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3 Current landscapes and legacies of land-use past: Understanding the distribution of juvenile coho
4 salmon (*Oncorhynchus kisutch*) and their habitats along the Oregon Coast, USA
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22 **Abstract**

23 The Oregon Coastal landscape has a high degree of spatial structure with respect to landscape
24 characteristics such as air temperature, precipitation, and geology. Despite this underlying
25 structure, we found that a suite of immutable or intrinsic attributes, e.g. reach gradient, drainage
26 area, mean elevation of the catchment, and percent weak rock geology of the watersheds draining
27 to each of our 423 study reaches, could explain much of the variation in pool surface area across
28 the landscape and could contribute to an estimate of how many juvenile coho salmon
29 (*Oncorhynchus kisutch*) one might expect to find in those pools. Further, we found evidence of
30 differences in pool surface area across land ownership categories that reflect differing
31 management histories. Our results suggest that historic land and river management activities, in
32 particular log drives that occurred at least 50 years ago, continue to influence the distribution of
33 juvenile coho salmon and their habitats today.

34
35 Key Words: land ownership, landscape-scale, salmonids, intrinsic potential, splash-dams

36 Introduction

37 Understanding the distribution of instream habitats and the density of fish within those habitats is
38 essential for effective watershed management and conservation of depressed fisheries
39 populations. For wide-ranging species with a complex life history, such as Pacific salmon,
40 untangling these relationships is particularly challenging. Field data describing instream habitats
41 are generally only available over a small fraction of a species range; occupied habitat types may
42 differ by life stage; and, even within a particular habitat type, suitability and capacity rarely
43 remain constant over time. Landscape-scale studies, based on the conceptual model that natural
44 features and human impacts across watersheds drive instream habitat conditions which in turn
45 regulate, at least to some degree, salmon distribution and productivity, have been relatively
46 successful at predicting adult spawners for coho salmon (Steel et al. 2012; Pess et al. 2002),
47 Chinook salmon (Feist et al. 2003), and steelhead (Steel et al. 2004). Juvenile salmonids and
48 their habitats, however, have rarely been evaluated at the landscape scale. Processes driving the
49 distribution of juveniles and their habitats cannot be inferred from studies of spawning habitats
50 or adults alone (Flitcroft et al. 2012; Gresswell et al. 2006), as juveniles do not simply rear in the
51 same habitats in which they emerged from the spawning gravel. Juvenile salmonids often move
52 over fairly long distances to occupy a separate habitat niche that is likely driven by different
53 suites of natural conditions and is uniquely impacted by human activities. A better
54 understanding of the location and condition of juvenile coho salmon habitats and of juvenile
55 coho density within freshwater streams can contribute to improved restoration and conservation
56 planning as well as a more holistic and detailed conceptual model of the relationship between
57 landscape drivers, instream conditions, and coho salmon during the freshwater phases of their
58 life-cycle.

59 Listed as threatened under the Endangered Species Act (ESA) (Weitkamp et al. 1995),
60 coho salmon (*Oncorhynchus kisutch*) along the Oregon Coast inhabit two distinct freshwater
61 habitat types over their three-year lifespan. Adults spawn in riffles and runs within low gradient,
62 gravel-based rivers; juvenile coho salmon rear in deep pool habitats during summer and may
63 redistribute into pools in more off-channel habitats with the onset of the fall rains (Sandercock
64 1991). Combinations of land use, land ownership, geology, and climate have repeatedly been
65 successful at describing and predicting the distribution of adult coho across the landscape (Pess
66 et al. 2002; Firman et al. 2011; Steel et al. 2012). Peak spawner counts within the Oregon Coast
67 were highest in reaches draining forest land with little area in weak rock types, low densities of
68 cattle and roads, less agriculture, gentle stream gradients, and relatively large fluctuations in
69 winter temperature (Firman et al. 2011; Steel et al. 2012). However, adult coho salmon densities
70 are only part of the story. When escapement is adequate, the availability of high quality winter
71 pool habitat for juveniles is thought to limit coho salmon smolt production along the Oregon
72 Coast (Nickelson et al. 1992; Solazzi et al. 2000). Landscape-scale studies have evidence that
73 these habitat features associated with high quality juvenile habitat can be influenced by human
74 activities such tree harvest and road building across watersheds. Pool density and large wood
75 volume were strongly influenced by these land management descriptors in the Oregon Coast
76 after accounting for natural landscape attributes such as gradient and geology (Anlauf et al.
77 2011).

78 River landscape analyses have been proliferating, effectively describing useful patterns
79 and making predictions about where on the landscape particular species or habitats are likely to
80 be found (Allan 2004; Steel et al. 2010; Johnson and Host 2010). Yet, untangling anthropogenic
81 impacts from the intrinsic suitability of river reaches to support high quality coho salmon habitat

82 as defined by natural features is a challenge. Across the Oregon Coast, a high level of covariation
83 between natural landscape gradients (e.g. land form, climate and geology), and human activities
84 (e.g. forest management), hinders the interpretation of statistical models and our ability to
85 establish causal linkages between landscape-scale variables and fish (Lucero et al. 2011). In
86 evaluating landscapes, we need to be able to differentiate between the potential of a site given
87 those factors that humans cannot reasonably change (intrinsic / immutable factors) and the
88 impact of human actions, both locally and across the watershed. One approach has been to
89 develop an index or summary metric that describes a stream's ability to provide high-quality
90 habitat in the absence of human impacts. Burnett et al. (2007) developed such an index of
91 intrinsic potential (IP), based on three immutable factors, stream flow, valley constraint, and
92 stream gradient, for juvenile coho salmon on the Oregon Coast. By separating, mapping, and
93 exploring immutable landscape features versus measures of human impacts, we can begin to
94 identify those streams which naturally do not support high quality juvenile habitat or large
95 densities of juvenile coho salmon versus streams which are likely to support high quality juvenile
96 habitat in the absence of human disturbance. This approach can theoretically identify streams
97 that fail to reach their potential in supporting high quality habitat or high densities of juvenile
98 fish because of human modifications of the natural landscape yet the efficacy of this IP has yet to
99 be tested on empirical observations over large spatial extents.

100 Not all human modifications to the landscape have occurred under current ownership and
101 land-use designations. Across the Oregon Coast, for example, there is a rich logging history that
102 includes removal of the primary forest and the transport of downed trees via the fluvial network
103 using log-drives and splash-damming to build up adequate water supply for moving logs
104 downstream. Splash damming and log drives were common across western Oregon from the

1880s through the 1950s (Miller 2010). Scouring from these activities has led to widespread stream simplification across the Pacific Northwest and evidence suggests that physical conditions in splash-dammed streams have yet to recover (Lichatowich 1999; Miller 2010; Sedell and Duval 1985; Dolloff 1996). Though no consistent record was kept of splash dams or log drives at the time, Miller (2010) used a combination of archival, historical aerial photograph and field searches to develop a geo-database of all known splash-dam sites and log drives in western Oregon. This comprehensive new resource enables investigation not only of effects of current land-management activities but also of the potential for legacies of past management activities across the Oregon Coast.

In this analysis, we quantify the ability of immutable features of the landscape to explain the observed distribution of pool habitats, on which juvenile coho salmon depend, and the observed density of juvenile coho salmon within those pools. We also evaluate whether the summary index of intrinsic potential (IP) (Burnett et al. 2007) adds additional information beyond our base immutable models. Further, we test whether we can detect effects of past land management or present land ownership on the distribution of pool surface area or on the density of juvenile coho within those pools after accounting for immutable landscape features. We initiate our analysis with a detailed exploration of the Oregon Coast to understand spatial gradients in landscape factors throughout the region and the nature of the expected co-variation between potential immutable and anthropogenic influences on habitat. Our work is novel in the blending of *a priori* knowledge and hypothesis testing, in our access to empirical data over a vast spatial extent, and in our consideration of both current land ownership and legacies of past management activities. Our results enable (a) a comparison of relationships between landscape features and pool surface area versus juvenile coho salmon density in pools; (b) an evaluation of

128 the degree to which immutable landscape characteristics and the summary index of intrinsic
129 potential (IP) describe the current distribution of pool surface area and of juvenile coho salmon
130 within these pools; and (c) tests of the degree to which current and past land management are
131 correlated with pool surface area and with the distribution of juvenile salmon in these habitats.

132

133 **Methods**

134 **Study Area**

135 All survey reaches in our analysis are within the Oregon Coastal Province (Fig. 1; 20,305
136 km²). This mountainous region is underlain primarily by marine sandstones and shales or by
137 basaltic volcanic rocks. Elevations range from 0 to 1250 m, though most coho salmon habitat is
138 in areas of lower gradients and below 700 m (Burnett et al. 2007). The temperate, maritime
139 climate provides mild, wet winters and dry summers. Base flows predominate in late summer;
140 peak flows occur in the fall following storm events.

141 The upland portion of the study area is dominated by coniferous forests with western red
142 cedar (*Thuja plicata*) and big leaf maple (*Acer macrophyllum*) in riparian areas. Current
143 disturbance regimes are driven by land use (including timber harvest, road building, and
144 agriculture) and fire suppression. Disturbance legacies that potentially continue to influence
145 upslope and riparian habitats include historic timber harvest activities, splash damming, log
146 drives, and infrequent but intense wildfires and windstorms (Franklin and Dyrness 1988). Most
147 of the current forestland is relatively young and the larger river valleys have been cleared for
148 agriculture (Ohmann and Gregory 2002). The majority of the land is privately owned; about a
149 third of the land is publicly owned (Spies et al. 2007).

150 Coho salmon in the study region belong to the Oregon Coastal Coho Evolutionarily

151 Significant Unit (ESU) (Weitkamp et al. 1995). In addition to coho salmon, four other salmonid
152 species reside in the study area: coastal cutthroat trout (*O. clarki*), Chinook salmon (*O.*
153 *tschawytscha*), chum salmon (*O. keta*), and steelhead (*O. mykiss*).

154

155 **Pool and coho salmon data**

156 The Oregon Plan for Salmon and Watersheds (<http://nrimp.dfw.state.or.us/OregonPlan/>)
157 defines the State of Oregon's system for monitoring instream habitat and coho salmon, including
158 both the juvenile and adult life stages, through a probabilistic sampling design of available
159 stream reaches (generalized random tessellation stratified (GRTS) design) (Stevens 2002). Using
160 the 1:24,000-scale high-resolution USGS NHD (<http://nhd.usgs.gov/>) drainage network, streams
161 and rivers have been attributed according to the current, known distribution of coho salmon and
162 steelhead trout; a random sample of these reaches was chosen for monitoring. A portion of sites
163 are visited annually, while the majority are resurveyed based on a rotating panel design of 3 and
164 9 years, meant to coincide with the 3-year life cycle of coho salmon. The design is intended to
165 balance the need to estimate population abundance in each year (for which precision improves by
166 sampling more reaches within a year) and the need to detect trends over time (for which power
167 improves by revisiting the same reaches year after year) (Larsen et al. 2001; Larsen et al. 2004).

168 Our dataset included two potential response variables: pool surface area within a reach
169 and juvenile coho salmon counts within pools. We used all available data for 1st through 4th
170 order streams within the distribution of coho salmon except for a few observations collected in
171 basins dominated by Siltcoos, Tahkenitch, and Tenmile Lakes or from reaches shorter than 0.6
172 km. Our final dataset contained a total of 1118 individual observations collected over 16 years
173 (1998 through 2013) at 423 reaches within 324 6th field HU's, referred to as "catchments" for

174 modeling purposes. Individual reaches ranged in length from 241 m to 1874 m with the majority
175 between 600 m and 1200 m. Each was visited between 1 and 16 times. Eleven reaches were
176 visited in all 16 years; 193 reaches were visited for 2 to 15 repeat surveys; and 219 reaches were
177 visited only once.

