				•			
Patch size							•
Distance				○		•	
Parameters	Carbon stocks (t/ha)	GHG emissions (kg e-CO2 ha yr)	U	N load (load_n)	N retention efficiency (eff_n)	Pollinator habitat	Attractiveness
Crops / Horticulture	5	1000	0.5	45	0.4	0	0
Intensive Grassland	10	8800	0.1	65	0.4	0	0.2
Extensive Grassland	18	1000	0.01	10	0.6	0.5	0.7
Shrubland	30	5	0.005	4	0.8	1	0.6
Exotic Forest	140	5	0.007	10	0.7	0.5	0.5
Native Forest	200	3	0.005	2	0.85	0.5	1

210

211 *Carbon stocks:* The carbon stocks model is a look-up table relating the land cover type of each pixel to
212 an estimated value of carbon stocks (Case and Ryan 2020; Mason et al. 2012; Thomas et al. 2021). The
213 standardised landscape sum of carbon stocks across all pixels in each landscape was calculated and
214 used for comparisons of carbon stocks between landscape fragmentation levels and proportions sets.

215 *Greenhouse gas emissions:* Likewise, the greenhouse gas emission model is a look-up table relating the
216 land cover value of each pixel in the landscape to an estimated annual value of greenhouse gas
217 emissions. Values were based on crop/land-cover and animal type-based emission values from Thomas
218 et al. (2021) and were further simplified (e.g. assuming uniform stocking-rates) and adapted, to reflect
219 a range of different land-uses. The landscape sum of greenhouse gas emissions for all pixels in each
220 landscape was calculated and used for comparisons of greenhouse gas emissions between landscape
221 fragmentation levels and proportions sets. For analyses of multifunctionality and pairwise interactions,
222 we considered the ES of avoided emissions, calculated as 1 minus the standardised emission value for
223 each pixel.

224 *Erosion:* We implemented a derivation of the Universal Soil Loss Equation model for New Zealand,
225 NZUSLE (Dymond 2010). The NZUSLE model is the product of a precipitation factor (P), a slope gradient
226 factor Z, a slope length factor L, a soil factor K, and a vegetation factor U with an equation of the
227 following form where E_s is the mean annual erosion rate due to surficial processes (in $t\ km^{-2}\ yr^{-1}$).

$$228\ E_s(x,y) = \alpha P^2(x,y) Z(x,y) L(x,y) K(x,y) U(x,y)$$

229 α is a constant calibrated with published surficial erosion rates (1.2×10^{-3}). The precipitation factor (P)
230 requires an estimate of mean annual rainfall per pixel. This was estimated for our virtual landscapes
231 with a sea surface level mean annual rainfall of 800mm for New Zealand. and a +1mm lapse per 1m
232 increase in altitude.

233 The slope gradient factor (Z) is calculated as:

$$234\ 0.065 + 4.56(dz/dx) + 65.41(dz/dx)^2$$

235 where dz/dx is the slope gradient.

236 The slope length factor (L) is calculated as $(\lambda/22)^{0.5}$ where λ is slope length in metres.

237 The slope length λ was calculated from the landscape DEM as presented by Barriuso Mediavilla et al.
238 (2017) and Bolton et al. (1995).

239 We set the soil erodibility factor (K) to 0.2, a value corresponding to medium level erodibility clay soil
240 types in Dymond (2010) as soil types were not simulated for this study.

241 Finally, values for the vegetation factor (U) were parameterised for the land cover types based on
242 expert assessment of the relative ability of each land cover to retain surface soil particles.

243 The landscape sum of erosion for all pixels in each landscape was calculated and used for comparisons
244 between landscape fragmentation levels and proportions sets. For analyses of multifunctionality and
245 pairwise interactions, we considered the ES of avoided erosion, calculated as 1 minus the standardised
246 erosion value for each pixel.

247 *Nitrogen retention* was modelled using the nutrient delivery ratio model (NDR) of the InVEST
248 ecosystem service modelling package (Sharp et al. 2020). This model uses a simple mass balance
249 approach, describing the movement of a mass of nutrient through space and represents the long-term,
250 steady-state flow of nutrients through empirical relationships. Sources of nutrient across the
251 landscape, also called nutrient loads, are determined based on land covers and associated loading
252 rates. Nutrients are then transported via surface flow (we chose to not model sub-surface flows).
253 Delivery factors are computed for each pixel based on the properties of pixels belonging to the same
254 flow path (in particular their slope and retention efficiency of the land cover). At the watershed level,
255 the nutrient export is computed as the sum of the pixel-level contributions. The parameterised
256 nitrogen loads and nitrogen retention efficiencies were determined by expert assessment of available
257 data for each land cover (Davis 2014; Elliott et al. 2005; Ledgard 2014; Pärn et al. 2012; Sharp et al.
258 2020). Total nitrogen retention for each landscape was calculated as the proportion between total
259 landscape nitrogen load and total landscape nitrogen export. For analyses of multifunctionality and
260 pairwise interactions, we calculated the standardised proportion of landscape nitrogen retained.

261 *Crop pollination*: The pollination model defines land covers on the basis of their capacity to provide
262 habitat for pollinators, and on their requirement for pollination (Maes et al. 2012; Schulp et al. 2014b).
263 To simulate pollinator movement, a 500 m buffer is implemented around patches of land covers
264 providing pollinator habitat, and the overlap between those areas requiring pollination and pollinator
265 availability is calculated. Considering provisioning services of crop (e.g. rape, clover seeds etc.),
266 horticultural (fruit, vegetable and horticultural seed production and honey production, we defined
267 crops / horticulture and shrublands as land covers requiring pollination. For pollinator habitat,
268 shrublands are assigned a pixel value of 1 (high quality pollinator habitat), extensive grasslands, exotic
269 forests and native forests a value of 0.5 (medium quality pollinator habitat) and crops / horticulture
270 and intensive grasslands a score of 0 (no pollinator habitat). After the extension of the buffer area
271 around each land cover patch (buffer pixels taking the value of the origin patch), the degree of overlap
272 between areas requiring pollination and areas of high and medium quality or no pollinator habitat are
273 identified. As shrublands are both pollinator requiring and high quality pollinator habitat, these are
274 always pollinated, and thus we considered the proportion of crops / horticulture pixels that are
275 overlapped by the differing degree of pollinator availability that becomes the variable of interest. We
276 calculated the % of crops without pollinators for comparisons of pollination availability between

277 landscape fragmentation levels and proportions sets. For analyses of multifunctionality and pairwise
278 interactions, we considered the ES of the proportion of crops covered by pollinator habitat (either high
279 or medium quality), calculated as 1 minus the standardised proportion of crops without pollinators for
280 each landscape.

