An ultra-dense haploid genetic map for evaluating the highly fragmented genome assembly of Norway spruce *(Picea abies)*

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Abstract

Norway spruce (*Picea abies* (L.) Karst.) is a conifer species with large

economic and ecological importance. As with most conifers, the *P. abies* genome

is very large (~20 Gbp) and contains high levels of repetitive DNA. The current

genome assembly (v1.0) covers approximately 60% of the total genome size, but

is highly fragmented consisting of more than 10 million scaffolds. Even though

66,632 protein coding gene models are annotated, the fragmented nature of the

assembly means that there is currently little information available on how these

genes are physically distributed over the 12 *P. abies* chromosomes. By creating

an ultra-dense genetic linkage map, we can anchor and order scaffolds at the

pseudo-chromosomal level in *P. abies*, which complements the fine-scale

information available in the assembly contigs. Our ultra dense haploid consensus

genetic map consists of 15,005 markers from 14,336 scaffolds and where 17,079

gene models (25.6% of protein coding gene annotations) have been anchored to

the 12 linkage groups (pseudo-chromosomes). Three independent component

maps, as well as comparisons to earlier published *Picea* maps are used to

evaluate the accuracy and marker order of the linkage groups. We can

demonstrate that approximately 3.8% of the scaffolds and 1.6% of the gene

models covered by the consensus map are likely wrongly assembled as they

contain genetic markers that map to different regions or linkage groups of the *P.*

abies linkage map. We also evaluate the utility of the genetic map for the conifer

research community by using an independent data set of unrelated individuals to

assess genome-wide variation in genetic diversity using the genomic regions

anchored to chromosomes. The results show that our map is dense enough to

allow detailed evolutionary analysis across the *P. abies* genome.

Introduction

Genetic linkage maps have been used to order genetic markers and link

phenotypic traits to genomic regions and chromosomes by calculating recombination

in crosses for over a century (Sturtevant 1913a; Sturtevant 1913b). With the recent

development of Next Generation Sequencing technologies (NGS), large numbers of

markers can now be scored at a relatively low cost and within a reasonable time,

which has enabled the possibility to create high-density genetic maps consisting of

thousands of markers that consequently can achieve very high resolutions. These

genetic maps enable a complementary approach to the local fine-scale genomic

information that is available in the scaffolds of a genome assembly, since a genetic

map adds information on genome organization over larger scales (chromosome level)

(Fierst 2015). By grouping markers into linkage groups (potential chromosomes), and

subsequently ordering them within each linkage group, it is possible to anchor

underlying scaffolds to putative chromosomes, here after referred to as pseudo-

chromosomes, and align them with high precision (Fierst 2015). If several genetic

markers, derived from a single scaffold, are placed on the map, information on their

relative placement in the genetic map can be used to orient the scaffold, but also to

evaluate scaffolding decisions made in the genome assembly and hence locate and

resolve possible assembly errors (Drost et al. 2009; Bartholomé et al. 2015). For

instance, when two markers originating from a single scaffold are mapped to different

linkage groups or to different regions within a linkage group, the contigs making up

the scaffold have probably been wrongly joined during the assembly process. On the

other hand, if markers are placed close to each other on the genetic map this indicates

that the scaffolding decision likely was correct.

Norway Spruce (*Picea abies*) is one of the most important conifer species in

Europe, both ecologically and economically. With a natural distribution ranging from

the west coast of Norway to the Ural mountains and across the Alps, Carpathians and

the Balkans in central Europe, it composes, together with *Pinus sylvestris*, the

majority of the continuous boreal forests of the Northern hemisphere. For these

reasons it is often considered as a key stone species for the region (Farjon 1990). *P.*

abies has a genome size of ~20 Gbp that is characterized by very high amounts of

repetitive sequences. Like most conifers, *P. abies* has a karyotype consisting of 2n=24

and where chromosomes are all uniformly sized (Sax and Sax 1933). Due to the large

and complex genome of conifers, this ecologically and economically important group

of plants was, until recently, lacking species with available reference genomes. In

2013 the first draft assembly of the Norway spruce genome was published (Nystedt et

al. 2013). Despite extensive whole-genome shotgun sequencing derived from both

haploid and diploid tissues, the *P. abies* genome assembly is still highly fragmented

due to the complex nature and size of the genome. The current *P. abies* genome

assembly (v1.0) consists of 10.3 million scaffolds that are longer than 500 bp and

contains 70,736 annotated gene models of which 66,632 are protein coding. Despite

the large size of the genome assembly, it still only covers about two thirds of the total

genome size (12 Gbp out of the 20 Gbp *P. abies* genome) (Nystedt et al. 2013; De La

Torre et al. 2014).

In this paper, we use probe capture sequencing to identify segregating SNP

markers in an open-pollinated half-sib family. These are used to create an ultra-dense

haploid genetic map consisting of 21,056 markers derived from 14,336 gene bearing

scaffolds in the Norway spruce (*Picea abies*) genome assembly. Our aim was to 1)

anchor and order these scaffolds in an effort to assign as many gene models as

possible to pseudo-chromosomes, and 2) to evaluate the accuracy of the *Picea abies*

genome assembly v1.0. To evaluate the accuracy of the map itself, we have also

performed scaffold order comparisons with previously published genetic maps for *P.*

abies and *Picea glauca*. Finally we evaluate the utility of the genetic map by

performing genome-wide analyses of genetic diversity for the genomic regions

anchored in the map in a sample of c. 500 unrelated *P. abies* trees.

Material and Methods

DNA extraction and exome sequencing

In the autumn of 2013, seeds were collected from cones of 30 putative ramets of

Z4006, the individual from which the reference genome for *Picea abies* was obtained

(Nystedt et al. 2013), and seeds from five of these ramets were used for the

construction of the genetic map. Megagametophytes were dissected from 2,000 seeds

by removing the diploid seed coat surrounding the haploid megagametophyte tissue.

DNA extraction from megagametophytes was performed using a Qiagen Plant Mini

Kit except that the AP1 buffer was replaced by the PL2 buffer from a Macherey-

Nagel NucleoSpin Plant II kit. Each extracted sample was measured for DNA quality

using a Qubit® ds DNA Broad Range (BR) Assay Kit, and all samples with a total

amount of DNA >354 ng were kept. The remaining 1,997 samples were sent to

RAPiD Genomics© (Gainesville, Florida, USA) in September 2014 for exome

capture sequencing using 31,277 haploid probes that had been specifically designed

for *P. abies* based on the v1.0 genome assembly (for further detail of the probes, see

Vidalis et al. 2018).

