# Least Chub cytb

POPULATION SIZE, MIGRATION, DIVERGENCE, ASSIGNMENT, HISTORY

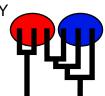
Bayesian inference using the structured coalescent

Migrate-n version 4.4.4(git:v4-series-26-ge85c6ff) [June-1-2019]

Compiled for a SYMMETRIC multiprocessors (Grandcentral)

Program started at Sat May 22 11:24:36 2021

Program finished at Sat May 22 13:23:07 2021 [Runtime:0000:01:58:31]



## **Options**

Inheritance scalers in use for Thetas:

All loci use an inheritance scaler of 1.0

[The locus with a scaler of 1.0 used as reference]

Random number seed: (with internal timer) 1189945524

Start parameters:

Theta values were generated RANDOM start value from the prior

M values were generated RANDOM start value from the prior

Connection matrix:

m = average (average over a group of Thetas or M,

s = symmetric migration M, S = symmetric 4Nm,

0 = zero, and not estimated,

\* = migration free to vary, Thetas are on diagonal

d = row population split off column population, D = split and then migration

Population 1 2 3 1 GSL \* d 0 2 GSLD 0 \* d 3 SEV 0 0 \*

Order of parameters:

 $\begin{array}{cccc} \mathbf{1} & & \Theta_1 & & \text{<displayed>} \\ \mathbf{2} & & \Theta_2 & & \text{<displayed>} \\ \mathbf{3} & & \Theta_3 & & \text{<displayed>} \end{array}$ 

					.12 1 -	1			ast Chub cytb
4	Δ	Δ <sub>2-</sub>	->1		<displa< td=""><td>yed&gt;</td><td></td><td></td><td></td></displa<>	yed>			
5	(	σ <sub>2-&gt;1</sub>			<displa< td=""><td>yed&gt;</td><td></td><td></td><td></td></displa<>	yed>			
6	۷	$\Delta_{3\rightarrow 2}$			<displa< td=""><td>yed&gt;</td><td></td><td></td><td></td></displa<>	yed>			
7	σ <sub>3-&gt;2</sub>				<displa< td=""><td>yed&gt;</td><td></td><td></td><td></td></displa<>	yed>			
Mutation ra	ate amor	ng lo	ci:					Mutation ra	ate is constant
Analysis s	trategy:							Baye	esian inference
-Populatio	on size e	stima	ation:					Exponen	tial Distribution
-Geneflov	v estimat	ion:						Exponen	tial Distribution
-Divergen	ce time e	estim	ation:		No	rmal Distrib	oution Shortcu	t (mean and	standard dev.)
•	distributio	ns fo	or paramete						
Parameter			B. /		oosal				
Theta			letropolis sam						
M Diagrama				letropolis sam	-				
Divergence				letropolis sam	-				
Divergence	Spread			letropolis sam	-				
Genealogy			IV	letropolis-Has	tings				
Prior distri	bution fo	r par	ameter						
Parameter			Prior	Minimum	MeantMa	aximum	Delta	Bins U	JpdateFreq
1	Theta	**	Uniform	0.000000	0.050	0.100	0.010	1500	0.07143
2	Theta	**	Uniform	0.000000	0.050	0.100	0.010	1500	0.07143
3	Theta	**	Uniform	0.000000	0.050	0.100	0.010	1500	0.07143
4 Splittim	e mean	**	Uniform	0.000000	0.250	0.500	0.050	1500	0.07143
5 Split	time std	**	Uniform	0.000000	0.250	0.500	0.050	1500	0.07143
6 Splittim	e mean	**	Uniform	0.000000	0.250	0.500	0.050	1500	0.07143
7 Split	time std	**	Uniform	0.000000	0.250	0.500	0.050	1500	0.07143
[* * means	priors w	ere s	set globally]						
Markov ch	ain settir	Jus.							Long chain

Markov chain settings:Long chainNumber of chains1Recorded steps [a]10000Increment (record every x step [b]1000Number of concurrent chains (replicates) [c]2Visited (sampled) parameter values [a\*b\*c]20000000Number of discard trees per chain (burn-in)1000

Multiple Markov chains:

Static heating scheme		4 chains with temperatures
	1000000.00	3.00 1.50 1.00
		Swapping interval is 1
Print options:		
Data file:		infile
Haplotyping is turned on:		NO
Output file:		outfile
Log file:		logfile
Posterior distribution raw histogram file:		bayesfile
Raw data from the MCMC run:		bayesallfile.gz
Print data:		No
Print genealogies [only some for some data type]:		None
Think genealogies formy some for some data type].		None

## Data summary

Data file: infile

Datatype: Haplotype data

Number of loci:

Mutationmodel:

