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Author(s)	Koizumi, Itsuro; Shimatani, Ichiro K.
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## Supplementary Fig. S1.

Location of the 30 small tributaries surveyed in the Sorachi River, Hokkaido, Japan. Each tributary (filled circle) is too small to see in the regional map. A zoomed map is shown in the right panel. An example of a typical spawning nest (i.e., redd) made by Dolly Varden is also shown in the bottom. Detailed information on the tributaries is described in Supplementary Table S1 and previous studies (e.g. Koizumi et al. 2006, 2008, 2012).





# **Supplementary Table S1**

Tributory	Main stem	Elevation	Total length	Mean width	Mean depth	Substrate score <sup>b</sup>
moutary	distance (km) <sup>a</sup>	(m)	(m)	(m)	(cm)	Substrate score
T4	0.0	697	131	$1.1\pm0.3$	$7.5\pm3.3$	$1.8 \pm 1.0$
T7	1.2	673	682	$1.8\pm0.9$	$12.3\pm10.9$	$4.3\pm1.7$
T7.5	1.3	671	306	$1.9\pm0.3$	$12.0\pm4.0$	$4.3 \pm 2.1$
Т8	1.4	667	261	$2.1\pm1.1$	$5.5\pm4.2$	$4.0\pm2.4$
Т9	2.0	658	334	$1.8\pm0.5$	$9.2\pm5.6$	$3.2 \pm 2.1$
T10a	4.1	619	1110	$1.3\pm0.5$	$8.7\pm6.0$	3.1 ± 1.5
T10	4.2	617	399	$1.6\pm0.5$	$12.6 \pm 11.4$	$4.9 \pm 1.1$
KS	9.2	649	328	$1.3\pm0.5$	$11.4\pm8.1$	$2.9 \pm 1.6$
T11	9.2	647	423	$1.8\pm0.5$	$7.1 \pm 3.7$	$2.3 \pm 1.2$
T13	6.8	610	198	$2.3\pm0.8$	$10.4\pm7.7$	$3.7 \pm 1.8$
T13b	6.8	610	$8^{\rm c}$	na	na	na
KU	6.3	599	283	$3.2 \pm 1.7$	$5.5 \pm 4.7$	$2.6 \pm 1.1$
SI	5.8	591	297	$1.9\pm0.8$	$3.7 \pm 2.4$	$3.2 \pm 1.2$
T16	6.2	586	140	$0.8\pm0.3$	$8.5\pm4.8$	$1.7 \pm 1.6$
T17	6.5	584	284	$0.7\pm0.2$	$6.8\pm4.0$	$2.1 \pm 1.2$
T18	7.0	578	211	$1.1\pm0.3$	$4.2 \pm 2.9$	$2.2 \pm 0.4$
T20	7.5	572	377	$1.0\pm0.3$	$9.6\pm3.9$	$3.3 \pm 1.1$
T23.5	9.0	556	324	$1.1 \pm 0.4$	$9.4\pm3.8$	$2.7 \pm 1.4$
ТА	8.9	561	146	$1.6 \pm 1.0$	$5.5\pm3.0$	$2.9 \pm 1.5$
TS	8.9	556	388	$2.2 \pm 0.4$	$9.3\pm4.8$	$2.6 \pm 1.5$
T25	9.6	552	794	$1.1\pm0.3$	$8.8\pm3.6$	3.3 ± 1.5
T28	10.6	553	541	$1.4\pm0.5$	$9.3 \pm 1.8$	$3.6 \pm 1.6$
T38	13.3	513	430	$2.5 \pm 1.2$	$19.2\pm8.1$	$3.1 \pm 1.8$
T47	15.7	488	771	$2.2 \pm 1.2$	$9.6\pm4.5$	$3.8 \pm 1.5$
T50	17.2	477	682	$2.0\pm0.9$	$13.4\pm9.1$	$3.9 \pm 1.2$
T50.5	17.4	475	128	$1.2\pm0.6$	$8.0\pm3.6$	$3.4 \pm 1.4$
T51	18.2	472	323 <sup>c</sup>	$1.4 \pm 0.4$	$6.6\pm2.3$	$4.0 \pm 0$
T54	19.8	451	106 <sup>c</sup>	$1.6 \pm 0.1$	$10.0\pm4.6$	$5.3\pm1.5$
T59.5	23.3	425	260 <sup>c</sup>	$1.0 \pm 0.3$	$8.3\pm5.0$	$2.5\pm0.5$
IK	35.1	585	302 <sup>c</sup>	$2.1\pm0.9$	$4.9\pm4.1$	$3.4 \pm 2.1$

Basic information on the 30 tributaries surveyed in the Sorachi River, Japan.

