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## Historical data reveal power-law dispersal patterns of invasive aquatic species

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1 **Historical data reveal power-law dispersal patterns of invasive**  
2 **aquatic species**

3  
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25 **Abstract**

26 Understanding how invasive species spread is of particular concern in the current era of  
27 globalisation and rapid environmental change. The occurrence of super-diffusive movements  
28 within the context of Lévy flights, has been discussed with respect to particle physics, human  
29 movements, microzooplankton, disease spread in global epidemiology and animal foraging  
30 behaviour. Super-diffusive movements provide a theoretical explanation for the rapid spread  
31 of organisms and disease (Viswanthan, 2010), but their applicability to empirical data on the  
32 historic spread of organisms has rarely been tested. This study focuses on the role of long-  
33 distance dispersal in the invasion dynamics of aquatic invasive species across three  
34 contrasting areas and spatial scales: open ocean (North-East Atlantic), enclosed sea  
35 (Mediterranean) and an island environment (Ireland). Study species included five freshwater  
36 plant species, *Azolla filiculoides*, *Elodea canadensis*, *Lagarosiphon major*, *Elodea nuttallii*  
37 and *Lemna minuta*; and ten species of marine algae, *Asparagopsis armata*, *Antithamnionella*  
38 *elegans*, *Antithamnionella ternifolia*, *Codium fragile*, *Colpomenia peregrina*, *Caulerpa*  
39 *taxifolia*, *Dasysiphonia sp.*, *Sargassum muticum*, *Undaria pinnatifida* and *Womersleyella*  
40 *setacea*. A simulation model is constructed to show the validity of using historical data to  
41 reconstruct dispersal kernels. Lévy movement patterns similar to those previously observed  
42 in humans and wild animals are evident in the re-constructed dispersal pattern of invasive  
43 aquatic species. Such patterns may be widespread among invasive species and could be  
44 exacerbated by further development of trade networks, human travel and environmental  
45 change. These findings have implications for our ability to predict and manage future  
46 invasions, and improve our understanding of the potential for spread of organisms including  
47 infectious diseases, plant pests and genetically modified organisms.

48

## 49 **Introduction**

50 Modelling the spread of species is a key issue in ecology and has important implications for  
51 many fields of environmental change research including palaeoecology (Clark, 1998),  
52 invasion biology (Shigesada *et al.*, 1995; Yamamura *et al.*, 2006), epidemiology (Mundt, *et*  
53 *al.* 2009), climate change modelling (Higgins & Harte, 2006) and restoration of degraded  
54 landscapes (Nathan *et al.* 2008). In invasion biology, predicting rates of species spread is  
55 essential in formulating guidance for managers (Bullock *et al.*, 2008) and in planning national  
56 control strategies.

57 Historically descriptions of patterns of species' spread have been based on classical  
58 'reaction diffusion' models, which incorporate parameters of species reproduction and  
59 dispersal rates. These models suggest that the spread of a population, in terms of the distance  
60 from the point of introduction, increases linearly with time (and therefore the square root of  
61 the occupied area also increases linearly due to the relationship between area and radius in a  
62 two dimensional plane: see Skellam 1951 for mathematical derivations). Reaction diffusion  
63 models assume that dispersal kernels conform to a normal distribution (Williamson *et al.*,  
64 2005). However, empirical data on dispersal are frequently leptokurtic (Kot *et al.*, 1996).  
65 Rates of spread are extremely sensitive to the frequency of long-distance dispersal events  
66 (Shigesada *et al.*, 1995; Clark, 1998; Kot *et al.*, 1996). Indeed, it has been demonstrated that  
67 rates of spread can increase by an order of magnitude even when the frequency of long-  
68 distance dispersal is extremely low, for example, 0.1 % of dispersal events (Higgins &  
69 Richardson, 1999). Classical reaction diffusion models are therefore likely to substantially  
70 underestimate rates of spread where long-distance dispersal occurs. In addition, theoretical  
71 models suggest that frequent long distance dispersal events may diminish the role of life  
72 history traits and landscape factors in determining the rate of species spread (Marco *et al.*,  
73 2011).

74 Simulations of the evolution of plant dispersal have shown that dispersal curves with a  
75 generalized power law form that predict a non-zero probability of propagules dispersing over  
76 very long distances are likely to evolve in natural landscapes (Hovestadt *et al.*, 2001).  
77 Empirical studies of plant spread have employed power laws to describe wind dispersal of  
78 seeds over relatively small spatial scales (e.g. Marco *et al.*, 2011), but have not addressed  
79 larger scale patterns that may result from the power law behaviour of human or animal  
80 vectors. Scaling up from local dispersal models to those which are applicable across spatial  
81 scales is one of the key difficulties in dispersal ecology and requires alternative approaches to  
82 those used on small scales (Bullock & Nathan, 2008).

83 Organisms which spread more rapidly than predicted by classical diffusion are referred to  
84 as having super-diffusive properties. One explanation for super-diffusive spread which has  
85 garnered much interest in recent scientific literature is the Lévy flight paradigm (Klafter &  
86 Sokolov, 2005; Viswanathan, 2010). Lévy flights are characterised by a power law  
87 distribution in the occurrence of long-distance dispersal events, the probability  $P(\ell)$  of a  
88 given dispersal step length ( $\ell$ ) occurring is  $\approx \ell^{-\mu}$  and the exponent  $\mu$  is  $> 1$  and  $\leq 3$ . Such  
89 Lévy flights predict super-linear rates of spread and have been shown to apply to population-  
90 level movements of humans on land (Brockmann *et al.*, 2006; González *et al.*, 2008), cargo  
91 ship movements (Kaluza *et al.*, 2010), and the foraging movements of diverse wild animals  
92 (Sims *et al.*, 2008; Bartumeus *et al.*, 2010; Humphries *et al.*, 2010).

93 Human activities are suggested to be the most important long distance vector for plants  
94 and animals (Nathan, 2006), with human transport playing a central role in invasion for many  
95 species (Catford *et al.*, 2009). Humans have been implicated as a principal long-distance  
96 dispersal vector in the spread of both marine and freshwater invasive species. Marine algae  
97 are commonly introduced to new regions by maritime traffic and aquaculture, while fishing  
98 gear is also likely to influence spread within regions (Williams & Smith, 2007). Freshwater

99 plants are most commonly introduced through the horticultural trade and may be  
100 inadvertently transported on boats or equipment (Keller *et al.*, 2009). However, natural long-  
101 distance transportation of some marine species (most notably, in this study, *Codium fragile*,  
102 *Colpomenia peregrina*, *Sargassum muticum*) may occur by flotation without human aid, and  
103 avichory of seeds or vegetative propagules may also be an alternative long-distance vector for  
104 some species (e.g. *Azolla filiculoides* and *Lemna minuta*).

105 Whilst long-distance dispersal is a crucial component in estimating the spread of species  
106 (Kot *et al.*, 1996; Higgins & Richardson, 1999; Cain *et al.*, 2000; Clark *et al.*, 2003), it is  
107 notoriously difficult to quantify directly (Cain *et al.*, 2000; Higgins *et al.*, 2003) and remains  
108 a major challenge in invasion ecology (Hastings *et al.*, 2005). This is mainly due to practical  
109 difficulties in quantifying rare dispersal events over large geographic areas using seed  
110 trapping and mark-recapture techniques. Genetic techniques, including parentage analysis,  
111 assignment methods and genealogical approaches have been applied successfully to dispersal  
112 kernel estimation (Cain *et al.*, 2000); however, such studies are very labour intensive and  
113 many statistical methods are still in development. In addition, these methods are of limited  
114 use in the case of introduced species with high levels of clonality, including many freshwater  
115 plants, such as those in this study. Conversely, for many invasive species there is a wealth of  
116 historical geographic records data available.

117 We present a simulation model to examine the validity of using historical data to  
118 reconstruct step-length distribution patterns (*i.e.* dispersal kernels). Specifically, we  
119 examined whether it was possible to distinguish between alternative step-length distributions  
120 patterns; exponential, representing thin-tailed dispersal processes; and the Lévy distribution  
121 with a power-law tail (also termed Truncated Pareto) representing fat-tailed dispersal  
122 processes.

123 We test the hypothesis that the Lévy flight step-length patterns are evident in the dispersal  
124 patterns of aquatic invasive species across spatial scales, using a historical dataset on  
125 freshwater and marine invasions, at three spatial scales: open ocean (North-East Atlantic),  
126 enclosed sea (Mediterranean) and an island environment (Ireland). This empirical dataset  
127 covers a range of species, 5 freshwater and 10 marine algae, which include a wide range of  
128 sizes (from less than  $< 3$  mm (*Lemna minuta*) to  $> 3$  m (*Undaria pinnatifida*) in length),  
129 reproductive traits and human uses including horticulture, food and aquaria planting (see  
130 Supplementary material, Table 1). Finally, the rates of range expansion of each species were  
131 examined to determine the link between fat-tailed (Lévy) step-length patterns and non-linear  
132 super-diffusive spread.