178 Pools within each reach were enumerated and measured to provide an estimate of total
179 pool surface area within each reach. All pools that had a max depth of ≥ 20 cm deep and were \geq
180 6 m^2 in surface area were snorkeled to identify and enumerate juvenile coho salmon. Snorkel
181 surveys consisted of a single pass conducted during base flows in August – September. Juvenile
182 coho salmon are known to move least in summer (Nickelson et al. 1992; Kahler et al. 2001),
183 making the snorkel survey a “snapshot” of the abundance and distribution of fishes in the
184 surveyed reach. Pools were assessed for water clarity or quality, receiving a rating based on
185 visibility. To ensure data quality, only density of juvenile coho salmon from pools receiving the
186 higher visibility ratings (85-92% of all pools) were included in this analysis.

187

188 **Landscape Data**

189 We focused on a set of immutable landscape attributes identified as important predictors
190 of the distribution of coho salmon and their habitats in previous analyses of this region (Firman
191 et al. 2011; Anlauf et al. 2011; Steel et al. 2012) and of the nearby Snohomish River in
192 Washington State (Pess et al. 2002), e.g., precipitation, proportion of the watershed with weak or
193 sedimentary geology, gradient, and elevation (Table 1). We did not include mean annual flow
194 because available estimates at study reaches are modeled as a function of drainage area, already
195 included in our list of potential predictors. In descriptive follow-up analyses to understand

196 differences across land ownership categories, we also employed a descriptor of forest cover at
197 the landscape scale, the proportion of watershed dominated by large conifers (Table 1).

198 We summarized landscape characteristics relevant to each survey reach across the entire
199 drainage area or watershed of each reach. Drainage area was defined as the area draining to the
200 downstream end of the reach. To quantify landscape predictor variables within each watershed,
201 we calculated the proportion of the total watershed in each category for categorical variables (i.e.
202 geology, land ownership) (Table 1). Land ownership was included as an index of management
203 history. USFS lands have been managed for a combination of goals including timber harvest,
204 old growth forest conservation, wildlife habitat, fish habitat, water quality, and recreation
205 (USDA Forest Service 1990). Management of BLM lands is also intended to balance a variety
206 of uses including energy development, livestock grazing, recreation, timber harvest and
207 protection of natural, cultural, and historical resources
208 (http://www.blm.gov/wo/st/en/info/About_BLM.html). Private industrial forest lands, on the
209 other hand, are, presumably, managed for long-term, sustainable timber production. Private non-
210 industrial forest lands include multiple management objectives across diverse ownerships. These
211 private non-industrial forest (PrivateNI) lands, while nearly half forested, also include a large
212 amount of agricultural land-use, residential development, and even a small amount of urban
213 development. For continuous variables (i.e. air temperature), we calculated the area-weighted
214 mean to provide an indication of average conditions over the entire watershed.

215 For each surveyed reach, we calculated the length-weighted average of intrinsic potential
216 (IP) for coho salmon (Burnett et al. 2007). To quantify total amount of high quality habitat
217 available to juvenile coho salmon within each catchment, we also calculated total length of
218 stream with intrinsic potential >0.75. We note that this variable (LengthHighIP) was missing for

219 three reaches and so the three reaches were excluded from models testing for the statistical
220 significance of this variable. Inputs used to calculate coho salmon IP were previously estimated
221 from field data and 10-m digital elevation models (DEMs) (Clarke et al. 2008).

222

223 **Habitat data**

224 Habitat data to further explore observed relationships between ownership and juvenile
225 coho salmon and their habitats were available because they were collected as part of the coast-
226 wide, integrated monitoring described above. In this analysis, we explored average values (1998
227 thru 2013) of three habitat variables: percent gravel, wood volume (m^3), and percent channel
228 shade. These three habitat characteristics, surveyed mid-June to late September, were included
229 because they are both important to juvenile coho salmon habitat and were found to be
230 particularly sensitive to land management actions (Anlauf et al. 2011). Gravel is the estimated
231 proportion of the stream-bed area that is classified as gravel (2–64 mm); it is quantified ocularly
232 in the field. Wood volume is the volume of in-stream wood per 100m of reach length (m^3 per
233 100 m); it includes all pieces of wood that are within the active channel and are ≥ 0.15 m in DBH
234 and ≥ 3 m in length. Percent channel shade is the percentage of the stream channel that is
235 shaded; it is collected on both the left and right sides of the stream using a clinometer. All three
236 habitat variables were collected by habitat unit (e.g. riffle, pool) and summarized by reach. For
237 further field details, see Moore et al. (2007).

238

239 **Statistical Methods**

240 Data analysis was completed in five steps. (1) We first conducted extensive exploratory and
241 graphical analysis to understand and display the spatial distribution of each potential predictor

242 and the relationships between potential predictors of pool distribution and of juvenile coho
243 salmon within pools across the landscape. (2) In our second step, we developed a base model of
244 pool surface area as a function of immutable landscape features found to be important for
245 predicting pool habitat in previous work. At this stage, we did not consider anthropogenic
246 impacts. (3) Third, we built a similar base model of fish density within pool habitat. The
247 juvenile coho base model used a similar collection of immutable variables found to be important
248 for predicting coho salmon habitat in previous work. With these two base models, we examine
249 how well our suite of immutable landscape variables explains observed spatial variation in pool
250 surface area or in juvenile coho salmon density. The two models form the basis for follow-up
251 analyses that test for additional explanatory power of our key variables of interest given the
252 landscape context of each site. Note that we did not conduct any statistical hypothesis tests or
253 variable selection to develop these base models. Inclusion of variables was based on our
254 ecological knowledge and past published analyses describing linkages between landscapes and
255 habitat characteristics that support coho salmon. (4) In our fourth step, we used these two base
256 models as the foundation for formal statistical hypothesis testing to detect effects of suites of key
257 variables of interest describing: (a) intrinsic potential (IP), (b) land ownership, and (c) legacies of
258 land-use past on both pool habitat and density of juvenile coho salmon within pools. (5) In the
259 final step of our analysis, we introduce habitat data from Anlauf et al. (2011) to explore whether
260 instream habitat conditions can explain observed relationships between land ownership and pool
261 surface area.

262
263 *(1) Landscape structure.* To best understand landscape structure, we conducted extensive
264 exploratory analyses including correlation tables, spatial maps, and boxplots comparing the

265 distribution of predictor variables across categories of, for example, land ownership. Given the
266 challenges of conducting analyses over large extents without true replication or control, the goal
267 of these exploratory analyses was to understand the underlying relationships that might cloud our
268 ability to interpret statistical models. We focused on relationships that concerned the spatial
269 distribution of variables about which we planned to conduct formal hypothesis tests (intrinsic
270 potential, land ownership, and legacies of land-use past, e.g. splash dams and log-drives).

271
272 *(2) Base model for pool surface area.* A linear mixed model was built using the natural logarithm
273 of pool surface area (m²) as the response and survey year, catchment, reach, and the catchment
274 by year interaction as random effects. Catchment was included as a random effect because, in
275 some cases, there were 2 to 4 reaches within one catchment.

276 We based our model of pool surface area on the work in Anlauf et al. (2011). They were
277 able to describe pools per 100 m using five immutable variables: reach gradient, drainage area,
278 mean elevation of the catchment, flow (cfs), and percent weak rock geology in the catchment.
279 We wanted to account for these relationships with immutable variables before testing our key
280 variables of interest. As explained above, we eliminated flow from our pool surface area model
281 because it is generally estimated from drainage area; therefore, these variables are highly
282 correlated. As in Anlauf et al. (2011), there appeared to be a linear relationship between the
283 natural log of pool surface area and the natural log of drainage area. We used an updated geology
284 layer and substituted percent sedimentary rock for the percent weak rock geology layer used in
285 previous analyses. In our dataset, survey lengths varied considerably both across and, somewhat
286 surprisingly, within reaches across years. Intuitively, pool surface area might depend on the
287 survey length and so survey length was included in the model.

288 The base model of $\ln(\text{pool surface area})$ contained gradient (%), elevation (m),
289 $\ln(\text{drainage area})$, percent sedimentary rock in the catchment, and survey length as fixed effects.
290 Residuals were checked for temporal and spatial autocorrelation using autocorrelation function
291 (ACF) plots and semivariograms respectively. Reported confidence intervals of coefficients are
292 95% profile likelihood confidence intervals. Overall model fit was assessed using marginal
293 pseudo- R^2 (Nakagawa and Schielzeth 2013).

294

295 *(3) Base model for juvenile coho salmon counts.* Juvenile coho salmon count data were
296 analyzed with a generalized linear mixed model (GLMM) using a Poisson distribution with a
297 natural logarithm link. Because the amount of pool habitat varied by reach and year, total pool
298 surface area (m^2) was used as an offset. Survey year, catchment, reach, and the catchment by
299 year interaction were included in the model as random effects. To account for overdispersion
300 (extra-Poisson variation), the observation-level random effect represented by the reach by year
301 interaction was also included as a random effect.

302 Our model of juvenile coho salmon counts was based on the suite of variables that
303 appeared in the “best” habitat models in Anlauf et al. (2011) to predict a wide range of habitat
304 conditions from instream wood to pool complexity. The seven variables were precipitation in
305 the catchment, percent intermediate sedimentary rock in the catchment, reach gradient (%),
306 drainage area (km^2), elevation (m), flow (cfs), and percent weak rock in the catchment. Again
307 we eliminated flow due to high correlation with drainage area and we substituted sedimentary
308 rock for “weak geology” and “intermediate sedimentary rock”, therefore the model had six
309 variables. Because we expect that habitat conditions, at least to some degree, drive juvenile coho
310 salmon numbers, we wanted to account for variation explained by these immutable variables

311 before testing for relationships between juvenile coho salmon numbers and the key variables of
312 interest. We included quadratic as well as linear relationships where there was graphical and
313 ecological evidence for such a relationship.

314 The base model of juvenile coho salmon contained precipitation, gradient (%), gradient²,
315 percent sedimentary rock in the catchment, elevation (m), and drainage area as fixed effects.
316 Residuals were checked for temporal and spatial autocorrelation using autocorrelation function
317 (ACF) plots and semivariograms, respectively. Overall model fit was assessed using marginal
318 pseudo-R² (Nakagawa and Schielzeth 2013).

319

320 *(4) Statistical tests for intrinsic potential, land ownership, and legacies of land-use past*

321 We tested for a relationship between either pool surface area or juvenile coho salmon counts and
322 each of the key variables of interest. The first variable of interest was intrinsic potential (IP)
323 which was measured in two ways: (a) the length weighted average of IP and (b) the total length
324 of habitat with high intrinsic potential (>0.75) in the catchment. We also note that there were 3
325 missing values for high IP; tests for high IP were computed on a dataset that did not include
326 these three study reaches. The second variable of interest was land ownership. We included
327 land ownership as (a) proportion public ownership in the catchment; (b) the proportion private
328 ownership used for industrial forestry (PI); (c) the proportion private ownership not used for
329 industrial forestry (PrivateNI). To better understand land ownership patterns, we also overlaid
330 the ownership classification with an existing land-use data layer (Burnett et al. 2007) and
331 summarized land-use by ownership category. Finally, we were interested in the potential legacy
332 of past land-uses including (a) counts of past splash dams in the catchment and (b) length of
333 historical log drives in the catchment.

334 To test for a relationship with either pool surface area or number of juvenile coho salmon,
335 these variables were added one-by-one to the base model. All test results are for each variable
336 when added alone to the base model. The one exception was intrinsic potential (IP). Because IP
337 is a summary index that includes gradient, it was tested against the full immutable model
338 including gradient as well as against the immutable model without gradient. Tests of coefficients
339 when key variables were added to the base pool surface area model were conditional F-tests
340 using the Kenward-Roger degrees of freedom correction (Kenward and Roger 1997). Tests of
341 coefficients when key variables were added to the base juvenile coho salmon model were 1
342 degree of freedom χ^2 likelihood ratio tests. Reported confidence intervals of coefficients are 95%
343 profile likelihood confidence intervals. Effect sizes are presented as the change in ln(pool surface
344 area) or in the number of juvenile coho salmon for a change of approximately 10% of the
345 observed range in each variable.