The exome capture sequence data was delivered from RAPiD Genomics© in

October 2015. The raw reads were mapped against the complete *P. abies* reference

genome v.1.0 using BWA-MEM v.0.7.12 (Li and Durbin 2009). Following read

mapping the genome was subset to only contain the probe bearing scaffolds (a total of

18,461 scaffolds) using Samtools v.1.2 (Li and Durbin 2009; Li et al. 2009). Mark

duplicates and local realignment around indels was performed using Picard

(http://broadinstitute.github.io/picard/) and GATK (McKenna et al. 2010; DePristo et

al. 2011). Genotyping was performed using GATK Haplotypecaller (version 3.4-46,

(DePristo et al. 2011; Van der Auwera et al. 2013) with a diploid ploidy setting and

gVCF output format. We used a diploid ploidy setting to detect possible sample

contamination from diploid tissue for the haploid samples. CombineGVCFs was then

run on batches of ~200 gVCFs to hierarchically merge them into a single gVCF and a

final SNP call was performed using GenotypeGVCFs jointly on the 10 combined

gVCF files, using default read mapping filters, a standard minimum confidence

threshold for emitting (stand-emit-conf) of 10, and a standard minimum confidence

threshold for calling (stand_call_conf) of 20. See Vidalis et al. (2018) for a full

description of the pipeline used for calling variants.

SNP filtration and megagametophyte relationships

Sites with insertions/deletions (indels), low quality flag, > 20% missing data, minor

allele frequency (MAF) < 0.4 as well as all sites outside the extended probe regions

(120 bp probes ±100 bp) were filtered out using vcftools (Danecek et al. 2011). A

final filtration step was set so that only markers confirmed as heterozygous in the

maternal genotype Z4006 were kept. All heterozygous calls in the haploid samples

were then recoded as missing and samples with > 40% missing data were also filtered

out to avoid samples with possible contamination of diploid tissue or with poor

sequencing quality. This resulted in a final data set of 1,559 samples containing a

total of 14,794 SNPs.

All 1,559 samples were used in a principal component analysis (PCA) to

evaluate the relationship among samples. The reference allele was coded as "0" while

the alternative allele was coded as "1", and all remaining missing data were re-coded

to the average value for that marker (i.e. the allele frequency of the alternate allele).

The first two axes of the PCA explained a total of 17% of the variation (10% and 7 %,

respectively for PC1 and PC2) while remaining axes individually explained 0.6-1%.

The samples grouped into three distinct clusters which all were oriented differently

along the PC1-PC2 axes, with a 4th group connecting the clusters in the center of the

plot (Figure S1). The PCA analysis indicate that our data are more heterogeneous than

what is expected for a single open-pollinated family, likely indicating that samples

came from more than one maternal trees (i.e.,ramets from different genotypes).

Samples were therefore split into clusters representing putatively different maternal

families using strict cutoffs: Cluster 1 (321 samples) - PC2 >5; Cluster 2 (279

samples) – PC1 >0 and PC2< -5; and Cluster 3 (858 samples) - PC1 < -2 (Figure S1).

To confirm that these clusters represent single segregating families, PCAs were

conducted on all clusters separately. For all three clusters, all axes explained roughly

the same amount of variation and all the samples grouped into a single cloud without

any detectable outliers (data not shown).

Since we detected multiple maternal families in the data set, a second SNP

filtration step was performed using vcftools (Danecek et al. 2011) and R (R Core

Team 2013) separately on the three clusters, keeping only samples with < 10%

heterozygous calls. SNPs within the extended probe regions (see above) having <

20% missing data (all calls not homozygous reference or homozygous alternative 1

treated as missing) and with a MAF > 0.4 were kept as informative markers

(supplementary file: Informative markers). For each unique probe in the three data

sets, only the most balanced marker (highest MAF and lowest amount of missing

data) was kept for map creation and named with an ID based on scaffold and probe

position. This resulted in 9,073 markers from 7,101 scaffolds for Cluster 1 (314

samples), 11,648 markers from 8,738 scaffolds for Cluster 2 (270 samples) and

19,006 markers from 13,301 scaffolds for Cluster 3 (842 samples) for a total of

21,056 markers from 14,336 scaffolds across all three clusters (Table 1). In total,

these scaffolds cover 0.34 Gb of the *P. abies* genome and contain 17,079 protein

coding gene models.

Table 1: Overview of the three component maps and the total number of

markers available in the consensus map. Cluster: Name of each family group

that was identified in the principal component analysis. Samples: Number of

megagametophytes in each cluster. Marker pre drop/ Markers post drop:

Number of markers in each component map before and after markers were

dropped if markers from the same scaffold were located within 15 cM from

each other in the first round of component map construction. Scaffolds:

Number of scaffolds represented in each component map.

Cluster	Samples	Markers pre-drop/post-drop	Scaffolds
Cluster 1	314	9,073 / 7,179	7,101
Cluster 2	270	11,647 / 8,821	8,738

Cluster 3	842	19,006 / 13,479	13,301
Total	1,426	21,056 / 15,005	14,336

Component and consensus maps

Genetic linkage maps were created with the R-package BatchMap (Schifthaler et al.

2017), a parallel implementation of the R-package Onemap (Margarido, Souza, and

Garcia 2007). All markers were recoded using the D1.11 cross-type (Wu et al. 2002)

and grouped into LGs with LOD = 8 and a maximum recombination fraction = 0.35.

LGs were then ordered using the RECORD algorithm (Van Os et al. 2005) with 40

times counting, parallelized over 20 cores, and mapped using the Kosambi mapping

function and the map batches approach (Schifthaler et al. 2017) over four parallel

cores. To reduce the noise in the maps, markers from the same scaffold that mapped

within 15 cM from each other, were dropped so that only one marker was used to

represent the scaffold in the final map. However, if any markers from the same

scaffold mapped more than 15 cM apart, all markers from that scaffold were kept.

This approach was motivated by the fact that sequence data from markers < 15 cM

apart did not show any evidence for recombination when using a visual inspection of

the data and that this inconsistency in marker ordering is probably due to a lack of

resolution in the mapping populations together with the usage of a heuristic ordering

approach (Mollinari et al. 2009). Finally, a heat map with pairwise recombination

fraction (lower triangular) and phase LOD score (upper triangular) for the ordered

markers was created to evaluate the ordering accuracy (data not shown).