<sup>a</sup> Watercourse distance from the uppermost tributary T4.

<sup>b</sup> 1, silt (< 0.063 mm); 2, sand (0.063-2 mm); 3, gravel (2-16 mm); 4, pebble (16-64 mm); 5, cobble (64-256 mm); 6, boulder (> 256 mm); 7, bedrock.

<sup>c</sup> Length for the reach where redd count survey was conducted.

## **Supplementary Fig. S2**

Number of redds observed in the 30 local populations of stream-dwelling Dolly Varden in the Sorachi River, Hokkaido, Japan. The x-axis is the same scale for all panels (from 1 September to 23 December 2007).



Date

# Supplementary Table S2

Values of summary statistics, estimates of the parameters in the null model, and AKB-estimates of the synchrony model for the 30 local populations of Dolly Varden.

Tributary	T4	T7	T7.5	T8	T9	T10a	T10	KS	T11	T13	T13b	KU	SI	T16	T17
Summary statistics															
Number of redds $S_1$	9	63	58	40	49	108	72	16	67	34	39	20	33	13	21
Mean spawning date S <sub>2</sub>	10/12	10/15	10/13	10/22	10/12	10/5	10/8	10/15	10/17	10/15	10/15	10/8	10/18	10/21	10/19
SD over spawning date $S_3$	3.40	14.98	15.63	11.28	13.47	21.75	13.63	18.95	19.28	10.35	18.82	20.69	20.98	7.20	9.49
Auto-covariance S <sub>4</sub>	-1.96	-7.08	-1.58	-2.48	-5.66	-1.47	-0.92	-0.28	-0.91	-2.41	-2.22	-0.90	-1.70	0.45	-0.09
Null model															
S <sub>1</sub> /1.8	5	35	32	22	27	60	40	9	37	19	22	11	18	7	12
Mean spawning date $\mu_k$	10/11	10/13	10/11	10/20	10/10	10/4	10/6	10/13	10/17	10/13	10/12	10/6	10/23	10/19	10/17
$SD \sigma_k$	3.26	14.34	15.02	11.09	13.25	25.42	13.58	18.29	22.66	10.13	20.23	20.09	29.24	7.06	9.15
AKB-estimates	-	24	22	22	27	<i>c</i> 0	10	0	27	10	22	1.1	10	7	10
Number of females $N_k$	5	54 10/15	32	10/22	27	10/2	40	9	5/	10/14	10/14	10/7	18	10/10	12
Nean spawning date $\mu_k$	10/11	10/15	10/12	10/22	10/12	10/3	10/6	10/13	10/15	10/14	10/14	10/7	10/17	10/19	10/17
$SD \sigma_k$	4.06	14.78	15.68	11.50	13.41	22.26	13.84	19.02	19.06	10.45	19.15	20.72	20.96	1.30	9.62
Synchonicity coefficient $a_k$	3.05	4.51	2.26	2.69	4.57	1.97	1.59	2.37	0.91	3.02	4.81	4.36	3.93	1.47	1.81
Tributary	T18	T20	T23.5	TA	TS	T25	T28	T38	T47	T50	T50.5	T51	T54	T59.5	IK
Tributary Summary statistics	T18	T20	T23.5	TA	TS	T25	T28	T38	T47	T50	T50.5	T51	T54	T59.5	IK
Tributary Summary statistics Number of redds S <sub>1</sub>	<u>T18</u> 21	<u>T20</u> 46	T23.5 19	TA 30	<u>TS</u> 47	T25 76	T28 101	T38 33	<u>T47</u> 27	T50 26	<u>T50.5</u> 24	<u>T51</u> 17	T54 13	<u>T59.5</u> 17	<u>IK</u> 63