346

347 (5) *Land ownership and instream habitat*

348 To observe possible differences in instream conditions or attributes of high quality forest habitat
349 across land-ownership categories, we graphically compared the distribution of these instream
350 habitat variables; % gravel, % shade and large wood volume, across land-ownership categories.
351 To evaluate terrestrial condition, we estimated the percent of the watershed with very large
352 conifers (Table 1) across four classes of land ownership: private (non-industrial and industrial)
353 and public (USFS and BLM).

354

355 **Results**

356 (1) *Landscape structure.* Spatial pattern appears in most of the potential predictors of pool

357 habitat and juvenile coho salmon (Fig. 2). For example, study reaches draining catchments with
358 large annual ranges in air temperature (TempRange) were found in the southeastern parts of the
359 study area and those with high mean annual precipitation (Precip) were found in the
360 northwestern portion of the study area. Study reaches draining catchments with high proportions
361 of sedimentary geology (Sedimentary) were more prevalent in the southern parts of the study
362 area and the northern tip. Log drives (LogDrives) and splash dams (SplashDams) appear to have
363 occurred predominantly in the southern portions of the study landscape. Intrinsic potential
364 (AvgIP and LengthHighIP) are mildly clustered but occur across the entire study area. Land
365 ownership was not distributed evenly across the study area (Fig. 2). Study reaches draining
366 catchments with the highest proportion of big tree cover (BigTrees) occurred in one large cluster
367 along the west coast of the study area, coincident with high amounts of public land (Fig. 2).

368 A closer inspection of the distribution of study reaches draining catchments with
369 particular public (BLM, USFS) and private (non-industrial and industrial) land ownership reveals
370 further landscape structure with the study reaches. Those draining catchments with higher
371 proportion of USFS land are located in two large clusters in the middle of the study region, study
372 reaches draining catchments with high proportions of private industrial (PrivateInd) lands are
373 located in clear bands, and private non-industrial (PrivateNI) lands concentrated along the coast
374 (Fig. 3). The uneven distribution of land ownership could also be observed in differences
375 between the distribution of immutable landscape variables describing areas with relatively high
376 versus relatively low ownership in each of three ownership categories, BLM, USFS, and private
377 (Fig. 4). For example, the elevation range was wider for catchments with high proportions of
378 land managed by the USFS. Areas with more land in private non-industrial use were generally at
379 lower elevations, had lower stream gradients, and high average intrinsic potential scores. In

380 summary, we observe that the lands under different ownership classes are intrinsically different
381 with respect to several key variables.

382

383 (2) *Pool surface area*. The base model for $\ln(\text{total pool surface area})$ included gradient,
384 elevation, $\ln(\text{drainage area})$, survey length, and sedimentary geology (Table 2). Marginal
385 pseudo- R^2 for this linear model was 0.632. The majority of the variance was at the reach level
386 (0.429) with a smaller amount of variance at the catchment level (0.141). Graphical assessment
387 of residuals indicated that the base pool surface area model did not have serious problems with
388 temporal autocorrelation; however there was some spatial autocorrelation primarily in the E-W
389 direction. Such anisotropic spatial autocorrelation may be difficult to eliminate as the rivers run
390 from the coast range to the ocean in a more or less east to west orientation. As might be
391 expected, there was very little overall annual variation in pool surface area (0.021). Unexplained
392 catchment by year, and reach by year (residual) variability were relatively high (0.203 and 0.106
393 respectively).

394

395 (3) *Juvenile coho density*. The marginal pseudo- R^2 for this Poisson model with a log link
396 including precipitation, sedimentary geology, gradient, gradient², elevation, and drainage area
397 was 0.338 (Table 3). The residuals from the base model did not appear to have any problems
398 with temporal or spatial autocorrelation. A relatively large amount of the variance (2.665) is the
399 distribution-specific variance (on the link scale) due to the variance of the Poisson distribution
400 being based on the mean; a Poisson GLMM will have this distribution-specific variance and so
401 it is important to remember that the pseudo- R^2 could never become 1 (Nakagawa and Schielzeth
402 2013). There was a large amount of unexplained variance at the catchment scale (2.437) and at

403 the reach scale (1.497). There was relatively less annual variance in juvenile coho counts
404 (0.443). There was also unexplained variability for catchment by year (1.409), and reach by
405 year (residual) (0.225).

406
407 *(4) Statistical tests for intrinsic potential, land ownership, and legacies of land-use past*

408 Intrinsic potential. Mean intrinsic potential (IP) provided only minor additional explanatory
409 power beyond that of gradient for pool surface area ($p=0.093$) and no additional explanatory
410 power for fish density in pools. There was a large and positive statistically significant effect of
411 average intrinsic potential when gradient was removed from the model (Table 4, Fig. 5). The
412 length of high intrinsic potential habitat (LengthHighIP) had a statistically significant effect on
413 pool surface area but not on the number of juvenile coho salmon (Table 4). We caution that
414 although the coefficient describing the effect of total length of high intrinsic potential is negative
415 (suggesting that study reaches in catchments with longer lengths of river estimated as high
416 intrinsic potential have lower pool surface areas), it is difficult or impossible to untangle the
417 effect of one predictor variable entered in a model that already contains so many similar and
418 potentially collinear variables.

419
420 Land ownership. There was a statistically significant positive effect of public ownership on pool
421 surface area (Table 4, Fig. 5). In other words, after accounting for geology, elevation, gradient,
422 and drainage area, reaches with a higher percentage of the catchment in public ownership had a
423 larger pool surface area. In reverse, we saw that reaches with a higher proportion of private
424 ownership and, in particular, private ownership that was classified as not industrial forestry, had
425 smaller pool surface areas. For a better understanding of the distribution between private

426 industrial forestry and private non-industrial forestry, we compared the ownership classification
427 to the existing land-use data layer (Burnett et al. 2007) and found that private industrial lands
428 (PrivateInd) were composed of just over 98% forest lands. Private non-industrial lands
429 (PrivateNI) represent a composition of urban (5.4%), residential (14.4%), agriculture (29.7%),
430 forest (46.3%), and other uses (4.1%).

431
432 Legacies of land-use past. The density of reaches with historical log drives in the catchment was
433 not statistically significant in either model though there were indications that log drive length
434 may have a negative effect on pool surface area ($p=0.109$). However, we did see a statistically
435 significant effect of splash dam presence versus absence in the watershed of the study reach on
436 juvenile coho salmon density ($p=0.049$). The effect of splash dam presence on juvenile coho
437 salmon density was fairly large, one splash dam is estimated to increase juvenile coho salmon
438 density by an estimated 139.5%; however there was also a large amount of associated
439 uncertainty (95% confidence interval equals 0.4 to 474.9%) reflecting the relatively small
440 number of sites ($n=24$) with splash dams present (Table 4).

441
442 *(5) Land ownership and instream habitat.* There was little qualitative difference in shade or
443 gravel across land ownership categories (Fig. 6). The distribution of instream wood volume was
444 somewhat reduced in the areas with greater than 30% private industrial (PrivateNI) ownership.
445 Reaches whose catchments drained areas with high proportions of public land were also those
446 whose catchments drained areas with high proportions of very large conifers. Note that big trees
447 did occur with distinct clusters. Throughout the study, the average proportion of a study
448 watershed in large trees was 16.7%. More than 40% of the study reaches drained watersheds

449 with less than 10% of the area in big trees; only 2% of the study reaches drained watersheds
450 with more than 50% of the area in big trees.

451

452 **Discussion**

453 Given that there is a great deal of spatial structure in landscape-scale variables on the Oregon
454 Coast, untangling relationships between landscape features, in-stream habitat, and aquatic biota
455 is particularly important for effective management of aquatic resources. We found that pool
456 surface area, an essential element of coho salmon habitat can be described fairly well by
457 relatively immutable landform features: drainage area, elevation, geology, and gradient. A
458 similar set of immutable landform features also play a role, albeit a smaller role, in explaining
459 juvenile coho salmon density within pools. Building on these landscape models, we
460 corroborated the management relevance of the concept of “intrinsic potential”, quantified
461 negative effects associated with private land ownership on pool surface area, and observed that
462 legacies of land-use past may continue to play a role in determining patterns of juvenile coho
463 salmon density across the landscape. By linking landscape-scale data on past and current land
464 management activities with a large dataset on the distribution of juvenile coho salmon and their
465 habitats, we provide insight into where on the landscape we might expect to find these fish and
466 how management of both terrestrial and aquatic ecosystems may have impacted their
467 distribution.

468

469 *Spatial structure of the Oregon Coastal Landscape.*

470 Landscape-scale approaches have been useful in informing management of freshwater fishes and
471 their habitats across a wide range of ecoregions (Steel et al. 2010) and yet the spatial structure of

472 landscape-scale data poses continuous challenges. To address these challenges, Lucero et al.
473 (2011) suggest that landscape-scale studies, particularly studies focusing on river systems, which
474 by nature are highly structured landscapes, follow a few principles: expect multicollinearity and
475 interpret any one particular landscape feature with caution; conduct thorough exploratory
476 analyses including maps of potential predictors; resist mechanistic or causal interpretations; and
477 resist extrapolation across regions.

478 In our exploratory analysis, we found, as expected, that immutable landscape features are
479 not distributed randomly across the Oregon Coast landscape nor have human impacts been
480 applied to the landscape at random. We observed strong spatial patterns in variables of interest,
481 both relatively immutable descriptors of the landscape and variables that reflect past and present
482 human impacts. These patterns can be as simple as “it is wetter in the north and the annual
483 range in air temperature tends to be higher at higher elevations” (Fig. 2). There are likely also
484 complex histories that are difficult to deduce from present day conditions. For example,
485 agriculture was likely initiated in floodplains by early settlers of the region as they were the
486 easiest to convert and had rich soils. These suitable conditions reflected a combination of
487 climate, geology, and landform; these same factors drive the distribution of suitable fish habitat
488 making it particularly challenging to untangle the effects of agriculture on fish distribution in
489 many basins. Lucero et al. (2011) found results similar to ours across the Oregon Coast. Of
490 course, the Oregon Coast is not the only region with considerable landscape structure. Looking
491 at 261 small watersheds across Idaho, Montana, Oregon, and Washington, Kershner et al. (2004)
492 noted that watersheds containing reference streams tended to be found at higher elevations,
493 receive more precipitation, and have a slightly higher percentage of federally-managed lands
494 than did managed watersheds.

495 We identified a few patterns across the Oregon Coast of particular importance for model
496 building and interpretation. First, there is a clear north-south gradient in terms of precipitation
497 and geology. River basins in the southern parts of our study area have less rainfall and more
498 sedimentary rock (Fig. 2). Models that include these two variables may also include
499 information about other, unmeasured variables that vary longitudinally such as air temperature
500 or landslide susceptibility. Second, there is an east-west gradient from areas of higher elevation
501 with greater air temperature ranges and smaller streams with steeper stream gradients (not
502 displayed) to lower-elevation, lower-gradient, wider streams (not displayed) that drain to the
503 ocean along the coast. These sets of variables co-vary in predictable ways and, in fact, we were
504 not able to eliminate all spatial covariance along this east-west gradient in our base model of
505 pool surface area. When any one of these variables is used in a model, information about the
506 others is also included by default. Third, land ownership is not distributed evenly across the
507 various parts of the study landscape.