To evaluate correspondence between LGs in maps from different clusters the

number of unique scaffolds shared between cluster LGs were counted (Figure S2). A

consensus map over all three clusters was then created for each chromosome with the

R-package LPmerge (Endelman and Plomion 2014) with clusters ordered according

to marker numbers, a maximum interval setting ranging from one to 10 and map

weights proportional to sample size. The consensus map with the lowest mean root

mean square error (RMSE), was then set as the best consensus map for each

chromosome. Order correlations between component maps and the consensus maps

were estimated with Kendall's tau (Table 2 and Figure S3a-l). For visual

representation of the consensus map and the characteristics of the anchored genomic

scaffolds we created a Circos plot using the R-package omicCircos (Hu et al. 2014),

available from Bioconductor (https://bioconductor.org/biocLite.R).

Accuracy of the reference P. abies genome assembly and distribution of
recombination hot spots/cold spots

To evaluate the accuracy of the *P. abies* reference genome v1.0, scaffolds carrying at

least two markers (here after called multi-marker scaffolds) were used to determine

whether markers were positioned in the same region of an LG, on different regions

from a single LG or on different LGs. In the consensus map, we considered markers

to be positioned in the same region on an LG if all markers from a scaffold mapped

within a 5 cM interval of each other. If any marker from the scaffold was positioned

further apart, the scaffold was tagged as a likely wrongly assembled scaffold. The

same considerations were made for scaffolds with markers positioned on different

LGs.

To analyze the distribution of recombination hot spots/cold spots, a sliding

window analysis using a window size of 5 cM was performed along the LGs of the

consensus map. In each window, the total physical length of all unique scaffolds

located within the window as well as the number of scaffolds and corresponding gene

models, was counted.

Comparative analyses of Picea linkage maps

To evaluate the consistency of our genetic map with earlier maps from *P. abies* we

compared our haploid consensus map to the *P. abies* linkage map from Lind et al.

2014. The Lind et al (2014) map was created using genetic markers generated using a

P. glauca SNP array (Pavy et al. 2013). The SNP array sequences from the *P. glauca*

array were blasted (tblastn) against the *P. abies* v1.0 genome assembly and reciprocal

best hits with >95% identity were extracted and assigned to the corresponding

scaffold in the *P. abies* genome. We performed similar analyses to also compare the

synteny between our consensus map and the *P. glauca* composite map from Pavy et al.

2017. Again, array sequences from the *P. glauca* SNP array (Pavy et al. 2013) were

blasted against the *P. abies* 1.0 genome and reciprocal best hits were assigned the

corresponding map positions from *P. abies* and *P. glauca*. In order to evaluate which

LGs that correspond to the same chromosome, we assessed the number of shared

scaffolds between our consensus map, the Lind et al. 2014 and Pavy et al. 2017 maps.

Consistency of scaffold order where then evaluated using a visual comparison (Figure

3 and 4) and by calculating correlations of marker order using Kendall's tau.

Population genetic analysis of the consensus genetic map

In order to independently evaluate the utility of the consensus map for downstream

research, we used a subset of the data from Baison et al. (2018) to estimate patterns of

nucleotide diversity across the Norway spruce genome. The data from Baison et al.

(2018) originally contained 517 individuals sequenced with 40,018 probes designed

for diploid spruce samples (Vidalis et al 2018). We extracted data for the probes that

were anchored in our genetic map and further hard filtered the data by only

considering bi-allelic SNPs within the extended probe regions (120bp probes ±100bp)

with a QD >5, MQ >50 and a overall DP between 3000 and 16000. Samples showing

>25% missing data were also removed from further analysis. We used the data to

calculate nucleotide diversity (π), the number of segregating sites and Tajima's D. We

used the R package vcfR (Knaus and Grünwald 2017) to read the VCF-file into R and

then used in-house developed scripts to perform all calculations. We assigned probes

to LGs and map positions by assigning them the coordinates of the physically closest

(in bp) probe. We also calculated pairwise linkage disequilibrium (LD) between

markers within probes using vcftools (Danecek et al. 2011) and imported the results

into R where they were used to calculate Zn scores (Kelly 1997) per probe using an

in-house developed script. Finally we ran sliding window analyses along the pseudo-

chromosomes for the different summary statistics using 10cM windows that were

moved in 1 cM incremental steps.

Results

A *P. abies* consensus linkage map was generated from three haploid component maps

containing a total of 15,005 unique markers from 14,336 gene containing scaffolds

from the *P. abies* genome assembly v1.0. The consensus map anchors 0.34 Gbp of the

P. abies 1.0 assembly, corresponding to only 1.7% of the complete *P. abies* genome

or 2.8% of the assembled genome. However, these scaffolds anchor 25.6% of all

predicted protein coding genes in *P. abies* and the the anchored scaffolds harbor

31.7%, 20.6% and 25.8% of the High-, Medium- and Low confidence gene models

from Nystedt et al (2013), respectively. The consensus map has a total length of 3,326 centiMorgan (cM), distributed over 12 linkage groups (LGs), which corresponds to the known haploid chromosome number of Norway spruce (Sax and Sax 1933), and with an average marker distance of 0.22 cM/marker (Table 2, Figure 1: track a).

Correlations of marker order between the three component maps and the consensus map ranged from 0.96 to 0.998, while the correlations between marker orders between individual component maps ranged from 0.943 to 0.993 (Table S1 and Figure S3). LG XI, which display the largest discrepancy in marker order between component maps, has a 200 marker region in the distal end of the chromosome where the resolution is too low to identify a correct order and where the whole region is positioned at 0 cM (Figure S3k), explain the lower order correlations for this LG.

Table 2: Marker density and size of each component genetic map created from the three clusters as well as for the consensus map. LG: Linkage group. Cluster 1-3: Component maps for cluster 1-3 with number of markers assigned and map size (in cM) for each of the LGs. Consensus: Number of markers and map size of the LGs in the consensus map.