Tributary Summary statistics Number of redds S <sub>1</sub> Mean spawning date S <sub>2</sub>	T18 21 10/22	T20 46 10/11	T23.5 19 10/21	TA 30 10/1	TS 47 10/20	T25 76 10/26	T28 101 10/24	T38 33 10/19	T47 27 10/31	T50 26 10/29	T50.5 24 11/13	T51 17 10/31	T54 13 11/12	T59.5 17 10/17	IK 63 10/13
<u>Tributary</u> Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$	T18 21 10/22 9.59	T20 46 10/11 19.95	T23.5 19 10/21 17.39	TA 30 10/1 22.26	TS 47 10/20 16.55	T25 76 10/26 18.40	T28 101 10/24 18.45	T38 33 10/19 13.29	T47 27 10/31 21.99	T50 26 10/29 23.09	T50.5 24 11/13 13.51	T51 17 10/31 21.82	T54 13 11/12 14.11	T59.5 17 10/17 10.29	IK 63 10/13 21.12
Tributary Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$	T18 21 10/22 9.59 -0.71	46 10/11 19.95 -1.41	19 10/21 17.39 -1.07	TA 30 10/1 22.26 -0.32	TS 47 10/20 16.55 -1.77	T25 76 10/26 18.40 -1.67	T28 101 10/24 18.45 -9.58	T38 33 10/19 13.29 -1.29	T47 27 10/31 21.99 -0.75	26 10/29 23.09 -0.34	T50.5 24 11/13 13.51 -1.70	T51 17 10/31 21.82 -0.51	13 11/12 14.11 -0.30	T59.5 17 10/17 10.29 -1.30	IK 63 10/13 21.12 -0.85
Tributary Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model	T18 21 10/22 9.59 -0.71	46 10/11 19.95 -1.41	19 10/21 17.39 -1.07	TA 30 10/1 22.26 -0.32	TS 47 10/20 16.55 -1.77	T25 76 10/26 18.40 -1.67	T28 101 10/24 18.45 -9.58	T38 33 10/19 13.29 -1.29	T47 27 10/31 21.99 -0.75	T50 26 10/29 23.09 -0.34	T50.5 24 11/13 13.51 -1.70	T51 17 10/31 21.82 -0.51	13 11/12 14.11 -0.30	17 10/17 10.29 -1.30	IK 63 10/13 21.12 -0.85
Tributary Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$	T18 21 10/22 9.59 -0.71 12	46 10/11 19.95 -1.41 26	T23.5 19 10/21 17.39 -1.07 11	TA 30 10/1 22.26 -0.32 17	TS 47 10/20 16.55 -1.77 26	T25 76 10/26 18.40 -1.67 42	T28 101 10/24 18.45 -9.58 56	T38 33 10/19 13.29 -1.29 18	T47 27 10/31 21.99 -0.75 15	T50 26 10/29 23.09 -0.34 14	T50.5 24 11/13 13.51 -1.70 13	T51 17 10/31 21.82 -0.51 9	T54 13 11/12 14.11 -0.30 7	T59.5 17 10/17 10.29 -1.30 9	IK 63 10/13 21.12 -0.85 35
Tributary Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$	T18 21 10/22 9.59 -0.71 12 10/20	T20 46 10/11 19.95 -1.41 26 10/14	T23.5 19 10/21 17.39 -1.07 11 10/19	TA 30 10/1 22.26 -0.32 17 9/29	TS 47 10/20 16.55 -1.77 26 10/18	T25 76 10/26 18.40 -1.67 42 10/23	T28 101 10/24 18.45 -9.58 56 10/21	T38 33 10/19 13.29 -1.29 18 10/17	T47 27 10/31 21.99 -0.75 15 10/28	T50 26 10/29 23.09 -0.34 14 10/26	T50.5 24 11/13 13.51 -1.70 13 11/11	T51 17 10/31 21.82 -0.51 9 10/28	T54 13 11/12 14.11 -0.30 7 11/9	T59.5 17 10/17 10.29 -1.30 9 10/15	IK 63 10/13 21.12 -0.85 35 10/10