133

## 134 **Methods**

### 135 **Collation of records**

136 We collated a database of location records for the five most common invasive freshwater  
137 plant species in Ireland; namely *Azolla filiculoides*, *Elodea canadensis*, *Lagarosiphon major*,  
138 *Elodea nuttallii* and *Lemna minuta* ( $n = 2993$ ) (Table 1, Supplementary material Fig. 1),  
139 spanning 171 years from 1836 to 2007. More than 98 % of records were at a precision of 1  
140 km or less, the remaining records were recorded at a precision of 10 km. In addition we used  
141 location records of invasive marine algae from an extensive dataset (Mineur *et al.*, 2010).  
142 Species were chosen for inclusion on the basis of having a sufficient number of records ( $>$   
143 50) (see Clauset *et al.* 2009) and being readily identifiable. Generalist habitat requirements  
144 and the widespread availability of suitable habitat across the study region were considered to  
145 be essential criteria for species inclusion. We selected ten of the most common invasive  
146 marine algae in the Mediterranean and European North Atlantic regions from this dataset for  
147 inclusion in this study namely *Asparagopsis armata*, *Antithamnionella elegans*,

148 *Antithamnionella ternifolia*, *Codium fragile*, *Colpomenia peregrina*, *Caulerpa taxifolia*,  
149 *Dasyisiphonia* sp., *Sargassum muticum*, *Undaria pinnatifida* and *Womersleyella setacea* ( $n =$   
150 1571) (Table 1, Supplementary material Figs. 2 and 3), spanning 153 years from 1853 to  
151 2006. Location data were provided in WGS 1984 format to a precision of 4 decimal places.  
152 All location records were assumed positive at all dates after first recording.

153

#### 154 **Dispersal step-length distributions**

155 We measured dispersal step-length distances of freshwater species as the shortest Euclidean  
156 distance from each new record to a previous record of the same species. This is likely to  
157 provide a conservative estimate of long distance dispersal, as some individuals may have  
158 dispersed from more distant populations. Further, we used Euclidean distances rather than  
159 distances by water as human movements over land have been previously shown to be a  
160 common vector for invasive freshwater species (Buchan & Padilla, 1999). In our study we  
161 also found that many new records of our freshwater species were not connected by  
162 waterways, and therefore it was feasible and logical to assume that transportation had  
163 occurred across land. In this sense, Ireland is unusual in European terms in that major  
164 catchments are not usually connected by canals. We included all records of each species,  
165 except *E. canadensis*, which had spread to more than 90 % of the region within 151 years,  
166 hence only the first 150 years of records were used representing the initial colonisation  
167 period. We calculated distances between marine species records as the shortest distance by  
168 sea (*i.e.* without crossing land). For eight of the eleven marine datasets, we calculated  
169 distances between records using the Pathmatrix 1.1 (Ray, 2005) extension for ArcGIS 3.2.  
170 These records were converted from WGS 1984 to the projected coordinate system ETRS 32  
171 UTM (zone 32N) prior to distance calculations. We calculated distances between records for  
172 the remaining three marine species (*A. armata*, *C. fragile* and *S. muticum*) in R 12.2.2 using



173 the 'gdistance' package, due to computational constraints on large datasets in the Pathmatrix  
174 package. Distances for these species were calculated using a 0.02 degree cell raster grid.  
175 Inaccuracies in distance measurements arising from WGS 1984 were corrected for using the  
176 geocorrection function within the 'gdistance' package.

177

### 178 **Dispersal step-length analysis**

179 We used Maximum Likelihood Estimation (MLE) to fit power law, truncated power law  
180 (truncated Pareto) and exponential distributions to the dispersal step-length distribution of  
181 each species. The methodology employed here is described in detail in Humphries *et al.*  
182 (2010). Briefly, we used an iterative method in each case to derive the best fitting value for  
183 the remaining parameters (*i.e.*  $x_{\min}$  for power law and exponential, and  $x_{\min}$  and  $x_{\max}$  for  
184 truncated Pareto). This resulted in reduced datasets in each case which included only the data  
185 that the distribution was deemed to fit. To enable robust model selection, MLE was used to fit  
186 each alternative, competing distribution to each reduced dataset (e.g. exponential and Pareto  
187 in the case of best-fitted truncated Pareto dataset) from which log-likelihoods and Akaike's  
188 Information Criteria weights ( $wAIC$ ) could then be calculated. The analysis of each data set  
189 therefore resulted in four pairs of  $wAIC$ : two pairs for the best fitting truncated power law vs.  
190 exponential (and vice versa) and two pairs for the best fitting exponential vs. power law (non-  
191 truncated) and vice versa.

192 We initially categorised datasets as Lévy or exponential based on the  $wAIC$  of the best  
193 fitting exponential vs. truncated Pareto and best fitting truncated Pareto vs. exponential.

194 Where one model was the best fit in both tests, that model was considered best for the  
195 dataset. In some cases, the exponent of the truncated Pareto distribution was  $< 1$  (*i.e.* outside  
196 the Lévy range), so it was not possible to calculate the log-likelihood or  $wAIC$ . In other cases  
197 there was a conflict between the  $wAIC$  results of the two tests and the best fitting exponential

198 vs. power law (non-truncated) was compared with the best fitting power law (non-truncated)  
199 vs. exponential results. If the exponential model performed better than the power law in both  
200 tests, the dataset was deemed to be exponential. All other datasets were considered  
201 unclassified, as they could not be assigned to either Lévy or exponential step-length  
202 distributions with confidence.

203 An underlying assumption of random walk analyses is that there is no strong relationship  
204 between the frequency distribution of step-length distances and time (e.g. that the pattern is  
205 not arising as the result of a few long-distance transport events at the end of a time-series  
206 characterised by short step-lengths). To ensure that this was not the case here, we visually  
207 assessed the pattern of step-lengths against time (see Supplementary, Fig. 4), and conducted a  
208 Spearman's rank correlation test on step-length distances (standardised by species mean and  
209 standard deviation) against time. The correlation between step-length distance and time was  
210 very low ( $\rho = -0.073$ ), indicating no strong relationship between step-length and time in  
211 this dataset.

212

### 213 **Simulation model**

214 To our knowledge, the Lévy flight framework has not been previously applied to empirical  
215 data on the dispersal of plants, or indeed to movement networks inferred from maps detailing  
216 historical invasion patterns. To explore the validity of the method we developed a simulation  
217 environment to generate records of historic invasion. Specifically, our simulation tested  
218 whether assigning dispersal distances based on the closest previous invasion record  
219 reproduced the original dispersal kernel with sufficient accuracy to distinguish between Lévy  
220 flight (fat-tailed) and exponential (thin-tailed) dispersal patterns. Simulations were applied in  
221 R 12.2.2.

222 Our models simulated the spread of a hypothetical invasive species based on alternative  
223 movement patterns of vectors (exponential and power law). The model was applied within  
224 the terrestrial boundary of Ireland (as used in the empirical study of freshwater invasions).  
225 The mean values of fitted power-law and exponential distributions in the empirical freshwater  
226 species datasets were used as prior parameters for candidate distributions. Initially, the  
227 simulation generated a random point of introduction, after which, the spread of propagules  
228 was simulated from that location. The number of new propagules at each point was drawn  
229 from a Poisson distribution. The Poisson distribution had a mean of 1.5 new records per  
230 source point, which was the mean number of the new records occurring in the first ten years  
231 after introduction in the freshwater study species. This was repeated for five ‘generations’  
232 (sufficient to recreate the number of records typical within historic records), with propagules  
233 ‘reproducing’ from every novel ‘invasion point’ created in the previous ‘generation’. The  
234 direction of travel followed by each propagule varied randomly. The dispersal distance  
235 travelled by each new propagule was drawn from two alternative distributions depending on  
236 the process being simulated, namely an exponential distribution (rate = 0.07) representing a  
237 Brownian-type diffusion process, or a power-law distribution ( $x_{\min} = 0.49$ , exponent = 1.26)  
238 representing the Lévy model. Each simulation model was run 100 times. The mean number of  
239 resulting points per model was 163 (s.d. = 124).

240 The resulting simulated invasion data were treated and analysed in exactly the same  
241 manner as the empirical freshwater datasets (i.e. dispersal distances were estimated based on  
242 the shortest Euclidean distance to a previous point, and dispersal step-lengths were analysed  
243 in the same way). In addition, we compared the mean exponents of resulting best fitting  
244 distributions with those used in the construction of the simulation to assess whether these  
245 could be accurately estimated from the resulting simulated distribution map.