LG	Cluster 1		Cluster 2		Cluster 3		Consensus	
	Markers	Length (cM)	Markers	Length (cM)	Markers	Length (cM)	Markers	Length (cM)
I	768	403.2	867	440.3	1,373	358.0	1,520	359.3
II	570	273.8	669	294.2	1,042	265.6	1,172	265.6
III	682	321.0	813	388.7	1,232	304.4	1,379	304.4
IV	602	315.1	718	353.0	1,078	271.5	1,199	271.5

V	593	278.4	815	401.2	1,160	309.6	1,305	299.7
VI	510	257.8	685	275.2	1,017	241.3	1,142	241.3
VII	532	324.0	688	395.5	1,141	275.9	1,245	275.9
VIII	613	325.2	710	361.6	1,048	279.6	1,158	279.5
IX	623	300.8	610	314.0	1,122	247.3	1,244	247.3
X	504	267.4	745	356.8	1,118	234.7	1,229	265.9
XI	553	216.0	774	304.7	1,040	205.3	1,167	205.2
XII	629	310.4	727	387.2	1,108	289.3	1,245	310.7
Total	7,179	3,592.9	8,821	4,262.5	13,479	3,282.4	15,005	3,326.3

Figure 1: Circos plot of the consensus map. A) Marker distribution over the

12 linkage groups (LG I-LG XII). Each black vertical line represents a marker

(15,005 in total) in the map and is displayed according to the marker

positions in cM. Track B-E visualizes a sliding window of size 5 cM, with 1

cM incremental steps, along the linkage groups. B) Number of scaffolds,

scaling 0-239. C) Number of gene models/scaffold, scaling 1-3. D) Physical

length of scaffolds, scaling 0-5,562 kb. E) Number of gene models/kb,

scaling 0-0.38. Track F-G visualizes multi marker scaffolds, where each line

is a pairwise position comparison of markers from the same scaffold. F)

Position comparisons of markers from the same scaffold that are located on

the same LG. Light grey lines indicate markers that are located < 5cM from

each other while dark grey lines indicate markers located > 5cM apart. G)

Position comparisons of markers from the same scaffold that are located on

different LGs. Orange lines indicated markers from the same scaffold split

over 2 LGs, while dark blue lines indicated markers split over 3 LGs.

Evaluation of the P. abies genome assembly v1.0

The average physical size of the scaffolds anchored per LG is 29 Mbp (26.1 - 35.3

Mbp). All chromosomes show variation in marker density along the linkage groups,

but number of markers, scaffolds, gene models and physical size are all highly

correlated (Figure 1: track b-e). However, a few regions show higher recombination

rates than the rest of the genome, where short physical length (in Kbp) co-occur with

high gene density (number of gene models/Kbp) (Figure 1: track d and e). The

average gene density is 0.05 genes/Kbp (0.047 – 0.059 per LG) with a standard

deviation of 0.02 (0.01 – 0.04 per LG). 1.41% of the windows have > 0.1 genes/Kbp

and 0.24% have > 0.2 genes/Kbp. The highest gene density can be seen in regions on

LGIII and LGV with 0.37 genes/Kbp. These regions contain one and two scaffolds,

respectively, are present in one or two of the three component maps and contain one

gene model each.

4,859 scaffolds (33.9%) had more than one unique marker combined over all

three component maps before marker pruning. Of these, 625 scaffolds (4.36%) had

multiple markers also in the consensus map, either due to suspicious grouping and/or

ordering in the component maps or that different markers were represented in

different component maps. 186 of these multi-marker scaffolds show a split over

several LGs (inter-split scaffolds) or over different parts of the same LG (intra-split

scaffolds). 22 scaffolds (0.15% of mapped scaffolds and 0.45% of original multi-

marker scaffolds) have markers positioned > 5 cM apart on the same LG and 164

scaffolds (1.14% of mapped scaffolds and 3.38% of original multi-marker scaffolds)

have markers mapped to 2 or 3 different LGs (Figure 2 and Table S2). All LGs harbor

inter-split scaffolds, while 10 LGs (LGII and LGXI are the exceptions) harbors intra-

split scaffolds (Figure 1: track f and g).

Figure 2: Fraction of scaffolds that are being represented by 1-8 unique

markers in the consensus map. Insert: Fraction of total number of scaffolds

that have multiple markers (2-8) that are distributed over 1-3 linkage

groups (inter-split scaffolds). Red dot indicate the fraction of scaffolds with

multiple markers which are positioned > 5cM apart on the same linkage

group (intra-split scaffolds).

The scaffolds covered by the map range in length from 0.22 to 208.1 Kbp with a

median of 17.1 Kbp, while multi-marker scaffolds range from 0.39 to 161.5 Kbp

(median of 21 Kbp) in length. The 186 scaffolds that are split within or across LGs

range in size from 2.5 to 121.6 Kbp, with a median length of 36.9 Kbp. Split scaffolds

are significantly longer than the multi-marker scaffolds in general ($t = -7.76$, $df =$

194.54, p-value = 4.77e-13; Figure 3), suggesting that longer scaffolds more often are

prone to assembly errors compared to shorter scaffolds. Split scaffolds are mostly

harboring high- and medium confidence gene models (Table 3). A visual inspection

of the split scaffolds shows that 75 and 10 of the inter-split and intra-split scaffolds,

respectively, have the predicted split(s) between different gene models on the same

scaffold where as 88 of the inter-split scaffolds and 12 of the intra-split scaffolds have

the predicted split within a single gene model (Table S3). In addition, 21 inter-split

scaffolds show an even more complicated picture, where an interior regions of the

gene model (most often containing an intron > 5kb) map to another chromosome

where as the 5' and 3' regions of the gene model map to the same chromosome

location (Table S3). Of the 17,079 gene models that are anchored to the consensus

genetic map, 330 are positioned on inter- or intra-split scaffolds (5.4% of those gene

models that are positioned on originally multi-marker scaffolds) and 100 show a split

within gene models (1.6% of gene models from multi-marker scaffolds) (Table 3).

Figure 3: Kernel density estimate of scaffold lengths for all multi-marker

scaffolds (black line) and for scaffolds showing a split within or across LGs

(red line). The split scaffolds are significantly longer than the multi-marker

scaffolds in general (t = -7.76, df = 194.54, p-value = 4.77e-13).

Table 3: Overview of annotated gene models anchored to the genetic map.

Gene models: Annotated protein coding gene models with High-, Medium-

and Low confidence level (Nystedt et al. 2013). Mapped scaffolds: Number

of gene models positioned on scaffolds that are anchored to the genetic map

(Percentage of total number of gene models for each confidence level).