508
509 *Landscape-scale predictors better at explaining the distribution of pool habitat than at*
510 *explaining the number of fish in pools*

511 The distribution of pools across the landscape is relatively easy to model with landscape-level
512 predictors. Summer pool surface area varied across reaches but was relatively stable over time
513 within a particular reach; there wasn't a great deal of correspondence in pool surface area for
514 reaches within the same catchment; and the base model of pool surface area, using only
515 immutable landscape-scale variables, was able to explain a relatively large amount of the
516 variability in pool surface area. There remains, however, a relatively large amount of
517 unexplained variability in pool surface area for any particular reach. Previous correlative

518 research in this and in other basins has also identified relationships between similar landscape
519 features and the distribution of pool habitat (Burnett et al. 2006; Hicks and Hall 2003). Our
520 results also have a well-understood mechanistic interpretation. Pools are formed by scour
521 around obstructions such as large boulders and via inputs of large wood as well as where
522 relatively soft substrates are eroded by streams with adequate stream power, resulting from a
523 combination of flow and gradient (Buffington et al. 2002; Frissell et al. 1986; Hicks and Hall
524 2003; Montgomery et al. 1999; Wohl et al. 1993).

525 Landscape-level predictors do not explain the number of juvenile coho salmon within
526 pools as well as they explain pool distribution. There was high annual variability in juvenile
527 coho salmon counts within a particular reach or catchment and this annual variability made it
528 relatively more difficult to identify consistent relationships between fish density and landscape
529 features that do not change through time. If a site were visited in one year and then again in the
530 following year, we would not expect to see the same number of juvenile coho salmon; however,
531 given similar flow conditions, we would expect to observe about the same pool surface area.
532 Given that we could not include predictors that varied over time, we can expect our model of
533 juvenile coho salmon abundance to estimate the mean abundance over time and therefore to
534 explain less of the variation in the data than our model of pool surface area. We chose to model
535 pool habitat and juvenile coho salmon independently to untangle how intrinsic features of the
536 landscape drive these two responses and to test specific hypotheses about human impacts.

537 Future efforts may benefit from an exploration of time variable predictors, such as annual
538 flow, descriptors of other stages of the coho salmon life cycle, such counts of spawning adults,
539 and incorporation of spatial patterns on stream networks. We might expect, for example, that
540 observed relationships between juvenile coho salmon and landscape conditions depend on

541 population dynamics; when marine survival is low, adult returns are few, and the number of
542 resulting juveniles can be very low. In years with low levels of adult returns, we might expect
543 juvenile coho salmon to inhabit only the best habitats (Flitcroft 2007) and in years with higher
544 levels of adult returns we might expect juvenile coho salmon to expand into more marginal areas
545 (Flitcroft et al. 2014). Additionally, the proximity of adult and juvenile habitats or the network
546 distances between suitable seasonal habitats may also play a strong role in juvenile coho salmon
547 distribution (Flitcroft et al. 2012). The most productive habitats are likely to be where there is
548 both suitable habitat for adults to spawn and juvenile coho salmon to rear and overwinter
549 (Anlauf-Dunn et al. 2014).

550

551 *Intrinsic attributes of a site are useful for explaining pool surface area*

552 The concept behind a site's intrinsic potential is that some areas are naturally, or intrinsically,
553 more suitable as fish habitat. Burnett et al. (2007) defined the intrinsic potential (IP) of a site for
554 juvenile coho salmon as the geometric mean of normalized variables describing gradient, stream
555 flow, and valley constraint. In the absence of human impacts, sites with a high intrinsic
556 potential would be expected to support a larger number of fish than sites with low intrinsic
557 potential. IP has been used to provide a reasonable estimate of where on the landscape one
558 might expect to find juvenile coho salmon across streams in Coastal Oregon, the Willamette
559 River valley, and a part of the lower Columbia River basin where actual habitat conditions and
560 juvenile coho salmon distribution were unknown (Burnett et al. 2007). Flitcroft et al. (2014)
561 also found that the intrinsic potential of stream reaches was useful in understanding
562 distributional patterns of juvenile coho salmon.

563 Using 16 years of observed pool surface area from randomly selected sites across the

564 Oregon Coast, we also found that a similar suite of variables could describe the distribution of
565 pool surface area, the defining feature of juvenile coho salmon habitat in summer (Nickelson et
566 al. 1992). Like the Burnett et al. (2007) index, our model was strongly influenced by stream
567 gradient. We did not have access to localized flow observations but our model included drainage
568 area which is highly correlated with flow in most regions. Our model included elevation and
569 sedimentary geology which, in these basins, we would expect to describe a very similar concept
570 to that of valley confinement as used in Burnett et al. (2007). Not surprisingly, the average of
571 the Burnett et al. (2007) IP index contributed little to explaining variance in pool surface area in
572 models that already contained such a similar suite of landscape descriptors. When gradient was
573 removed from our landscape models, we found a large and statistically significant effect of
574 mean IP index (Burnett et al. 2007) on pool surface area as well as on the density of juvenile
575 coho salmon within those pools. Although gradient is clearly a primary driver of where on the
576 landscape pool habitat is likely to be found, the other features in IP, flow and valley constraint,
577 are also necessary for understanding pool habitats. In our model, IP showed a very weak
578 additional influence beyond gradient likely because our model also already contained elevation,
579 drainage area, and geology, all of which are highly correlated with valley constraint and mean
580 annual flow.

581 Our results provide further evidence that the concept of intrinsic potential, a combination
582 of relatively immutable landform features, is a useful management tool for understanding where
583 across the Oregon Coast we might expect to find juvenile coho salmon. Similar indices have
584 been used successfully for predicting the distribution of key habitat features for other salmonid
585 species and other life stages. Busch et al. (2013) used a combination of valley confinement,
586 stream width, and gradient to successfully identify potential Chinook salmon spawning habitat

587 in the nearby Lower Columbia River Basin. Bidlack et al. (2014) used mean annual flow,
588 gradient, and glacial influence to identify probable habitat for juvenile Chinook salmon across
589 the vast Copper River watershed, Alaska. Similar indices may, in fact, be useful for a wide
590 range of fishes across a wide range of geographies. Using 1,548 pan-European sample sites,
591 Logez et al. (2012) modeled the distribution of 21 common fish species and found that stream
592 power, a function of gradient and stream flow, was the only variable retained in the best model
593 for all 21 species.

594 Intrinsic potential (Burnett et al. 2007) can also be used to estimate the quantity of
595 available habitat that is potentially highly suitable (LengthHighIP). In our dataset, and in most
596 situations, field data describing in-stream habitat conditions are only available for a subset of a
597 basin or for a particular reach of interest. Therefore, the total length of stream habitat of highly
598 suitable habitat available to migratory species cannot be calculated or estimated from on-the-
599 ground observations. In our models, the quantity of available habitat that is potentially highly
600 suitable (LengthHighIP), total length of reaches within the catchment that have a high intrinsic
601 potential, improved our models of pool surface area even for a model that already included a
602 suite of landscape variables similar to those in the primary intrinsic potential index. The
603 additional information provided by this metric was expected to be an estimate of the total
604 amount of high quality habitat potentially available to fish, regardless of basin size. We
605 hypothesize that, in addition to describing total habitat available to fish, LengthHighIP also
606 provides a general indication of the location and condition of the catchment surrounding the
607 study reach.

608
609 *Land ownership is correlated with the distribution of pool habitat*

610 Even after considering a set of basic immutable landscape characteristics, land ownership was an
611 important factor in explaining the amount of available pool habitat, the defining element of
612 juvenile coho salmon habitat (Fig. 5). Looking at the relative contributions of public, private
613 industrial, and private non-industrial ownership, we see that pool surface area was higher in areas
614 with higher proportions of public ownership and lower in areas with higher proportions of
615 private ownership. Furthermore, this negative effect was stronger for private lands not used for
616 industrial forestry (PrivateNI) than areas with high proportions of private industrial forestry
617 (PrivateInd). Similar results have been observed elsewhere. Looking at over 200 watersheds
618 distributed across the Columbia River Basin, Kershner et al. (2004) found that pools in
619 unmanaged watersheds tended to be deeper and to have fewer fine sediments in the pool tails as
620 compared to managed watersheds. As for most of our potential predictors, ownership did not
621 have a statistically significant effect on juvenile coho salmon density within pools.

622 One possible explanation for these results is that differences in aquatic conditions across
623 land ownerships reflect the history of terrestrial and aquatic land management. In the nearby
624 Puget Sound region, trends in adult coho salmon over time were correlated with trends in forest
625 cover, and inversely correlated with urbanization (Bilby and Mollot 2008). Across 156
626 watersheds on Vancouver Island, Canada, just a bit further north, a legacy of current and historic
627 forest management, indicated by features such as forest fragmentation, no-forest cover, and early
628 successional forests, was the one landscape characteristic that had a generally negative effect on
629 anadromous salmon populations across species (Andrew and Wulder 2011).

630 Interpreting our results with respect to land management requires caution and further
631 investigation. The first consideration is the underlying correlation between land ownership and
632 topography; for example, high elevation lands are much more likely to be managed by the USFS

633 than to be in non-industrial private ownership. The history of ownership combined with natural
634 landscape patterns has led to the highly structured nature of the Oregon Coastal landscape as
635 described above. Testing for the effect of ownership only after incorporating the effects of
636 various immutable landscape features can account for some of the unbalanced and co-varying
637 spatial patterns but cannot eliminate the issue. As such, our analysis cannot be interpreted as a
638 causal relationship between ownership and pool habitat. Rather, our results show that differences
639 in the amount of pools differs by ownership.

640

641 *Legacies of past human activities persist*

642 Although the practice of log drives and splash damming streams and rivers ended over fifty years
643 ago, we observed an effect on current stream habitat conditions. The length of stream affected
644 by log drives was associated with a reduction in pool area even after accounting for landscape
645 configuration, and there is a potentially large effect of splash damming on the number of juvenile
646 coho salmon observed within a reach. In the few reaches where splash dams were present, we
647 observed an over 100% increase in juvenile coho salmon given available pool habitat. The
648 evidence is not particularly strong due to a small sample size and variable data, but the potential
649 effect size is large (Table 4). Although our landscape-scale models were not able to detect an
650 effect of splash dams on pool surface area, Miller (2010) found there to be fewer deep pools in
651 reaches affected by splash dams and significantly more exposed bedrock (by isolating the effects
652 of splash dams through upstream downstream comparisons). In combination, our results suggest
653 that log drives and splash dams reduced pool surface area leaving juvenile coho salmon to be
654 present at much higher densities than might otherwise be expected in the remaining pool habitat.
655 Current and future fish habitat assessments will benefit from knowledge of these and other

656 disturbance legacies.

657

658 *Land ownership and current habitat conditions*

659 Ignoring the spatial structure of the data and simply comparing the distribution of
660 various immutable variables across areas with high and low (relatively) proportions of ownership
661 classes, we can again see that ownership was not assigned randomly (Figure 4). Areas with high
662 proportions of private non-industrial lands are at lower elevations, have lower stream gradients,
663 somewhat larger drainage areas, and therefore somewhat higher average intrinsic potential.
664 These streams are in downstream coastal areas that should have large amounts of pool habitat.
665 After accounting for immutable variables to the best of our ability, we observed that reaches
666 draining watersheds with higher amounts of private non-industrial lands have lower pool surface
667 areas (Table 4, Figure 5).

668 To further explore the relationship between ownership, land management, and pool
669 habitat, we considered whether in-stream or terrestrial habitat conditions were also different in
670 reaches draining watersheds under different ownerships. We observed a potential reduction in
671 wood volume for sites in private non-industrial ownership and large differences in the proportion
672 of a watershed with large trees between public and private ownership (Figure 6) suggesting an
673 additional legacy of timber harvest and development on the landscape; public lands have retained
674 more big trees (Fig. 6). Few sites in private ownership maintained more than 30% of the
675 watershed in big trees. Effects of forest harvest on instream habitats and, in particular, on pool
676 distribution, are well-known. For example, clearcutting without riparian buffers has been
677 associated with reduced pool areas in Alaskan streams (Heifetz et al. 2011). A meta-analysis of
678 effects of riparian harvest across many published studies found reductions in pool size,

679 frequently associated with stream cleaning, following logging across a wide variety of stream
680 sizes and stream gradients (Mellina and Hinch 2009). We note, however, that public forests are
681 still relatively young with nearly all sites having less than 50% of the watershed in big trees.
682 Given the 150-250 years required for stream adjacent forests to approach pre-harvest function
683 (Bilby et al. 2003), present day forests across our sites, distributed throughout the Coast Range,
684 rarely achieve this goal.

