

**University of Arizona**  
**Southern California Tree-Ring Study**

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Final Report to California Department of Water Resources

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## Appendix A. Observed Flows and Precipitation

Refer to Table 1 and text of report for definition of individual series

P is precipitatio (inches); Q is full natural flow (thousands of acre-ft)

water year	Q Arroyo	P SanGab	Q SantaAna	P LakeArrow	P Ojai	P Cuyam	Q Kern	Q Colo
1887								
1888						22.4		
1889						53.39		
1890						62.21		
1891						62.43		
1892						38.58		
1893						40.71		
1894						14.35		
1895						56.98		
1896						23.6		
1897						36.11		
1898						28.65		
1899						22.07		
1900						28.86		
1901			47.16		21.69	41.78		
1902			25.06		14.86	37.37		
1903			66.38		23.54	37.62		
1904			24.66		13.53	23.42		
1905			59.81		22.74	57.3		
1906			121.77		23.66	59.23	18214.7	
1907			164.42		37.45	40.91	21234.3	
1908			59.34		20.42	34.83	11774	
1909			89.15		27.75	39.85	21841.4	
1910			96.08		23.78	33.6	14736.7	
1911	3.14		102.6		30.01	31.16	15125.1	
1912	1.19		43.14		13.07	32.47	19082.1	
1913	0.72		32.44		18.24	32.46	14472.2	
1914	32.98		94.96		39.53	33.48	21066.8	
1915	8.63		137.75		24.02	55.19	14137.6	
1916	1.48		249.88		29.68	61.47	19187.5	
1917	5.58		70.33		20.76	35.92	23849.3	
1918	5.59		84.62		26.86	29.73	15750.7	
1919	1.52		37.95		12.82	30.83	12951.5	
1920	3.64		81.29		15.54	38.5	21928	
1921	3.17		52.05		18.5	30.77	22703.1	
1922	25.45		190.5		26.67	46.53	18669.6	
1923	3.2		62.9		19.35	37.24	18343.7	

1924	0.84		36.51		6.88	28.42		14639.1
1925	1.08		28.49		11.99	36.1		13410.8
1926	6.2		48.28		21.68	36.98		16114
1927	6.8		112.64		26.23	66.98		18551.9
1928	1.29		19.64		16.25	20.83		17577.9
1929	1.41		26.3		13.21	40.61		21407.1
1930	1.64		34.69		14.01	38.14	331.57	15283.5
1931	1.48		21.84		17.29	28.18	184.13	8631.72
1932	5.32		86.1		26.06	50.6	696.03	17545.5
1933	2.79		26.15		11.64	40.72	427.2	12130.1
1934	2.97		22.02		13.78	20.91	230.12	6627.51
1935	9.02		46.3		22.45	37.84	455.89	12280
1936	3.91		37.42		20.36	39.33	747.7	14485.4
1937	11.93		150.84		29.14	65	1107.78	14161.8
1938	21.87	44.32977	193.04		33.97	48.72	1288.42	17920.1
1939	4.69	29.41008	59.08		14.44	44.07	451.46	11718.1
1940	3.99	20.10999	41.69		15.46	30.11	694.97	9380.28
1941	25.22	53.3	105.34		45.25	65.92	1245.64	18319.3
1942	2.46	17.58996	42.47	32.19	17.16	31.44	750.26	19428.3
1943	21.26	47.56003	77.03	60.8	28.07	37.77	1002.67	13624.5
1944	13.74	33.23004	52.2	46.47	24.16	40.39	577.92	15512.5
1945	5.82	28.89009	64.2	52.15	18.9	41.24	806.76	13912.7
1946	4.98	28.88035	49.16	42.13	13.84	35.29	646.41	11062.7
1947	5.9	29.30988	34.38	43.23	15.37	28.98	425.27	15916.3
1948	1.2	13.88002	22.51	28.9711444	9.34	28.77	331.72	15880.2
1949	1.27	16.1	30.58	38.34	11.12	34.31	295.07	16662.2
1950	1.52	20.61	23.37	34.2	16.71	32.33	434.24	13317.9
1951	0.54	12.69	14.8	20.6	10.1	26.71	528.28	12485.8
1952	11.5	49.19	78.1	70.65	35.72	53.73	1392.99	20900
1953	1.5	16.71	26.4	25.18	13.85	26	540.763	11204
1954	3.04	25.6	51.2	44.45	19.4	40.8	503.176	8368.14
1955	1.3	19.88	26	34.5	16.59	26.01	355.811	9795.47
1956	2.2	24.32	18.52	29.07	18.78	23.42	870.49	11505.1
1957	1.19	21.82	25.21	35.4	13.83	29.34	438.647	20159.8
1958	11.29	45.95	86.71	63.13	40.07	49.25	1057.54	16899.9
1959	1.61	15.82	19.79	20.88	12.22	18.6	276.534	9232.54
1960	0.78	14.24	18.93	25.72	13.48	27.66	279.179	11974.8
1961	0.8	11.57	11.63	19.46	8.97	12.13	174.99	9247.78
1962	6.61	33.73	39.43	43.64	30.4	34.43	653.654	17769.4
1963	1.8	17.37	13.88	24.57	17.5	22.98	737.823	9169.05
1964	1.39	15.73	17.83	27.27	11.69	33.04	323.11	10355.5
1965	2.239	22.32	23.19	35.39	19.22	27.87	697.863	18433.7
1966	14.56	39.56	66.39	51.66	23.2	37.49	399.603	11139.8
1967	16.98	47.42	109.4	72.22	31.92	47.04	1576.05	11787

