# 6 Appendix

## A.1 Groundwater Well Data

Groundwater elevation measurements collected in the spring were evaluated as a potential predictor of river flow behavior the following fall. The length of the records and number of spring-season measurements were variable, limiting the number of wells that could be used as predictor sites. Two wells were selected for the final predictor evaluation.

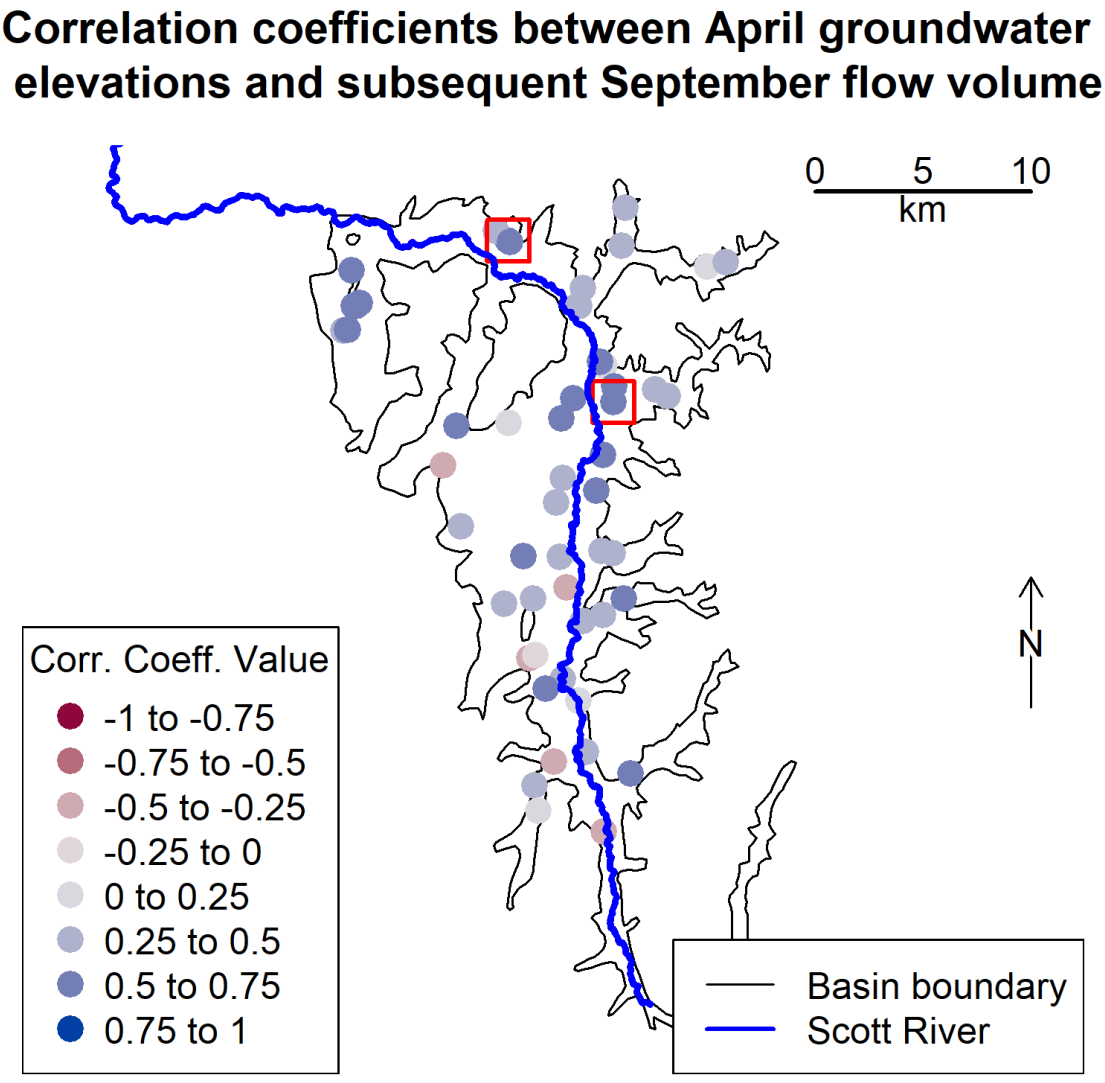


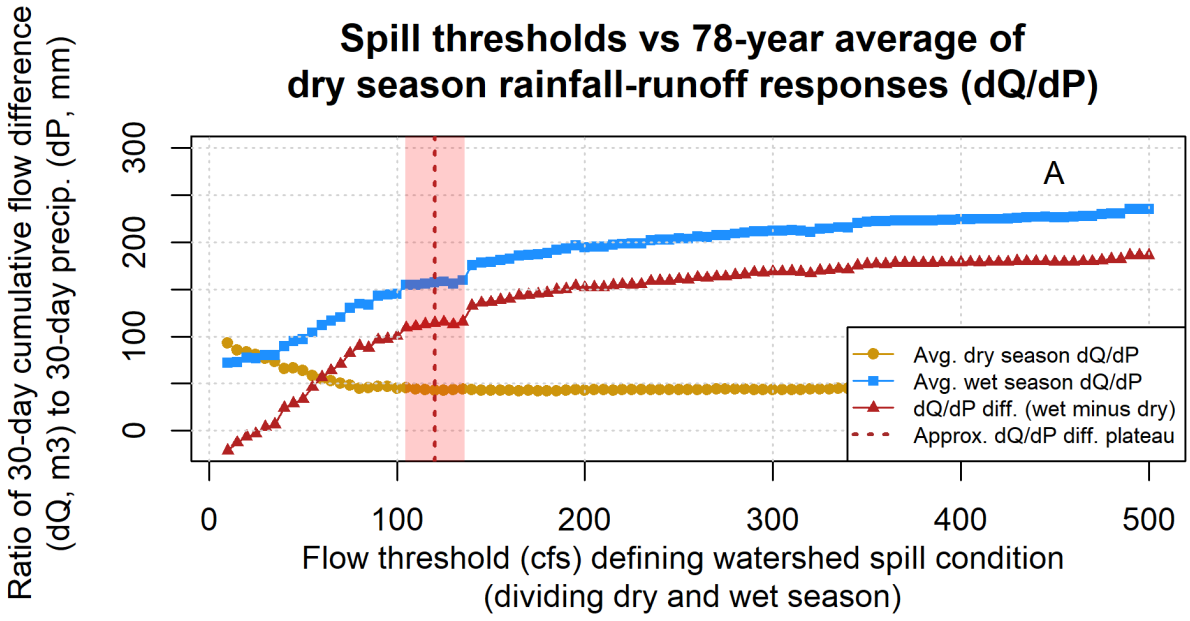

**Figure A1.** Boundary of the groundwater basin (corresponding approximately to the extent of the flat valley floor in the Scott River watershed) and selected well locations. Colors correspond to the correlation coefficients between April groundwater elevations and September flow volume. The wells included in the predictor comparison are highlighted with a red outer square. 54 wells had enough spring-season water level measurements to be included in this correlation exercise, though some wells are so close together that their symbols overplot on this map.

## A.2 Selection of the $Q_{spill}$ threshold value

The $Q_{spill}$ value of 120 cfs (294 thousand $m^3$/day or approximately 9 $Mm^3$ per month) was determined by testing a range of potential $Q_{spill}$ values (10 to 500 cfs [24 to 1223 thousand $m^3$/day]) as a dividing threshold between dry- and wet-season flow behavior. Specifically, the threshold, $Q_{spill}$, was here operationally defined as the