Locus Sublocus Mutationmodel Mutationmodel parameters

1 1 HKY [Bf:0.25 0.28 0.16 0.30, kappa=0.000]

Sites per locus

Locus Sites

1 1113

Site rate variation and probabilities:

Locus Sublocus Region type Rate of change Probability Patch size

1	1	1	1.000	1.000	1.000		
Populat	ion				Locus	Gene co	ppies
						data	(missing)
1 GSL					1	17	
2 GSLD	)				1	15	
3 SEV					1	11	
Total of	all popu	ılations			1	43	(0)

# Bayesian Analysis: Posterior distribution table

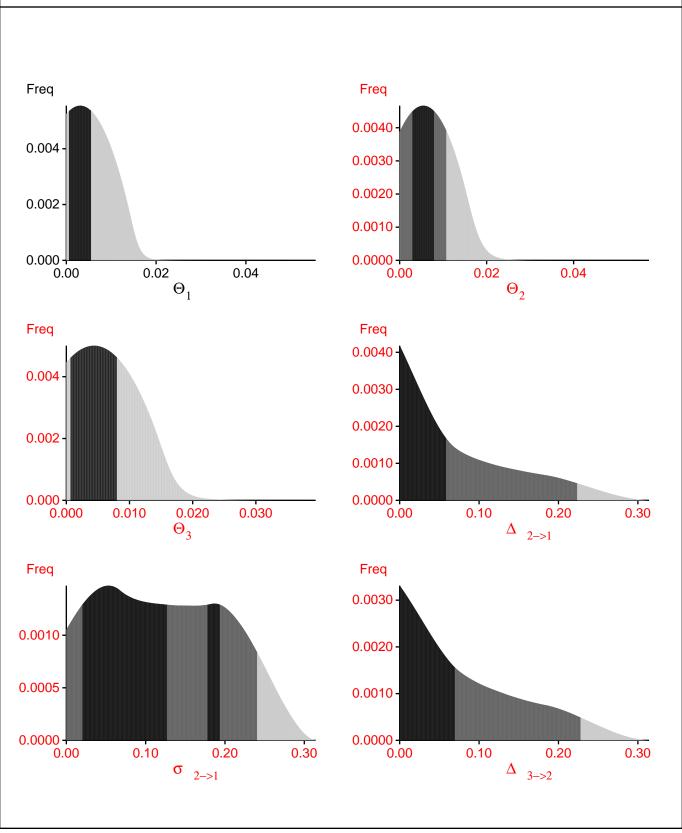
Locus	Parameter	2.5%	25.0%	Mode	75.0%	97.5%	Median	Mean
1	Θ1	0.00053	0.00053	0.00310	0.00553	0.00553	0.00617	0.00310
1	$\Theta_2$	0.00007	0.00287	0.00543	0.00793	0.01073	0.00757	0.00546
1	$\Theta_3^2$	0.00060	0.00060	0.00437	0.00800	0.00800	0.00690	0.00439
1	D <sub>2-&gt;1</sub>	0.00000	0.00000	0.00017	0.05867	0.22367	0.05883	0.14839
1	S <sub>2-&gt;1</sub>	0.00000	0.02000	0.05350	0.12700	0.24067	0.12450	0.25398
1	D <sub>3-&gt;2</sub>	0.00000	0.00000	0.00017	0.06967	0.22800	0.06983	0.15317
1	S <sub>3-&gt;2</sub>	0.00000	0.04467	0.06117	0.10067	0.25733	0.13183	0.26005

#### Citation suggestions:

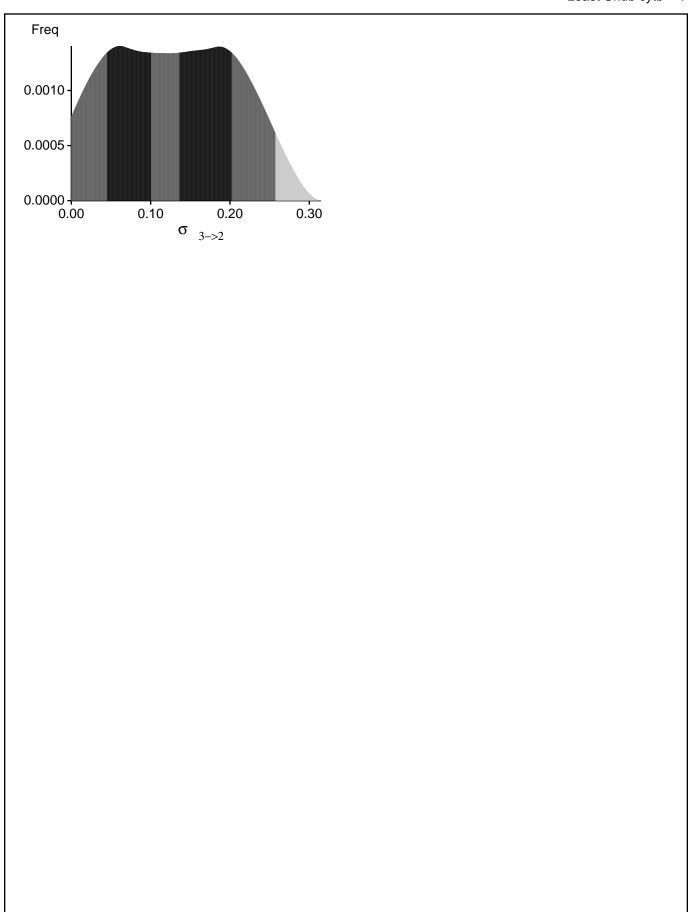
Beerli P., 2006. Comparison of Bayesian and maximum-likelihood inference of population genetic parameters. Bioinformatics 22:341-345