1968	5.18	19.04	33.49	30.79	14.57	28.48	489.596	13307.3
1969	41.8	65.09	233.41	98.24	47.23	46.72	2226.73	14543.5
1970	4.13	20.35	35.32	22.49	16.32	20.48	604.213	15040.9
1971	4.48	21.16	26.79	28.78	14.31	30.25	429.092	14867.4
1972	1.54	13.15	25.93	28.4	11.22	20.98	256.778	12398.4
1973	8.18	36.24	62.41	45.88	32	52.13	912.298	19270.8
1974	5.26	25.33	32.76	34.25	19.49	23.59	788.363	12965.3
1975	2.77	21.8	24.05	30.92	22.44	34.79	558.051	16563.8
1976	2.371	20.33	21.45	37.67	15.74	34.49	237.793	11199.8
1977	1.873	18.8	15.079	25.41	11.05	25.14	186.015	5436.47
1978	26.435	62.6	130.28	93.03	48.04	54.82	1523.86	14892.8
1979	6.44	30.38998	109.27	47.6	24.38	42.28	678.004	17609.8
1980	21.76	58.22	206.65	66.99102564	29.96	72.4	1549.91	17312.2
1981	2.55	16.38	33.45	21.05265899	14.52	21.8	458.657	8647.97
1982	5.81	33.7	48.68	47.0478465	19.22	39.21	1102.67	16718.4
1983	31.576	58.46	147.658	71.41	42.87	74.43	2317.93	23717.8
1984	3.65	15.63	37.31	26.48361891	13.06	28.44	889.275	24192.6
1985	2.412	23.71	27.59	34.01	12.03	33.02	677.717	21040
1986	4.947	34.19	45.461	50.81	22.32	40.57	1359.5	22305.4
1987	0.981	11.46	21.376	23.74	7.74	21.73	402.671	16554.7
1988	3.11	30.13	18.88	40.39	17.95	31.06	291.418	11638.2
1989	1.882	20.55	18.316	29.7	11.59	22.45	388.367	9529.57
1990	0.809	15.45	10.627	26.1	9.02	20.97	204.308	8965.07
1991	2.644	21.99	28.67	35.36	19.19	34.63	383.631	12326.5
1992	13.536	36.51	39.547	45.24	27.4	34.74	288.096	11077.5
1993	30.36	64.5802	161.04	90.88	42.25	60.47	833.587	18681.8
1994	2.389	16.95	35.244	28.7	13.72	32.28	335.364	10586.5
1995	17.954	50.16	125.53	74.51	42.41	57.48	1281.82	19859.1
1996	5.034	27.85994	38.968	32.95	16.93	19.94	921.196	14053.1
1997	3.911	30.40007	37.901	40.97878773	21.03	26.6	1199.32	21184.6
1998	20.365	54.63981	123.823	69.05	48.57	54.32	1530.53	16968.6
1999	2.118	14.23997	22.127	18.88843132	12.46	21.35	473.181	16451.9
2000	3.044	21.10993	16.951	24.92	18.84	19.35	464.485	10541.3
2001	3.216	23.10983	14.14	22.28	20.54	14.39	371.423	11025.4
2002	0.473	10.93002	2.987	8.4	7.27	9.45	355.821	5869.16
2003	2.277	26.05	21.407	40.46	22.23	34.48	575.196	10451.9
2004	1.29	18.06989	10.008	21.51	13.65	20.14	399.718	9444.49
2005	37.886	72.36012	120.743	84.65	47.31	52.97	1089.5	17111.2
2006	5.236	28.17993	60.711	39.24	25.37	26.12	1043.82	12627.7
2007	0.617	10.62	10.884	8.81	7.42	14.9	274.07	12565.1
2008	5.753	31.81004	34.149	46.06	11.84	27.42	502.431	16312.2
2009	1.87	19.18987	23.687	8.46	11.46	19.78	456.813	14304
2010	9.712	33.41993	52.957	20.12201213	21.49	37.83	794.932	12330.4
2011	14.079	42.23	96.997	31.31903325	24.89	44.26	1395.03	20063.2

2012	2.908	16.74	23.772	20.72382206	10.37	24.29	383.394	8223.92
2013	1.304	12.96	9.461	17.50644503	8.71	19.51	220.172	8850.57
2014	1.372	14.23	8.339	23.33381716	9.51	16.75	177.552	14137.1
2015	1.629	17.23	10.108	27.02774126			129.841	

## Appendix B. Tree-Ring Metadata

Metadata for the 46 site chronologies. Tables (2 pages), followed by key (2 pages)

Code	N	SiteName.lePrefix	First	Last	EPS	Species	Lat	Lon	Elevm	PI	DataFrom
B27	1	Rock Springs Ranch UçB27c	1379	2016	1404	QUDG	36.490	-120.878	1067	r	our files, Griffin
B32	2	Wright Mountain UpdatB32c	1409	2016	1460	QUDG	36.340	-120.520	1219	r	our files, Griffin
BFB	3	Beef Basin Update BFBM#ec	350	2015	585	PSME	37.928	-109.794	2270	t	our files, ITRDB and Knig
BIG	4	Bigrock Campground BIG#e	1393	2015	1575	PSMA	34.396	-117.828	1481	q	our files
BMC	5	Black Mountain BMC#e	-210	2012	965	SEGI	36.104	-118.655	1950		Our files
KR2	6	Kern River ca621c	1585	2003	1640	QUDG	35.532	-118.628	715		ITRDB
JOA	7	San Joaquin River Milca627c	1710	1996	1770	QUDG	37.030	-119.675	137		ITRDB
BFA	8	Boreal Plateau ca636#e	831	1992	1065	PIBA	36.450	-118.550	3420		ITRDB
UWL	9	Upper Wright Lakes ca637#e	-215	1992	640	PIBA	36.620	-118.370	3519		ITRDB
DEN	10	Dennison Peak ca651c	1601	2003	1660	QUDG	36.286	-118.776	1132		ITRDB
DMS	11	Dead Mule Saddle ca653c	1468	2003	1493	QUDG	35.908	-118.667	1237		ITRDB
KAW	12	North Fork Kaweah Rivca659c	1494	2004	1550	QUDG	36.549	-118.893	701		ITRDB
SJR	13	San Joaquin Experimerca664c	1557	2004	1582	QUDG	37.090	-119.747	345		ITRDB
CTN	14	Crabtree North (SierrCTNM#e	941	2015	1125	PIBA	36.558	-118.363	3285	q,	our files, Caprio
CTS	15	Crabtree South (SierrCTSM#e	1150	2015	1195	PIBA	36.543	-118.368	3254	q,	our files, Caprio
DJU	16	Dutch John Update DJUM#e	1365	2015	1366	PIED	40.953	-109.454	2190	t	our files, ITRDB
DOU	17	Douglas Pass Update DOUM#e	1382	2015	1490	PSME	39.597	-108.812	2560	t	our files, ITRDB
EVG	18	Evans Grove Merged EVGM	-350	2011	1100	SEGI	36.776	-118.818	2183	i	Our files
FCU	19	Fry Creek Update FCUM#e	1617	2015	1695	PSMA	33.346	-116.880	2083	t	our files, ITRDB
FIG	20	Figueroa Mountain UpcFIGc	1293	2016	1318	QUDG	34.742	-119.987	971	r	our files, Griffin
GFE	21	Guyot Flat East (SierGFEM#e	890	2015	1075	PIBA	36.519	-118.348	3327	q,	our files, Caprio
GFN	22	Guyot Flat North (SieGFN	1080	2015	1190	PIBA	36.528	-118.358	3276	q	our files
GFS	23	Guyot Flat South (SieGFSM#e	931	2015	1065	PIBA	36.504	-118.346	3158	q,	our files, Caprio
HLC	24	Hard Luck Campground HLC	1645	2015	1705	PSMA	34.675	-118.841	890	q	our files