flow rate that generated the largest, difference in rainfall-runoff response on either side of the dry season-wet season divide (Figure A2, Panel A). The rainfall-runoff response was measured as the ratio $dQ/dP$, where $dQ$ is the change in runoff and $dP$ is the cumulative precipitation over the same moving 30-day period. Hence, the objective of this analysis was to find $Q_{spill}$ such that the difference between the two $dQ/dP$ values for the 30 days immediately prior to reaching $Q_{spill}$ and the 30 days immediately following the day when $Q_{spill}$ reaches an initial maximum.

For the Scott Valley watershed, the difference between the wet and dry season rainfall-runoff responses reaches an initial plateau (113 cfs [275 $m^3$/day] of increased flow per mm of precipitation) for spill thresholds from 105-135 cfs (256-330 $10^3$ $m^3$/day) (Figure A2, Panel A). This indicates that in a large number of water years, flows in the range of 105-135 cfs (257 to 330 thousand $m^3$/day) range are preceded by a dry season flow-response regime and followed by a distinct, flashier flow regime regime. Though higher wet-dry flow response differences were calculated at higher threshold values (i.e., up to 500 cfs [1,223 thousand $m^3$/day]), these progressively higher wet-season flow responses likely reflect the falling limb of individual large storms that over-fill the watershed rather than separating filling from spilling behavior.