685

686 *Management Implications*

687 Despite the high degree of spatial structure across the Oregon Coastal landscape, we found that
688 the immutable or intrinsic landscape attributes of a particular site can provide a good
689 understanding of the distribution of pool surface area and can contribute to an understanding of
690 juvenile coho salmon distribution within these pools. Where on-the-ground observations are
691 lacking, estimates based on immutable features or IP can provide managers with information for
692 identifying and prioritizing restoration and conservation opportunities. Comparisons between
693 empirical observations and estimates based on immutable landscape features can suggest where
694 streams are failing to reach their potential in supporting high quality habitat or high densities of
695 juveniles, providing a foundation on which to quantify and understand human effects on the
696 landscape. We found fairly strong evidence of differences in pool surface area across lands with
697 varying current ownership and therefore differing management histories. Further, we found
698 evidence that historic land and river management activities, in particular log drives that occurred
699 at least 50 years ago, continue to influence the distribution of juvenile coho salmon and their
700 habitats today.

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706 **References**

- 707 Allan, J.D. 2004. Landscapes and riverscapes: The influence of land use on stream ecosystems.
708 *Annual Review of Ecology Evolution and Systematics* **35**: 257-284.
- 709 Andrew, M.E., and M.A. Wulder. 2011. Idiosyncratic responses of Pacific salmon species to
710 land cover, fragmentation, and scale. *Ecography* **34**: 780-797.
- 711 Anlauf, K.J., Jensen, D.W., Burnett, K.M., Steel, E.A., Christiansen, K., Firman, J.C., Feist, B.E.
712 and Larsen, D.P. 2011. Explaining spatial variability in stream habitats using both natural
713 and management-influenced landscape predictors. *Aquatic Conservation: Marine and*
714 *Freshwater Ecosystems* **21**: 704–714.
- 715 Anlauf-Dunn, K.J, Ward, E.J., Strickland, M., and Jones, K. 2014. Habitat connectivity,
716 complexity, and quality: predicting adult coho salmon occupancy and abundance. *Can. J.*
717 *Fish. Aquat. Sci.* **71(12)**: 1864-1876.
- 718 Bidlack, A.L., Benda, L.E., Miewald, T., Reeves, G.H., and McMahan, G. 2014. Identifying
719 suitable habitat for Chinook salmon across a large, glaciated watershed. *Trans. Am. Fish.*
720 *Soc.* **143**:689-699.
- 721 Bilby, R.E. and Molloy, L.A. 2008. Effect of changing land use patterns on the distribution of
722 coho salmon (*Oncorhynchus kisutch*) in the Puget Sound region. *Can. J. Fish. Aquat. Sci.*
723 **65**: 2138-2148.
- 724 Bilby R, Reeves G, Doloff C. 2003. Sources of variability in aquatic ecosystems; factors
725 controlling biotic production and diversity. *In Strategies for Restoring River Ecosystems:*
726 *Sources of Variability and Uncertainty in Natural and Managed Systems.* Wissmar R,

- 727 Bisson P (eds). American Fisheries Society: Bethesda, MD: pgs 129–146.
- 728 Buffington, J.M., Lisle, T.E., Woodsmith, R.D., and Hilton, S. 2002. Controls on the size and
729 occurrence of pools in coarse-grained forest rivers. *River Research and Applications*
730 **18**:507-531.
- 731 Burnett, K.M., Reeves, G.H., Clarke, S., and Christiansen, K. 2006. Comparing riparian and
732 catchment influences on stream habitat in a forested, montane landscape. *Am. Fish. Soc.*
733 *Symp.* **48**: 175-197.
- 734 Burnett, K.M., Reeves, G.H., Miller, D.J., Clarke, S., Vance-Borland, K., and Christiansen, K.
735 2007. Distribution of salmon-habitat potential relative to landscape characteristics and
736 implications for conservation. *Ecological Applications* **17**: 66-80.
- 737 Busch, D.S., Sheer, M., Burnett, K., McElhany, P., and Cooney T. 2013. Landscape-level
738 model to predict spawning habitat for Lower Columbia River fall Chinook Salmon
739 (*Oncorhynchus Tshawytscha*). *River Research and Applications* **29**: 297-312.
- 740 Clarke, S.E., Burnett, K.M., and Miller, D.J. 2008. Modeling Streams and Hydrogeomorphic
741 Attributes in Oregon from Digital and Field Data. *J. Am. Water Resour. Assoc.*
742 **44**(2):459-477.
- 743 Daly, C., Neilson, R.P., and Phillips, D.L. 1994. A statistical topographic model for mapping
744 climatological precipitation over mountainous terrain. *J. Appl. Meteorol.* **33**:140–158.
- 745 Dolloff, C.A. 1996. Large woody debris, fish habitat, and historical land use. *In* Proceedings of
746 the Workshop on Coarse Woody Debris in Southern Forests: Effects on Biodiversity
747 Athens, GA October 18-20, 1993, USDA Forest Service General Technical Report SE

748 94, pp. 130-138.

749 Feist, B. E., Steel, E. A., Pess, G.R. and Bilby, R.E. 2003. The influence of scale on salmon
750 habitat restoration priorities. *Animal Conservation* **6**: 271-282.

751 Firman, J. C., Steel, E. A., Jensen, D.W., Burnett, K.M., Christiansen, K., Feist, B.E., Larsen,
752 D.P., and Anlauf, K. J. 2011. Landscape models of adult coho salmon density examined
753 at four spatial extents. *Trans. Am. Fish. Soc.* **140**(2): 440-455.

754 Flitcroft, R. L. 2007. Regions to streams: spatial and temporal variation in stream occupancy
755 patterns of coho salmon (*Oncorhynchus kisutch*) on the Oregon coast. Doctoral
756 dissertation. Oregon State University, Corvallis, Oregon, USA.

757 Flitcroft, R.L., Burnett, K.M, Reeves, G.H., and Ganio, L.M. 2012. Do network relationships
758 matter? Comparing network and instream habitat variables to explain densities of
759 juvenile coho salmon (*Oncorhynchus kisutch*) in mid-coastal Oregon, USA. *Aquatic
760 Conservation: Marine and Freshwater Ecosystems* **22**:288-302.

761 Flitcroft, R., Burnett, K., Snyder, J., Reeves., G., and Ganio L. 2014. Riverscape patterns
762 among years of juvenile coho salmon. *Trans. Am. Fish. Soc.* **143**:26-38.

763 Franklin, J.F., and Dyrness, C.T. 1988. *Natural Vegetation of Washington and Oregon*. Oregon
764 State University Press, Corvallis, Oregon, USA.

765 Frissell C.A., Liss, W.J., Warren, C.E., and Hurley, M.D. 1986. A hierarchical framework for
766 stream habitat classification. *Environ. Manage.* **10**: 199–2.

767 Gresswell, R. E., Torgersen, C. E., Bateman, D. S., Guy, T. J., Hendricks, S. R., and Wofford, J.

- 768 E. B. 2006. Spatially explicit approach for evaluating relationships among coastal
769 cutthroat trout, habitat, and disturbance in small Oregon streams. *Amer. Fish. Soc. Sym.*
770 **48**: 457-471.
- 771 Heifetz, J., Murphy, M.L., and Koski, K.V. 2011. Effects of logging on winter habitat of
772 juvenile salmonids in Alaskan streams. *North American Journal of Fisheries*
773 *Management* **6**:52-58.
- 774 Hicks, B.J., and J.D. Hall. 2003. Rock type and channel gradient structure salmonid populations
775 in the Oregon Coast Range. *Trans. Am. Fish. Soc.* **132**:468-482.
- 776 Johnson, L.B., and Host, S.H. 2010. Recent developments in landscape approaches for the study
777 of aquatic ecosystems. *Journal of the North American Benthological Society* **26**: 41–66.
- 778 Kahler, T.H., Roni, P., and Quinn, T.P. 2001. Summer movement and growth of juvenile
779 anadromous salmonids in small western Washington streams. *Can. J. Fish. Aquat. Sci.*
780 **58**: 1947–1956.
- 781 Kenward, M.G., and Roger, J.H. 1997. Small sample inference for fixed effects from restricted
782 maximum likelihood. *Biometrics* **53**: 983–997.
- 783 Kershner, J.L., Roper, B.B., Bouwes, N., Henderson, R., and Archer, E. 2004. An analysis of
784 stream habitat condition in reference and managed watersheds on some federal lands
785 within the Columbia River Basin. *North American Journal of Fisheries Management* **24**:
786 1363-1375.
- 787 Larsen, D.P., Kincaid, T.M., Jacobs, S.E., and Urquhart, N.S. 2001. Designs for evaluating local
788 and regional scale trends. *Bioscience* **51**: 1069-1078.

- 789 Larsen, D.P., Kaufmann, P.R., Kincaid, T.M., and Urquhart, N.S. 2004. Detecting persistent
790 change in the habitat of salmon-bearing streams in the Pacific Northwest. *Can. J. Fish.*
791 *Aquat. Sci.* **61**: 283-291.
- 792 Lichatowich, J. 1999 *Salmon without rivers: a history of the Pacific salmon crisis*. Island Press,
793 Washington, D.C.
- 794 Logez M, Bady, P., and Pont D. 2012. Modelling the habitat requirement of riverine fish species
795 at the European scale: sensitivity to temperature and precipitation and associated
796 uncertainty. *Ecology of Freshwater Fishes* **21**: 266–282.
- 797 Lucero, Y., Steel, E.A., Burnett, K.M., and Christiansen, K.. 2011. Untangling human
798 development and natural gradients: Implications of underlying correlation structure for
799 linking landscapes and riverine ecosystems. *River Syst.* **19**(3): 207-224.
- 800 Mellina, E., and Hinch, S.G. 2009. Influences of riparian logging and in-stream large wood
801 removal on pool habitat and salmonid density and biomass: a meta-analysis. *Can. J. For.*
802 *Res.* **39**: 1280-1301.
- 803 Miller, R.R. 2010. Is the past present? Historical splash dam mapping and stream disturbance
804 detection in the Oregon coast range, Corvallis. M.Sc. thesis, Department of Fisheries and
805 Wildlife, Oregon State University, Corvallis, OR, USA..
- 806 Montgomery, D.R., Beamer, E.M., Pess, G.R., and Quinn, T.P. 1999. Channel type and salmonid
807 spawning distribution and abundance. *Can. J. Fish. Aquat. Sci.* **56**: 377–387.
- 808 Moore K.M.S., Jones, K.K., and Dambacher, J.M. 2007. Methods for stream habitat surveys:
809 Aquatic Inventories Project. Oregon Department of Fish and Wildlife Information

- 810 Report, Salem, Oregon.
- 811 Nakagawa, S., and Schielzeth, H. 2013. A general and simple method for obtaining R^2 from
812 generalized linear mixed-effects models. *Methods in Ecology and Evolution* **4**: 133–142.
- 813 Nickelson T.E., Rodgers J.D., Johnson S.L., and Solazzi M.F. 1992. Seasonal changes in habitat
814 use by juvenile coho salmon (*Oncorhynchus kisutch*) in Oregon coastal streams. *Can. J.*
815 *Fish. Aquat. Sci.* **49**: 783–789.
- 816 Ohmann, J. L., and Gregory, M. J. 2002. Predictive mapping of forest composition and
817 structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon,
818 USA. *Can. J. For. Res.* **32**: 725–741.
- 819 Oregon Department of Forestry. 2004. 1:24 000-scale land ownership in Oregon. Oregon
820 Department of Forestry, Salem, Oregon, USA. Available from
821 <http://www.oregon.gov/DAS/CIO/GEO/pages/alphalist.aspx#1> [accessed 19 November
822 2015].
- 823 Pess, G.R., Montgomery, D.R., Steel, E.A., Bilby, R.E., Feist, B.E., and Greenberg, H.M. 2002.
824 Landscape characteristics, land use, and Coho salmon (*Oncorhynchus kisutch*)
825 abundance, Snohomish River, Washington, USA. *Can. J. Fish. Aquat. Sci.* **59**: 613-623.
- 826 Sandercock, F.K. 1991. Life history of coho salmon (*Oncorhynchus kisutch*). *In* *Pacific Salmon*
827 *Life Histories. Edited by C. Groot and L. Margolis.* UBC Press, Vancouver, Canada, pp.
828 397-445.
- 829 Sedell, J.R., and Duval, S.. 1985. Influence of forest and rangeland management on anadromous
830 fish habitat in western North America: Water transportation and storage of logs. USDA