281 *Recreation:* We focused on landscape attractiveness from the Recreation Opportunity Spectrum
282 approach (Byczek et al. 2018). The recreation model comprises of 3 components of landscape
283 attractiveness that are summed to provide a compound final raster of overall landscape attractiveness.
284 The first component relevant to fishing, swimming, scenic value defines areas close to a watercourse
285 (determined from the landscape DEM) as more attractive for recreation than areas distant from a
286 watercourse. Buffers of 500-meter size are created around aquatic features in the landscape (rivers)
287 and are classified as attractive for recreation (pixel value = 1), while the remainder of the landscape is
288 classified 0. The second component classifies areas located in elevated areas of the landscape (hills,
289 ridges) as being more attractive for recreation than non-elevated areas. Such areas are considered to
290 provide scenic views attractive for recreation. A topographical position index is calculated for each
291 DEM pixel using a circle of 200 meters diameter, and a breakpoint of 1.5 used to classify pixels as
292 elevated (>1.5) or not (<1.5). Elevated pixels are given a score of 1, and non-elevated pixels a score of
293 0. The third component weights each pixel depending on the attractiveness of its land cover and the
294 size of patch of that land cover. Land covers such as native forests are considered as more attractive
295 for recreation than, for example, intensive grasslands (Richards and Lavorel, unpublished). Larger
296 contiguous areas of any given land cover are considered as more attractive for recreation than small,
297 disjunct areas of that land cover (Cordingley et al. 2015; Wartmann et al. 2021). Each pixel is assigned
298 a subjective recreation attractiveness score according to its land cover (Table 1). The model then
299 calculates the proportion of the landscape occupied by each patch and multiplies the land cover
300 attractiveness score of each pixel by the proportional size of the patch in which the pixel is found.
301 Finally, the three components of landscape recreation attractiveness are summed to provide a
302 compound score of recreation attractiveness. The mean of this value across each landscape is used for
303 comparisons of recreation attractiveness between landscape fragmentation levels and proportions
304 sets. For analyses of multifunctionality and pairwise interactions, we calculated the standardised value
305 of the recreation attractiveness score.

306 The six ES models were coded into a software pipeline using the Snakemake framework (Mölder et al.
307 2021). Snakemake is a framework for linking together multiple models, originally programmed in
308 different environments and languages, into an analysis workflow for making analyses reproducible and
309 scalable (Mölder et al. 2021). In this case the workflow was used to process the large number of virtual
310 landscapes that were simulated. The six ES models were programmed using Python and the Python

311 packages RasterStats (Perry 2021), Pandas (The pandas development team, 2021), SciPy (Virtanen et
312 al. 2020), InVEST (Sharp et al. 2020), and Rasterio (Gillies et al. 2013); the R language and the R
313 packages landscapemetrics (Hesselbarth et al. 2019), raster (Hijmans 2021), and dplyr (Wickham et al.
314 2021); GDAL (GDAL/OGR contributors 2021); GRASS GIS (Neteler 2021); Docker and Debian Buster.

315

316 **Data analysis**

317 Landscape pattern was quantified using common spatial metrics. After screening for correlations we
318 retained: mean and land cover specific patch number and mean patch size, nearest neighbour distance,
319 connectivity and Shannon diversity for characterising individual landscapes (Rieb and Bennett 2020).

320 Responses of individual ES to combinations of landscape composition and fragmentation were tested
321 using General Linear Models with topography (3 types), and the combination of intensification level (4
322 categorical land cover parameter sets) and mean patch size (continuous) as explanatory variables.

323 We then related spatial pattern for each unique simulated landscape to multifunctionality indices and
324 underpinning ES pairwise interactions.

325 We selected four indicators to characterise different aspects of multifunctionality. We aimed to reflect
326 the different ways in which multifunctionality can be provided; either by providing multiple functions
327 everywhere across a landscape, or through providing different functions in areas where conditions are
328 suitable (van der Plas et al 2019). Hence we selected indicators to reflect average multifunctionality
329 and its variability at each of the landscape and pixel scales. The first two indicators consider the
330 magnitude and evenness of provision by each landscape as a whole, while the second two consider
331 within-landscape variation by comparing scores across different pixels. Multifunctionality is commonly
332 quantified as the average or sum of all ecosystem service scores provided by a landscape, hence our
333 two indicators of mean scaled provision at landscape and pixel scale (Hölting et al. 2019). The mean
334 landscape-scale ecosystem service score indicates whether a landscape is providing a high total level
335 of functionality, but can be susceptible to bias towards one ecosystem service, if the scores for that
336 service are very high in some landscapes. To also characterise the extent to which a landscape provides
337 multiple services, we quantified the evenness of provision of the selected ES (Richards et al. 2018). At
338 the within-landscape (pixel) scale, it is important to understand whether the landscape is providing
339 multifunctionality uniformly, or whether it exhibits spatial heterogeneity and complementarity across
340 the landscape mosaic. We thus quantified the within-landscape heterogeneity in the sum of the scaled
341 ES scores within each pixel (Lavorel et al. 2017b).

342 For the landscape scale indicators, each ES score for each landscape was scaled against the minimum
343 and maximum values across all landscapes. For the pixel-level indicators, each ES score was scaled
344 against the minimum and maximum values found in any one pixel across all virtual landscapes. Each
345 indicator was calculated across the six ES, and then repeated only for the three configuration-sensitive
346 ES (pollination, nitrogen retention and recreation) so as to focus on fragmentation effects and their
347 interactions with configuration.

348 We modelled all multifunctionality indicators as mixed-effects generalized linear models fitted using
349 penalized quasi-likelihood and assuming a quasibinomial error structure. Models were fitted using the
350 topography type factor as a random effect and the mean patch size and landscape composition
351 treatment group as fixed effects. An interaction was fitted between the two fixed effects. Models were
352 fitted using the glmmPQL R function (Venables and Ripley 2002).

353 Trade-offs and synergies between pairs of ecosystem services are commonly analysed using a Pareto
354 front approach, also known as a production-possibility front, or non-dominated sorting, approach
355 (Seppelt et al. 2013; Vallet et al. 2018). Under this approach, the relationships between two or more
356 ecosystem services are analysed by quantifying their provision across a range of different land cover
357 scenarios (Vallet et al. 2018). The ecosystem services performance of the scenarios can be visualised
358 by plotting the scores for one ecosystem service against another, and the shape of the resulting cloud
359 of points can be informative in understanding the nature of trade-off or synergistic relationships
360 between the services (Seppelt et al. 2013; Vallet et al. 2018). Several attributes of this cloud of points
361 can be informative in understanding the nature of the relationships between two ecosystem services
362 (Seppelt et al. 2013; Vallet et al. 2018).

363 Here we analysed pairwise ecosystem service trade-offs following the method proposed by Vallet et
364 al. (2018), which was previously used to analyse a cloud of points resulting from a series of iterative
365 but not optimised scenarios – similar to our case. For each pair of ecosystem services, the scaled
366 indicator scores for each virtual landscape (considered as a ‘scenario’) were plotted against each other,
367 and we quantified three indicators of the trade-off or synergy relationship between the two services.
368 First, we quantified the Pareto front of each pair of ecosystem services, to identify the virtual
369 landscapes that were technically efficient in providing ecosystem services. Efficient scenarios are those
370 in which the provision of one ecosystem service cannot be improved upon without degrading the
371 provision of the second service (Seppelt et al. 2013). The efficient scenarios were found using non-
372 dominated sorting of the ecosystem service provision scores, after scaling the scores between zero
373 and one based on the maximum and minimum scores recorded across all scenarios. The shape of the
374 Pareto front is related to strength of the trade-off between two services (Richards et al. 2018). In

375 particular, cases where only one scenario makes up the Pareto front can be described as synergies,
376 because there is one efficient scenario that maximises the provision of both services (Richards et al.
377 2018; Vallet et al. 2018). Pareto fronts that contain multiple scenarios indicate a trade-off between
378 maximising the two services. Second, for each pair of ecosystem services we quantified the overall
379 shape of the bounding box enclosing the cloud of points. We characterised the shape of this cloud of
380 points as the alpha-convex hull (Pateiro-Lopez and Rodriguez-Casal 2019), and quantified its shape
381 using the shape index I , which characterises the “roundness” or “elongatedness” of the cloud (Vallet
382 et al. 2018). Pairs of ecosystem services that show a round cloud of points (I values close to 1) show
383 little relationship, while those that show an elongated cloud of points show a stronger relationship
384 that may represent an indicative trade-off or synergy, depending on the direction of the elongation
385 (Vallet et al. 2018). Third, we quantified the shape of and elongation in the cloud of points as the
386 Pearson correlation coefficient r of the cloud of points (Vallet et al. 2018). Larger positive r values are
387 indicative of a positive relationship – or synergy – between the two ecosystem services, while more
388 negative values indicate a likely trade-off (Vallet et al. 2018).