TributarySummary statisticsNumber of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$	T18 21 10/22 9.59 -0.71 12 10/20 9.58	T20 46 10/11 19.95 -1.41 26 10/14 27.57	T23.5 19 10/21 17.39 -1.07 11 10/19 17.48	TA 30 10/1 22.26 -0.32 17 9/29 22.08	TS 47 10/20 16.55 -1.77 26 10/18 16.03	T25 76 10/26 18.40 -1.67 42 10/23 18.20	T28 101 10/24 18.45 -9.58 56 10/21 17.88	T38 33 10/19 13.29 -1.29 18 10/17 12.80	T47 27 10/31 21.99 -0.75 15 10/28 21.47	T50 26 10/29 23.09 -0.34 14 10/26 22.12	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83	T51 17 10/31 21.82 -0.51 9 10/28 21.89	T54 13 11/12 14.11 -0.30 7 11/9 13.21	17 10/17 10.29 -1.30 9 10/15 9.66	IK 63 10/13 21.12 -0.85 35 10/10 21.79
Tributary Summary statistics Number of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$	T18 21 10/22 9.59 -0.71 12 10/20 9.58	46 10/11 19.95 -1.41 26 10/14 27.57	19 10/21 17.39 -1.07 11 10/19 17.48	TA 30 10/1 22.26 -0.32 17 9/29 22.08	TS 47 10/20 16.55 -1.77 26 10/18 16.03	T25 76 10/26 18.40 -1.67 42 10/23 18.20	T28 101 10/24 18.45 -9.58 56 10/21 17.88	T38 33 10/19 13.29 -1.29 18 10/17 12.80	27 10/31 21.99 -0.75 15 10/28 21.47	26 10/29 23.09 -0.34 14 10/26 22.12	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83	T51 17 10/31 21.82 -0.51 9 10/28 21.89	T54 13 11/12 14.11 -0.30 7 11/9 13.21	17 10/17 10.29 -1.30 9 10/15 9.66	IK 63 10/13 21.12 -0.85 35 10/10 21.79
TributarySummary statisticsNumber of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$ AKB-estimates	T18 21 10/22 9.59 -0.71 12 10/20 9.58	46 10/11 19.95 -1.41 26 10/14 27.57	19 10/21 17.39 -1.07 11 10/19 17.48	TA 30 10/1 22.26 -0.32 17 9/29 22.08	TS 47 10/20 16.55 -1.77 26 10/18 16.03	T25 76 10/26 18.40 -1.67 42 10/23 18.20	T28 101 10/24 18.45 -9.58 56 10/21 17.88	T38 33 10/19 13.29 -1.29 18 10/17 12.80	T47 27 10/31 21.99 -0.75 15 10/28 21.47	T50 26 10/29 23.09 -0.34 14 10/26 22.12	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83	T51 17 10/31 21.82 -0.51 9 10/28 21.89	T54 13 11/12 14.11 -0.30 7 11/9 13.21	1759.5 17 10/17 10.29 -1.30 9 10/15 9.66	IK 63 10/13 21.12 -0.85 35 10/10 21.79
TributarySummary statisticsNumber of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$ AKB-estimatesNumber of females $N_k$	T18 21 10/22 9.59 -0.71 12 10/20 9.58 12	T20 46 10/11 19.95 -1.41 26 10/14 27.57 26	T23.5 19 10/21 17.39 -1.07 11 10/19 17.48 11	TA 30 10/1 22.26 -0.32 17 9/29 22.08 17	TS 47 10/20 16.55 -1.77 26 10/18 16.03 26	T25 76 10/26 18.40 -1.67 42 10/23 18.20 42	T28 101 10/24 18.45 -9.58 56 10/21 17.88 56	T38 33 10/19 13.29 -1.29 18 10/17 12.80 18	T47 27 10/31 21.99 -0.75 15 10/28 21.47 15	T50 26 10/29 23.09 -0.34 14 10/26 22.12 15	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83 13	T51 17 10/31 21.82 -0.51 9 10/28 21.89 10	T54 13 11/12 14.11 -0.30 7 11/9 13.21 7	T59.5 17 10/17 10.29 -1.30 9 10/15 9.66 9	IK 63 10/13 21.12 -0.85 35 10/10 21.79 35