Multi-marker scaffolds: Number of gene models positioned on scaffolds with

multiple markers in the genetic map (Percentage of gene models on mapped

scaffolds). Inter-split scaffolds: Number of gene models positioned on the

164 scaffolds that are split between LGs in the genetic map (Percentage of

gene models on mapped scaffolds / Percentage of gene models on multi-

marker scaffolds). Intra-split scaffolds: Number of gene models positioned

on the 22 scaffolds that are split between different regions of the same LG

(Percentage of gene models on mapped scaffolds / Percentage of gene

models on multi-marker scaffolds). Split within gene models: Number of

gene models that have an internal split (Percentage of gene models on

mapped scaffolds / Percentage of gene models on multi-marker scaffolds).

Gene models	Mapped scaffolds	Multi-marker scaffolds	Inter-split scaffolds	Intra-split scaffolds	Split within gene models
High confidence	8,379 (31.7%)	3,122 (37.3%)	145 (1.7% / 4.6%)	15 (0.18% / 0.48%)	58 (0.69% / 1.9%)
Medium confidence	6,624 (20.6%)	2,215 (33.4%)	114 (1.7% / 5.1%)	15 (0.23% / 0.68%)	29 (0.44% / 1.3%)
Low confidence	2,076 (25.8%)	762 (36.7%)	35 (1.7% / 4.6%)	6 (0.29% / 0.79%)	13 (0.63% / 1.7%)
Total	17,079 (25.6%)	6,099 (35.7%)	294 (1.7% / 4.8%)	36 (0.21% / 0.59%)	100 (0.59% / 1.6%)

Comparative analyses to other Picea linkage maps

In order to assess the accuracy and repeatability of the *P. abies* genetic maps we

compared our consensus map to a *P. abies* QTL map from Lind et al. (2014). This

map consists of 686 markers, genotyped in 247 offspring from a full sib family using

markers derived from a *P. glauca* SNP array. 353 comparisons between 298 markers

from Lind et al. (2014) and 288 scaffolds contained in our consensus map were

identified at a > 95 % identity threshold. Of these markers, 96.7% group to the same

chromosome in the two maps while the remaining 3.3% (11 out of 353) are

distributed across several linkage groups (Figure 4). Correlations of marker order

between the two *P. abies* maps ranged from 0.53 to 0.99 across the 12 LGs. The

comparison between the haploid consensus map LG I and LG 7 from Lind et.al

(2014), which has the lowest correlation of marker order, show inconsistencies of

marker order where several markers are arranged in the opposite order from the rest

of the markers. The remaining chromosomes show high synteny with a consistent

marker order between the two genetic maps.

P. abies, haploid consensus map

Figure 4: Marker order comparison between the haploid consensus map

and the *P. abies* map from Lind et al. 2014. Consensus LG I - LG XII are

located on the x-axis from left to right. Lind et al. 2014 LG 1 - LG 12 are

located on the y-axis from top to bottom. Each dot represents a marker

comparison from the same scaffold, where black coloration displays the LG

where the majority of marker comparisons are mapped. Grey coloration

display markers mapping to a different LG compared to the majority of

markers.

Synteny between *P.* abies and *P. glauca* species was assessed by comparing

chromosome location and marker order between our *P. abies* consensus map and the

composite map of *P. glauca* from Pavy et al. (2017). 11,458 comparisons from 4,934

gene models in the composite map in *P. glauca* (Pavy et al. 2017) and 5,451 scaffolds

in the *P. abies* consensus map could be retrieved. 93.3% (10,733 out of 11,458 hits)

of these were found to be located on homologous chromosomes while the remaining

6.7% (725 comparisons) are distributed across the 12 linkage groups (Figure 5). The

correlations of marker order between the two maps were comparable to the

corresponding correlations between component maps in *P. abies* showing that synteny

is largely conserved between *P. abies* and *P glauca*.

Figure 5: Marker order comparison between the haploid consensus map
and the *P. glauca* map from Pavy et al. 2017. Consensus LG I - LG XII are
located on the x-axis from left to right. Pavy et al. 2017 LG 1 - LG 12 are
located on the y-axis from top to bottom. Each dot represents a marker
comparison from the same scaffold, where black color display markers
mapping to the same LG in the two species where as grey color indicate
markers mapping to different LGs.

Population genetic analyses based on the consensus map

22,413 probes, covering 12,908 scaffolds, were used in the population genetic analyses based on the consensus genetic map. On a per probe basis, we observe substantial variation in all neutrality statistics, with the number of segregating sites ranging from 0 - 77 (mean 15.9), nucleotide diversity (π) from 0 - 0.4 (0.005), Zns from 0 - 1 (mean 0.04) and Tajima's D from -2.4 – 3.5 (mean -0.85). To study large-scale trends and possible chromosomal differences we performed sliding window analyses across the linkage groups for the different summary (Figure 6). One interesting large-scale feature we observe is that SNP densities are often highest at the distal or central regions of linkage groups, indicating the possible location of centromers and telomeres where recombination rates are expected to be reduced (Gaut et al 2007) and where we hence would expect higher densities of probes per cM (Figure 6a). The large-scale analyses also reveal several instances where entire chromosomal arms might be under different evolutionary regimes (Figure 6b-c). Finally we can identify regions that appear to be evolving under the influence of natural selection. For instance, several regions show higher than average levels of nucleotide diversity and positive Tajima's D (eg. on LG IV, V and XII), suggesting that they might harbor genes under balancing selection. Similarly, regions with low nucleotide diversity, an excess of rare alleles and strong linkage disequilibrium (i.e. negative Tajima's D and high Z_{ns} scores, e.g. on LG III) could indicate regions of possible selective sweeps (Figure 6c-d).

Figure 6. Sliding window analysis of neutrality statistics. Analyses were

performed using 10 cM windows with 1 cM incremental steps along the

consensus map linkage groups. A) Number of segregating sites. B) Pairwise

nucleotide diversity (π). C) Tajima's D and D) Linkage disequilibrium Zn

scores.

Discussion

This is, to our knowledge, the densest genetic linkage map ever created for a conifer

species and possible even for any tree species. We have successfully used this genetic

map to anchor 1.7% of the 20 Gbp *P. abies* genome, corresponding to 2.8% of the

v1.0 genome assembly (Nystedt et al. 2013), to the 12 linkage groups that constitute

the haploid chromosome number in spruces (Sax and Sax 1933). The Norway spruce

genome has a very large proportion of gene-poor heterochromatin, so while the

fraction of the genome that we successfully anchor to the assembly may seem small,

these scaffolds cover 24% of gene bearing scaffolds and 25% of all protein coding

gene models from Nystedt et al. (2013).