389 All statistical analyses were conducted in R version 4.0.4. (R Core Team, 2021).

390 **Results**

391 **Virtual landscape realisations**

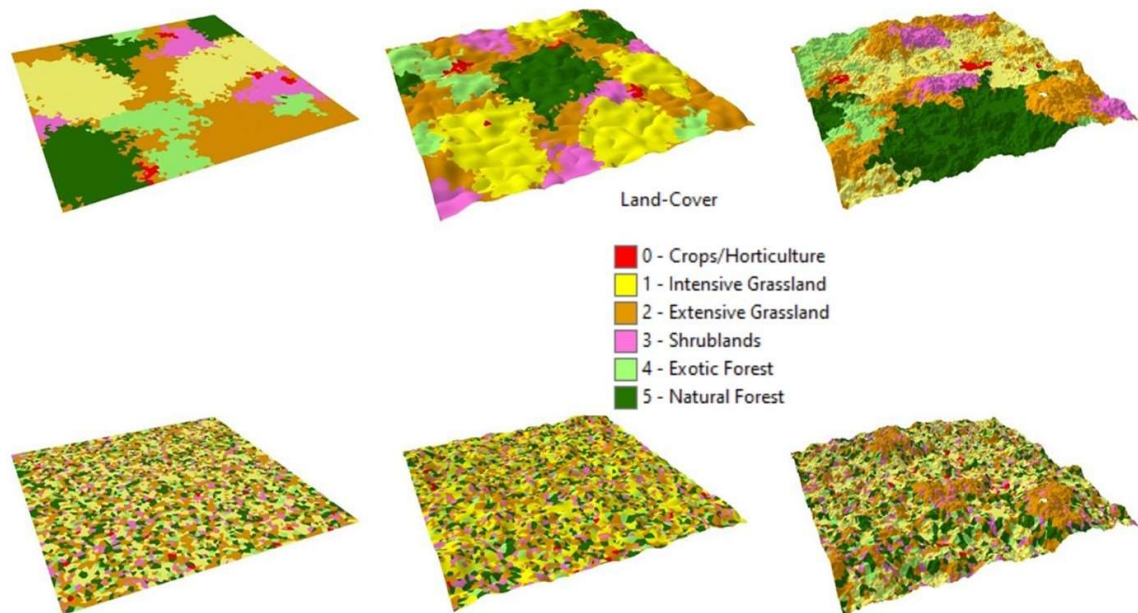
392 Our simulations produced a range of landscapes ranging from highly segregated, large land cover
393 patches to fine-grained mosaics (Figure 1; Supplementary Figure 1). Hereafter ‘fragmentation’ refers
394 to increasing mean patch number (conversely decreasing mean patch size), which was retained the
395 most parsimonious descriptor of spatial pattern.

396 Overall, mean patch size was significantly greatest (with slightly fewer, more distant patches) in
397 extensive, and especially less fragmented landscapes, while intensive landscapes had smaller patches
398 in least fragmented landscapes and fewest patches at higher fragmentation levels. Contagion
399 decreased as expected by design from least to more fragmented landscapes and was higher in either
400 extensive or intensive landscapes than in the two intermediate composition treatments, creating the
401 opposite pattern for Shannon diversity. These patterns reflect well-known phenomena near
402 theoretical thresholds of 60% land cover where individual patches start to coalesce (Gardner et al.
403 1987).

404 While for plains and hills landscapes target proportions for individual land uses were always reached,
405 in mountains constraints on allocation of intensive grassland and crops resulted in lower realised
406 proportions than maximum targets (0.8% for crops; 34% rather than 36% for intermediate-intensive
407 and 39% rather than 54% for intensive), and filling of available land by extensive grassland (40% rather
408 than 20% in intensive landscapes, 25% rather than 20% intermediate-intensive). This resulted in fewer
409 and much smaller patches of either intensive land cover than in plains or hills, especially for lower
410 fragmentation treatments. Conversely there were much fewer, larger patches of extensive grassland
411 than in plains or hills, especially in intensive as compared to intermediate landscapes, reflecting the
412 coalescence of extensive grassland patches in less suitable landscape positions. This pattern is a
413 realistic reflection of actual land use distribution in pastoral regions like New Zealand.

414

415 **Figure 1** –Examples of landscape patterns for the intensive-even composition on plains (left), hills
416 (middle) and mountains (right) for least (top row) and most (bottom row) fragmented configurations.
417 Each landscape spans 50 x 50 km, with 25 x 25 m pixels.



418

419

420 Initial data exploration showed the four composition treatments to best explain variations in modelled
421 ES as compared to any single or simple combination of land covers. We therefore retained composition
422 as a qualitative explanatory variable, depicting increasing land use intensities.

423 In the following we first summarise interacting effects of landscape composition and fragmentation on
424 individual ES. Secondly, we demonstrate how changes in fragmentation can mitigate the effects of
425 increasing land use intensity on multifunctionality. Thirdly, we explore underpinning responses of
426 pairwise ES interactions to landscape pattern.

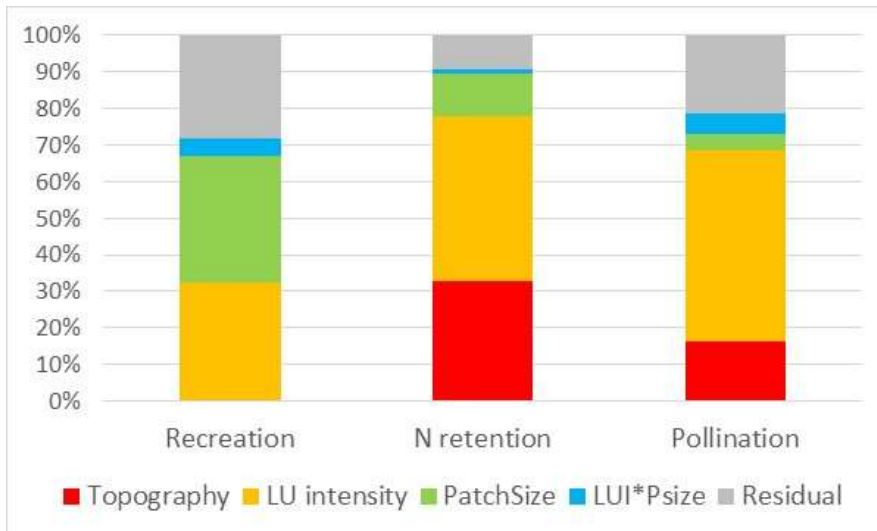
427

428 **Effects of landscape pattern on individual ecosystem services**

429 Different ES showed a range of sensitivities to landscape composition, fragmentation and their
430 interactions (Figure 2, Supplementary Table 2; Figure 3, Supplementary Figure 2).