246

## 247 **Rates of spread**

248 We calculated the ‘invaded area’ of each empirical species as the convex hull containing all  
249 records of the species at each time point. Convex hulls were calculated using the Geospatial  
250 Modelling Environment version 0.5.3 Beta (Hawthorne, 2011) and ArcGIS 10. Convex hulls  
251 were clipped to the available range (*i.e.* land mass of Ireland for freshwater species, sea for  
252 marine species) using ArcGIS. Spread rates were defined as the increase in the square root of  
253 the area within the ‘invaded area’ over time.

254 We then fitted linear, 2 parameter exponential and 3 parameter sigmoidal functions to  
255 spread rates (square root of ‘invaded area’ as a function of time since introduction) by MLE.  
256 We compared the fits of these three functions using Akaike Information Criteria corrected for  
257 small sample sizes (AICc) and corresponding AICc. Linear spread rates represented expected  
258 spread under classical reaction diffusion. Initial super-linear rates characteristic of anomalous  
259 diffusion were represented by an exponential curve (*i.e.* continuously accelerating spread)  
260 and a sigmoid curve (*i.e.* initial accelerating spread followed by a decline in spread rate). This  
261 represents the common scenario in natural systems where the observed expansion rate slows  
262 as the maximum available range is approached (Mack *et al.*, 2000). Equation fitting and  
263 model comparison were conducted in R 12.2.2 (R Development Core Team, 2011) and  
264 plotted with SigmaPlot 10 (Systat, 2010).

265

## 266 **Results**

267

### 268 **Simulation analysis**

269 The rate of false positives was 1 % (*i.e.* datasets created from an exponential dispersal  
270 distribution that were incorrectly assigned to the Lévy model or vice versa). The rate of true  
271 positives was 83 % for Lévy distributions and 82 % for exponential distributions. In the

272 remaining 16.5 % of cases, results were ambiguous and it was not possible to assign them to  
273 either distribution (Supplementary material Table 2). In the empirical data, these were treated  
274 as unclassified, as it was unclear whether species had Lévy or exponential dispersal kernels.  
275 Additionally, the fitted truncated Pareto (power law) distributions provided a good  
276 approximation of the  $x_{\min}$  and exponents used to simulate dispersal patterns. In Lévy  
277 (truncated Pareto) based simulations the estimated mean exponent of 1.27 (s.d. = 0.43)  
278 (generated from 1.26) and the estimated mean  $x_{\min}$  of 0.431 (sd = 0.13) (generated from 0.49)  
279 recovered the modelled dispersal pattern reasonably well. In exponential based simulations,  
280 the estimated mean rate was 0.24 (s.d. 0.07) (generated from 0.07), suggesting that the  
281 method of assigning dispersal distances may under-estimate the amount of long-distance  
282 dispersal occurring when the real dispersal step-length distribution is exponential. Despite  
283 this, the low rate of false positives indicates that the method is useful for distinguishing  
284 between historical distribution patterns arising from Lévy (fat-tailed) and exponential (thin-  
285 tailed) dispersal step-length distributions.

286

### 287 **Dispersal step-length analysis**

288

289 Three of the five freshwater species were fitted best by the truncated power law and showed  
290 exponents within the Lévy range (mean exponent,  $1.38 \pm 0.15$  s.d.). One species, *Lemna*  
291 *minuta*, was fitted best by an exponential, while *Lagarosiphon major* could not be reliably fit  
292 best by either model (Table 2, Fig. 2). In eight of the eleven invasions of marine algae,  
293 dispersal distributions were fitted best by the truncated power law with exponents within the  
294 Lévy range (mean,  $1.20 \pm 0.16$  s.d.). Three species (*Antithamnionella ternifolia*,  
295 *Dasyisiphonia sp.* and *Undaria pinnatifida*) were not reliably fit best by either model (Table 2,  
296 Fig. 2). Maximum step lengths for individual species were between 141 km and 275 km in

297 freshwater species, and 614 km and 2012 km in marine species, suggesting that population  
298 establishment after long-distance dispersal events occurs for all study species across habitats  
299 (Table 2).

300

### 301 **Rates of spread**

302 Sigmoid curves fit best to the spread rates of the freshwater invasive species - *A. filiculoides*  
303 and *E. nuttallii*, and an exponential fit best for *E. Canadensis*, consistent with the finding of  
304 Lévy dispersal distributions for these species. *L. major* and *L. minuta* were fitted best by  
305 linear spread rates consistent with classical reaction diffusion, although the sigmoidal model  
306 had some support for *L. minuta*. In the marine algae, 9 of the 11 spread rates were non-linear  
307 (sigmoidal) (Table 3, Fig. 3). Overall, the analysis showed that the vast majority of species  
308 had a Lévy distribution of step lengths and exhibited non-linear, initially accelerating spread  
309 rates. The spread of *Dasysiphonia sp.* was linear and did not show a Lévy pattern (Fig. 2m).  
310 Interestingly, *A. armata* in the Mediterranean was best fitted by a linear spread model, despite  
311 its Lévy step-length pattern (Fig 2g, Fig. 3g): however the spread of this species was also  
312 well described by a sigmoidal curve (Table 3, Fig. 3g).

313

314

315

316

317

## 318 **Discussion**

319 In this study, we demonstrate through simulation that dispersal step-length distributions  
320 (dispersal kernels) of invasive species can be reconstructed from historical distribution data,  
321 and that the accuracy of this method is sufficient to differentiate between fat-tailed Lévy step-  
322 length dispersal distributions and thin-tailed exponential dispersal distributions. In the great  
323 majority of simulation runs, the dispersal distribution used in the model input could be  
324 inferred from the spatial pattern of location records outputted by the simulation. The Lévy  
325 framework, and especially the use to step-length analysis, is an increasingly common tool  
326 used to examine ecological and behaviour processes. Here, it is shown that it can be extended  
327 to explore the processes of range expansion and colonisation over both protracted time  
328 periods and large spatial scales to extract generalised patterns of invasion biology.

329 Lévy dispersal patterns were detected in the majority of study species, despite differences  
330 in size, reproductive traits and human uses of species. This suggests that Lévy dispersal  
331 patterns may be common amongst aquatic plants and algae.

332 In the case of freshwater plants, Lévy dispersal patterns were coincident with non-linear  
333 spread in three species, while *Lagarosiphon major* and *Lemna minuta* showed non-Lévy  
334 dispersal and linear spread. *L. minuta* differs from the other freshwater species in that  
335 individual plants are very small (< 3mm) and unlikely to be intentionally transported by  
336 humans for ornamental or aquaculture purposes. *L. major* belongs to the same family as  
337 *Elodea nuttallii* and *Elodea canadensis* and has a very similar morphology and association  
338 with human trade. However, *L. major* differs from these species in that it is associated with  
339 alkaline conditions: in Ireland 71 % of its recorded distribution is within one lake system  
340 (Lough Corrib, Co. Galway). Therefore, the recorded distribution of this species may reflect  
341 the availability of this specialized habitat, rather than purely the dispersal dynamics of its  
342 vectors.

343 In eight of the 11 invasions of marine algae, showed Lévy dispersal patterns and seven  
344 of these showed concordant sigmoidal non-linear spread. Only one marine species showed a  
345 solely linear range expansion (*Dasysiphonia sp.*). This species showed no evidence of a Lévy  
346 step-length distribution pattern. While some long-distance jump dispersal events early in the  
347 spread of this species have been documented (Mineur *et al.*, 2010), these are not as frequent  
348 as would be expected in a Lévy spread pattern. The contrast between the linear spread of  
349 *Asparagopsis armata* in the Mediterranean and the sigmoidal spread in the Atlantic is  
350 interesting given that it exhibited a Lévy step length distribution in both regions. The cause of  
351 this disparity between regions is unclear, but it could result from multiple factors, including  
352 those associated with community dynamics, algal life-history traits and environmental  
353 conditions (Lyons & Scheibling, 2009). Two further species (*Antithamnionella ternifolia* and  
354 *Undaria pinnatifida*) showed no evidence of Lévy patterns, but did have sigmoidal spread. In  
355 these cases, there may have been a higher frequency of long distance dispersal than predicted  
356 by an exponential model, but not as high as in Lévy models (Figs 2i, 2o).

357 This study has combined the previously observed high levels of long-distance dispersal in  
358 plant populations and invasion ecology with the developing framework of Lévy flight. Whilst  
359 the classification of Lévy flights has received significant recent attention in animal foraging  
360 ecology (González *et al.*, 2008; Sims *et al.*, 2007; Humphries *et al.*, 2010, Lundy *et al.* 2012),  
361 their role in longer term species spread has received relatively little attention.

362 The super-diffusive patterns of invasive spread by freshwater plants and marine algae may  
363 arise as an emergent property of human translocations over land (Gonzalez *et al.* 2008), or by  
364 commercial shipping (Kaluza *et al.* 2010) on hulls or in ballast water. Previous studies have  
365 suggested a correlation between invasive species human factors such as trade, travel (Catford  
366 *et al.*, 2009), population density and gross national product (Keller *et. al.*, 2009). Trends in the



367 trade of particular commodities (*e.g.* aquaculture plants) are also likely to correlate with the  
368 rate spread of species (Hulme *et al.* 2009).