TributarySummary statisticsNumber of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$ AKB-estimatesNumber of females $N_k$ Mean spawning date $\mu_k$	T18 21 10/22 9.59 -0.71 12 10/20 9.58 12 10/21	T20 46 10/11 19.95 -1.41 26 10/14 27.57 26 10/9	T23.5           19           10/21           17.39           -1.07           11           10/19           17.48           11           10/20	TA 30 10/1 22.26 -0.32 17 9/29 22.08 17 9/29	TS 47 10/20 16.55 -1.77 26 10/18 16.03 26 10/19	T25 76 10/26 18.40 -1.67 42 10/23 18.20 42 10/24	T28 101 10/24 18.45 -9.58 56 10/21 17.88 56 10/24	T38 33 10/19 13.29 -1.29 18 10/17 12.80 18 10/18	T47 27 10/31 21.99 -0.75 15 10/28 21.47 15 10/29	T50 26 10/29 23.09 -0.34 14 10/26 22.12 15 10/27	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83 13 11/12	T51 17 10/31 21.82 -0.51 9 10/28 21.89 10 10/30	T54 13 11/12 14.11 -0.30 7 11/9 13.21 7 11/10	T59.5 17 10/17 10.29 -1.30 9 10/15 9.66 9 10/16	IK 63 10/13 21.12 -0.85 35 10/10 21.79 35 10/10
TributarySummary statisticsNumber of redds $S_1$ Mean spawning date $S_2$ SD over spawning date $S_3$ Auto-covariance $S_4$ Null model $S_1/1.8$ Mean spawning date $\mu_k$ SD $\sigma_k$ AKB-estimatesNumber of females $N_k$ Mean spawning date $\mu_k$ SD $\sigma_k$	T18 21 10/22 9.59 -0.71 12 10/20 9.58 12 10/21 9.76	T20 46 10/11 19.95 -1.41 26 10/14 27.57 26 10/9 20.10	T23.5           19           10/21           17.39           -1.07           11           10/19           17.48           11           10/20           17.47	TA 30 10/1 22.26 -0.32 17 9/29 22.08 17 9/29 22.53	TS 47 10/20 16.55 -1.77 26 10/18 16.03 26 10/19 16.42	T25 76 10/26 18.40 -1.67 42 10/23 18.20 42 10/24 18.23	T28 101 10/24 18.45 -9.58 56 10/21 17.88 56 10/24 18.43	T38 33 10/19 13.29 -1.29 18 10/17 12.80 18 10/18 13.25	T47 27 10/31 21.99 -0.75 15 10/28 21.47 15 10/29 22.02	T50 26 10/29 23.09 -0.34 14 10/26 22.12 15 10/27 22.75	T50.5 24 11/13 13.51 -1.70 13 11/11 12.83 11/12 13.30	T51 17 10/31 21.82 -0.51 9 10/28 21.89 10 10/30 21.76	T54 13 11/12 14.11 -0.30 7 11/9 13.21 7 11/10 13.96	T59.5 17 10/17 10.29 -1.30 9 10/15 9.66 9 10/16 10.28	IK 63 10/13 21.12 -0.85 35 10/10 21.79 35 10/10 21.40