431

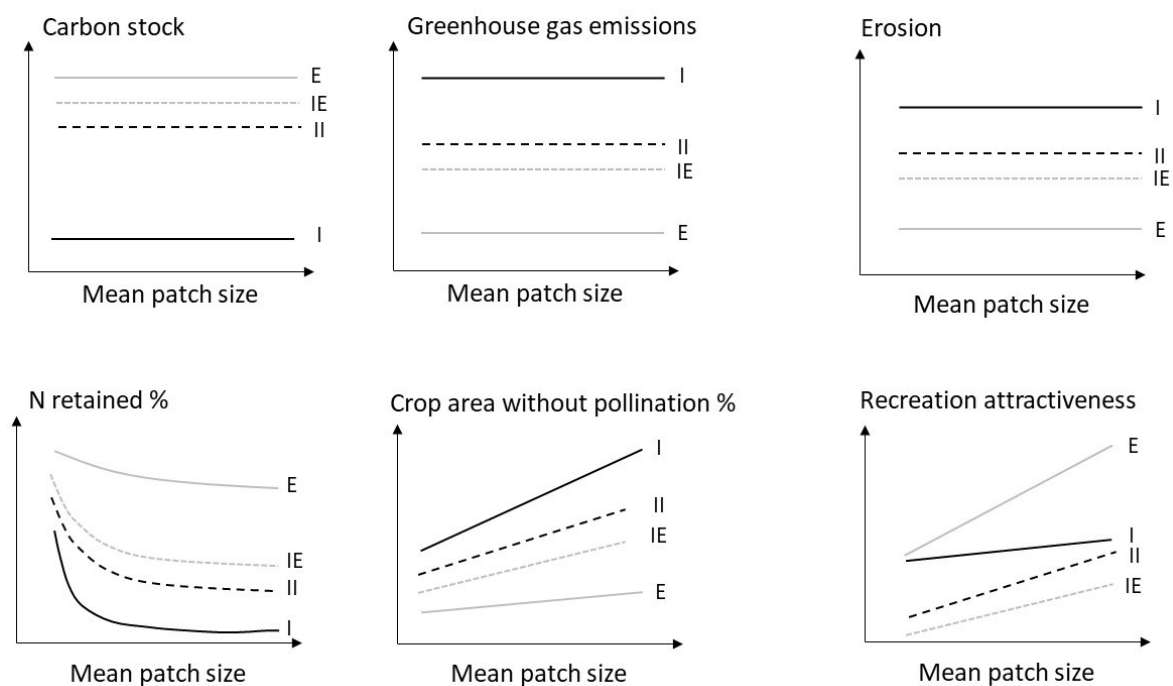
432 **Figure 2** - Variance partition across topography, land use intensity and patch size from the GLM
 433 analysis for the recreation, nitrogen retention and pollination models. Each segment represents the
 434 % variance explained in the GLM by topography, land use intensity (LUI), mean patch size and their
 435 interactions (LUI*PatchSize). Data from Supplementary Table 2.



436

437

438 **Figure 3** - Summary single ecosystem service responses to land use intensity (composition treatment)
 439 and fragmentation (mean patch size). Composition treatments are: E - extensive, IE - intermediate
 440 even, II -intermediate intensive, I - intensive. Data for each topography are presented in
 441 Supplementary Figure 2.



442

443 Our GLM analyses confirmed that, consistent with model specifications, carbon stock, GHG emissions
444 and erosion were determined by landscape composition and not by any aspect of configuration.
445 Emissions and erosion increased and carbon stocks decreased for increasing LU intensity, reflecting
446 their respective land cover based parameters (Table 2). Carbon stocks decreased in intensive
447 landscapes largely because of their lower total forest cover and were largely similar across other
448 composition treatments. Similarly, mitigation of GHG emissions was markedly greater in extensive
449 landscapes given strong reduction of intensive grassland cover.

450 Recreation was equally sensitive to composition and fragmentation. Attractiveness was greatest for
451 the extensive landscapes which contain more forests and native vegetation, followed by intensive
452 landscapes. Greater mean patch size increased attractiveness, with the few larger forest or extensive
453 grassland patches being most beneficial in intensive landscapes. Greater patches also increased
454 attractiveness in extensive landscapes, reflecting the presence of multiple large forest and extensive
455 grassland patches, especially in mountains.

456 In contrast pollination and N retention decreased with intensification but were less sensitive to
457 fragmentation (respectively 11% and 4% variance), which increased both ES. Fragmentation had
458 strongest effects in intensive landscapes, especially for pollination.

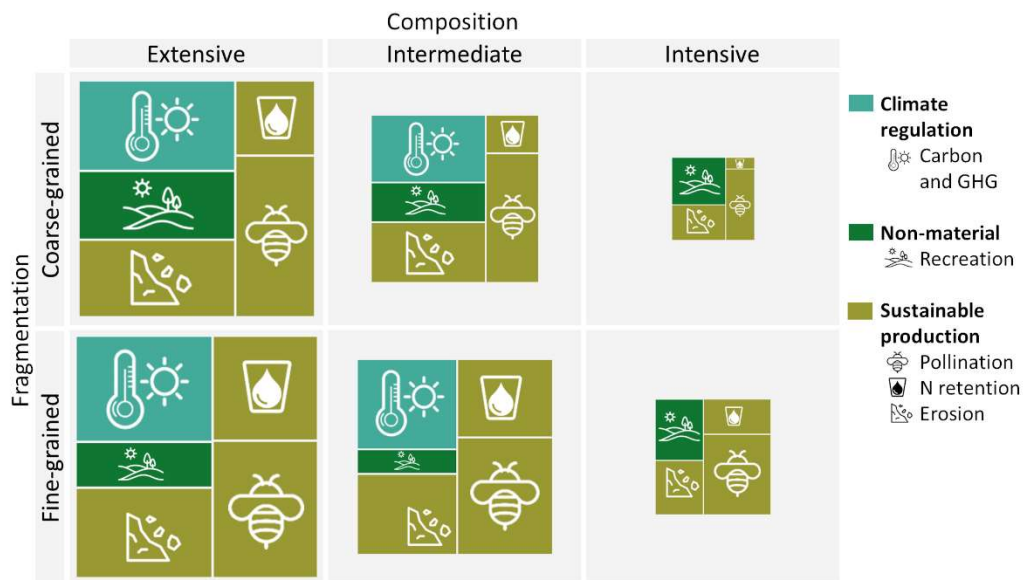
459 Topography was most influential for erosion and N retention through its effects on lateral water flows,
460 highlighting the value of our novel incorporation of terrain and hydrological networks into virtual
461 landscapes. Other significant (16% total variance for pollination) or minor effects (other ES) reflected
462 the effects of topography on land cover allocation in mountains.

463

464

465 **Effects of landscape pattern on multifunctionality**

466 **Figure 4** – Graphic summary of effects of landscape composition and fragmentation on landscape-level
 467 multifunctionality. Plot columns show the effect of increasing land use intensity across composition
 468 treatments. Plot rows show the effect of increasing fragmentation from coarse-grained (highest mean
 469 patch size) to fine-grained (lowest mean patch size) landscape configuration. The overall size of each
 470 panel is proportional to the mean ES value. Within each panel, the area of a given ES is proportional to
 471 its standardised value, showing evenness across ES. The plot was generated using the R treemapify
 472 package (Wilkins and Rudis 2021).