Beerli P., 2009. How to use MIGRATE or why are Markov chain Monte Carlo programs difficult to use? In Population Genetics for Animal Conservation, G. Bertorelle, M. W. Bruford, H. C. Hauffe, A. Rizzoli, and C. Vernesi, eds., vol. 17 of Conservation Biology, Cambridge University Press, Cambridge UK, pp. 42-79.

## Bayesian Analysis: Posterior distribution for locus 1



Migrate 4.4.4(git:v4-series-26-ge85c6ff): (http://popgen.sc.fsu.edu) [program run on 11:24:36]



### Log-Probability of the data given the model (marginal likelihood)

Use this value for Bayes factor calculations:

BF = Exp[ ln(Prob(D | thisModel) - ln( Prob( D | otherModel) or as LBF = 2 (ln(Prob(D | thisModel) - ln( Prob( D | otherModel)) shows the support for thisModel]

Method	In(Prob(D Model))	Notes
Thermodynamic integration	-1953.395270	(1a)
	-1750.598467	(1b)
Harmonic mean	-1719.155856	(2)

(1a, 1b and 2) are approximations to the marginal likelihood, make sure that the program run long enough! (1a, 1b) and (2) should give similar results, in principle.

But (2) is overestimating the likelihood, it is presented for historical reasons and should not be used (1a, 1b) needs heating with chains that span a temperature range of 1.0 to at least 100,000.

(1b) is using a Bezier-curve to get better approximations for runs with low number of heated chains

#### Citation suggestions:

Beerli P. and M. Palczewski, 2010. Unified framework to evaluate panmixia and migration direction among multiple sampling locations, Genetics, 185: 313-326.

# Acceptance ratios for all parameters and the genealogies

Parameter	Accepted changes	Ratio
$\Theta_1$	485377/1427304	0.34007
$\Theta_2$	782057/1429895	0.54693
$\Theta_3$	879674/1428799	0.61567
$\Delta_{2\rightarrow 1}$	994018/1428718	0.69574
$\sigma_{2\rightarrow 1}$	1083975/1429657	0.75821
$\Delta_{3\rightarrow 2}$	1022376/1428039	0.71593
$\sigma_{3\rightarrow 2}$	1104462/1428258	0.77329
Genealogies	4205795/9999330	0.42061

# MCMC-Autocorrelation and Effective MCMC Sample Size

Parameter	Autocorrelation	Effective Sampe Size
$\Theta_1$	0.25604	11883.15
$\Theta_2$	0.17268	14116.08
$\Theta_3$	0.53792	8444.40
$\Delta_{2\rightarrow 1}$	0.04070	18433.94
$\sigma_{2\rightarrow 1}$	0.05829	17795.23
$\Delta$ 3->2	0.01561	19383.47
$\sigma_{3\rightarrow 2}$	0.03879	18504.41
Genealogies	0.03879	18504.41

### Potential Problems

This section reports potential problems with your run, but such reporting is often not very accurate. Whith many parameters in a multilocus analysi s, it is very common that some parameters for some loci will not be very informative, triggering suggestions (for example to increase the prior ran ge) that are not sensible. This suggestion tool will improve with time, therefore do not blindly follow its suggestions. If some parameters are fla

gged, inspect the tables carefully and judge wether an action is required. For example, if you run a Bayesian inference with sequence data, for mac roscopic species there is rarely the need to increase the prior for Theta beyond 0.1; but if you use microsatellites it is rather common that your prior distribution for Theta should have a range from 0.0 to 100 or more. With many populations (>3) it is also very common that some migration rou
tes are estimated poorly because the data contains little or no information for that route. Increasing the range will
not help in such situations, reducing number of parameters may help in such situations.
No warning was recorded during the run