### **Supplementary Fig. S3**

The distributions of the synchrony coefficients estimated by the AKB-algorithm from redd count data simulated by the null model (open bars) and synchrony model (filled bars) in populations T7, T9, T20 and T28. The arrows indicate the values of the synchrony coefficients estimated by the observed data.



# Supplementary Table S3.

Results of Poisson and ZIP regressions for the number of redds and an environmental

Domulation	Poisson re	gression		ZIP regression (count model)			
Population	Intercept	Precipitation	Temperature	Intercept	Precipitation	Temperature	
T4	-1.528	-0.005	0.045	4.192	0.136 **	-0.369	
T7	1.981	-0.017 *	-0.410	1.213	-0.037 **	0.066	
T7.5	-1.137	-0.029 *	0.152 *	0.565	-0.024	0.082	
Т8	3.354	-0.020 *	-0.157 *	1.368	-0.045 **	0.047	
Т9	-0.510	-0.019 *	0.098	-0.070	0.023	0.004	
T10a	1.220	0.007	0.007	2.173	0.003	-0.031	
T10	0.779	-0.001	0.026	1.618	-0.010	0.021	
KS	-0.930	0.002	0.025	3.011	0.018	-0.211	
T11	1.321	-0.001	-0.016	1.576	-0.001	-0.010	
T13	1.702	-0.062	-0.622	1.472	0.012	-0.030	
T13b	1.375	0.007	-0.052	2.173	0.006	-0.074	
KU	-2.308	0.005	0.126 *	-0.102	-0.011	0.055	
SI	-0.506	0.004	0.050	2.632	-0.019	-0.089	
T16	0.140	-0.021	-0.016	-8.306	-0.149 *	0.697 *	
T17	1.031	-0.018	-0.045	3.488	0.108 **	-0.261 *	
T18	-0.235	-0.031	0.041	-3.764	-0.017	0.295	
T20	-2.672	0.013 *	0.188 **	-0.697	0.016 *	0.089	
T23.5	-0.297	-0.008	0.018	-5.379	-0.024	0.380 **	
ТА	1.601	0.009	-0.101	2.519	0.003	-0.125 *	
TS	0.255	-0.007	0.039	-2.233	-0.017	0.225 *	
T25	1.274	-0.015 *	0.013	1.208	-0.021 *	0.045	
T28	0.111	-0.011 *	0.100 **	0.778	-0.009 *	0.068 *	
T38	-1.370	-0.004	0.114 *	-1.188	-0.005	-0.070	
T47	1.303	-0.006	-0.062	2.271	0.003	-0.091	
T50	0.002	-0.019	0.026	-0.949	0.012	0.072	
T50.5	1.124	0.007	-0.076	-0.890	0.044 *	0.069	
T51	-2.820	-0.011	0.160 *	-4.550	0.048	0.235 *	
T54	3.798	-0.052	-0.234 *	2.916	-0.019	-0.135	
T59.5	-0.995	-0.055 *	0.080	-5.686	-0.032	0.398 *	
IK	1.871	-0.009	-0.041	5.093	-0.014	-0.211 *	
(mean)	0.298	-0.012	-0.017	0.215	-0.001	0.038	

variable (i.e., precipitation or temperature) in each population.

\* P < 0.05, \*\* P < 0.00167 (after Bonferroni correction, 0.05/30)

# Supplementary Fig. S4.

Cross-correlation coefficients (i.e., synchrony) of redd counts between each pair of the 30 tributary populations. The cross-correlation was plotted against geographic distance (km, in watercourse distance).



#### Supplementary Appendix A

#### Redd count procedure for Dolly Varden in the upper Sorachi River

The redds can be discriminated in the field with varying degrees of certainty depending on the fish species, fish size, stream environment (velocity, substrate, cover, etc.), and the observer's experience (Dunham et al. 2001; Gallagher et al. 2007). Because Dolly Varden in the Sorachi River are small (< 200 mm) and construct relatively small redds (30-70 cm in length), they can sometimes be difficult to identify. In order to minimize the potential for observational error, all redd counts were done by the same person (I. Koizumi) who had been studying this population for 10 years by the time of the survey.

The procedure for counting redds involved first selecting 30 suitable tributaries as mentioned in the main text. Overhead cover (mostly shrubs) was removed by the start of redd counts to make observation easier. Suitable spawning areas in the tributaries are generally limited and can roughly be recognized. Second, because redds can disappear for long periods of time, we conducted redd counts every 3-5 days for most of the breeding period. Disappearance mainly occurs due to to water currents that make typical pot-tailspill shapes of redds ambiguous (Gallagher et al. 2007). Also, animal footprints (by sika deer and brown bear) occasionally disrupted the redd's shape. Fortunately, there were no heavy rains during the study period to make redds disappear or make field observation difficult. Third, to prevent double counts, each redd was labeled with pink tape indicating the date and other pertinent remarks. Fourth, four levels of certainty criteria (C1-C4) were recorded for each redd based on past experience digging and confirming nests (I. Koizumi, personal observation). A redd was given a C1 classification if its appearance was unambiguous. C1 is, therefore, the highest level of certainty. A C2 classification, also highly certain, is given if the shape of the fish was clear. C3 is only potentially a redd. Such potential redds tend to be old and have less typical appearances, often together with obstacles, such as rocks, logs, or rapids, that can generate water currents that produce redd-like hole-mount shapes. C4 is probably a non-redd. We conservatively used only redds having a high reliability (C1-C2) of being identified correctly. When we observed spawning behavior (i.e., construction of redds, often accompanied with multiple males), we recorded them as redds on the same day.