473
 474
 475 Figure 4 provides a graphic summary of combined effects of landscape composition and patch size (i.e.
 476 fragmentation) on the six ES and hence on multifunctionality. Increasing land use intensity decreased
 477 multifunctionality by reducing all ES (Figure 4, horizontal axis). However, greater fragmentation
 478 mitigated some of these effects because relative increases in nitrogen retention and pollination
 479 exceeded losses in recreation (Figure 4, vertical axis showing greater multifunctionality in fine-grained
 480 landscapes for a given land use intensity). Land use intensity and fragmentation influenced all
 481 multifunctionality indicators interactively. Pixel-level and landscape-scale multifunctionality or
 482 evenness indicators decreased with LU intensity (Figure 5; Supplementary Table 3a). Across all
 483 multifunctionality indicators increasing mean patch size had greatest effects in most fragmented
 484 landscapes (smallest mean patch sizes – left hand parts of response curves in Figures 5a-5d).
 485 Response of average pixel-level multifunctionality to fragmentation depended on LU intensity (Figure
 486 5a). Pixel-level multifunctionality was mostly insensitive to mean patch size for intermediate
 487 landscapes. In contrast, increasing mean patch size (i.e. decreasing fragmentation) had greatest

488 benefits to pixel-level multifunctionality in extensive landscapes, due to larger forest patches
489 increasing attractiveness for recreation. Conversely pixel-level multifunctionality decreased with
490 increasing patch size in intensive landscapes, where fragmentation mitigated negative land use
491 impacts on pollination and N retention.

492 These responses of average pixel-level multifunctionality were underpinned by varying levels of cross-
493 pixel heterogeneity (standard deviation of pixel-level scaled provision) (Figure 5b). Overall, in either
494 intensive or extensive landscapes most pixels perform poorly (intensive) or very highly (extensive)
495 across ES, whereas at intermediate intensities there is a more even mix of performance. As a result,
496 cross-pixel heterogeneity was greatest in intermediate landscapes. It increased markedly with
497 increasing mean patch size due to disproportional benefits of larger patches for recreation combined
498 with losses in N retention or pollination. Conversely, spatial heterogeneity in multifunctionality was
499 lowest for extensive landscapes, though increasing with increasing mean patch size, and slightly
500 greater but less sensitive to fragmentation for intensive landscapes.

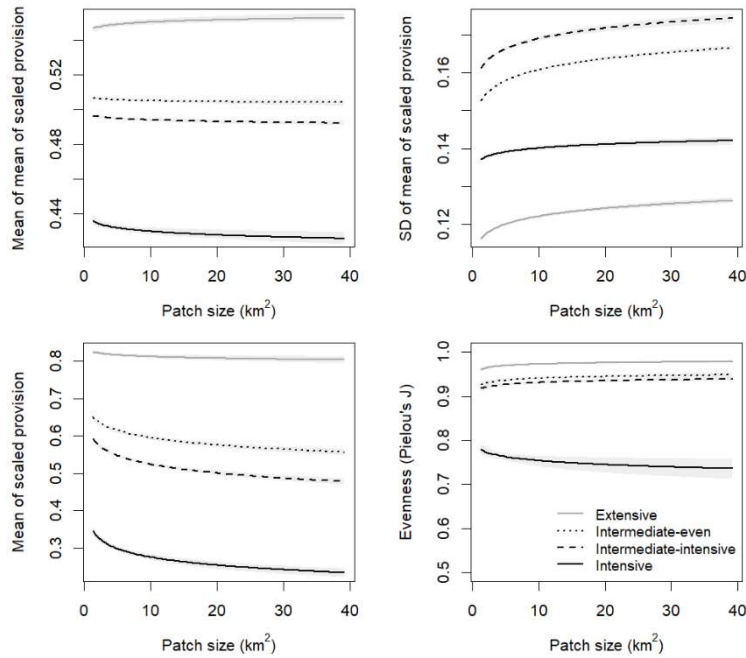
501 Pixel-level responses scaled to losses in landscape-scale multifunctionality with LU intensity increasing
502 with patch size (lower fragmentation), due to simultaneous losses for N retention and pollination
503 (Figure 5c). The sensitivity of landscape-scale evenness in ES provision to fragmentation was limited,
504 with a reduced evenness for greater patch size only in intensive landscapes (Figure 5d).

505 To discount spatially insensitive ES (carbon, GHG, erosion) we now focus on multifunctionality for
506 pollination, N-retention and recreation only (Figure 6; Supplementary Table 3b). Patterns of pixel-level
507 multifunctionality (Figure 6a) were the same as when considering all six ES, confirming negative effects
508 of increasing patch size at higher LU intensity and opposite effects in extensive landscapes. Likewise,
509 heterogeneity of scaled provision across pixels (SD; Figure 6b) was greatest for intermediate
510 landscapes and increased with patch size except for intensive land use.

511 Landscape-scale multifunctionality decreased markedly with land use intensity as for the complete set
512 of six ES, and decreased with increasing patch size, especially at highest fragmentation levels, except
513 in extensive landscapes (Figure 6c). Focusing on the three configuration-sensitive ES as compared to
514 the complete set of six ES (Figure 5d) revealed that, except for highest land use intensity, evenness
515 increased rapidly with increasing patch size, especially in most fragmented landscapes (lowest mean
516 patch sizes) (Figure 6d). This showed how benefits of increasingly large extensive grassland and forest
517 patches for recreation offset losses in pollination and N retention.

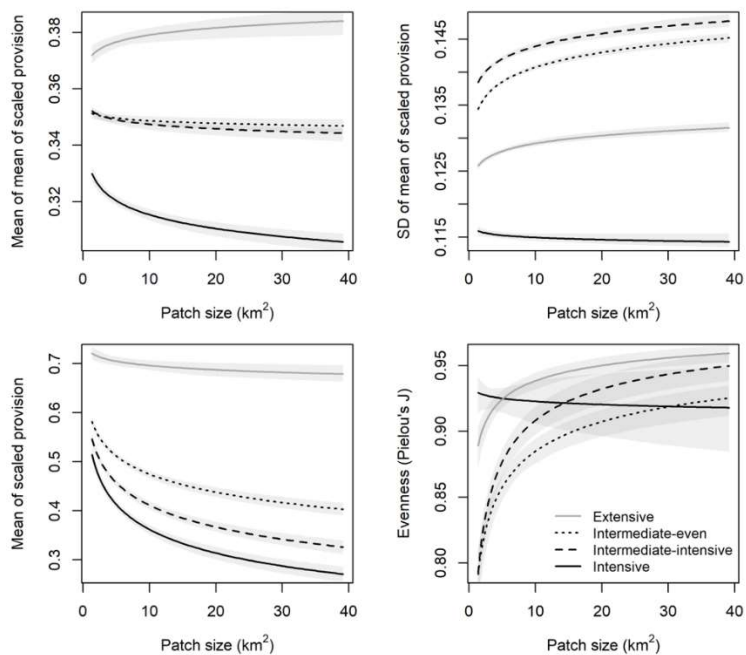
518

519 **Figure 5** – Multifunctionality indicators for the six ecosystem services considered at landscape (top
 520 row) or pixel (bottom row) scale depending on landscape mean patch size. (a) Mean pixel-scale
 521 provision; (b) Standard deviation of provision across pixels within each landscape; (c) Mean landscape-
 522 scale provision; (d) Evenness of landscape-scale provision across the six services. All indicators are
 523 calculated using standardised values for each ecosystem service.



524

525 **Figure 6** - Multifunctionality indicators for nitrogen retention, pollination and recreation considered at
 526 landscape (top row) or pixel (bottom row) scale depending on landscape mean patch size. (a) Mean
 527 pixel-scale provision; (b) Standard deviation of provision across pixels within each landscape; (c) Mean
 528 landscape-scale provision; (d) Evenness of landscape-scale provision across the three services. All
 529 indicators are calculated using standardised values for each ecosystem service.