Code	N	Site Name	Prefix	First	Last	EPS	Species	Lat	Lon	El	PI	Data From
KAI	25	Kaiser Pass Merged	KAIM	720	2011	980	JUOC	37.306	-119.110	2685	g	Our files; Caprio
KSU	26	Keen Camp Summit	(UpcKSUM#e	1458	2015	1515	PSMA	33.682	-116.692	1463	t	our files, ITRDB
LCM	27	Log Cabin Mine Update	LCMM#e	1420	2016	1467	PSMA, PIJE	37.950	-119.150	2499	t	our files, ITRDB, Ziaco (
LCU	28	Lion Canyon Update	LCUM#e	1494	2015	1535	PSMA	33.626	-116.715	1478	v	our files, LTRR archive
LGU	29	Mount Laguna Update	LGUM#e	1648	2015	1685	PSMA	32.869	-116.419	1813	t	our files, ITRDB
LOB	30	Los Lobos Creek Update	LOBc	1333	2016	1390	QUDG	34.923	-119.240	1017	r	our files, Griffin
LPK	31	Lake Peak Update	(ToSLPKM#e	340	2015	800	PIFL	34.116	-116.812	3017	v	our files, LTRR archive
LSC	32	Little Sycamore Canyon	LSCc	1378	2016	1455	QUDG	34.510	-118.430	1128	r	our files, Griffin
MHC	33	Mountain Home	MHC#e	1297	2012	1575	SEGI	36.240	-118.672	1970		Our files
MPS	34	Maple Springs Update	MPSM#e	1657	2015	1695	PSMA	33.732	-117.548	1283	t	our files, ITRDB
MWC	35	Mount Wilson Combines	MWC#e	1190	2015	1325	PSMA	34.261	-118.107	1481	q	our files
NPC	36	North Park Update	NPCM#e	1486	2015	1491	PIED	40.956	-106.338	2450	t	our files, ITRDB
PMN	37	Pine Mountain Update	PMNM#e	1333	2015	1425	PSMA	34.673	-119.372	1176	t	our files, ITRDB
PT2	38	Peterson 552 Update	PT2M#e	1628	2015	1715	PSMA	34.108	-116.976	1412	t	our files, ITRDB
PT9	39	Peterson 539 Update	PT9M#e	1692	2015	1775	PSMA	33.999	-116.758	1412	t	our files, ITRDB
PUM	40	Pumphouse Update	PUMM#e	1175	2015	1200	PIED	39.955	-106.525	2385	t	our files, ITRDB
RCK	41	Red Creek Update	RCKM#e	1270	2015	1541	PIED	38.558	-107.210	2835	t	our files, ITRDB
RED	42	Red Canyon Update	REDM#e	1336	2015	1416	PIED	39.703	-106.735	2164	t	our files, ITRDB
RRT	43	Red Reef Trail	RRT	1411	2015	1595	PSMA	34.502	-119.116	1412	q	our files
SBP	44	Siberian Pass Trail	(SBPM#e	783	2015	1190	PIBA	36.467	-118.272	3332	q, u	our files, Caprio
TRG	45	Trail Gulch Update	TRGM#e	996	2015	1141	PIED	39.715	-106.979	2210	t	our files, ITRDB
WIL	46	Wild Rose Update	WILM#e	1000	2015	1116	PIED	39.012	-108.245	2636	t	our files, ITRDB

### **Headings of metadata columns**

Code = site code, usually 3 characters, unique to the site

N site number

SiteName.... self-explanatory

FilePrefix = the part of the crn and rwl filename before the suffix

First = first year of data in the chronology

Last = last year of data in the chronology

EPS = first year EPS>0.85 for the chronology

Species = 4 letter species code

Lat = latitude in decimal degrees

Lon = longitude in decimal degrees (west negative)

Elev = representative elevation of site (meters a

PI = Principal Investigator for the collection (see codes above)

DataFrom = where we obtained the rwl data



## Appendix C. Tree-Ring Site Cross-Reference to Models.

Cross-reference table of tree-ring chronologies to reconstruction models. The four numbers for each basin (last 8 columns) and chronology (row) indicate whether a chronology was included (1) or not included (0) in the reconstruction model. From left to right, these models are Rec1, Rec2, Rec3, and Rec4 as defined in the report. The “longest” reconstruction uses only Rec1. The “most skillful” reconstruction is a spliced version of Rec2 and Rec3. Only the last year of the “most-skillful” reconstruction is contributed by Rec4. Chronologies are numbered as in the table of tree-ring metadata (Appendix B). As an example of interpretation, to identify the sites used in the “longest” Colorado River reconstruction, refer to the first sub-column under “COLO.” Number “1” occurs in just rows 3 and 46, indicated that chronologies BFB and WIL were used. Chronologies used at any time in the “most skillful” version of COLO are those with a “1” in any of the last 3 sub-columns under COLO. These are the 9 sites: 3, 16, 17, 36, 40, 41, 42, 45, and 46.