Additionally, in visual inspection of 78 years of Fort Jones hydrographs, the 120 cfs (294 $10^3$ $m^3$/day ) $Q_{spill}$ threshold generated a plausible breakpoint between dry and wet season river behavior in all water years (e.g., water year 2018 in Figure A2, Panel B). Furthermore, this value corroborates local observations that an approximate value of 100 cfs represents "fully connected" river conditions (see Discussion section).



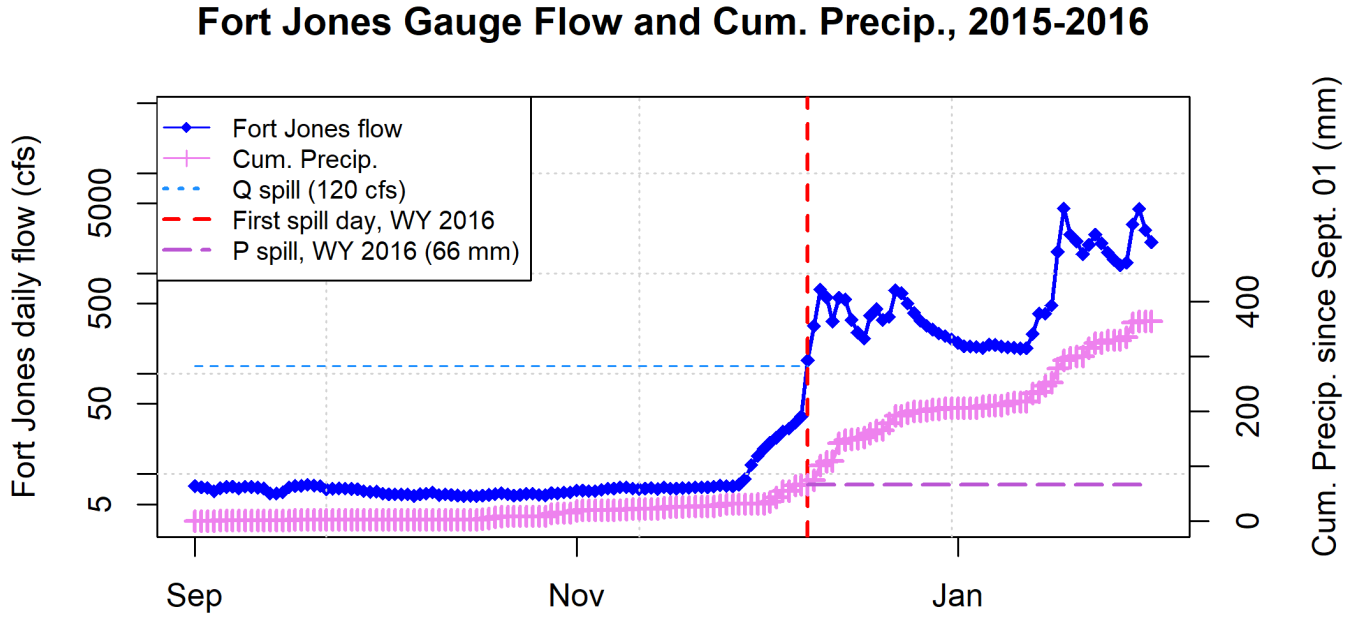




**Figure A2.** This analysis (Panel A) aimed to identify the flow threshold that approximately defines the boundary between filling (i.e. dry season) and spilling (i.e. wet season) flow behavior at the Fort Jones gauge. For each threshold value, for each water year, a rainfall-runoff response was calculated before and after the flow threshold. The rainfall-runoff response consisted of the 30-day cumulative flow difference (dQ) per 30-day cumulative rainfall difference (dP). 120 cfs was selected as the threshold value dividing the dry and wet seasons (e.g., Panel B).

## A.3 Model selection criteria - $V_{min}$

Diagnostics used to select the predictive models for $V_{min}$ are shown below and discussed in Results. Predictors are abbreviated in tables and described briefly in Table A1; for more information on potential predictors see Section 2.3.