530

531

532 **Pairwise ecosystem service interactions**

533 Pairwise ES interactions showed multiple synergistic effects among modelled regulating ES, and trade-
534 offs with recreation (Figure 7). Interaction patterns were consistent across the three topographies,
535 though not for erosion regulation which was artificially high in plains with limited erosive flow
536 (Supplementary Figure 3).

537 GHG mitigation was synergistic with pollination, nitrogen retention and regulation of soil erosion due
538 to their coinciding responses to landscape composition, and especially to proportion of intensive
539 grassland. Given lack of sensitivity of GHG emissions to spatial pattern, so were interactions with other
540 ES. Regulation of soil erosion was also synergistic with pollination and nitrogen retention. The apparent
541 negative relationship between regulation of soil erosion and recreation was only driven by artificially
542 high regulation values in those landscapes with low erosion flow (plains or extensive), and thus
543 considered spurious.

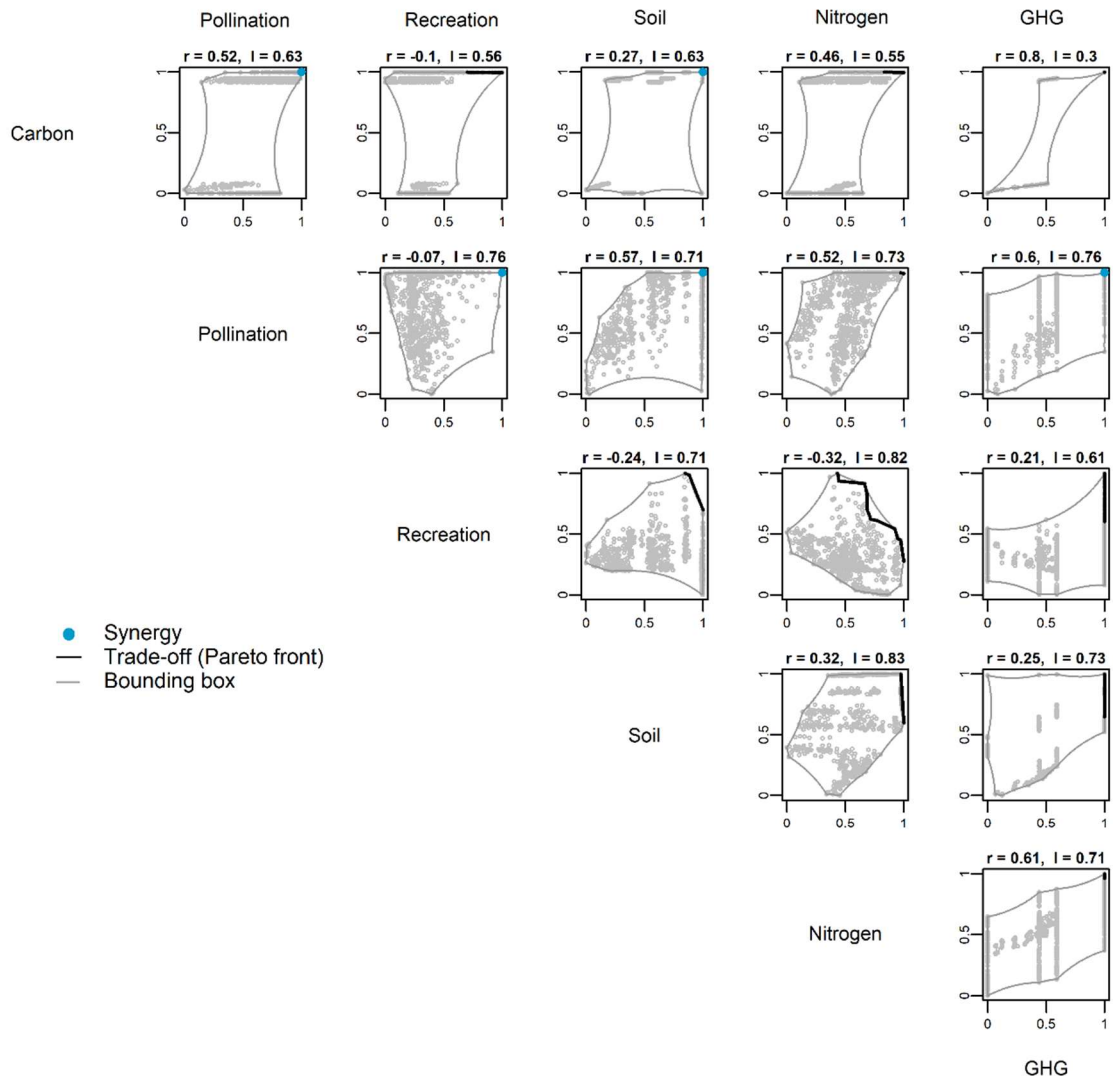
544 Pollination and N retention were synergistic, with fragmentation providing simultaneous large benefits
545 to both, especially at high LU intensity. There was a strong trade-off between N retention and
546 recreation attractiveness. At higher land use intensity increasing fragmentation benefits N retention
547 but with strong costs to recreation. There was also a weak trade-off between pollination and
548 recreation attractiveness, especially in mountains (Supplementary Figure 3). Modest increases in
549 fragmentation mitigated the effects of land use intensity on pollination with relatively small costs to
550 recreation.

551 Interaction patterns were overall more sensitive to land use intensity (composition) than to
552 fragmentation (Supplementary Figure 4), reflecting individual ES sensitivities (Figure 2). Overall,
553 fragmentation did not change synergies to trade-offs (cloud shape) or conversely, but altered
554 interaction strength (correlation coefficient). Consistent with individual ES sensitivities as well,
555 interactions with recreation were most sensitive to fragmentation for cloud shape, though not for the
556 strength of the correlation (correlation coefficient). Interactions between pollination and nitrogen
557 retention had low sensitivity to either LU intensity or fragmentation given their similar individual
558 responses.

559

560 **Figure 7-** Pairwise ecosystem service interactions among the six ecosystem services for the full set of
561 topographies. This matrix is a symmetrical grid. The names of ecosystem services are labelled along
562 the top of the columns and in the diagonal grid cells. Each cell above the diagonal shows a bivariate
563 scatterplot for each pair of services. Within each bivariate scatterplot, each point plots the ecosystem
564 performance of one virtual landscape, with respect to the two ecosystem services used as the x and y
565 axes. The scores for each ecosystem service have been scaled and normalised between zero and one,
566 such that the range of points is equivalent to the difference between the highest and lowest scores
567 across all virtual landscapes. The solid black line or blue point shows the Pareto frontier, with a blue
568 point indicating only one scenario and thus a synergy, and a black line indicating multiple scenarios
569 that plot a trade-off. Above each plot, summary statistical measures for each bivariate comparison are
570 included. The shape index I characterises the roundness of the cloud, with higher I values representing
571 more elongated clouds and thus stronger interactions. The correlation coefficient r indicates the
572 overall trend in the cloud of points, with more positive values indicating likely synergies and negative
573 values indicating trade-offs.