N	CODE	SPECIES	SECO	GABRIEL	ANA	ARROW	OJA	CUYAM	KERN	COLO
1	B27	QUDG	0111	0111	0111	0111	0011	0111	0111	0000
2	B32	QUDG	0011	0011	0000	0011	0010	0011	0011	0000
3	BFB	PSME	0000	0000	0000	0000	0000	0000	0000	1111
4	BIG	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
5	BMC	SEGI	0000	0000	0000	0000	0000	0000	0000	0000
6	KR2	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
7	JOA	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
8	BFA	PIBA	0000	0000	0000	0000	0000	0000	0000	0000
9	UWL	PIBA	0000	0000	0000	0000	0000	0000	0000	0000
10	DEN	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
11	DMS	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
12	KAW	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
13	SJR	QUDG	0000	0000	0000	0000	0000	0000	0000	0000
14	CTN	PIBA	1110	1110	1110	1110	1110	1110	1110	0000
15	CTS	PIBA	0110	0110	0000	0110	0110	0000	0110	0000
16	DJU	PIED	0000	0000	0000	0000	0000	0000	0000	0011
17	DOU	PSME	0000	0000	0000	0000	0000	0000	0000	0010
18	EVG	SEGI	0000	0000	0000	0000	0000	0000	0000	0000
19	FCU	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
20	FIG	QUDG	0111	0111	0111	0111	0111	0111	0111	0000
21	GFE	PIBA	0000	1110	1110	0000	0000	1110	1110	0000
22	GFN	PIBA	0110	0110	0000	0110	0110	0110	0110	0000
23	GFS	PIBA	1110	1110	1110	1110	1110	0000	1110	0000
24	HLC	PSMA	0010	0010	0010	0010	0010	0000	0000	0000
25	KAI	JUOC	0000	0000	0000	0000	0000	0000	0000	0000
26	KSU	PSMA	0010	0010	0010	0010	0000	0010	0010	0000
27	LCM	PSMA	0000	0001	0000	0001	0000	0000	0001	0000
28	LCU	PSMA	0000	0010	0010	0010	0010	0010	0010	0000
29	LGU	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
30	LOB	QUDG	0111	0111	0111	0111	0111	0111	0111	0000
31	LPK	PIFL	1110	1110	1110	1110	1110	1110	1110	0000
32	LSC	QUDG	0011	0011	0011	0011	0011	0011	0011	0000
33	MHC	SEGI	0000	0000	0000	0000	0000	0000	0000	0000
34	MPS	PSMA	0000	0000	0000	0000	0000	0010	0000	0000
35	MWC	PSMA	0000	0110	0110	0000	0110	0110	0110	0000
36	NPC	PIED	0000	0000	0000	0000	0000	0000	0000	0011
37	PMN	PSMA	0010	0000	0000	0110	0010	0000	0010	0000
38	PT2	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
39	PT9	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
40	PUM	PIED	0000	0000	0000	0000	0000	0000	0000	0111
41	RCK	PIED	0000	0000	0000	0000	0000	0000	0000	0011
42	RED	PIED	0000	0000	0000	0000	0000	0000	0000	0111
43	RRT	PSMA	0000	0000	0000	0000	0000	0000	0000	0000
44	SBP	PIBA	0110	0110	0110	0110	0110	0110	0110	0000
45	TRG	PIED	0000	0000	0000	0000	0000	0000	0000	0111
46	WIL	PIED	0000	0000	0000	0000	0000	0000	0000	1111

## Appendix D. Statistical Methods

This appendix provides details of statistics and modeling. All methods described in this appendix were implemented in Matlab.

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## D1. Descriptive Statistics

Descriptive statistics used in the study are the mean, median, standard deviation, skew and lag-1 autocorrelation. These statistics are described in most standard texts on statistics in hydrology or the atmospheric sciences (e.g., Panofsky and Brier 1968; Salas et al. 1980; Wilks 1995; Haan 2002). Let  $x_1, x_2, \dots, x_N$  be a time series of length  $N$ .

The **mean** is a measure of the central tendency of the time series. The mean is also called the arithmetic average, and is one of several possible estimates of the “typical” values of a time series. The mean is computed as

$$\bar{x} = \frac{1}{N} \sum_{i=1}^n x_i \quad (1)$$

The **median** is another measure of the central tendency of a time series, and is defined as the “middle” value of the series. It is defined such that half the  $N$  values of the time series are larger than the median and half are smaller. If the  $N$  is odd, the median is equivalent to the middle-ranking member of  $x$ . If  $N$  is even the median is computed as the average of the two values of  $x$  with ranks  $N/2$  and  $N/2 + 1$ . For example if the time series has length  $N = 10$ , the median is the average of the 5<sup>th</sup> largest and 6<sup>th</sup> largest values. Unlike the mean, the median is insensitive to extreme values of the time series. Therefore, raising the highest value of the series by an arbitrary amount will increase the mean, but have no effect on the median

The **variance** is a measure of spread, or variability, of a time series. The variance is the average of the squared departures of a time series from its mean, and is computed as

$$s^2 = \frac{1}{(N-1)} \sum_{i=1}^N (x_i - \bar{x})^2 \quad (2)$$

The denominator in the above equation is  $N-1$  rather than  $N$  to ensure that the computed variance is an unbiased estimate of the unknown population variance. Large departures from the mean have an amplified effect on the variance because of the squared term. For example, a departure  $(x_i - \bar{x}) = 2$  contributes  $2^2 = 4$  to the summation, while a departure twice as large,  $(x_i - \bar{x}) = 4$ , contributes  $4^2 = 16$  to the summation.

The **standard deviation** is the square root of the variance, and so is also a measure of the spread of the series:

$$s = \sqrt{s^2} \quad (3)$$

The standard deviation is perhaps more intuitively meaningful than the variance because the standard deviation is in the units of the time series itself, rather than in squared time series units. If the variance is referred to as the mean square departure (from the mean) of the series, the standard deviation is the root mean square departure.