- 831 United States Forest Service General Technical Report GTR-PNW-186, Pacific
832 Northwest Research Station, Portland, OR. 68 p.
- 833 Solazzi, M.F., Nickelson, T.E., Johnson, S.L., and Rodgers, J.D. 2000. Effects of increasing
834 winter rearing habitat on abundance of salmonids in two coastal Oregon streams. *Can. J.*
835 *Fish. Aquat. Sci.* **57**(5): 906-914.
- 836 Spies, T.A., Johnson, K.N., Burnett, K.M., Ohmann, J.L., McComb, B.C., Reeves, G.H.,
837 Bettinger, P., Kline, J.D., and Yonts, B.G. 2007. Cumulative ecological and
838 socioeconomic effects of forest policies in coastal Oregon. *Ecological Applications* **17**:
839 5–17.
- 840 Steel, E.A., Feist, B.E., Jensen, D.W., Pess, G.R., Sheer, M.B., Brauner, J.B., and Bilby, R.E.
841 2004. Landscape models to understand Steelhead (*Oncorhynchus mykiss*) distribution
842 and help prioritize barrier removals in the Willamette Basin, Oregon, USA. *Can. J. Fish.*
843 *Aquat. Sci.* **61**: 999-1011.
- 844 Steel, E.A., Hughes, R.M., Fullerton, A.H., Schmutz, S., Young, J.A., Fukushima, M., Muhar, S.,
845 Poppe, M., Feist, B.E., and Trautwein, C. 2010. Are we meeting the challenges of
846 landscape-scale riverine research? A review. *Living Reviews in Landscape Research* 4.
847 Available from <http://lrlr.landscapeonline.de> [accessed 19 November 2015]
- 848 Steel, E.A., Jensen, D.W., Burnett, K.M., Christiansen, K., Firman, J.C., Feist, B.E., Anlauf, K.,
849 and Larsen, D.P. 2012. Landscape characteristics and coho salmon (*Oncorhynchus*
850 *kisutch*) distributions: explaining abundance versus occupancy. *Can. J. Fish. Aquat. Sci.*
851 **69**: 457-468.

- 852 Stevens, D.L. 2002. Sampling design and statistical analysis methods for the integrated
853 biological and physical monitoring of Oregon streams. Oregon State University, OPSW-
854 ODFW-2002-07, Corvallis, Oregon, USA.
- 855 USDA Forest Service.1990. Land and resource plan for the Siuslaw National Forest, Siuslaw
856 National Forest, Corvallis. Available from
857 http://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fsbdev7_007057.pdf [accessed 19
858 November 2015].
- 859 Walker, G.W., MacLeod, N.S., Miller, R.J., Raines, G.L., and Connors, K.A. 2003. Spatial
860 digital database for the geologic map of Oregon. U.S. Geological Survey, Open-File
861 Report 03-67, Menlo Park, California.
- 862 Weitkamp, L.A., Wainwright, T.C., Bryant, G.J., Milner, G.B., Teel, D.J., Kope, R.G., and
863 Waples, R.S. 1995. Status review of Coho salmon from Washington, Oregon, and
864 California. U.S. Dept. Commerce, NOAA Tech. Memo. NMFS-NWFSC-24. Available
865 from http://www.nwfsc.noaa.gov/assets/25/5585_06172004_123333_coho.pdf [accessed
866 19 November 2015]
- 867 Wohl, E.E., K.R. Vincent, D.J. Merritts. 1993. Pool and riffle characteristics in relation to
868 channel gradient. *Geomorphology* 6(2): 99-110.

869 **Table 1.** Geospatial data layers and variables extracted for use in exploratory analysis, base
 870 models, and hypothesis testing.

Geospatial Datalayer	Map Scale Gridcell Size	Variable
<u>Modeled Air Temperature</u> : Ambient air temperatures (1961 - 1990) expressed as means over the subtypes described in Precipitation Elevation Regressions on Independent Slopes Model (PRISM) (Daly et al. 1994). Variables calculated as an area-weighted mean across grid cells within the catchment area.	N/A ----- 4,000 m	<u>MaxAirTemp</u> : maximum annual temperature (°C). <u>TempRange</u> : annual temperature range (°C).
<u>Modeled Precipitation</u> : Cumulative mean annual precipitation (1961 - 1990), from Precipitation Elevation Regressions on Independent Slopes Model (PRISM) (Daly et al. 1994). Calculated as area-weighted mean across grid cells within the	N/A ----- 500 m	<u>Precip</u> : mean annual precipitation (mm).

catchment area.		
<u>Geology</u> : Classification of geologic map units according to major lithology (Walker et al. 2003).	1:500k ----- N/A	<u>Landslide</u> : Proportion of watershed with an estimated delivery weighted landslide density above 2.3 landslides/kmsq. <u>Sedimentary</u> : Proportion of watershed classified as sedimentary geology.
<u>Land Ownership</u> : Land ownership classification (Oregon Department of Forestry 2004).	1:24k ----- N/A	<u>BLM</u> : Proportion of watershed owned by U.S. Bureau of Land Management. <u>USFS</u> : Proportion of watershed owned by U.S. Forest Service. <u>Public</u> : BLM + USFS + proportion of watershed owned by State of Oregon. <u>PrivateInd</u> : Proportion of watershed that is private industrial forest and all other private lands. <u>PrivateNI</u> : Proportion of watershed that is private non-industrial forest.
<u>Tree Size and Type</u> : Predictive mapping of forest composition using direct gradient analysis and nearest neighbor imputation (Ohmann and Gregory, 2002).	NA ----- 25 m	<u>BigTrees</u> : Proportion of watershed estimated to be in the following classes: Conifers (50-75 cm) + Very Large Conifers (>75 cm) + Large Mixed (50-75 cm) + Very Large Mixed (>75 cm).

		<u>VLConifers</u> : Proportion of watershed estimated to be in Very Large Conifers (>75 cm).
<u>Digital elevation model (DEM)</u> : USGS 10 m DEM.	NA ----- 10 m	<u>DrainageArea</u> : Total area upslope of the downstream end of any given index reach. Generated from a USGS 10 m DEM (m ²). <u>Gradient</u> : Change in elevation (upstream elevation minus downstream elevation) divided by length of the reach (%). <u>Elevation</u> : Elevation of downstream terminus of reach, as measured from 10 m DEM (m).
<u>Intrinsic Potential</u> : Predicted total area of instream rearing habitat for juvenile Coho salmon (<i>O. kisutch</i>) based on the geometric mean of normalized values for flow, gradient, and valley constraint (Burnett et al. 2007; Clarke et al. 2008).	1:24k ----- NA	<u>AvgIP</u> : Average value of intrinsic potential for the reach (unitless). <u>LengthHighIP</u> : Total length of stream with intrinsic potential > 0.75 in catchment (unitless).
<u>Historical Stream Disturbances</u> : Historical archives were used to create a geodatabase of historical splash-dam and log-drive sites in Western Oregon (Miller 2010)	1:24k ----- N/A	<u>SplashDams</u> : Presence of historical splash dams (count). <u>LogDrive</u> : Length of historical log drives within the catchment area (m).

872 **Table 2.** Linear model estimating ln(pool surface area) using immutable variables from Anlauf et
 873 al. (2011).

Predictor variable	Unit [†]	Coefficient ^{††}	Lower 95% CI	Upper 95% CI
Gradient	0.016	-0.251	-0.322	-0.181
Elevation	65.427	0.062	0.014	0.110
Ln (Drainage area)	0.558	0.412	0.358	0.465
Survey length	133.200	0.196	0.143	0.250
Sedimentary	0.100	-0.010	-0.038	0.018

874 [†] The unit column describes approximately 1/10th of the observed range of the predictor variable.

875 ^{††} The coefficients describe the effect of a 1-unit change in the predictor variable on the log scale
 876 response. CI = confidence interval

877

878 **Table 3**, The Poisson model (log link) for juvenile coho salmon counts using immutable
 879 variables from Anlauf et al. (2011).

Predictor variable	Unit [†]	Coefficient ^{††}	Lower 95%	Upper 95%
			Confidence Interval	Confidence Interval
Precip	292.553	-0.114	-0.257	0.029
Sedimentary	0.100	0.091	-0.005	0.186
Gradient	0.016	-0.211	-0.399	-0.023
Gradient ²	0.016	-0.074	-0.147	-0.001
Elevation	65.427	0.011	-0.122	0.143
Drainage area	16.919	-0.382	-0.545	-0.218

880 [†]The unit column describes approximately 1/10th of the observed range of the predictor variable.

881 ^{††}The coefficients describe the effect of a 1-unit change in the predictor variable on the log-scale
 882 response.

883

884

885 **Table 4.** Hypothesis tests for key variables of interest in which p-values describe 1 degree of
 886 freedom chi-square tests (GLMM) or Kenward-Roger F tests (LMM) for the addition of a key
 887 variable of interest to a model that already contains immutable variables (see Table 2 for base
 888 pool model and Table 3 for base juvenile coho salmon model).