574



575

576

577 **Discussion**

578 Our results showcase how a systematic exploration with virtual simulations of ES responses to land use
579 composition and configuration within realistic topographic and land use constraints can advance
580 mechanistic understanding of multifunctionality and underpinning ES trade-offs and synergies, as
581 required for advancing landscape sustainability science (Wu 2021). This novel approach allowed us to
582 show how knowledge of sensitivities of individual ES to landscape composition, fragmentation and
583 their interactions can help explain their effects on pixel- and landscape-level multifunctionality. As
584 expected, increasing land use intensity decreased all six ES relevant to climate mitigation (carbon
585 stocks and GHG mitigation), sustainable production (erosion control, pollination and nitrogen
586 retention) and local livelihoods (recreation), and thus multifunctionality at both landscape and pixel
587 scales. However, the simulations revealed that greater fragmentation mitigated some of these effects
588 because its benefits to nitrogen retention and pollination exceeded losses in landscape attractiveness
589 for recreation, especially in finer-grained landscapes. Landscape pattern effects on multifunctionality
590 were underpinned by ES pairwise interactions. The five regulating ES were synergistic and showed
591 trade-offs with recreation. Although these interactions were most sensitive to intensity given its
592 dominant effects on individual ES, fragmentation mediated interaction strength. Lastly our simulation
593 design demonstrated the critical role of extensive grasslands and of spatial complementarity for
594 achieving multifunctionality goals in climate-smart landscapes comprising no more than 30% intensive
595 use, no less than 30% native shrubland and forest and 40% extensive grassland.

596

597 **Virtual land cover simulations**

598 Virtual landscape simulations allow a systematic understanding through a quasi-experimental
599 approach. Neutral landscape models have been applied for understanding effects of landscape pattern
600 on movements of single and interacting biota (Etherington 2016; With 1997), or on lateral processes
601 like fire spread (Gardner and Urban 2007; Plotnick and Gardner 2002). Virtual landscapes offer an
602 important approach to complement real landscape scenarios, which address potential changes in
603 landscape composition (Ausseil et al. 2013; Lamarque et al. 2014; Mitchell et al. 2015a; Qiu et al. 2018;
604 Schirpke et al. 2020) and configuration (Cordingley et al. 2015; Richards et al. 2018; van Strien et al.
605 2016; With 2019). Our systematic generation of combined topography and land cover patterns also
606 adds to simulations of changed patch sizes on actual topographies (Thomas et al. 2020). By capturing
607 some of the main constraints to land use distribution and ecosystem service supply they allow a
608 structured approach to understand and predict ES interactions and multifunctionality. With this
609 approach we first described individual ES spatial distribution and responses to landscape composition

610 and fragmentation. Then, from this understanding of the relative sensitivities of individual ES and of
611 their resulting interactions we could explain patterns of multifunctionality, which could not have been
612 predicted a priori from basic model characteristics.

613 For the first time in neutral landscape approaches we include topography and hydrological network,
614 as a critical driver of land use distribution and ES physical flows (energy, matter e.g. water, nutrients
615 and biota). However, fractal neutral landscape methods, such as the Perlin noise we used, produce
616 topography with many depressions. We filled these pits to produce hydrologically valid river networks,
617 but this occasional resulted in unrealistically straight rivers crossing large depressions. More
618 hydrologically realistic landscape models could be developed either by extending the Perlin noise
619 topography approach to include the application of hydrologic erosional process (Musgrave et al. 1989)
620 or by exploring procedural modelling approaches from computer graphics that reverse the process by
621 first generating a river network around which topography is then developed (Smelik et al. 2014).

622 Our model was driven by the statistical distribution of land cover across New Zealand and appropriately
623 reflected land use allocation especially in mountains where topography strongly constrained intensive
624 land use. Simulations however produced simple landscapes as compared to actual patterns of land use
625 distribution due to the even initial patch numbers across land covers. In actual landscapes intensive
626 land uses are often clustered for infrastructure, labour and energy costs (Verburg et al. 2002), thus
627 deviating from even, random spatial allocation. In extensive rural landscapes they can also form
628 smaller patches than forest and successional shrubland, leading to uneven patch sizes across land
629 cover types (Verburg et al. 2006). Lastly, we did not include soils as drivers of land use allocation
630 because of their lack of statistical effects on land use distribution within New Zealand regions. This
631 reflects the current ability for fertilisers and irrigation to substitute for soil quality as in the case of
632 intensive dairy farming on stony soils of the Canterbury region. These would have obvious moderating
633 effects on soil erosion, nutrient leaching and retention, carbon sequestration rates and GHG emissions
634 and can in principle be incorporated into virtual landscape generation as long as statistical rules can
635 support distribution modelling (Lilburne et al. 2020).

636

637 **Systematically exploring landscape effects on interactions of ecosystem services with set** 638 **properties**

639 While spatial sensitivities of individual ES are broadly known (Qiu 2019), there are both context-specific
640 (Lamy et al. 2016; Qiu et al. 2021; Rieb and Bennett 2020) and model-related (Verhagen et al. 2016)
641 discrepancies in presence and magnitude of responses. Our observation that the relative contributions
642 of composition and configuration vary significantly among ES (Lamy et al. 2016) is consistent with their

643 underpinning biophysical processes. Our set of replicable models enables a systematic exploration of
644 spatial sensitivities by structured ES model comparisons across landscape properties (topography,
645 composition, configuration) offering useful avenues for analysing sources of uncertainty (Lavorel et al.
646 2017a; Schulp et al. 2014a).

647 We used simple models for proof of concept, which could be substituted in any specific application by
648 more complex phenomenological, trait-based or process-driven ES models (Lavorel et al. 2017a). Our
649 selection incorporated realistic, commonly used models with known spatial sensitivities of relevant
650 processes. This allowed us to conduct a structured exploration of interactions with outcomes easy to
651 link to single ES model properties. Further developments could incorporate in a controlled and modular
652 fashion greater representation of biogeochemical processes, hydrological, solute and particulate flows
653 or animal movement ecology to capture more complex spatial effects including edge effects (Didham
654 et al. 2015; Ziter et al. 2014) and legacies (Ziter et al. 2017).

655 Effects of landscape fragmentation on individual ES have been formalised (Mitchell et al. 2015b), but
656 effects of landscape configuration on pairwise interactions or multifunctionality have not been
657 analysed systematically. Conceptualisations of landscape effects on ES interactions have addressed
658 amount of land conversion and intensity of land use (Qiu et al. 2021; Seppelt et al. 2016), but
659 considered effects of spatial pattern as uncertain (Seppelt et al. 2016). Furthermore, evidence for the
660 effects of landscape pattern on ES interactions is scant, but confirms trade-offs and synergies can vary
661 depending on composition (e.g. land use intensity) (Qiu et al. 2021) and fragmentation (Rieb and
662 Bennett 2020). Our simulations showed that, although land use intensity is the main driver of
663 interactions given its dominant effects on ES values, fragmentation interacts with composition in
664 mediating interaction strength, though not direction (compare top and bottom rows in Figure 4).
665 Hence, strongest trade-offs with recreation reflected primary differences in beneficial land covers
666 (Table 2) combined with greatest and opposite responses to fragmentation as compared to pollination
667 and N retention. Landscape diversity is considered essential for multifunctionality (Mastrangelo et al.
668 2014; Stürck and Verburg 2017). Van der Plas et al. (2019) showed how in heterogenous landscapes
669 spatial complementarity can support the provision of multiple ES. This mechanism for scaling
670 multifunctionality from pixels to landscapes operated especially in our intermediate landscapes with
671 higher Shannon diversity, where we observed higher spatial variability and evenness in supply of
672 multiple ES. Yet van der Plas et al. (2019) did not consider the spatial grain of heterogeneity. Our
673 simulations showed landscape-scale multifunctionality to decrease and both cross-pixel spatial
674 heterogeneity and landscape-scale evenness to increase in coarser-grained landscapes (increasing
675 mean patch size), due to increasing recreation attractiveness while pollination and N retention
676 declined. This was consistent with expectations for greater landscape diversity with finer-grain

677 patterns to favour multifunctionality (and ES resilience) by supporting a variety of ecosystem services
678 and greater species and genetic diversity (Lavorel et al. 2017b; Schippers et al. 2015; Tschardt et al.
679 2021). Due to our selection of ES that were rather favoured by fine-grained landscapes (pollination, N
680 retention) and to not including habitat functions for forest biota our simulations were unable to
681 confirm observations of multiple ES benefits of larger forest patches (Arroyo-Rodríguez et al. 2020;
682 Valdés et al. 2020). Relationships between landscape diversity, spatial grain and multifunctionality do
683 vary depending on specific ES considered and their respective spatial sensitivities (Stürck and Verburg
684 2017). A priori understanding of individual ES sensitivities as supported by our set of models is thus
685 essential to anticipate actual effects of spatial pattern.