The individual linkage groups from the three component maps (36 LGs from

three independent maps) consists of 648-1,967 markers before and 504-1,373 markers

after marker elimination and it is, therefore, not feasible to analyze the maps using an

exhaustive ordering algorithm (Mollinari et al. 2009). Instead, we decided to use

RECORD (Van Os et al. 2005) with 40 times counting, parallelized over 20 cores, for

each linkage group to find the most likely marker order. A heuristic approach, such as

RECORD, will undoubtedly introduce some errors in marker ordering, but analyses

from simulated data suggest that the distance between estimated and true marker

position is quite small (20-30 markers) for a data sets of similar size as ours

(Schiffthaler et al. 2017). However, reliable marker ordering require robust data and

the more genotyping errors and missing data that is present the harder it will be to

find the true order. This in turn will impact the final size of the map, where both

errors in marker order and genotyping results in inflation in the size of the map

(Cartwright et al. 2007).

By collecting our 2,000 megagametophytes from what were initially thought to

be five different ramets of Z4006 we accidentally sampled three unrelated families.

This error stemmed from a mix-up of genotypes due to wrong assignment of ramet ID

to the different ramets in the seed orchard. Unfortunately, we were not able to assess

which megagametophytes that were collected from the different putative ramets since

seeds were pooled prior to DNA extraction and the sampling errors were not detected

until after all sequencing was completed. We used a PCA to assign samples into three

independent clusters and used subsequent PCAs of the putative individual families to

verify the reliability of these clusters. However, we cannot completely rule out that a

small fraction of samples have been wrongly assigned to the three families and this

would further inflate map size by introducing excess recombination events. Another

potential confounding issue is tissue contamination. Norway spruce

megagametophytes are very small and are surrounded by a diploid seed coat that

needs to be removed before DNA extraction. If traces of the diploid seed coat remain

in the material used for DNA extractions, the haploid samples will be contaminated

with diploid material. To identify and eliminate this possibility, we called sequence

variants using a diploid model and any heterozygous SNP calls were subsequently

treated as missing data. Samples with a high proportion of heterozygous (> 10 %) or

missing calls (> 20%) were excluded from further analyses to reduce the possibilities

of genotyping error due to tissue contamination influencing downstream analyses.

Both sample- and tissue contaminations will affect the accuracy of the genetic

map, both with regards to marker order and map size. The smaller family sizes

resulting from dividing our original 2,000 samples into three independent families

yield lower resolution of the component maps. However, fortuitously enough it also

allows us to incorporate more markers into the consensus map since different markers

were segregating in the different mother trees from which the three families were

derived. Furthermore, it also allowed us to evaluate marker ordering across three

independently derived maps. Although our consensus map is 60-70% larger than

previously estimated *Picea* maps (3,326 cM vs. 1,889-2,083 cM), it also contain 2-22

times more markers than earlier maps (Pavy et al. 2012; Lind et al. 2014; Pavy et al.

2017). When comparing marker order between our three independent component

maps (cluster 1-3), we found overall high order of correlations (0.94-0.99, Table S1),

which is similar to what is observed between maps derived from simulated data

without genotyping errors but with 20% missing data (Schiffthaler et al. 2017). Also,

earlier *Picea* maps were all diploid F_1 crosses and even the densest composite map

only contained 2,300-2,800 markers per framework map (Table 1 - Pavy et al. 2017),

compared to our haploid component maps that contain between 7,179 and 13,479

markers each (Table 2).

The comparisons between our haploid consensus map and earlier maps in *Picea*

show an overall high correlation of marker order, which is in line with previous

studies suggesting highly conserved synteny within *Picea* and in conifers in general

(de Miguel et al. 2015; Pavy et al. 2017). LG I from our haploid consensus map and

LG 7 from Lind et al. 2014 show a inverted order for approximately half of the

markers that were compared (Figure 4). However, if this inversion is due to ordering

errors in one of the maps or represents true biological differences between the parents

used for the respective maps is not known at the moment, and further investigations

are needed to resolve this issue.

A small percentage of the marker comparisons in both the intra and interspecific

maps do not co-align to homologous LGs. These errors likely arise form the repetitive

nature of the Norway spruce genome (and conifer genomes in general) where regions

with high sequence similarity often can be found interspersed through out the genome.

If the true homologous region between different maps is missing or has been

collapsed in the Norway spruce genome assembly due to high sequence similarity,

pairwise sequence comparisons may end up assigning homology to regions that are

located on different chromosomes.

4% of the scaffolds carrying multiple makers show a pattern where different

markers are mapping to different regions either within or between chromosomes in

the consensus map. This likely indicates errors in scaffolding during the assembly of

the v1.0 *P. abies* genome (Nystedt et al. 2013). If this estimate represents the overall

picture of the Norway spruce genome assembly, as many as 400,000 of the ~10

million total scaffolds, and 2,400 of the ~60,000 gene containing scaffolds, may

suffer from assembly errors. Approximately half of these, 2% of the multi-marker

scaffolds (100/4,859), have splits that occur within a single gene model. It is likely

that many of these problematic scaffolds stem from incorrect scaffolding of exons

from paralogous genes with a high sequence similarity. Since the Norway spruce

genome contains a high proportion of repetitive content, that also includes a large

number of pseudo genes, this is perhaps not surprising. Additional work is needed to

disentangle these issues and to resolve any assembly errors. False scaffold joins in a

genome assembly is not a unique feature for *P. abies*, rather it appears to be a

frequent problem in the assembly process. For instance, dense genetic maps in both

Eucalyptus and *Crassostrea* have identified and resolved false scaffold joins, thereby

improving the genome assemblies in these species (Bartholomé et al. 2015;

Hedgecock et al. 2015). Our goal for the Norway spruce genetic map is not only to

identify incorrect scaffolding decisions in the v1.0 genome assembly, but to also help

improve future iterations of the genome.