Nonetheless, we do acknowledge that there might still be observation errors. First, redds of very small females (< 120 mm) can be difficult to identify. We might have missed such redds, but this omission should be negligible because small females are rare (Koizumi et al. 2006). Second, from 20 November roads were closed due to the accumulation of snow. Since we then had to travel by foot (or snowmobile), the frequency of redd counts in each tributary was reduced to every 8-10 days. Because the probability of redd disappearance is expected to increase with increasing time intervals, we might have missed some redds. However, we believe that such biases, if any, would not be significant because spawning activities were largely finished by that time (see Results) and because the probability of redd disappearance would have been reduced as water discharge became more stable with the end of rain (changed to snow).

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#### **Supplementary Appendix B**

#### The AKB-algorithm and the prior distributions for the synchrony model

Here, we describe the general procedure of the AKB algorithm, after the prior distributions used in this study. Mathematical details are described in Nakagome et al. (2013a) and a brief summary can be seen in Osada et al. (2013) and Nakagome et al. (2013b).

#### Prior distributions

We used the following prior distributions for the four parameters:

$$N_{k} \sim \text{Unif } (S_{1}^{k}/1.8 - 2, S_{1}^{k}/1.8 + 2)$$
(S1)  

$$\mu_{k} \sim \text{Unif } (S_{2}^{k} - 10, S_{2}^{k} + 10)$$
(S2)  

$$\sigma_{k} \sim \text{Unif } (S_{3}^{k} - 3, S_{3}^{k} + 3)$$
(S3)  

$$a_{k} \sim \text{Unif } (0, 8)$$
(S4)

The first prior (i.e., number of females in population k) is because, on average, one female produced 1.8 redds (equation 2), and  $S_1^k$  should be close to  $1.8 \times N_k$ . The next two (i.e., mean and SD of spawning date) are because each of these parameters should be close to the values of each summary statistic. For the synchrony coefficient,  $a_k$ , female reproductive periods in salmonids are heritable and restricted to a short time (Hendry et al. 1999), and in cases of artificial breeding, fertilization success quickly drops 1-2 weeks after ovulation (Craik and Harvey 1984; Brooks et al. 1997). Thus, we assumed that females were able to adjust spawning timing within a week or so, and we used equation (S4) and (3). Note that the synchrony affects not only  $S_4^k$  but also  $S_1^k$  and  $S_2$  as hastening and aggregating spawning dates and that the AKB algorithm reflects all the summary statistics simultaneously..

#### Simulating redd count data

Let random samples from the prior distributions be  $(N^{(j)}, \mu^{(j)}, \sigma^{(j)}, a^{(j)})$  (j = 1, ..., n = 2000; here, we omit the index for population *k* for simplicity). Using these parameters, and equations (1)-(4) we simulated spawning dates and produced redd count data,  $O_t^j$ , for each population separately.

We then calculated the summary statistics and let their values be  $\bar{s}^{j} = (S_{1}^{j}, S_{2}^{j}, S_{3}^{j}, S_{4}^{j})$ . For real data, denote as  $\bar{s} = (S_{1}, S_{2}, S_{3}, S_{4})$ .