369 Previous studies have reported maximum dispersal distances by non-human transport for  
370 plants of 1–20 km (Cain *et al.*, 2000), thus corroborating the likelihood that extreme long-  
371 distance transport may be attributable to human transport. However, avichory (seed dispersal  
372 by birds) cannot be dismissed as a candidate non-human vector. The seeds of many  
373 freshwater aquatic plants remain viable after transport in the intestines of wildfowl and this  
374 may account for dispersal over hundreds of kilometres (Brochet *et al.*, 2010). However, more  
375 than half of the freshwater species in the current study reproduced by vegetative means only  
376 and are probably too large for extensive epizoochory (*E. canadensis*, *E. nuttallii*, *L. major*),  
377 further supporting the role of humans as the key long-distance vector.

378 Increases in human trade and transportation during the present period of globalisation  
379 may, therefore, increase rates of spread of these species. However, as we found no correlation  
380 between step-length distances and year, we suggest that this results from the frequency of  
381 introductions, rather than changes in the relative frequency of long-distance transport.  
382 However, as this study only investigates European invasion patterns we can not comment on  
383 larger global scale patterns between continents.

384 Furthermore, species traits are likely to influence the extent to which particular organisms  
385 can benefit from long-distance dispersal opportunities (Theoharides & Dukes, 2007; van  
386 Klunen *et al.*, 2010). For example, the rare super-diffusive movements of Lévy flight are  
387 likely to be of most benefit to organisms that can establish new populations from single  
388 introductions, such as, self-fertile and asexually reproducing taxa (*e.g.* clonal plants and many  
389 plant pests (*e.g.* Ash disease *Chalara fraxinea*), and those with short generation times are  
390 ideally suited to this condition.

391 This type of analysis, which relies on detailed geographic records of established  
392 populations, is best suited to species with generalist habitat requirements and those species  
393 for which suitable habitat is available across the region at the spatial scale of the study, such  
394 as generalist invasive species. In the case of specialist species, landscape heterogeneity is  
395 likely to confound observed patterns due to its role as a barrier to the establishment of species  
396 post-dispersal.

397 The identification of Lévy patterns does not necessarily imply the existence of a Lévy  
398 movement process. It is possible that the observed Lévy patterns arise as the result of a  
399 combination of vectors, or vector behaviour, operating at different scales, consistent with the  
400 observations of a Lévy distribution of displacements being present at the population-level in  
401 human mobility patterns (Brockmann *et al.* 2006; Gonzalez *et al.* 2008, Petrovskii *et al.*,  
402 2011). Similarly, short distance dispersal might be explained by water or wind dispersal, mid-  
403 distance by mammals and wind, and long distance by bird or human transport.

404 Information on the frequency of long-distance dispersal events is essential for the  
405 formulation of strategic management plans in invasion biology. This study shows that fat-  
406 tailed dispersal patterns with high rates of long-distance dispersal can be inferred from  
407 historical data, and occur frequently in aquatic invasive species across large spatial scales.  
408 High rates of long-distance dispersal frequently lead to accelerating spread rates (Higgins &  
409 Richardson, 1999), increase the difficulty of predicting where invasions will occur next in a  
410 landscape (Clark *et al.*, 2003) and may overwhelm the role of life history and landscape  
411 heterogeneity in determining rates of spread (Marco *et al.*, 2011). The identification of these  
412 patterns in these species emphasizes the importance of focusing management not only on  
413 short-distance movements, but also on rarer long-distance vectors which increase uncertainty  
414 and cause rates of spread to accelerate, such as trade and transport.

415

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428

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572 **Tables**

573

574 **Table 1.** Dates of introduction, number of records, region and prevalence of study species.

575 MCP denotes minimum convex polygon.

Habitat	Species name	Number of records	Year of introduction	Region	Invasive range MCP (sq. km)
Freshwater	<i>Azolla filiculoides</i>	168	1893	Ireland	52,004
	<i>Elodea canadensis</i>	2,348	1836	Ireland	73,952
	<i>Elodea nuttallii</i>	201	1970	Ireland	52,753
	<i>Lagarosiphon major</i>	147	1966	Ireland	66,136
	<i>Lemna minuta</i>	129	1987	Ireland	50,072
Marine	<i>Asparagopsis armata</i>	155	1923	Atlantic	623,170
	<i>Asparagopsis armata</i>	118	1923	Mediterranean	1,237,195
	<i>Antithamnionella elegans</i>	67	1882	Mediterranean	2,163,856
	<i>Antithamnionella ternifolia</i>	80	1906	Atlantic	658,072
	<i>Codium fragile</i>	207	1845	Atlantic	1,345,940
	<i>Colpomenia peregrine</i>	104	1905	Atlantic	1,350,104
	<i>Caulerpa taxifolia</i>	86	1984	Mediterranean	628,499
	<i>Dasysiphonia sp.</i>	54	1994	Atlantic	997,160
	<i>Sargassum muticum</i>	544	1972	Atlantic	1,210,447
	<i>Undaria pinnatifida</i>	87	1982	Atlantic	253,584
	<i>Womersleyella setacea</i>	69	1987	Mediterranean	1,191,008

576 **Table 2.** Summary of the empirical data and results of MLE fitted to dispersal step lengths, showing best fit parameters and model comparison  
577 analysis wAIC. TP and Exp denote truncated Pareto (power law) and exponential models respectively. U is where neither model reliably  
578 accounted for the data. TP wAIC is given as NA when TP exponent <1 (outside Lévy range).

579

<b>Species</b>	<b>N</b>	<b>Min Step Length (km)</b>	<b>Max step length (km)</b>	<b>Best fitting distribution</b>	<b>Best fit exponent</b>	<b>Best fit X-min</b>	<b>Best fit X-max</b>	<b>Exp AIC w</b>	<b>TP AIC w</b>
<i>Azolla filiculoides</i>	135	< 0.1	191	TP	1.54	0.99	191.70	< 0.01	1.00
<i>Elodea canadensis</i>	261	< 0.1	275	TP	1.36	0.49	59.46	< 0.01	1.00
<i>Elodea nuttalli</i>	178	0.1	218	TP	1.23	0.14	218.41	< 0.01	1.00
<i>Lemna minuta</i>	124	0.1	220	E	0.07	0.05	220.62	1.00	NA
<i>Lagarosiphon major</i>	119	0.1	141	U	0.02	0.10	141.61	1.00	NA
<i>Asparagopsis armata</i> (Atl)	118	1.0	1390	TP	1.09	3.83	298.28	< 0.01	1.00
<i>Asparagopsis armata</i> (Med)	155	1.2	1255	TP	1.21	1.24	345.07	< 0.01	1.00
<i>Antithamionella elegans</i>	67	1.4	2032	TP	1.17	2.41	2032.68	< 0.01	1.00
<i>Antithamionella ternifolia</i>	80	0.3	1300	U	0.004	79.01	1300.83	0.51	0.49
<i>Codium fragile</i>	207	1.1	865	TP	1.03	1.20	312.56	< 0.01	1.00
<i>Colpomenia peregrina</i>	104	0.1	853	TP	1.01	10.66	470.27	< 0.01	1.00
<i>Caulerpa taxifolia</i>	86	1.0	834	TP	1.34	2.00	258.57	< 0.01	1.00
<i>Dasyisiphonia</i> sp.	54	0.2	1015	U	0.003	49.73	1015.23	1.00	NA
<i>Sargassum muticum</i>	544	1.4	612	TP	1.40	1.38	262.70	0.00	1.00
<i>Undaria pinnatifida</i>	87	1.0	805	U	0.01	16.07	805.68	0.55	0.45
<i>Womersleyella setacea</i>	69	0.5	2014	TP	1.35	12.66	1157.64	< 0.01	1.00