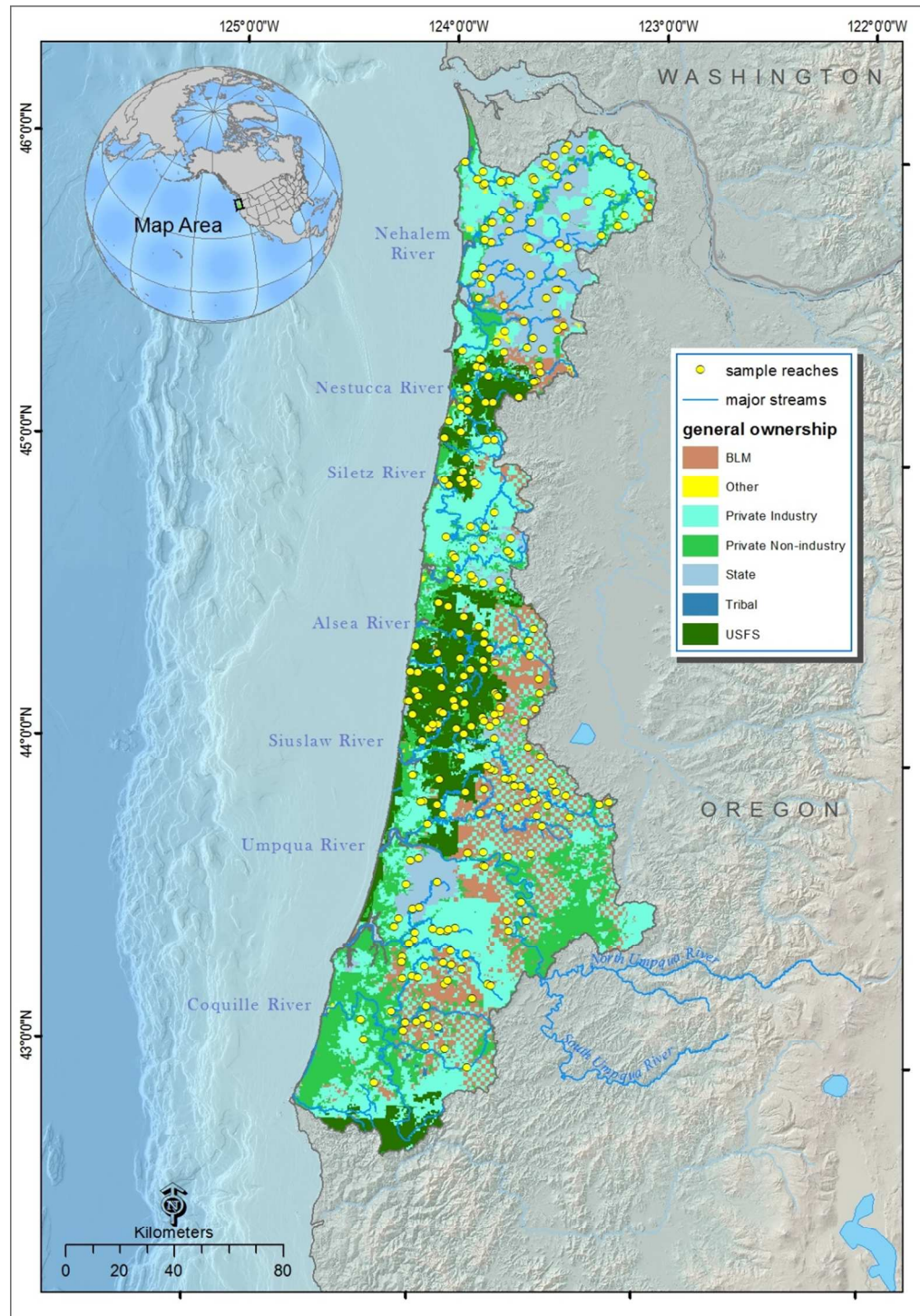
Variable	Unit [†]	Pool Surface Area			Juvenile coho salmon		
		P-value	Effect ^{††}	95% CI	P-value	Effect ^{††}	95% CI
AvgIP (full model)	0.1	0.093	-5.2%	(-10.9, 0.9)	0.567	-5.6%	(-22.4, 14.9)
AvgIP (w/out grad.)	0.1	<0.0001	9.2%	(4.8, 13.7)	<0.0001	30.7%	(19.2, 44.2)
LengthHighIP (m)	2641	<0.0001	-10.5%	(-14.8, -6.0)	0.828	-1.5%	(-14.5, 13.4)
Public	0.1	<0.0001	7.7%	(4.8, 10.8)	0.827	0.9%	(-7, 9.5)
PrivateInd	0.1	<0.0001*	-6.1%	(-8.8, -3.3)	0.972*	-0.2%	(-8.8, 9.1)
PrivateNI	0.1	<0.0001*	-15.6%	(-20.9, -9.9)	0.972*	-2.4%	(-20.1, 19.1)
SplashDams**	+	0.514	11.4%	(-19.2, 53.5)	0.049	139.5%	(0.4, 474.9)
LogDrive (m)	0.0001	0.109	-3.5%	(-7.6, 0.7)	0.466	-4.4%	(-15.5, 8.0)

889 [†]The unit column describes approximately 1/10th of the observed range of the predictor variable.

890 ^{††}The effect sizes (Effect) are for a 1-unit change in the predictor variable. A positive number
 891 indicates the percent increase and a negative number indicates a percent reduction.

892 *Tests for private ownership were conducted by adding private industrial and private non-
 893 industrial to the immutable model simultaneously. The two p-values therefore reflect a chi-
 894 squared test with 2 degrees of freedom.

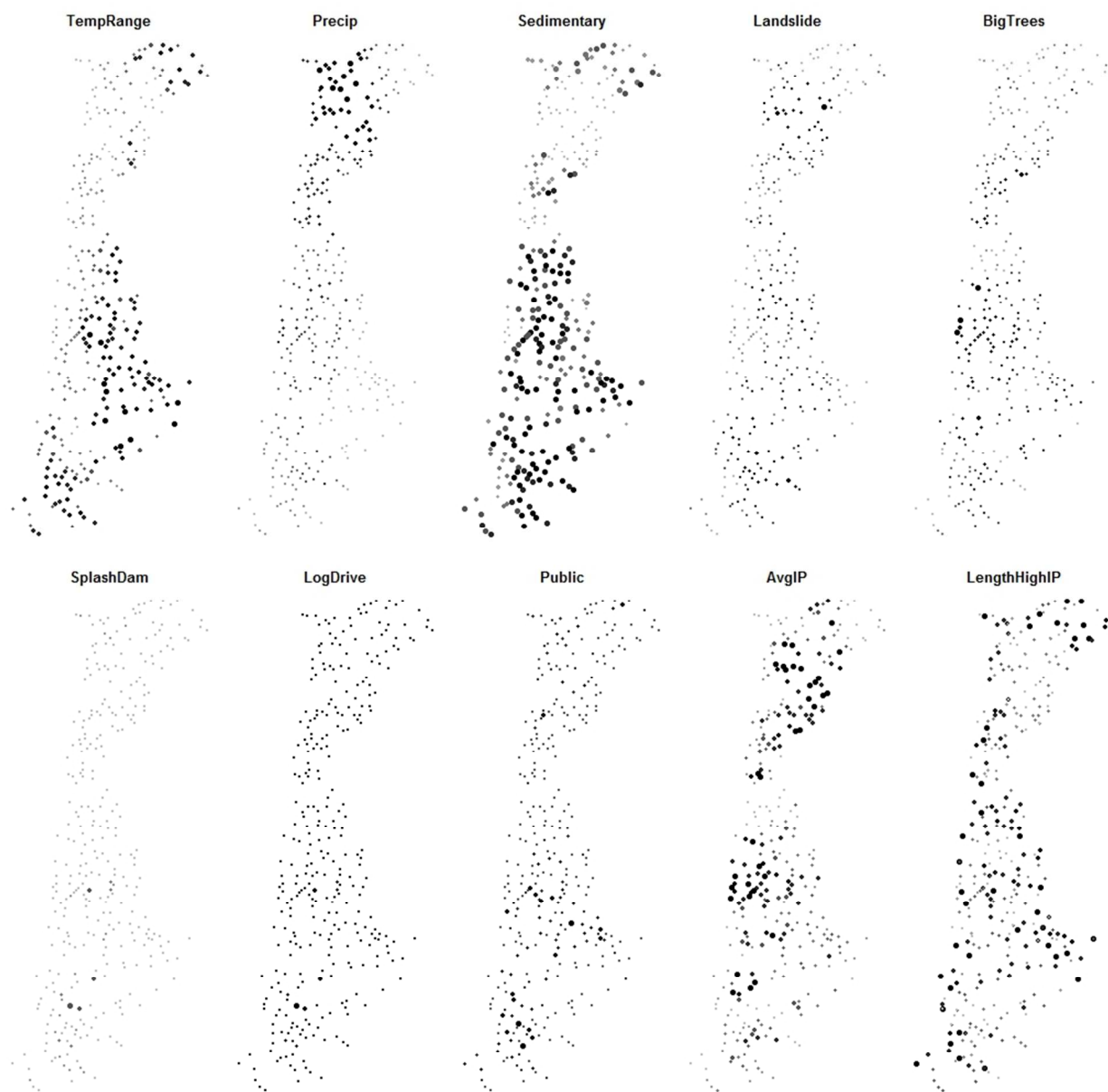
895 **The plus symbol for the unit size of splash dams indicates that this effect is for presence versus
896 absence of any splash dams in the watershed draining to the study reach.



897

898 **Fig. 1.** Map of the Oregon Coast, USA with study reaches identified by points and land

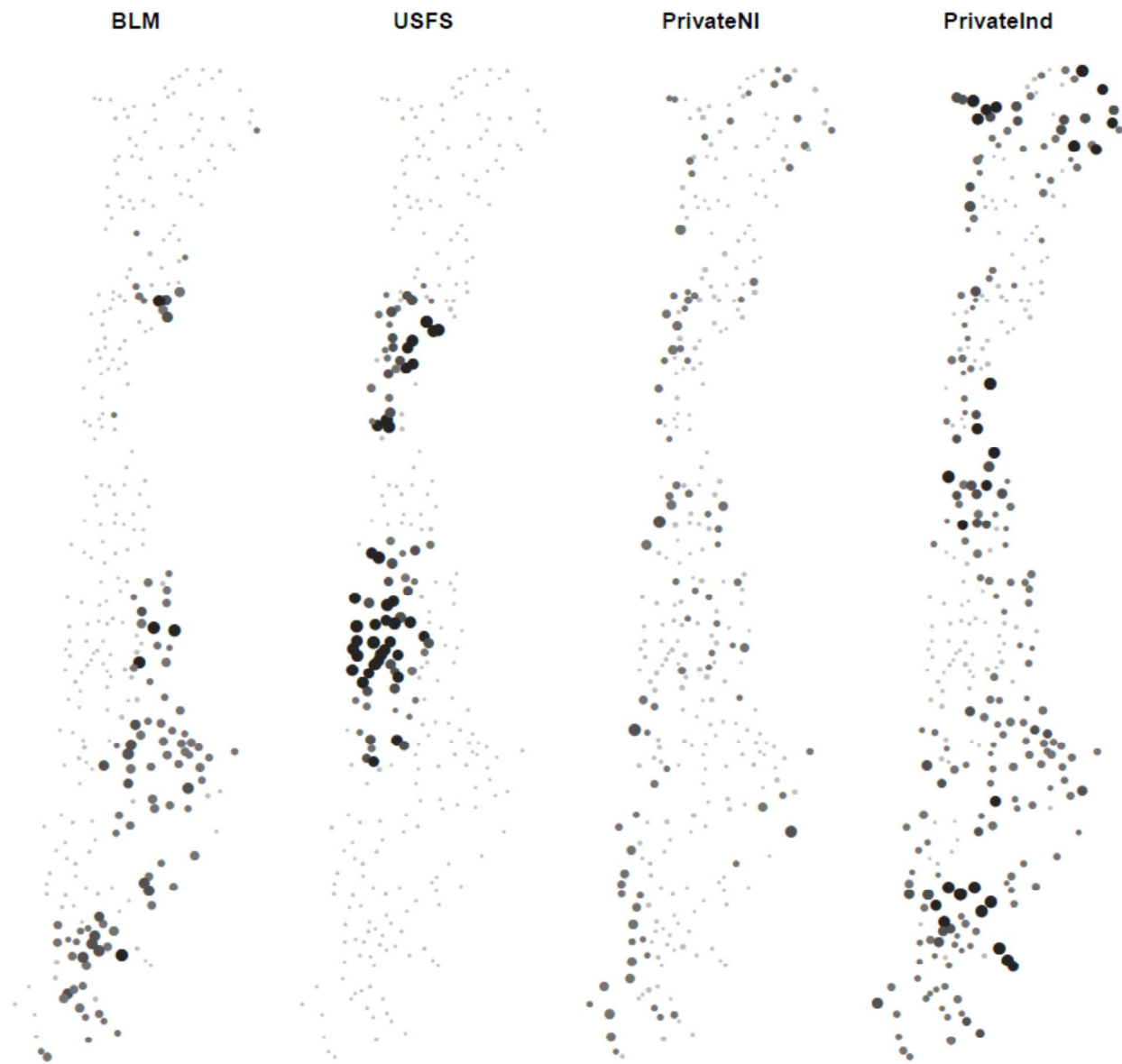
899 ownership (Table 1; Oregon Department of Forestry 2004).