In the AKB algorithm, the estimator of the posterior mean (hereafter we called it *AKB estimate*) is given by, in the case of parameter  $\mu_k$ ,

$$\hat{\mu}_{k} = \sum_{j=1}^{n} w_{j} \mu_{k}^{(j)}$$
 (S5)

(for the other parameters, replace  $\mu$  with *N*,  $\sigma$ , or *a*) in which  $w_j$  is the weight for the *j*-th sample and given by the following

$$\begin{pmatrix} w_{1} \\ w_{2} \\ \vdots \\ w_{n} \end{pmatrix} = \begin{pmatrix} k(\bar{s}^{1}, \bar{s}^{1}) & k(\bar{s}^{1}, \bar{s}^{2}) & \cdots & k(\bar{s}^{1}, \bar{s}^{n}) \\ k(\bar{s}^{2}, \bar{s}^{1}) & k(\bar{s}^{2}, \bar{s}^{21}) & \cdots & k(\bar{s}^{2}, \bar{s}^{n}) \\ \vdots & \vdots & \ddots & \vdots \\ k(\bar{s}^{n}, \bar{s}^{1}) & k(\bar{s}^{n}, \bar{s}^{2}) & \cdots & k(\bar{s}^{n}, \bar{s}^{n}) \end{pmatrix} + n \mathcal{A}_{n} \end{pmatrix}^{-1} \begin{pmatrix} k(\bar{s}^{1}, \bar{s}) \\ k(\bar{s}^{2}, \bar{s}) \\ \vdots \\ k(\bar{s}^{n}, \bar{s}) \end{pmatrix}$$
(S6)

Here, k(x, y) is the Gaussian kernel;

$$k(\bar{s}^{i}, \bar{s}^{j}) = \exp(-\sum_{l=1}^{4} (\bar{s}_{l}^{i} - \bar{s}_{l}^{j})^{2} / 2\sigma_{0}^{2}), \quad (S7)$$

in which  $\bar{s}^{j} = (\bar{s}_{1}^{j},...,\bar{s}_{4}^{j})$  consists of standardized  $S_{l}^{j}$  by subtracting the mean and dividing by the standard deviation over *n* replicates. The same standardization was done for the real data and denote them as  $\bar{s}$ .  $I_{n}$  is the  $n \times n$  identity matrix.  $\sigma_{0}$  is the band width of the kernel function.  $\varepsilon$  is an arbitrary fixed constant for stabilizing the matrix inversion (the Tykhonov-type regularization. Equation S6 is a modification of a commonly seen statistical technique called the ridge regression). In general, if a small  $\varepsilon$  is used, weights  $(w_{j})$  sensitively depend on simulated datasets, resulting in different estimates, whereas a large  $\varepsilon$  stabilizes estimates but may not capture properties of simulated datasets.

In the AKB algorithm, determining  $\sigma_0$  and  $\varepsilon$  are arbitrary. Following the previous studies (Nakagome et al. 2013ab; Osada et al. 2013),  $\sigma_0$  was fixed as

$$\sigma_0^2 = median(\sum_{l=1}^{4} (\bar{s}_l^i - \bar{s}_l^j)^2) \quad (i, j = 1, ..., n, i \neq j).$$
(S8)

We tested  $\varepsilon = 1, 10^{-1}, ..., 10^{-4}$  for various real and artificial datasets and determined to use  $\varepsilon = 0.01$  because this value was the smallest value that visually stabilized estimates. (Nakagome et al. (2013) proposed the cross-validation for determining  $\varepsilon$ , although this requires huge computation but generally involves few differences from when determined as described above.)

The AKB algorithm was conducted by Mathcad ver. 14 (PTC Inc.). We carried out n = 2000 simulations. The AKB algorithm does not necessarily require so many simulations, and partly because of the simplicity of our model,  $n \ge 1000$  gave similar estimates, suggesting convergence as proved by Fukumizu et al. (2013).

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#### **Supplementary Appendix C**

## **Comparison of conventional ABC and AKB methods**

We have also conducted a conventional ABC method, the rejection method.

We simulated 100,000 datasets using the same prior distributions as above and accepted parameter sets if all the following was satisfied.

$$\left|S_1 - S_1^{(j)}\right| \le 2, \ \left|S_2 - S_2^{(j)}\right| \le 2, \ \left|S_3 - S_3^{(j)}\right| \le 1, \ \left|S_4 - S_4^{(j)}\right| \le 1$$

Table S2 compares the posterior means estimated by the conventional ABC-method with those by the AKB-algorithm for three local populations. The means are close for all populations.

Table S2. The posterior means estimated by the ABC rejection method and those by the AKB-algorithm.

	T7	T9	T28
ABC rejection	4.78	4.58	4.40
AKB	4.51	4.57	4.19