580

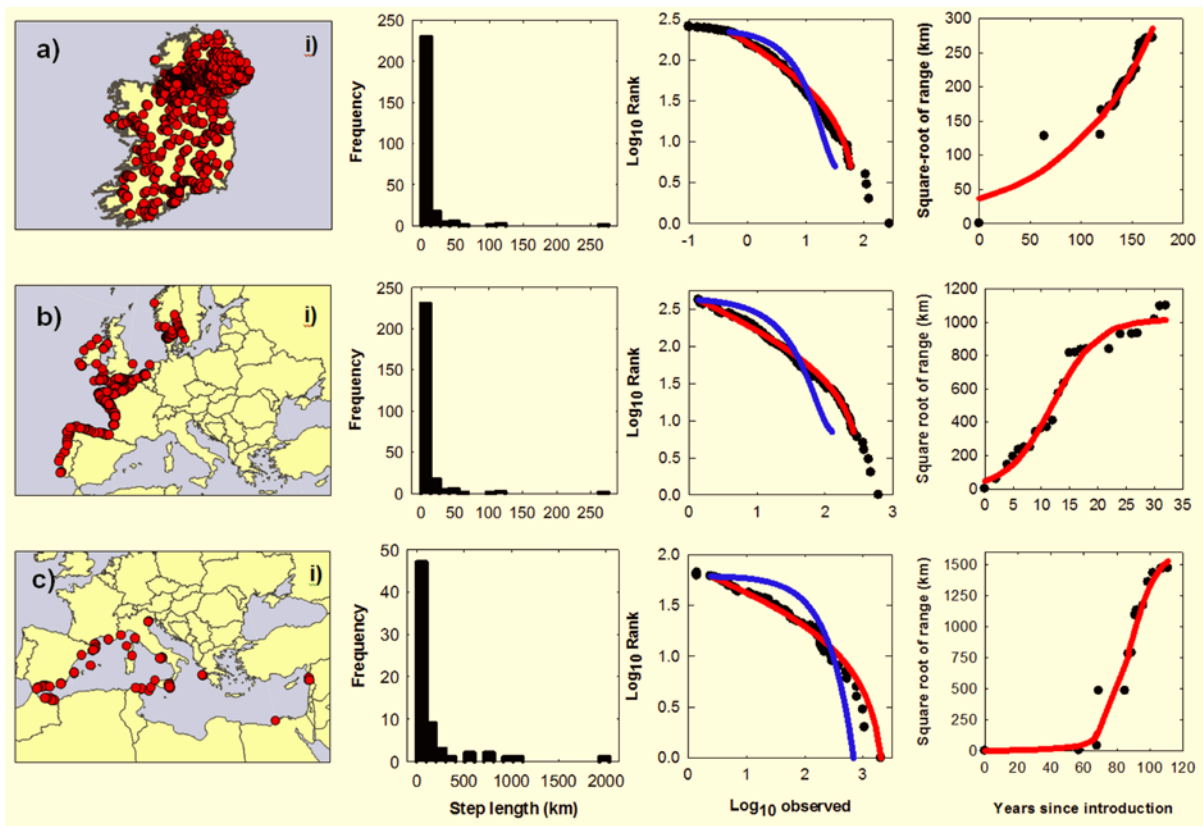
581 **Table 3.** Model fit of curves describing rates of range expansion and colonisation. n =  
582 number of years in which invasion range increased. Grey shading highlights the best fitting  
583 function for each species.

584

Habitat	Species	n	Function	AICc	$\Delta$ AIC	% $\omega_i$
Freshwater	<i>Azolla filiculoides</i>	24	Linear	251.73	44.08	0
			Exponential	248.91	41.26	0
			Sigmoidal	207.65	0.00	100
	<i>Elodea canadensis</i>	36	Linear	314.86	22.58	0
			Exponential	292.29	0.00	77
			Sigmoidal	294.65	2.36	23
	<i>Elodea nuttallii</i>	16	Linear	153.89	17.87	0
			Exponential	153.14	17.12	0
			Sigmoidal	136.02	0.00	100
	<i>Lagarosiphon major</i>	15	Linear	123.82	0.00	96
			Exponential	142.55	18.74	0
			Sigmoidal	130.20	6.39	4
	<i>Lemna minuta</i>	13	Linear	102.12	0.00	53
			Exponential	105.58	3.42	9
			Sigmoidal	102.79	0.67	37
Marine	<i>Asparagopsis armata (Atl)</i>	21	Linear	266.85	22.28	0
			Exponential	274.75	30.17	0
			Sigmoidal	244.58	0.00	100
	<i>Asparagopsis armata (Med)</i>	16	Linear	282.71	0.00	58
			Exponential	296.49	4.92	5
			Sigmoidal	207.68	0.87	37
	<i>Antithamnionella elegans</i>	15	Linear	219.03	23.50	0
			Exponential	206.46	10.93	0
			Sigmoidal	195.53	0.00	100
	<i>Antithamnionella ternifolia</i>	14	Linear	165.55	4.12	11
			Exponential	179.34	17.91	0
			Sigmoidal	161.43	0.00	89
	<i>Codium fragile</i>	28	Linear	342.16	21.69	0
			Exponential	NS	NA	NA
			Sigmoidal	320.47	0.00	100
	<i>Colpomenia peregrina</i>	28	Linear	367.71	55.02	0
			Exponential	384.11	71.42	0
			Sigmoidal	312.69	0.00	100
	<i>Caulerpa taxifolia</i>	8	Linear	109.27	11.36	0
			Exponential	114.72	16.82	0
			Sigmoidal	97.91	0.00	100
<i>Dasyisiphonia sp.</i>	11	Linear	147.57	0.00	92	
		Exponential	152.53	4.96	8	
		Sigmoidal	NS	NA	0	
<i>Sargassum muticum</i>	24	Linear	293.35	20.59	0	
		Exponential	315.34	42.58	0	
		Sigmoidal	272.76	0.00	100	
<i>Undaria pinnatifida</i>	13	Linear	150.12	17.69	0	
		Exponential	162.66	30.24	0	
		Sigmoidal	132.43	0.00	100	

585 **Figures**

586



587

588

589 **Figure 1** Super-diffusive invasion dynamics of freshwater plants and marine algae.

590 Geographical distributions of **a**, *Elodea canadensis* in Ireland, **b**, *Sargassum muticum* in the  
591 north-eastern Atlantic Ocean and **c**, *Antithamnionella elegans* in the Mediterranean Sea, each  
592 showing **i**) their geographical distributions, **ii**) a frequency histogram of invasion step lengths,  
593 **iii**) competing models showing best fit for a truncated Pareto function (red line) and an  
594 exponential function (blue line), and **iv**) non-linear spread based on the increase of the square  
595 root of the invaded area over time.

596

597 **Figure 2** Best fitting models to ranked step-length/frequency plots. Truncated power law  
598 (TP) (red line) and exponential (E) (blue line) models to observed data (black circles), or  
599 unclassified (U). For details of fitting results see Table 2. Best fit model given in parentheses  
600 following species name. Freshwater species: (a) *Azolla filiculoides* (TP); (b) *Elodea*  
601 *canadensis* (TP); (c) *Elodea nuttallii* (TP); (d) *Lagarosiphon major* (U); (e) *Lemna minuta*  
602 (E). Marine species: (f) *Asparagopsis armata* (Atl) (TP); (g) *Asparagopsis armata* (med)  
603 (TP); (h) *Antithamnionella elegans* (TP); (i) *Antithamnionella ternifolia* (U); (j) *Codium*  
604 *fragile* (TP); (k) *Colpomenia peregrina* (TP); (l) *Caulerpa taxifolia* (TP); (m) *Dasysiphonia*  
605 *sp.* (U); (n) *Sargassum muticum* (TP); (o) *Undaria pinnatifida* (U) and (p) *Womersleyella*  
606 *setacea* (TP).

607

608 **Figure 3** Spread rates of invasive species. Solid red line indicates best fitting model. Dashed  
609 red line indicates second best model where  $\Delta AICc < 2$ . Freshwater species: (a) *Azolla*  
610 *filiculoides* (sigmoidal); (b) *Elodea canadensis* (exponential); (c) *Elodea nuttallii* (sigmoidal);  
611 (d) *Lagarosiphon major* (linear); (e) *Lemna minuta* (linear(solid line)/sigmoidal(dashed  
612 line)). Marine species: (f) *Asparagopsis armata* (Atl) (sigmoidal); (g) *Asparagopsis armata*  
613 (med) (linear(solid line)/sigmoidal (dashed line)); (h) *Antithamnionella elegans* (sigmoidal);  
614 (i) *Antithamnionella ternifolia* (sigmoidal); (j) *Codium fragile* (sigmoidal); (k) *Colpomenia*  
615 *peregrina* (sigmoidal); (l) *Caulerpa taxifolia* (sigmoidal); (m) *Dasysiphonia* sp. (linear); (n)

616 *Sargassum muticum* (sigmoidal); (o) *Undaria pinnatifida* (sigmoidal); (p) *Womersleyella*

617 *setacea* (sigmoidal).