900

901 **Fig. 2.** Spatial distribution of a set of potential landscape-scale predictor across the Oregon

902 Coast study area. For variable definitions see Table 1.

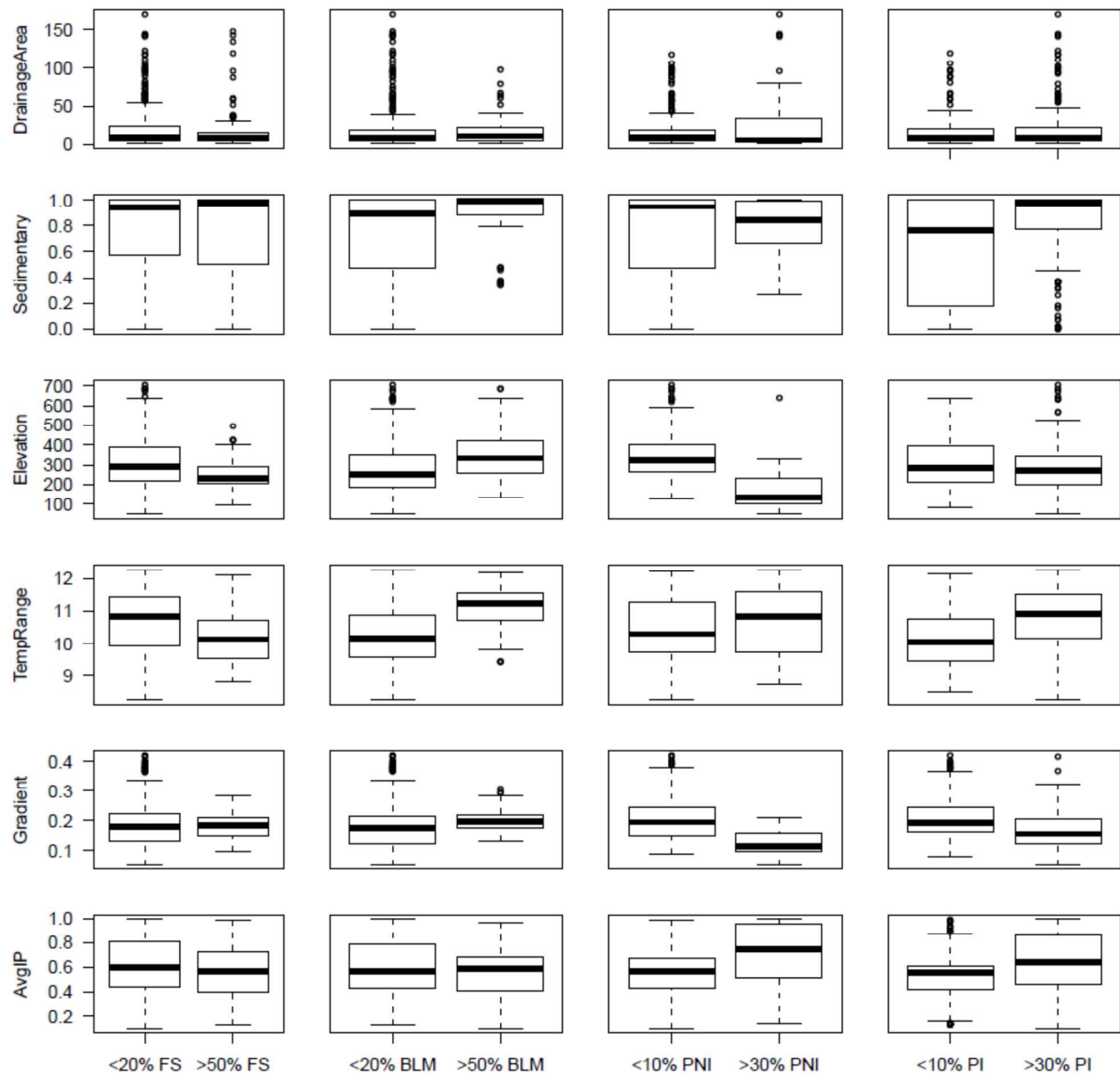


903

904 **Fig. 3.** Spatial distribution of landownership across the study watersheds. PrivateNI = Private

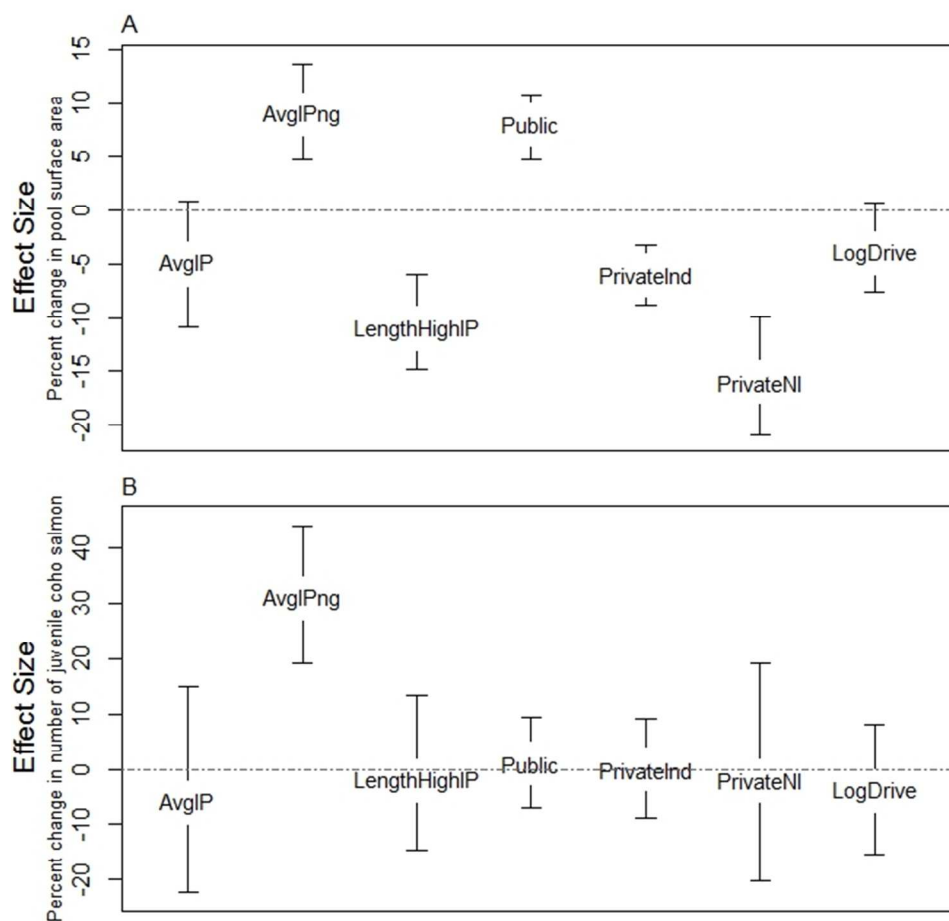
905 non-industrial forest lands. PrivateInd = private industrial forests.

906

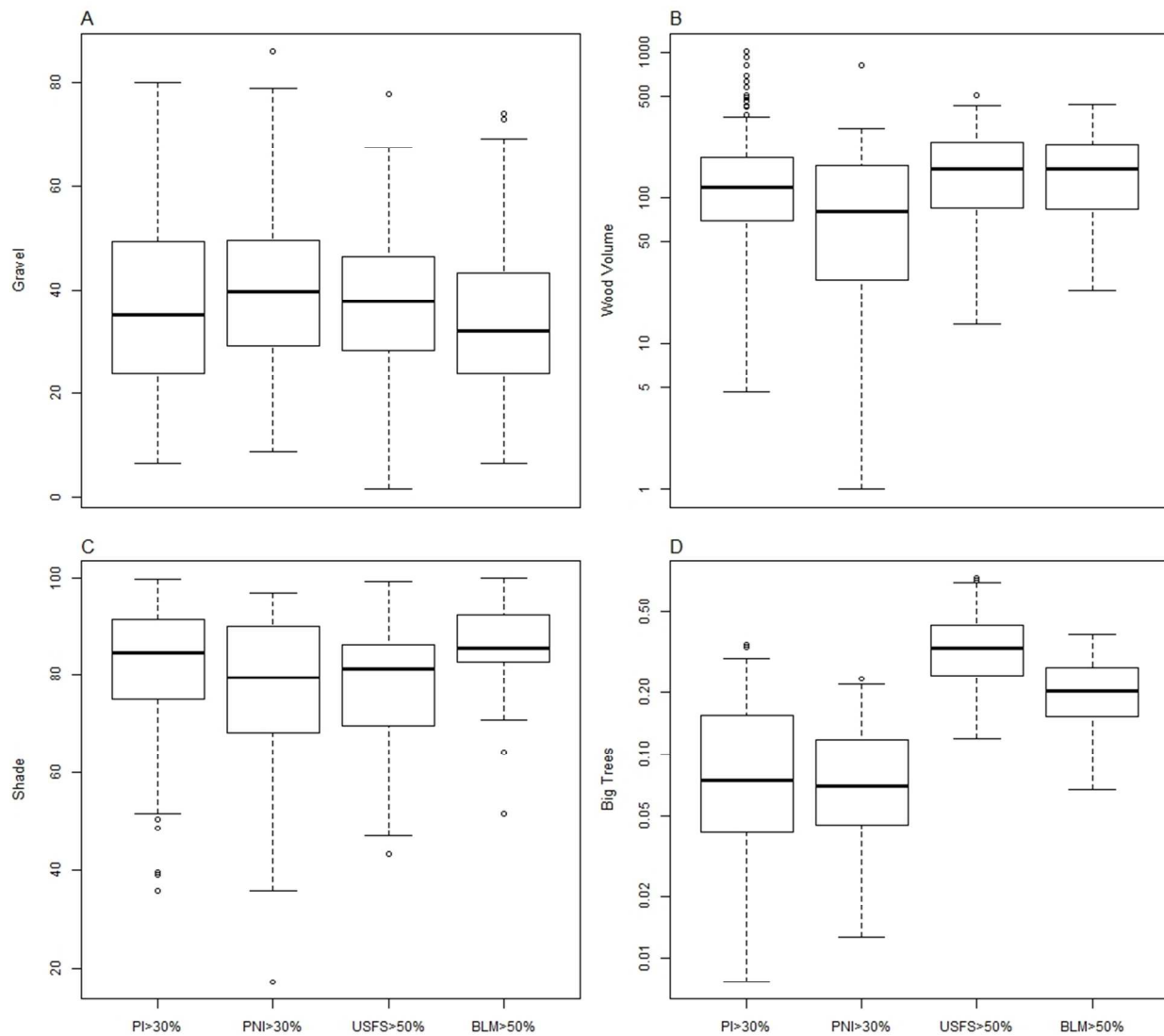


907

908 **Fig. 4.** Comparison of landscape attributes for sites that have relatively more of a particular
 909 ownership classification versus relatively less. The exact cut-offs differ between the two private
 910 and the two public ownership categories in order to provide a reasonable sample size in both
 911 categories. PI = Private industrial (PrivateInd); PNI = Private non-industrial (PrivateNI).



912
 913 **Fig. 5.** Effect sizes for key variables when entered in to either (a) the pool surface area model or
 914 (b) the model for number of juvenile coho salmon. In each case the unit of the effect is
 915 approximately $1/10^{\text{th}}$ of the observed range of that variable within our data (See Table 4). Note
 916 that Average Intrinsic Potential is tested in two ways: once on the full immutable model (AvgIP)
 917 and once on the immutable without gradient (AvgIPng). The effect of the length of stream with
 918 high intrinsic potential in the watershed draining to the reach (LengthHighIP) is statistically
 919 significant in the pool surface model but not in the number of juvenile coho salmon model.
 920 Splash dams were not included in the Fig. because there was no equivalent effect of $1/10^{\text{th}}$ of the
 921 observed range of the data for presence/absence of splash dams.



922

923 **Fig. 6.** The distribution of (A-C) instream habitat variables associated with high quality juvenile

924 coho habitat as a function of land ownership and (D) percent of the watershed with big trees

925 (Table 1). Gravel is the proportion of the stream-bed area that is classified as gravel (2–64 mm).

926 Wood volume is the volume of in-stream wood per 100m of reach length (m^3 per 100 m).

927 Percent shade is the percentage of the stream channel that is shaded. PI = Private industrial

928 (PrivateInd); PNI = Private non-industrial (PrivateNI).