**Table A1.** Linear model diagnostics for one-predictor models of minimum fall flows (V min).

| Predictor ID | Predictor Descrip. | n | Log Likelihood | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | Snow maximum | 70 | -131 | 269 | 2.7 | 0.53 |
| USC00043182_oct_apr_mm | Oct.-Apr. Precip. | 75 | -142 | 290 | 2.7 | 0.49 |
| SWJ_jday_of_max | Snow maximum timing | 70 | -154 | 314 | 5.1 | 0.11 |
| springWL_415635N1228315W001 | March-May WLs | 50 | -100 | 206 | 3.6 | 0.39 |
| et0_oct_apr | ET Ref. | 17 | -21 | 48 | 0.9 | 0.46 |
| mar_flow | March flow vol. | 78 | -162 | 330 | 4.1 | 0.25 |

**Table A2.** Linear model diagnostics for two-predictor models of V min. See table of one-predictor models for description of predictor IDs. Reference ET was not included in two- and three-predictor models due to an insufficient sample size.

| Predictor 1 | Predictor 2 | n | Log Likelihood | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | 67 | -119 | 246 | 2.3 | 0.62 |
| SWJ_max_wc_mm | SWJ_jday_of_max | 70 | -131 | 270 | 2.8 | 0.53 |
| SWJ_max_wc_mm | springWL_415635N1228315W001 | 50 | -91 | 191 | 2.7 | 0.57 |
| SWJ_max_wc_mm | mar_flow | 70 | -128 | 264 | 2.6 | 0.57 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | 67 | -127 | 263 | 2.9 | 0.52 |
| USC00043182_oct_apr_mm | springWL_415635N1228315W001 | 47 | -91 | 190 | 3.3 | 0.48 |
| USC00043182_oct_apr_mm | mar_flow | 75 | -139 | 286 | 2.8 | 0.52 |
| SWJ_jday_of_max | springWL_415635N1228315W001 | 50 | -97 | 203 | 3.3 | 0.45 |
| SWJ_jday_of_max | mar_flow | 70 | -141 | 291 | 3.8 | 0.37 |
| springWL_415635N1228315W001 | mar_flow | 50 | -94 | 197 | 3.1 | 0.51 |