618



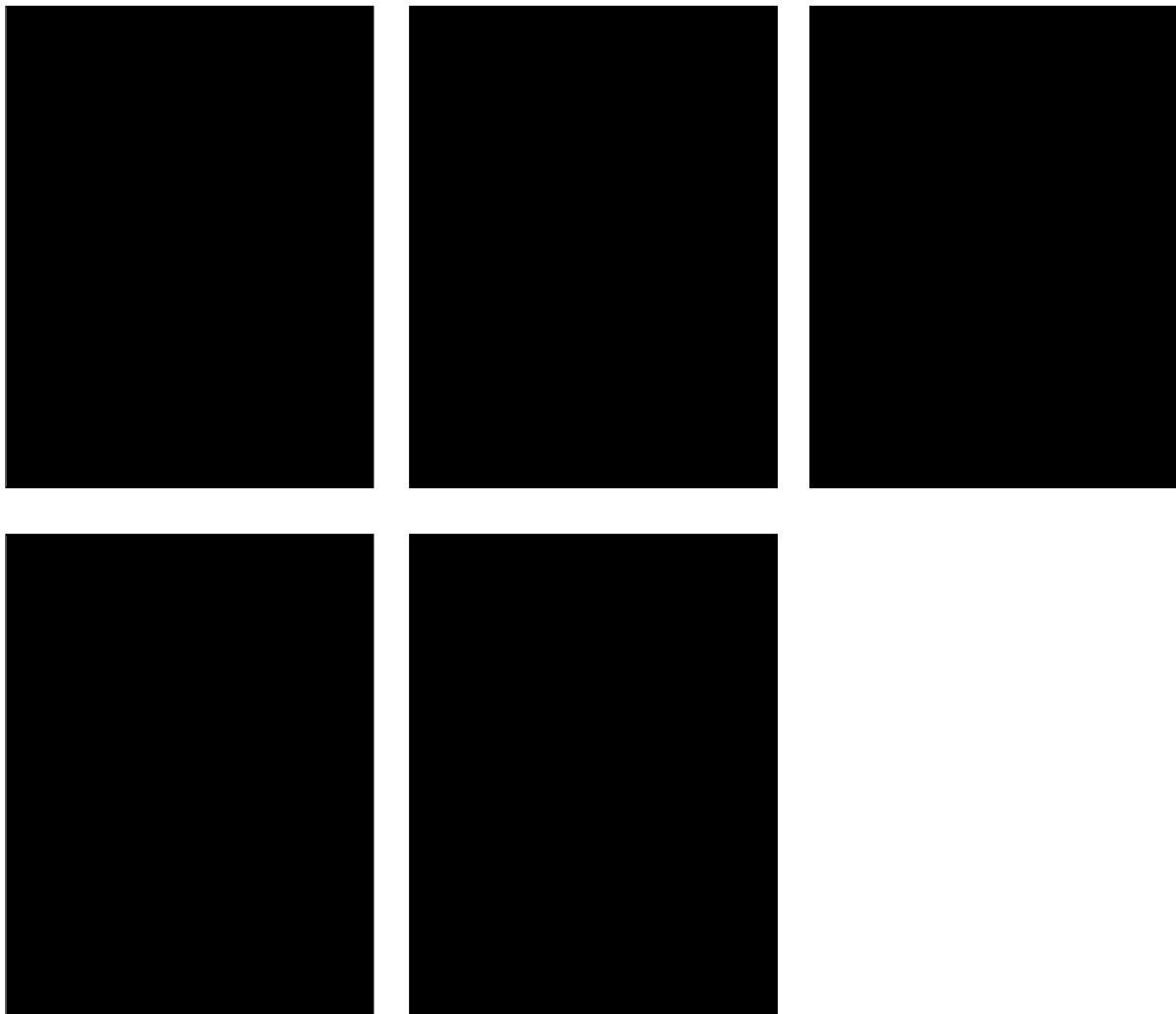
## Supplementary material

**Table 1** Names, size, reproductive traits and human uses of study species

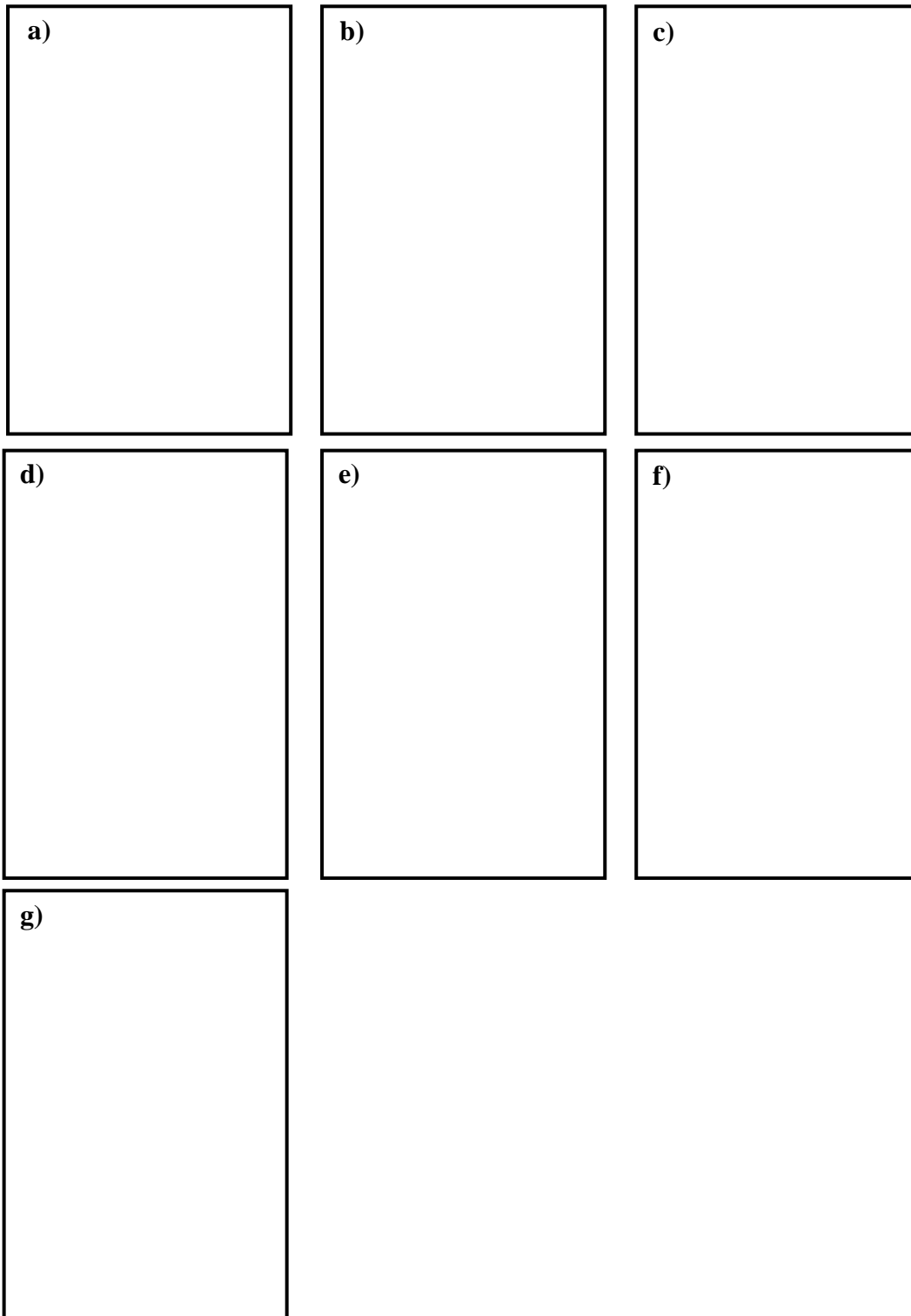
Scientific Name	Common name	Maximum height/length (cm)	Reproduction in invaded European range	Human use in invaded range
<b>Freshwater plants</b>				
<i>Azolla filiculoides</i> Lam.	A water fern	5	Sexual (fern) and vegetative (fragmentation)	Ornamental
<i>Elodea canadensis</i> Michx	Canadensis Pondweed	300	Vegetative (stolons and fragmentation)	Ornamental in horticulture and aquaria
<i>Elodea nuttallii</i> (Planch.) H St. John	Nuttall's Pondweed	300	Vegetative (stolons and fragmentation)	Ornamental in horticulture and aquaria
<i>Lagarosiphon major</i> (Ridl.) Moss	Curly Waterweed	300	Vegetative (stolons and fragmentation)	Ornamental in horticulture and aquaria
<i>Lemna minuta</i> Kunth	A duckweed	0.3	Primarily vegetative (budding), also sexual (dioecious)	
<b>Marine algae</b>				
<i>Asparagopsis armata</i> Harvey	Harpoon Weed	30	Sexual (dioecious), vegetative propagation abundant	
<i>Antithamnionella elegans</i> (Berthold) J.H.Price & D.M.John	A red alga	5	Sexual (dioecious), vegetative propagation abundant	
<i>Antithamnionella ternifolia</i> (J.D.Hooker & Harvey) Lyle	A red alga	5	Sexual (dioecious), vegetative propagation abundant	
<i>Codium fragile</i> subspecies <i>tomentosoides</i> (van Goor) P.C.Silva	Green Sea Fingers/ Dead Man's Fingers	50	Parthenogenetic spores	
<i>Caulerpa taxifolia</i> (M. Vahl) C. Agardh	Feather Caulerpa	100	Primarily vegetative	Ornamental in marine aquaria
<i>Colpomenia peregrina</i> Sauvageau	Oyster Thief	15	Sexual (dioecious), vegetative propagation abundant	
<i>Dasysiphonia</i> sp.	A red alga	50	Sexual (dioecious), vegetative propagation abundant	
<i>Sargassum muticum</i> (Yendo) Fensholt	Japanese Wireweed	200	Sexual (Self-fertile monoecious)	
<i>Undaria pinnatifida</i> (Harvey) Suringar	Wakame	300	Sexual (many minute gametophytes)	Food crop
<i>Womersleysella setacea</i> (Hollenberg) R.E. Norris	A red alga	10	Vegetative propagation abundant	

**Table 2.** Sorting of simulation results based on AICw. E, exponential; TP, truncated power law; P, power law; U, unclassified.