The **skew** is the average of the cubed departures from the mean, scaled by the cubed standard deviation:

$$g = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^3}{s^3} \quad (4)$$

The cubed departure can be positive or negative, following the sign of the departure itself, and is greatly influenced by outliers, due to the raising of the departure to the 3<sup>rd</sup> power. A time series with higher departure from the mean on the positive side than on the negative side tends to have a positive skew. Precipitation and streamflow time series often have positive skew, because the departures from mean are limited on the negative side (precipitation or streamflow cannot be less than zero), while very large positive values of precipitation or

streamflow are possible. Statistically, skew is related to the “shape” of a distribution, as might be graphed with histogram. A histogram with a tail extended to the right (large positive departure from mean) is a sign of positive skew, and a histogram with a tail extended to the left (large negative departures from mean) is a sign of negative skew.

The **lag-1 autocorrelation** is the correlation of a time series with itself shifted in time by one time unit. For an annual time series (e.g., water year streamflow), the shift is one year. Lag-1 autocorrelation is computed as

$$r_1 = \frac{\sum_{i=1}^{N-1} (x_i - \bar{x})(x_{i+1} - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (5)$$

For an annual time series, positive lag-1 autocorrelation means that positive departures from the mean in year  $t$  tend to be followed by positive departures in year  $t+1$ , and conversely that negative departures from the mean in year  $t$  tend to be followed by negative departures in year  $t+1$ . Lag-1 autocorrelation is therefore a measure of persistence in a time series: tendency of same-sign departures from the mean to persist from one year to the next. Persistence is an important statistical property relevant to the duration of droughts and wet periods. In tree-ring reconstruction of streamflow it is important to recognize that the hydrologic system and the biological system of the tree have different sources of persistence, such that tree-ring estimates of drought duration, say, can be distorted. For example, a tree-ring width series may have persistence caused by carryover in food storage within the tree from year to year that is unrelated to year-to-year climate variations.

## D2. Testing for Significant Change in Mean and Variance

A **difference of means test** (Wilks 1995) was used to test the null hypothesis that the mean of the population for the instrumental period reconstruction is the same as the mean of the population for the full-length reconstruction. The test statistic is

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (6)$$

where the sample sizes are  $n_1$  for the instrumental period and  $n_2$  for the full-length reconstruction,  $\bar{x}_1$  and  $\bar{x}_2$  are the corresponding sample means, and  $s_1$  and  $s_2$  are the corresponding standard deviations. The statistic  $t$  is tested for significance with a  $t$ -distribution with  $n_1 + n_2 - 2$  degrees of freedom. Matlab function **ttest2** was used for the test.

A **ratio of variance test** (Benjamin and Cornell 1970) was applied to test the null hypothesis that the variance of the population for the instrumental period reconstruction is the same as the variance of the population for the full-length reconstruction. In other words, the two samples represented by the reconstructed flows for the instrumental period and the long-term tree-ring period are considered to represent two populations, and null hypothesis is that those populations have the same variance. The test statistic is

$$F = \frac{s_1^2}{s_2^2} \quad (7)$$

where  $s_1$  and  $s_2$  are the two sample standard deviations. The statistic is tested with an  $F$ -distribution with numerator degrees of freedom  $N_1 - 1$  and denominator degrees of freedom  $N_2 - 1$ , where  $N_1$  and  $N_2$  are the samples sizes of the two data sets. The closer this ratio is to one, the less likely to reject the null hypothesis. Matlab function **vartest2** was used for the test

**Caveats.** There are a couple of caveats to consider in the evaluation of the tests described here. The tests assume normally distributed populations, which may not be strictly true. The tests also assume that the two samples are independent, which they are not: the small sample for the instrumental period is also part of the longer sample for the full reconstruction. This latter deviation from the assumptions would tend to make it even more difficult to get a significant  $t$  or  $F$ . On the other hand, positive autocorrelation of the time series would lower the effective degrees of freedom for the  $t$ -test and  $F$ -test and lead to over-estimation of the significance of statistics (Wilks 1995).

### D3. Reconstruction Method

Reconstructions for this project were generated in a two-stage process of multiple linear regression (Weisberg 1985; Myers 1990, Wilks 1995) followed by locally weighted regression, or “loess” (Cleveland 1979; Martinez and Martinez 2005). The two-stage approach was introduced in a methods paper framed around a tree-ring reconstruction of precipitation Meko (1997), and later modified and extended in reconstructions of streamflow for the Sacramento River (Meko et al. 2001), Colorado River (Meko et al. 2007), and San Joaquin River (Meko et al. 2014). The predictand ( $y$ ) for a basin is either river discharge ( $Q$ ) averaged over the water year, or precipitation ( $P$ ) summed for the water year. The method described below is applied independently to produce each of the sub-period reconstructions defined as Rec1, Rec2, Rec3 and Rec4 in the main text of this report.

In the first stage, single-site reconstruction (SSR), each tree-ring chronology is individually converted to an estimate of  $y$  by stepwise regression. The pool of potential predictors includes the standard site tree-ring chronology concurrent and lagged one year earlier and later than  $y$ . Squared terms on the predictors are included in the pool to allow for possible nonlinear relationships between tree-ring variables and  $y$ . The SSR model for a particular tree-ring chronology is

$$\hat{y}_t = \hat{a}_0 + \sum_{i=-1}^1 \hat{b}_i x_{t+i} + \sum_{i=-1}^1 \hat{c}_i x_{t+i}^2 \quad (8)$$

Where  $\hat{a}_0$ ,  $\hat{b}_i$ , and  $\hat{c}_i$  are estimated regression coefficients, and  $x_t$  is the chronology in year  $t$ . The equation is estimated on the calibration period defined by the overlap of the tree-ring chronology and  $y$ . Although this model has 6 predictors in the predictor pool, some much smaller subset is generally selected in stepwise regression, such that for the simplest possible model all estimated parameters except  $\hat{a}_0$  and one parameters on an  $x$  or  $x^2$  term are zero. The variables are entered or removed step-by-step according to the significance of a computed F-statistic (Weisberg 1985). Settings of  $p_{\text{enter}} = 0.05$  and  $p_{\text{remove}} = 0.05$  were used in the stepwise fitting. This first stage of reconstruction is repeated separately each tree-ring chronology that might reasonably be expected to have a physical relationship with  $P$  or  $Q$  (e.g., because of geographical proximity), such that a large number of SSRs,  $\hat{y}_{i,j}, j = 1, n_1$  is produced, one for each of the  $n_1$  tree-ring chronologies. After the long-term tree-ring data is substituted into the regression equations, each of the single-site reconstructions might cover a different span of years, depending on the time coverage of the chronology itself.