Our populations genetic analyses based on the scaffolds anchored to the

consensus map shows the utility of having a dense, accurate genetic map and suggest

that the map will facilitate further analyses of genome-wide patterns in Norway

spruce. Assigning even a small fraction of the genome to linkage groups allows us to

analyze patterns of genetic diversity in approximately a quarter of all predicted genes

from Norway spruce. This allows for analyses of broad-scale patterns of variation

across the spruce genome and as the genome assembly is further improved it should

allow us physically anchor a larger fraction of the genome to chromosomes and

thereby allow for even more fine-scaled analyses of how different evolutionary forces

have interacted in shaping patterns of genetic diversity across the Norway spruce

genome.

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Author contribution

PKI and MRGG conceived the study. AV collected cones and extracted DNA. CB,

AV, DS and JB set up bioinformatics pipeline for analyzing sequence capture data.

AV and CB performed PCA and identified samples belonging to the three clusters.

CB, DS and BS created the genetic maps. CB and PKI performed intra- and

interspecific map comparisons. CB, XW and PKI performed population genetic

analysis. CB performed all remaining analyses and wrote first draft of manuscript. All

authors commented on the manuscript at various stages during the writing.

Data availability

BatchMap input files for the three clusters, component maps and consensus map files

are available from zenodo.org at https://doi.org/10.5281/zenodo.1209842. All scripts

needed to recreate the analyses described in the paper are publically available at

https://github.com/parkingvarsson/HaploidSpruceMap. Raw sequence data for all samples included in this study are available though the European Nucleotide Archive under accession number PRJEB25757.

References

Baison, J., Vidalis, A., Zhou, L., Chen, Z-Q., Li, Z, Sillanpää, M.J., Bernahrdsson, C., Scofield, D.G., Forsberg, N., Olsson, L., Karlsson, B., Wu, H., Ingvarsson, P.K., Lundqvist, S-O., Niittylä, T., Garcia Gil, M.R. 2018. Association mapping identified novel candidate loci affecting wood formation in Norway spruce. bioRxiv https://doi.org/10.1101/292847

Bartholomé, Jérôme, Eric Mandrou, André Mabiala, Jerry Jenkins, Ibouniyamine Nabihoudine, Christophe Klopp, Jeremy Schmutz, Christophe Plomion, and Jean-Marc Gion. 2015. High-Resolution Genetic Maps of Eucalyptus Improve Eucalyptus Grandis Genome Assembly. *New Phytologist* 206: 1283–96. doi:10.1111/nph.13150.

Cartwright, Dustin A, Michela Troggio, Riccardo Velasco, and Alexander Gutin. 2007. Genetic Mapping in the Presence of Genotyping Errors. *Genetics* 176: 2521–27. doi:10.1534/genetics.106.063982.

Danecek, P., A. Auton, G. Abecasis, C. A. Albers, E. Banks, M. A. DePristo, R. E. Handsaker, et al. 2011. The Variant Call Format and VCFtools. *Bioinformatics* 27: 2156–58. doi:10.1093/bioinformatics/btr330.

De La Torre, Amanda R., Inanc Birol, Jean Bousquet, Pär K. Ingvarsson, Stefan Jansson, Steven J.M. Jones, Christopher I. Keeling, et al. 2014. Insights into

Conifer Giga-Genomes. *Plant Physiology* 166: 1724 – 1732.

http://www.plantphysiol.org/content/166/4/1724.short.

de Miguel, Marina, Jérôme Bartholomé, François Ehrenmann, Florent Murat,

Yoshinari Moriguchi, Kentaro Uchiyama, Saneyoshi Ueno, et al. 2015. Evidence

of Intense Chromosomal Shuffling during Conifer Evolution. *Genome Biology*

and Evolution 7: 2799–2809. doi:10.1093/gbe/evv185.

DePristo, Mark A, Eric Banks, Ryan Poplin, Kiran V Garimella, Jared R Maguire,

Christopher Hartl, Anthony A Philippakis, et al. 2011. A Framework for

Variation Discovery and Genotyping Using next-Generation DNA Sequencing

Data. *Nat Genet* 43: 491–98. doi:10.1038/ng.806.

Drost, Derek R., Evandro Novaes, Carolina Boaventura-Novaes, Catherine I.

Benedict, Ryan S. Brown, Tongming Yin, Gerald A. Tuskan, and Matias Kirst.

2009. A Microarray-Based Genotyping and Genetic Mapping Approach for

Highly Heterozygous Outcrossing Species Enables Localization of a Large

Fraction of the Unassembled *Populus Trichocarpa* Genome Sequence. *The Plant*

Journal 58: 1054–67. doi:10.1111/j.1365-313X.2009.03828.x.

Endelman, Jeffrey B., and Christophe Plomion. 2014. LPmerge: An R Package for

Merging Genetic Maps by Linear Programming. *Bioinformatics* 30: 1623–24.

doi:10.1093/bioinformatics/btu091.

Farjon, A. 1990. Pinaceae. Drawings and Descriptions of the Genera Abies, Cedrus,

Pseudolarix, Keteleeria, Nothotsuga, Tsuga, Cathaya, Pseudotsuga, Larix and

Picea. *Pinaceae. Drawings and Descriptions of the Genera Abies, Cedrus,*

Pseudolarix, Keteleeria, Nothotsuga, Tsuga, Cathaya, Pseudotsuga, Larix and

Picea. Koeltz Scientific Books.

https://www.cabdirect.org/cabdirect/abstract/19920656698.

Fierst, Janna L. 2015. Using Linkage Maps to Correct and Scaffold de Novo Genome

Assemblies: Methods, Challenges, and Computational Tools. *Frontiers in*

Genetics 6: 220. doi:10.3389/fgene.2015.00220.

Gaut, Brandon S., Stephen I. Wright, Carène Rizzon, Jan Dvorak, and Lorinda K.

Anderson. 2007. Recombination: An Underappreciated Factor in the Evolution

of Plant Genomes. Nature Reviews Genetics 8: 77–84.

Hedgecock, Dennis, Grace Shin, Andrew Y Gracey, David Van Den Berg, and Manoj

P Samanta. 2015. Second-Generation Linkage Maps for the Pacific Oyster

Crassostrea Gigas Reveal Errors in Assembly of Genome Scaffolds. G3: Genes,

Genomes, Genetics: 5: 2007–19. doi:10.1534/g3.115.019570.

Hu, Ying, Chunhua Yan, Chih-Hao Hsu, Qing-Rong Chen, Kelvin Niu, George

Komatsoulis, and Daoud Meerzaman. 2014. OmicCircos: A Simple-to-Use R

Package for the Circular Visualization of Multidimensional Omics Data. *Cancer*

Informatics 13: 13. doi:10.4137/CIN.S13495.