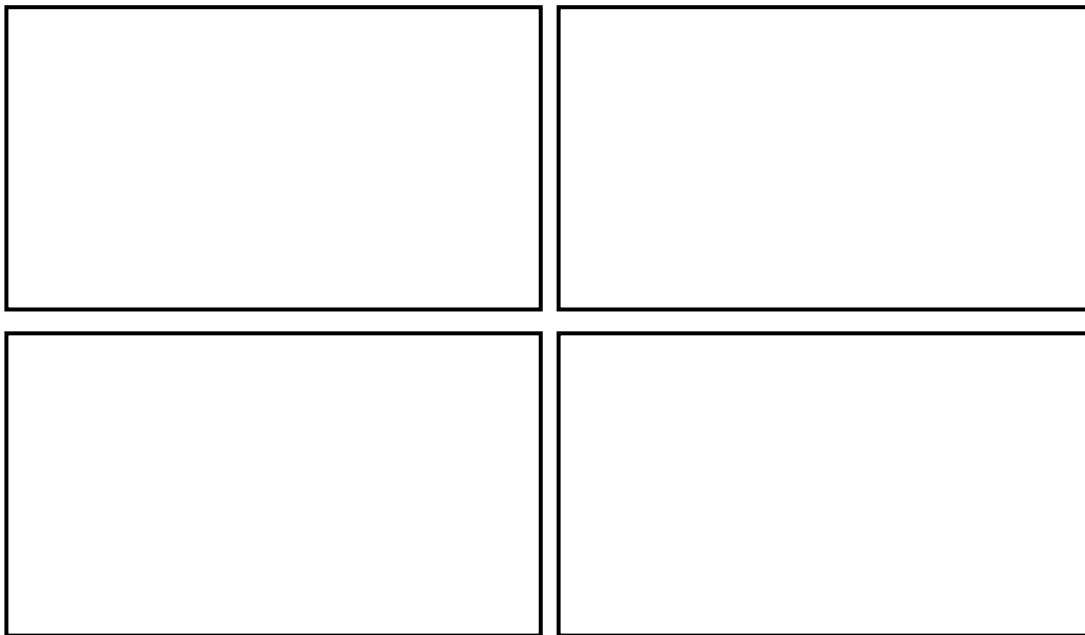
Overall Result	Breakdown of result subset types	Simulation based on exponential dispersal (%)	Simulation based on power law dispersal (%)
<b>Exponential (All)</b>		<b>82</b>	<b>1</b>
Exponential (subsets)	E better than TP on both tests	2	0
	Conflict between E and TP, and E better than P on both tests	7	1
	Default E, and E better than P on both tests	73	0
<b>Truncated Pareto (All)</b>	TP better than E on both tests	<b>1</b>	<b>83</b>
<b>Unclassified, U</b>	All other combinations	<b>17</b>	<b>16</b>



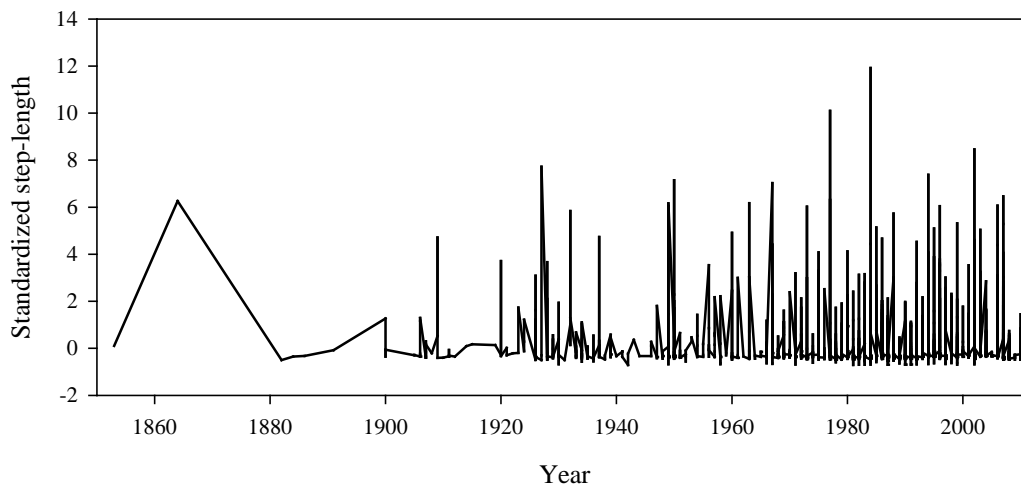
**Fig. 1** Locations of freshwater invasive species records in Ireland; a) *Azolla filiculoides*, b) *Elodea canadensis*, c) *Elodea nuttallii*, d) *Lagarosiphon major* and e) *Lemna minuta*.



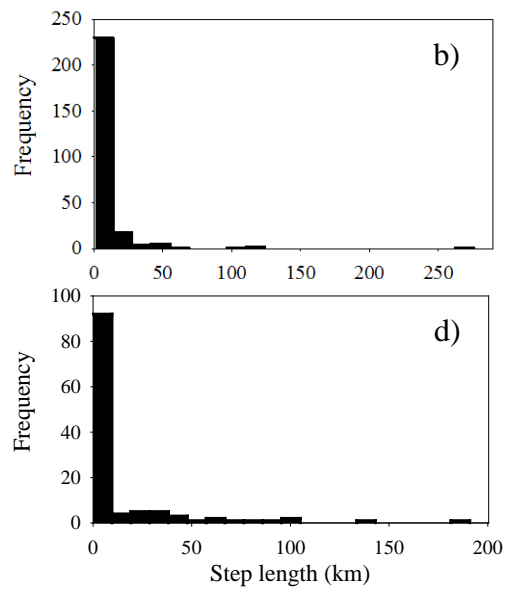
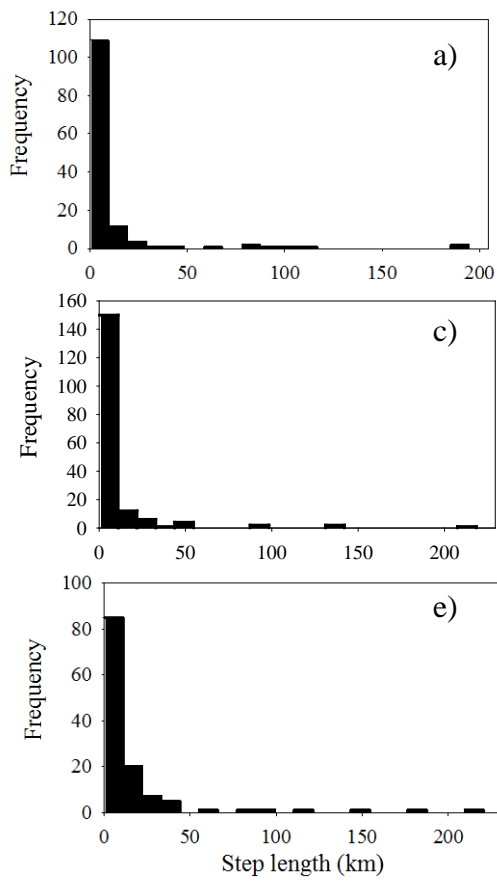
**Fig. 2** Distribution of invasive algal species in the Atlantic Ocean. (a) *Asparagopsis armata*, (b) *Antithamnionella ternifolia*, (c) *Codium fragile*, (d) *Colpomenia peregrina*, (e) *Dasysiphonia* sp., (f) *Sargassum muticum* and (g) *Undaria pinnatifida*.