In the second stage, multi-site reconstruction (MSR), a reconstructed value  $\hat{y}_t$  is estimated for each year by linear interpolation from a smoothed scatter plot of the observed predictand,  $y_t$ , against the average  $\bar{y}_{\{j\}}$  of some subset  $n_2 < n_1$  of the SSRs. Here,  $\{j\}$  denotes the subset, chosen following a set of rules described below in the detailed steps for computer programming of the Matlab reconstruction scripts. Some of the more important criteria in culling the  $n_2 < n_1$  SSRs to be used are as follows:

- The SSR model explains at least 10% of the variance of  $y$
- The SSR model has positive reduction-of-error statistic (RE) in leave-5-out cross-validation (Meko 1997)
- The SSR model has positive RE for both validation halves in split-sample calibration/validation
- Representation of multiple species is favored (see rules below)

The scatter plot itself is smoothed by loess (Martinez and Martinez 2005), which is piecewise locally weighted regression that does not assume a linear relationship. Controls are imposed on the fitting such that the fitted loess curve must increase monotonically. The fitting procedure itself is guided by a single smoothing parameter,  $\alpha$ , described in the programming steps below. Some modifications of the loess procedure described in Martinez and Martinez (2005) are necessary to deal with the specific problem of reconstruction of a hydrologic time series from tree rings. Most important is the extension of the smoothed scatterplot to the right or left to enable interpolation of  $\hat{y}_t$  for some reconstruction year in which  $\bar{y}_{\{j\}}$  might fall outside its range in the calibration period. This is essentially a “no analog” year. The handling of such years is described in the programming steps at the end of this section.

SSR is intended to deal with lags and curvilinear relationships between  $y$  and tree-growth at the level of the

individual tree-ring site. Subsequent MSR has the goal of efficiently combining the signal for  $y$  in the various chronologies, while screening out chronologies with weak or temporally unstable signals for  $y$ . Overfitting (Wilks 1995) is unlikely to be a problem with combining the SSRs into a MSR because the MSR model requires estimation of just the single smoothing parameter for loess. While the loess reconstruction method does not yield an “ $R^2$ -squared for regression”, an ad hoc explained variance statistic,  $R^2 = 1 - (SSE/SST)$ , was computed as a single metric for comparison of the “typical” accuracy of these reconstruction with that of other published reconstructions. Here SSE is the sum of squares of departures of observed minus reconstructed  $y$ , and SST is the sum of squares of departures of observed  $y$  from its calibration period mean.  $R^2$  multiplied by 100 can be interpreted as “percentage of variance explained” by the model.

A 95% confidence interval is assigned to each reconstructed value using the method of upper and lower smooths (Martinez and Martinez 2005): confidence bands are interpolated from separate loess models fit to the positive and negative cross-validation residuals of the MSR. The width of the resulting confidence bands varies with magnitude of reconstructed discharge or precipitation, and reflects, for example, the amplified uncertainty of reconstruction in wet years (Meko and Woodhouse 2011).

The statistical procedure of reconstruction of is expanded here step-by-step, first for SSR and then for MSR.

**1 Single-site reconstruction (SSR).** SSR is the filtering and scaling of a single tree-ring chronology,  $x$ , into an estimate of a predictand  $y$ . The goal is an SSR with desirable statistical properties resembling those of the observed  $y$ , and with variance proportional to the strength of the relationship between the  $x$  and  $y$ . The SSR procedure moreover is intended to screen out chronologies whose signal for  $y$  is either weak or temporally unstable, to adjust for possible lagged dependence of  $y$  on  $x$ , and for possible curvature in the relationship between  $x$  and  $y$ .

#### 1.1 Preliminary stepwise regression

1.1.1 Define calibration period as the overlap of  $y$  and  $x$ , possibly shortened by 1 year on the recent end to accommodate a +1 year lag in the model. For example, the calibration value of  $y$  for 2016 might require a tree-ring value  $x$  in 2017; if the tree-ring records ends in 2016, the calibration period of the model must be truncated to end with 2015.

1.1.2 Regress  $y$  on  $x$  and  $x^2$  lagged -1, 0 and +1 years from  $y$  in stepwise regression. The predictand  $y$  for regression is  $\log_{10}(Q)$  for reconstruction of river discharge, and  $P$  (no transformation) for reconstruction of precipitation. The resulting equation has at most has 6 predictors -- original and squared  $x$  at lags 0, -1 and +1 years from  $y$ . Predictors are entered stepwise, with  $p$ -to-enter of 0.05 and  $p$ -to-remove of 0.10. If no variables enter stepwise, the default model is assumed to be  $y$  on  $x$  without lags or squared terms.

1.1.3 Store the order of entry of predictors in the above preliminary stepwise regression

#### 1.2 Cross-validation of preliminary regression

1.2.1 Repeat the stepwise regression above, using the same order of entry of predictors, and cross-validating (Myers 1990; Michaelsen 1987) at each step by leave-5-out cross-validation. Omitting 5 observations instead of 1 observation and predicting for central observation of the omitted segment ensures that none of the same predictor observations are used for the calibration and validation data when a model includes lags up to  $\pm 1$  year on the predictor time series (Meko 1997).

1.2.2 Compute and store the cross-validation reduction of error statistic (RE; Fritts et al. 1990) at each step

1.2.3 Mark as the stopping step for the final SSR model the last step before RE begins to decline (cross-validation stopping rule; Myers 1990; Wilks 1995)

#### 1.3 Final SSR

1.3.1 Re-calibrate the model for the stopping step defined in step 1.2.3. If no lag +1 term is needed for the model, the calibration period can be extended by 1 year on the recent end.

1.3.2 Store the regression  $R^2$  as a measure of accuracy of the SSR model

1.3.3 Substitute the long-term tree-ring index into the model to generate the single-site reconstruction (SSR). If no lags in the model, this reconstruction extends from last year of the available tree-ring series back to the first year the chronology reaches the EPS threshold of 0.85 (Wigley et al. 1984).