686

687 **Developing templates for multifunctional climate-smart landscapes**

688 Knowledge syntheses have proposed based on empirical evidence and landscape ecological principles
689 that optimal landscapes for biodiversity and therefore ES, especially linked to mobile biota, comprise
690 no more than 30% intensive, no less than 30% extensive or protected (including 10% to 20% high
691 quality habitat) and 40% intermediate intensity use (Arroyo-Rodríguez et al. 2020; Garibaldi et al. 2021;
692 Smith et al. 2013). Such landscape composition templates (McIntyre et al. 2000) have however not
693 been tested systematically for how they actually deliver on multiple ES. Our simulations support three
694 mechanisms through which such templates effect multifunctionality.

695 First, given spatial heterogeneity is a key mechanism supporting multifunctionality (see previous
696 section) these land cover compositions are indeed those that provide greatest spatial diversity
697 (Supplementary Figure 1).

698 Secondly, we demonstrated the irreplaceable contribution of intermediate intensity land use, here
699 extensive grasslands, to multifunctionality. To shift from extensive to intermediate landscape
700 composition treatments, we increased intensive land uses (crops and intensive grassland) by
701 substitution of dominant extensive grassland while keeping both total forest and native woody
702 vegetation (shrubland and forest) constant. Such land use change scenarios are consistent with
703 transitions to intensification in New Zealand and may other livestock production regions (Levers et al.
704 2016; MacLeod and Moller 2006; McIntyre and Lavorel 2007). The decreased supply of individual ES
705 and multifunctionality highlights that woody vegetation could not compensate for losses in extensive
706 grasslands. This demonstrates the critical, yet under-recognised role of retaining or restoring
707 substantial areas of ecosystems at intermediate management intensity like permanent grasslands or
708 woodlands in supporting multifunctionality and climate adaptation (Bardgett et al. 2021; Cordingley
709 et al. 2015; Lavorel et al. 2015; Valdés et al. 2020). Such benefits are recognised in future land use

710 scenarios with intermediate intensity land use mosaics (Burton et al. 2019; Hanspach et al. 2014;
711 Martínez-Sastre et al. 2017; Verkerk et al. 2018).

712 Thirdly, whilst proposed landscape templates include recommendations about patch sizes, e.g. 10%
713 landscape area as large forest patches (Arroyo-Rodríguez et al. 2020), interactions between proposed
714 land cover values and landscape fragmentation are not known. Part of the logics of landscape
715 templates is embedded in understanding that 30-40% cover supports sufficient biotic connectivity in
716 landscapes with contagious spatial patterns, e.g. fractal (Fahrig et al. 2019; With 2016). Indeed, our
717 landscapes with intermediate intensity compositions had nearest neighbour distances similar to
718 extensive landscapes (Supplementary Figure 1). Adding to these known effects of composition on
719 connectivity, our simulations clearly showed that patch size influences the supply of multiple ES in rural
720 landscapes. In most fragmented landscapes especially, modest increases in patch size resulted in
721 significant trade-offs between those ES favoured by more scattered extensive grassland and woody
722 patches (pollination, N retention) and gains from larger patches for landscape attractiveness.
723 Management decisions towards slight increases or decreases in patch size are thus expected to have
724 disproportional effects in multifunctionality outcomes. In particular, reduction in patch size through
725 the planting or regeneration of small patches of woody vegetation will favour multiple regulating
726 services in farmed landscapes (Case et al. 2020; Thomas et al. 2020; Tschardt et al. 2021; Valdés et
727 al. 2020). Conversely, small increases in patch size and hence connectivity disproportionately benefit
728 services dependent on large habitat patches for valued species (Arroyo-Rodríguez et al. 2020;
729 Kimberley et al. 2021) or cultural preferences (Cordingley et al. 2015; Sutherland et al. 2016).

730 This understanding is essential to design climate-smart landscapes that support climate mitigation,
731 sustainable and climate resilient production and fulfilling local livelihoods. Our simulations did not
732 include food or timber production, given it would not be spatially sensitive and is largely proportional
733 to our GHG parameterisation. Given the comparison between three and six ES we expect including
734 production (yields per surface area), which is not sensitive to spatial configuration, would just decrease
735 overall levels of multifunctionality – and hence also differences between proportion sets, without
736 changing responses to fragmentation.

737

738 We conclude that the understanding of interactions between landscape composition and especially
739 level of intensification and spatial configuration gained from virtual simulations is an essential step to
740 designing multifunctional, climate smart-landscapes tailored to regional geographies (e.g.
741 topography), land use allocation and ES priorities. Our virtual simulation approach will support future
742 developments for refining these contexts and producing hybrid studies for real landscapes.

743 **Acknowledgements**

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745 from the New Zealand Ministry of Business, Innovation and Employment's Science and Innovation
746 Group. Sandra Lavorel dedicates this work to Robert H. Gardner for a life-long inspiration to seek
747 generality in landscape processes. We thank Bruno Locatelli for generous insights into trade-off
748 analyses and graphic support.

749

750

751 **List of figures and tables**

752 Table 1. Parameterisation for the allocation of the six landcover types

753 Table 2 – Ecosystem service models used and parameterisation

754 Figure 1 – Examples of landscape patterns for the intensive-even composition on plains, hills and
755 mountains for least and most fragmented configurations.

756 Figure 2 - Variance partition across topography, land use intensity and patch size

757 Figure 3 – Summary single ecosystem service responses to land use intensity (proportion set) and
758 fragmentation (mean patch size)

759 Figure 4 - Graphic summary of effects of landscape composition and fragmentation on landscape-
760 level multifunctionality

761 Figure 5 – Multifunctionality indicators for the set of six ecosystem services

762 Figure 6 - Multifunctionality indicators for three spatially sensitive ecosystem services

763 Figure 7 – Pairwise ecosystem service interactions among the six ecosystem services

764

765 **Supplementary Materials**

766 Supplementary Table 1 - Parameterisation of three topography types

767 Supplementary Figure 1 – Selected landscape statistics across landscape topographies

768 Supplementary Figure 2 – Responses of individual ecosystem services to fragmentation (mean patch
769 size) according to land use intensity (proportion set)

770 Supplementary Table 2 –GLM analysis of effects of topography, proportion set (PSet) and mean patch
771 size (PSize) for the six ecosystem service modelled indicators.

772 Supplementary Table 3 – Mixed models of effects of proportion set and mean patch size on
773 multifunctionality indices for virtual landscapes

774 Supplementary Figure 3 – Pairwise ecosystem service interactions across the three topographies

775 Supplementary Figure 4 – Sensitivity of ecosystem service pairwise interactions to land use
776 composition and fragmentation

777

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