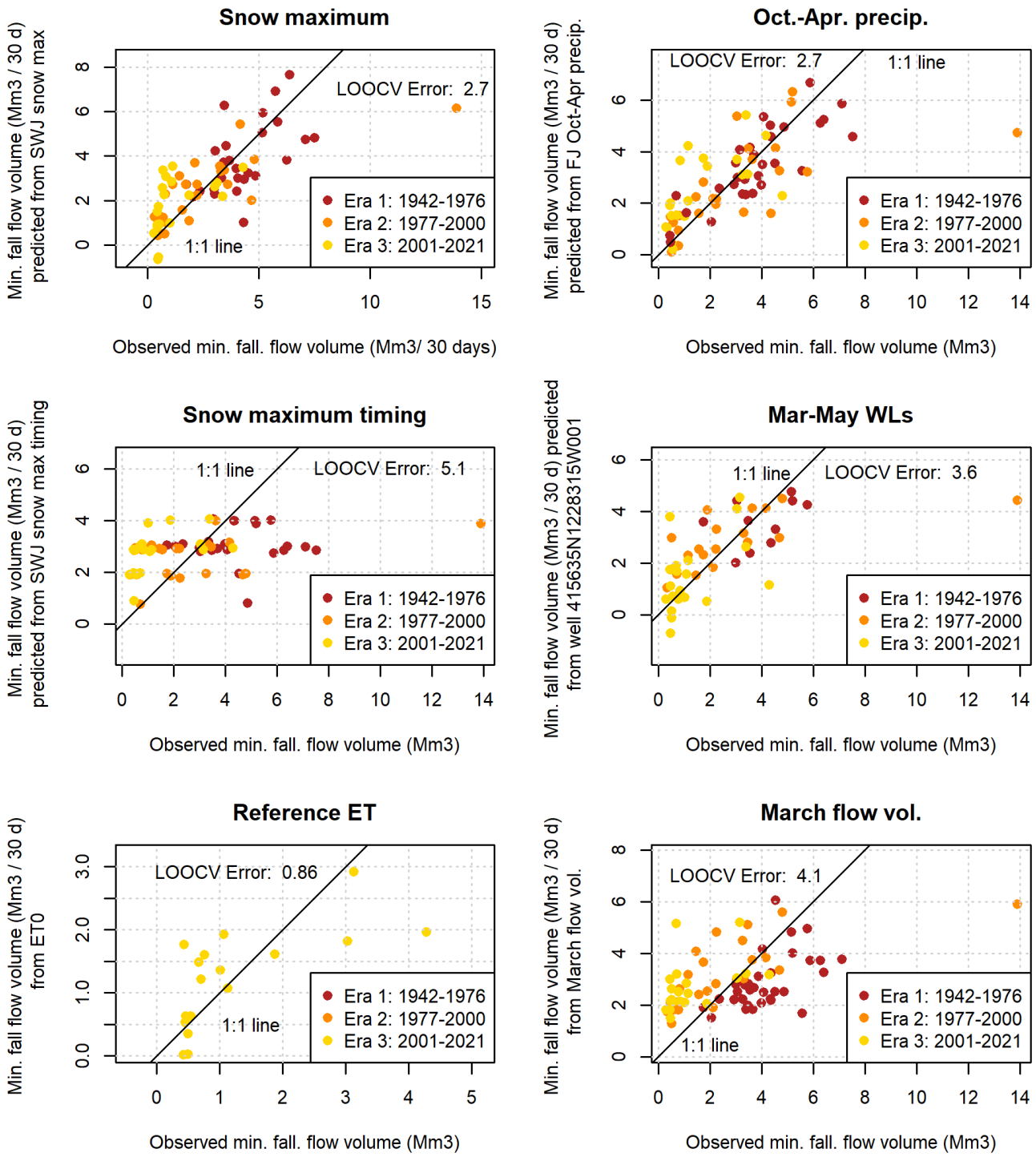



**Figure A3.** Single-predictor models of minimum 30-day dry season baseflows in the Scott River.

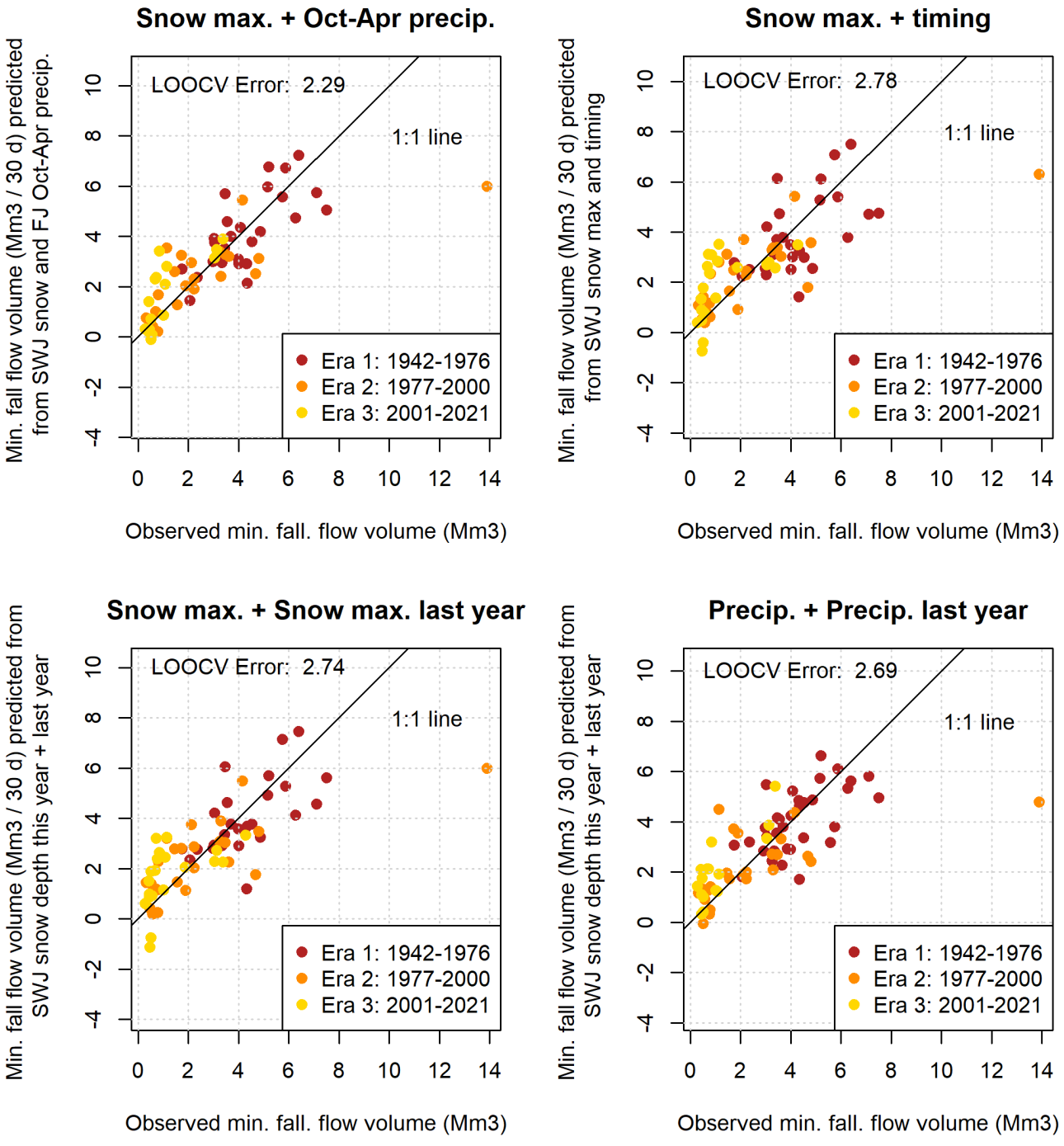



**Figure A4.** Two-predictor models of minimum 30-day dry season baseflows in the Scott River.

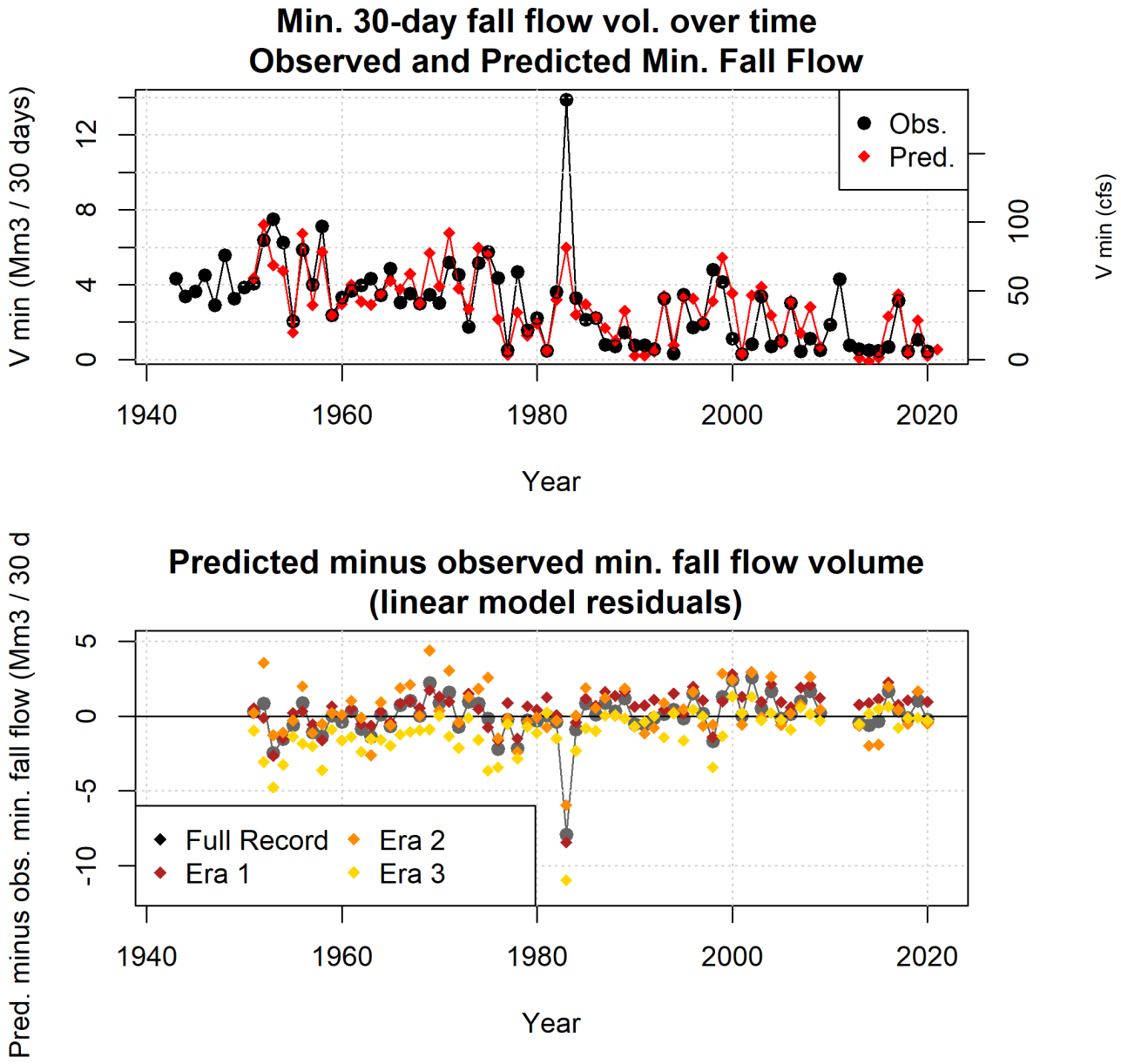



**Figure A5.** Observed and predicted minimum 30-day dry season baseflows both trend downward between the three eras of the period of record (top panel). The predicted-minus-observed difference (residual) over time also reflects this trend, underpredicting minimum flows pre-1977 and overpredicting them post-2000 (middle panel). The predictive model is based on observations from the full record, but three additional models were generated based on only the observations from Eras 1, 2, and 3. Residuals based on Era 1 data are similar to those of the full record; Era 2 residuals tend to overpredict more than the full record; and Era 3 residuals show better performance post-2000 than the full record, but significant underprediction pre-2000.

**Table A3.