1.3.4 Validate the SSR model using both leave-5-out cross-validation and split-sample validation. For

split sample validation, the full calibration period is split in half, and the model is fit and validated in turn on separate halves (e.g., Meko and Graybill 1995).

1.3.5 Flag the chronology's SSR as unusable in subsequent steps of the reconstruction if any of the following conditions are true:

1.3.5.1 Calibration overall- $F$  statistic not significant at  $p=0.05$  (no signal)

1.3.5.2  $R^2 < 0.10$  for SSR model

1.3.5.3 Cross-validation  $RE \leq 0$

1.3.5.4 Split sample  $RE \leq 0$  for either half of the validation

1.4 Repeat steps 1.2-1.3 for each of the  $n_1$  tree-ring chronologies ( $n_1 = 9$  for Colorado River,  $n_1 = 37$  for other basins)

1.5 Backtransform the  $n_1$  SSRs to the original units of the predictand; this step is necessary only if the predictand for SSR was transformed (e.g.,  $\log_{10}$  transform for river discharge)

**2 Multi-site reconstruction (MSR).** MSR is the combining of the SSRs from individual tree-ring chronologies into a single reconstructed time series. The idea is that averaging SSRs over tree-ring sites will emphasize the common signal and de-emphasize local and non-climatic noise. Because the SSRs as defined have variance proportional to strength of their signal for  $y$ , no differential weighting is needed: an unweighted average emphasizes those tree-ring sites with stronger signal. Broadly, the MSR is interpolated from a smoothed scatterplot of observed  $y$  on the average of  $n_2$  SSRs, where  $n_2 < n_1$ . Which of the original  $n_1$  SSRs are included among the  $n_2$  SSRs for a particular basin and nested model? This depends on several factors. Obviously, to be considered a candidate for a particular nested model (e.g., Rec1) an SSR must completely cover the specified time period for the model. To qualify as a candidate, we also require the SSR have a regression  $R^2 > 0.10$ , which, for the lengths of calibration period used here, is a stricter requirement than just a significant ( $p < 0.05$ ) overall- $F$  of regression. Other requirements are that the SSR must a positive RE of cross-validation and a positive RE in both halves of its split-sample validation. These constraints rule out many of the original  $n_1$  SSRs. Remaining SSRs make up the pool of SSRs from which the  $n_2$  SSRs for use in MSR are selected. MSR models are built chronologically (Rec1, Rec2, ...) by the steps described in detail below.

2.1 Identify the SSRs for the Rec1 reconstruction model (earliest nested model)

2.1.1 Identify qualified (see above) SSRs covering the common interval, and consider just those SSRs

2.1.2 Identify how many different species are represented in that set of SSRs

2.1.3 For each species represented, include the 3 SSRs with strongest signal as measured by  $R^2$  of the SSR model (see 1.3.2). If fewer than 3 SSRs available, include all of them.

2.1.3.1 Aim is to favor representation from multiple species, and to use those chronologies with the strongest bivariate signal for the predictand  $y$

2.1.3.2 Will end up with some subset of  $n_2$  SSRs, where  $n_2 < n_1$

2.1.4 Compute the time series of reconstructed predictand averaged over the selected  $n_2$  SSRs; call this average  $v$

2.2 Plot the observed predictand,  $y$ , against  $v$  in a scatterplot

2.3 Fit a loess model to the scatterplot

2.3.1 Make loess estimates of  $y$  at 6 points along the abscissa of the scatterplot: minimum, maximum and percentiles 20 40 60 and 80 of  $v$ .

2.3.2 Begin with a loess smoothing parameter,  $\alpha=0.6$

2.3.3 Fit the loess model. Check that the resulting loess curve is monotonic increasing; if not, increase  $\alpha$  by 0.1 (less flexible curve), and check again; repeat until monotonic increasing curve is attained. The resulting is a final value of smoothing parameter,  $\alpha$ .

2.4 Validate the loess model

2.4.1 Cross-validate, leaving out 5 observations at each iteration and predicting  $y$  for the middle year of the omitted segment

2.4.2 Split-sample validate, exchanging the first and last halves of the overlap of  $v$  and  $y$

2.4.3 Check that the final loess model has positive RE of cross-validation and positive RE of split-

- sample validation on both halves (temporal stability)
- 2.5 Extend the loess curve to cover the full range of  $v$  over the full nested period (not just calibration years)
    - 2.5.1 Identify extreme high and low values in the time series of  $v$  of SSRs averaged over  $n_2$  tree-ring sites. Usually these extremes lie outside the range of  $v$  in the calibration period of the fitted loess curve
    - 2.5.2 Extend the loess curve to the left and right on the scatterplot cover the identified high and low extremes of  $v$ . The loess curve before extension is monotonic increasing and piecewise linear, with segments joining the minimum, 20<sup>th</sup>, 40<sup>th</sup>, 60<sup>th</sup>, 80<sup>th</sup> percentiles and maximum of  $v$  for the calibration period. Call the segments joining these 6 points segment 1-5. Two new straight-line segments (segment 0 on the left and segment 6 on the right) will be added.
      - 2.5.2.1 On the right side, set the slope of segment 6 such that the change in slope from segment 5 to 6 is the same as the change in slope from segment 4 to 5
      - 2.5.2.2 On the left side, set the slope of segment 0 such that the change in slope from segment 0 to segment 1 is the same as the change in slope from segment 1 to segment 2.
  - 2.6 Interpolate the multi-site reconstruction (MSR) from the extended loess curve
 

For each year of the current nest, or set of tree-ring chronologies with common time coverage, linearly interpolate a reconstructed value of  $y$  from the extended loess plot of observed  $y$  against  $v$
  - 2.7 Estimate error bars for the MSR (50% confidence band around annual reconstructed  $y$ )
 

The method of “upper and lower smooths” (Martinez and Martinez 2005) was used to estimate a 50% confidence band for reconstructed  $y$ . This method is specifically applicable where, as here, the reconstructed values are estimated from a smoothed scatterplot and the error variance is a function of the size of reconstructed  $y$ .