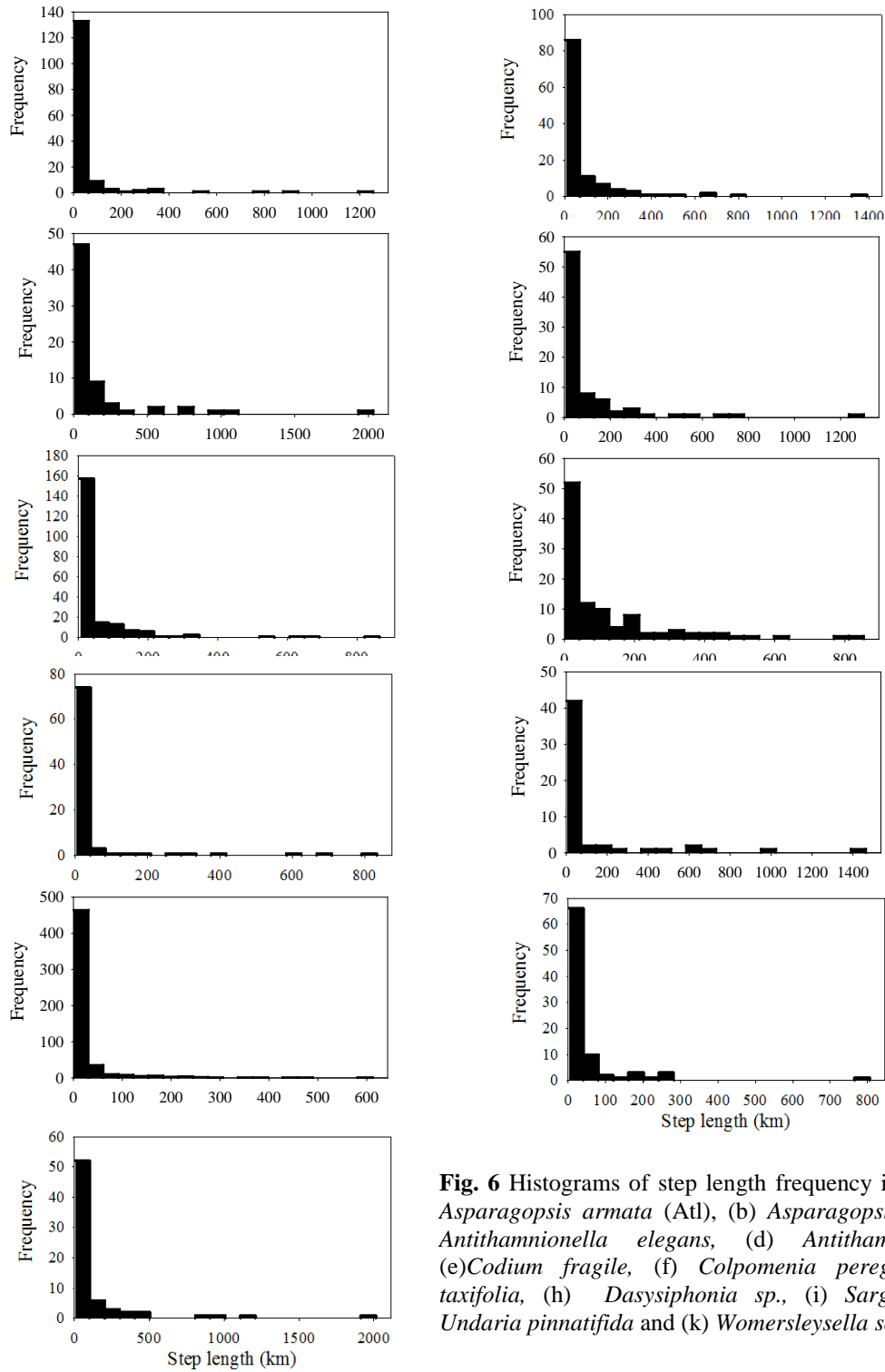
**Fig. 3** Distribution of invasive Mediterranean species, a) *Asparagopsis armata*, b) *Antithamnionella elegans*, c) *Caulerpa taxifolia* and d) *Womersleysella setacea*.



**Fig. 4** Distribution of standardised step-length distances across time. Step-lengths of all 16 invasions (11 marine and 5 freshwater) plotted together. Step-lengths standardised to standard deviation in step length within species. Note that, whilst the frequency of transport increases over time there long distance transport events are evident throughout the time line.



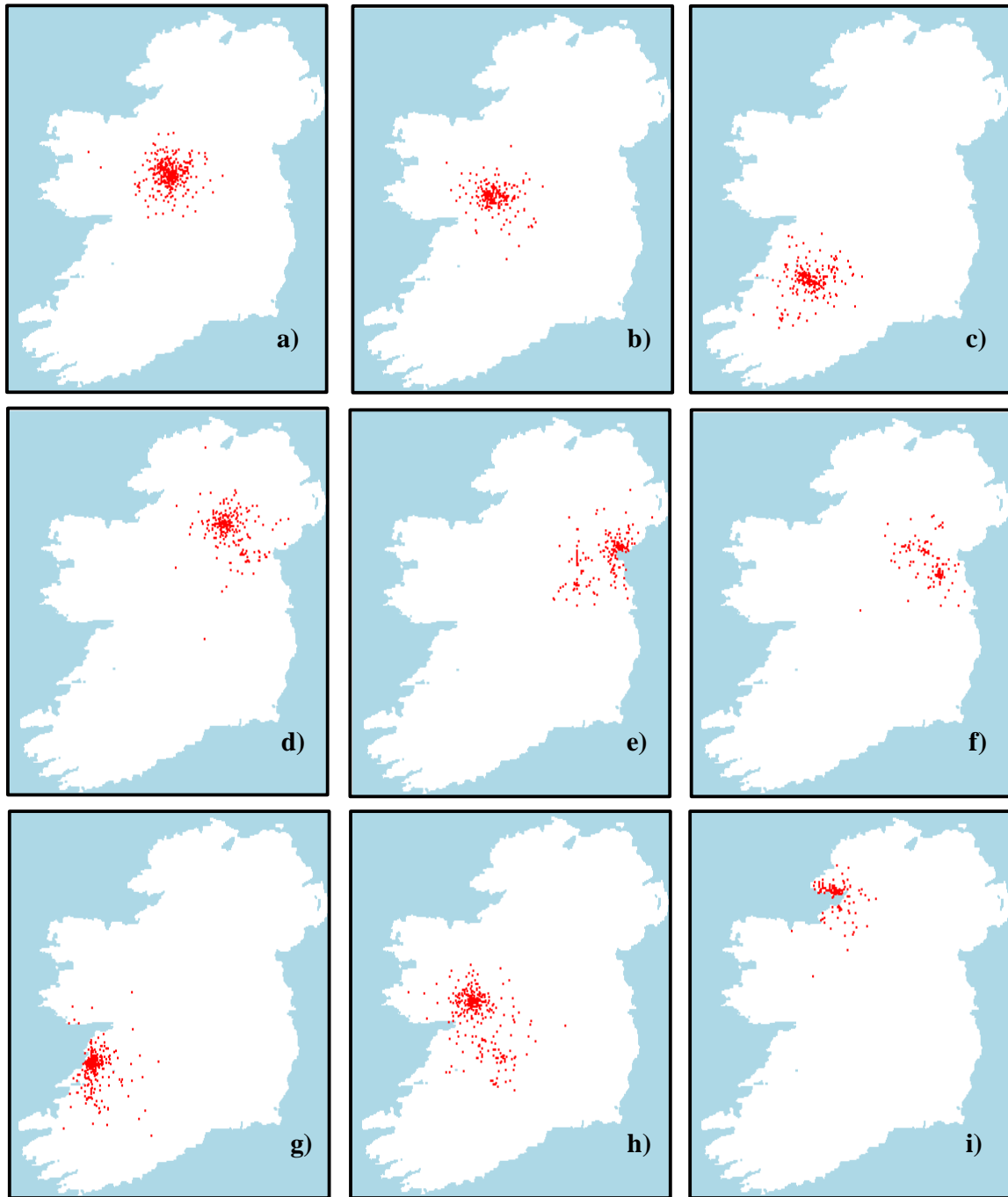
**Fig. 5** Histograms of the step-length frequency distributions of freshwater species, a) *Azolla filiculoides*, b) *Elodea canadensis*, c) *Elodea nuttallii*, d) *Lagarosiphon major* and e) *Lemna minuta*.



**Fig. 6** Histograms of step length frequency in marine species. (a) *Asparagopsis armata* (Atl), (b) *Asparagopsis armata* (Med), (c) *Antithamnionella elegans*, (d) *Antithamnionella ternifolia*, (e) *Codium fragile*, (f) *Colpomenia peregrine*, (g) *Caulerpa taxifolia*, (h) *Dasysiphonia* sp., (i) *Sargassum muticum*, (j) *Undaria pinnatifida* and (k) *Womersleysella setacea*.



**Fig. 7** Example plots of simulation model output based on power law (Lévy) dispersal. Images were selected at random from simulations, final number of points, a) 70, b) 143, c) 63, d) 55, e) 175, f) 189, g) 120, h) 131 and i) 72.



**Fig. 8** Example plots of simulation model output based on exponential dispersal. Images were selected at random from simulations, final number of points (a) 419, (b) 239, (c) 229, (d) 251, (e) 227, (f) 115, (g) 316, (h) 351 and (i) 122.