Kelly, J. K. 1997. "A Test of Neutrality Based on Interlocus Associations." *Genetics*

146: 1197–1206.

Knaus, Brian J., and Niklaus J. Grünwald. 2017. vcfR : A Package to Manipulate and

Visualize Variant Call Format Data in R. *Molecular Ecology Resources* 17: 44–

53. doi:10.1111/1755-0998.12549.

Li, H., and R. Durbin. 2009. Fast and Accurate Short Read Alignment with Burrows-

Wheeler Transform. *Bioinformatics* 25: 1754–60.

doi:10.1093/bioinformatics/btp324.

Li, H., B. Handsaker, A. Wysoker, T. Fennell, J. Ruan, N. Homer, G. Marth, G.

Abecasis, R. Durbin, and 1000 Genome Project Data Processing Subgroup. 2009.

The Sequence Alignment/Map Format and SAMtools. *Bioinformatics* 25: 2078–

79. doi:10.1093/bioinformatics/btp352.

Lind, Mårten, Thomas Källman, Jun Chen, Xiao-Fei Ma, Jean Bousquet, Michele

Morgante, Giusi Zaina, et al. 2014. A Picea Abies Linkage Map Based on SNP

Markers Identifies QTLs for Four Aspects of Resistance to Heterobasidion

Parviporum Infection. *PloS One* 9: e101049. doi:10.1371/journal.pone.0101049.

Margarido, G R A, A P Souza, and A A F Garcia. 2007. OneMap: Software for

Genetic Mapping in Outcrossing Species. *Hereditas* 144: 78–79.

doi:10.1111/j.2007.0018-0661.02000.x.

McKenna, Aaron, Matthew Hanna, Eric Banks, Andrey Sivachenko, Kristian

Cibulskis, Andrew Kernytsky, Kiran Garimella, et al. 2010. The Genome

Analysis Toolkit: A MapReduce Framework for Analyzing next-Generation

DNA Sequencing Data. *Genome Research* 20: 1297–1303.

doi:10.1101/gr.107524.110.

Mollinari, M, G R A Margarido, R Vencovsky, and A A F Garcia. 2009. Evaluation

of Algorithms Used to Order Markers on Genetic Maps. *Heredity* 103: 494–502.

doi:10.1038/hdy.2009.96.

Nystedt, Björn, Nathaniel R. Street, Anna Wetterbom, Andrea Zuccolo, Yao-Cheng

Lin, Douglas G. Scofield, Francesco Vezzi, et al. 2013. The Norway Spruce

Genome Sequence and Conifer Genome Evolution. *Nature* 497: 579–84.

doi:10.1038/nature12211.

Pavy, Nathalie, Astrid Deschênes, Sylvie Blais, Patricia Lavigne, Jean Beaulieu,

Nathalie Isabel, John Mackay, and Jean Bousquet. 2013. The Landscape of

Nucleotide Polymorphism among 13,500 Genes of the Conifer Picea Glauca,

Relationships with Functions, and Comparison with Medicago Truncatula.

Genome Biology and Evolution 5: 1910–25. doi:10.1093/gbe/evt143.

Pavy, Nathalie, Manuel Lamothe, Betty Pelgas, France Gagnon, Inanç Birol, Joerg

Bohlmann, John Mackay, Nathalie Isabel, and Jean Bousquet. 2017. A High-

Resolution Reference Genetic Map Positioning 8.8 K Genes for the Conifer

White Spruce: Structural Genomics Implications and Correspondence with

Physical Distance. *The Plant Journal* 90: 189–203. doi:10.1111/tpj.13478.

Pavy, Nathalie, Betty Pelgas, Jérôme Laroche, Philippe Rigault, Nathalie Isabel, and

Jean Bousquet. 2012. A Spruce Gene Map Infers Ancient Plant Genome

Reshuffling and Subsequent Slow Evolution in the Gymnosperm Lineage

Leading to Extant Conifers. *BMC Biology* 10: 84. doi:10.1186/1741-7007-10-84.

R Core Team. 2013. R: A Language and Environment for Statistical Computing. *R*

Foundation for Statistical Computing, Vienna, Austria. http://www.r-project.org.

Sax, Karl, and Hally Jolivettte Sax. 1933. Chromosome Number and Morphology in

the Conifers. *Journal of the Arnold Arboretum* 14: 356-375.

Sturtevant, A. H. 1913a. The Linear Arrangement of Six Sex-Linked Factors in

Drosophila, as Shown by Their Mode of Association. *Journal of Experimental*

Zoology 14: 43–59. doi:10.1002/jez.1400140104.

———. 1913b. A Third Group of Linked Genes in Drosophila Ampelophila. *Science*

37: 990–92. doi:10.1126/science.37.965.990.

Van der Auwera, Geraldine A., Mauricio O. Carneiro, Christopher Hartl, Ryan Poplin,

Guillermo del Angel, Ami Levy-Moonshine, Tadeusz Jordan, et al. 2013. From

FastQ Data to High-Confidence Variant Calls: The Genome Analysis Toolkit

723  Best Practices Pipeline. In *Current Protocols in Bioinformatics*, 11.10.1-

724  11.10.33. Hoboken, NJ, USA: John Wiley & Sons, Inc.

725  doi:10.1002/0471250953.bi1110s43.

726 Van Os, Hans, Piet Stam, Richard G F Visser, and Herman J Van Eck. 2005.

727  RECORD: A Novel Method for Ordering Loci on a Genetic Linkage Map.

728  *Theoretical and Applied Genetics*. 112: 30–40. doi:10.1007/s00122-005-0097-x.

729 Vidalis, A. Scofield, D.G., Neves, L-G., Bernhardsson, C., García-Gil, M.R.,

730  Ingvarsson, P.K. 2018. Design and evaluation of a large sequence-capture

731  probe set and associated SNPs for diploid and haploid samples of Norway

732  spruce (*Picea abies*) *BioRxiv* doi: https://doi.org/10.1101/291716

733 Wu, Rongling, Chang-Xing Ma, Ian Painter, and Zhao-Bang Zeng. 2002.

734  Simultaneous Maximum Likelihood Estimation of Linkage and Linkage Phases

735  in Outcrossing Species. *Theoretical Population Biology* 61: 349–63.

736  doi:10.1006/tpbi.2002.1577.