    - 2.7.1 Scatterplot the positive cross-validation residuals against the fitted values, or estimated  $y$
    - 2.7.2 Fit a piecewise-linear loess model to the scatterplot
    - 2.7.3 Smoothing parameter  $\alpha = 0.95$ . Use this same setting for all basins and nested models. This setting was selected from exploratory analysis, and is not claimed to be optimal in a statistical sense
    - 2.7.4 Set estimation points at the minimum, maximum, and percentiles 20, 40, 60, and 80 of calibration-period predicted  $y$
    - 2.7.5 Extend the loess curve by adding leading and trailing straight-line segments connecting to the lowest (left) and highest (right) reconstructed  $y$  in the full-length reconstruction. Unlike the extension used for the loess models of the reconstruction itself (see 2.5), the extension is set to horizontal. Thus the confidence interval for extremely low or high reconstructed  $y$  is assumed to stay at the same width as for the extremes in reconstructed  $y$  for the calibration period.
    - 2.7.6 Repeat steps 2.7.1-2.7.5 for the negative cross-validation residuals
    - 2.7.7 Linearly interpolate from the 2 smoothed scatterplots (upper and lower smooths) to get estimated upper and lower 50% confidence bands for each year of reconstructed  $y$
  - 2.8 Repeat steps 2.1-2.7 for nested models Rec2, Rec3, and Rec4
    - 2.8.1 Each nested model has a specified time coverage (e.g., 1405-2015)
    - 2.8.2 More sites, and SSRs, become available in Rec2 and Rec3; site density declines for Rec4
    - 2.8.3 If an SSR is used in an earlier nested model and that SSR covers the current nested period, include the SSR in the current model. This approach favors continuity in the mix of tree-ring predictors from one period to the next.
    - 2.8.4 The rule of using the 3 “best” SSRs (highest  $R^2$ ) for each available species is followed at each nest. Any SSRs retained from an earlier model do not count toward this 3. It is therefore possible for an MSR model for Rec2, Rec3 or Rec4 to be represented by more than 3 chronologies of the same species

#### D4. Spectral Analysis

Spectra are estimated by the smoothed-periodogram method (Bloomfield 2000). Preliminary steps include the following: 1) subtract the mean from the time series, 2) taper the series (5% of each end), and 3) pad the tapered series with zeros to such that its length is a power of two, 3) compute the discrete Fourier Transform, and raw periodogram of the padded tapered time series, and 4) smoothed with convoluted spans of Daniell filters to achieve spectral estimates with the desired bandwidth. The mathematical and statistical operations in these methods are described in Bloomfield (2000).

In testing spectral peaks for significance, it is necessary to specify a “null continuum”, which is a baseline spectrum. For a spectral peak to be deemed “significant”, the spectrum at that frequency must be significantly greater than the baseline. Depending on the lag-1, or first-order, autocorrelation of the time series, the null continuum for testing significance in this study is set to either white noise or red noise. White noise has variance distributed evenly across frequencies, while red noise has variance distributed preferentially toward low frequencies (spectrum slopes upward to left). If the computed lag 1 autocorrelation of the time series is zero or negative, white noise is used for the null continuum. If the lag-1 autocorrelation is positive, red noise is used for the null continuum.

The bandwidth describes the range of frequencies in the raw periodogram contributing to a spectral estimate a particular frequency. The bandwidth depends on the spans of the individual Daniell filters convoluted to produce the resultant filter applied to smooth the raw periodogram. In this study, a 41-weight resultant filter with a bandwidth of about 0.18 frequency units is used to smooth the raw periodogram for spectral analysis of full-length reconstructions. This filter was arrived at by convolution of five 9-weight Daniell filters. A 13-weight resultant filter with a bandwidth of 0.06 frequency units is used to smooth the raw periodogram for spectral analysis of the observed and reconstructed series for the instrumental period. This filter was arrived at by convolution of three 5-weight Daniell filters.

Red noise theoretical spectra, for null continua, are computed by equations in Wilks (1995). White noise spectra are drawn as horizontal lines such that the total area under the white-noise spectrum corresponds to the variance of the time series itself and equals the area under the spectrum of the time series. Confidence intervals for estimated spectra are computed using a  $\chi^2$  distribution with appropriate number of degrees of freedom, adjusted for such factors as padding and trimming of the time series and smoothing by Daniell filters (Bloomfield 2000, p. 184).

## D5. Wavelet Analysis

Wavelet and cross-wavelet analyses were done with the aid of the Matlab-based wavelet package developed by Grinsted et al. (2004) and made available for download by the National Oceanography Centre (<http://noc.ac.uk/using-science/crosswavelet-wavelet-coherence>). Matlab scripts that call the Grinsted et al. (2004) functions and add interpretive graphics were written to produce plots for this report. The primary wavelet graphic used is the continuous wavelet transform (CWT) which display spectral power of a time series as a function of wavelength and time. The primary cross-wavelet graphic used is the wavelet transform coherency (WTC), which plots coherency (similar to correlation) and phase of two time series as a function of wavelength and time. Both the CWT and the WTC allow assessment of significance ( $\alpha=0.05$ ), and for this use a red-noise background. In other words, the significance is determined relative to a red-null hypothesis for the time series.

As wavelet and cross-wavelet analysis assume normality, our Matlab implementation of the cross-wavelet tool has additional functionality that allows square-root or log-10 transformation of the time series prior to wavelet analysis. The user is able to view histograms of the time series before and after alternative transformation, and to choose transformation of one or both (if cross-wavelet) series before calling the Grinsted et al. (2004) functions.

Wavelet and cross-wavelet plots are augmented by smoothed time series plots designed to emphasize variations at decadal-and-longer wavelengths. The smoothing filter for these plots is a 9-weight Gaussian filter (Mitchell et al. 1966) with a frequency response of 0.50 at a wavelength of about 10 years. The weights for the filter used for all smoothed time series plots in Section 3.3 (Cycles and Quasi-Periodic Behavior) are as follows:

1. 0.027630898004301
2. 0.066282614593644
3. 0.123831607604267
4. 0.180173385402692
5. 0.204162988790191
6. 0.180173385402692
7. 0.123831607604267
8. 0.066282614593644
9. 0.027630898004301

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