** Linear model diagnostics for three-predictor models of minimum fall flows (V min). See table of one-predictor models for description of predictor IDs. Reference ET was not included in two- and three-predictor models due to an insufficient sample size.

| Predictor 1 | Predictor 2 | Predictor 3 | n | Log Like. | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | SWJ_jday_of_max | 67 | -119 | 247 | 2.3 | 0.63 |
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | springWL_415635N1228315W001 | 47 | -86 | 181 | 2.8 | 0.59 |
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | mar_flow | 67 | -117 | 244 | 2.3 | 0.64 |
| SWJ_max_wc_mm | SWJ_jday_of_max | springWL_415635N1228315W001 | 50 | -91 | 192 | 2.7 | 0.58 |
| SWJ_max_wc_mm | SWJ_jday_of_max | mar_flow | 70 | -127 | 265 | 2.7 | 0.58 |
| SWJ_max_wc_mm | springWL_415635N1228315W001 | mar_flow | 50 | -89 | 187 | 2.6 | 0.61 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | springWL_415635N1228315W001 | 47 | -90 | 190 | 3.3 | 0.51 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | mar_flow | 67 | -123 | 256 | 2.8 | 0.58 |
| USC00043182_oct_apr_mm | springWL_415635N1228315W001 | mar_flow | 47 | -87 | 184 | 3.0 | 0.56 |
| SWJ_jday_of_max | springWL_415635N1228315W001 | mar_flow | 50 | -91 | 191 | 2.9 | 0.58 |

### A.4 Model selection criteria - $P_{spill}$

Diagnostics used to select the predictive models for $P_{spill}$ are shown below and discussed in Results. Predictors are abbreviated in tables and described briefly in Table A4; for more information on potential predictors see Section 2.3.

**Table A4.** Linear model diagnostics for one-predictor models of P spill.

| Predictor ID | Predictor Descrip. | n | Log Likelihood | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | Snow maximum | 70 | -333 | 673 | 850 | 0.38 |
| USC00043182_oct_apr_mm | Oct.-Apr. Precip. | 75 | -351 | 708 | 718 | 0.43 |
| SWJ_jday_of_max | Snow maximum timing | 70 | -347 | 699 | 1243 | 0.09 |
| springWL_415635N1228315W001 | March-May WLs | 50 | -245 | 495 | 1123 | 0.24 |
| et0_oct_apr | ET Ref. | 17 | -81 | 167 | 932 | 0.23 |
| mar_flow | March flow vol. | 78 | -380 | 767 | 1061 | 0.14 |

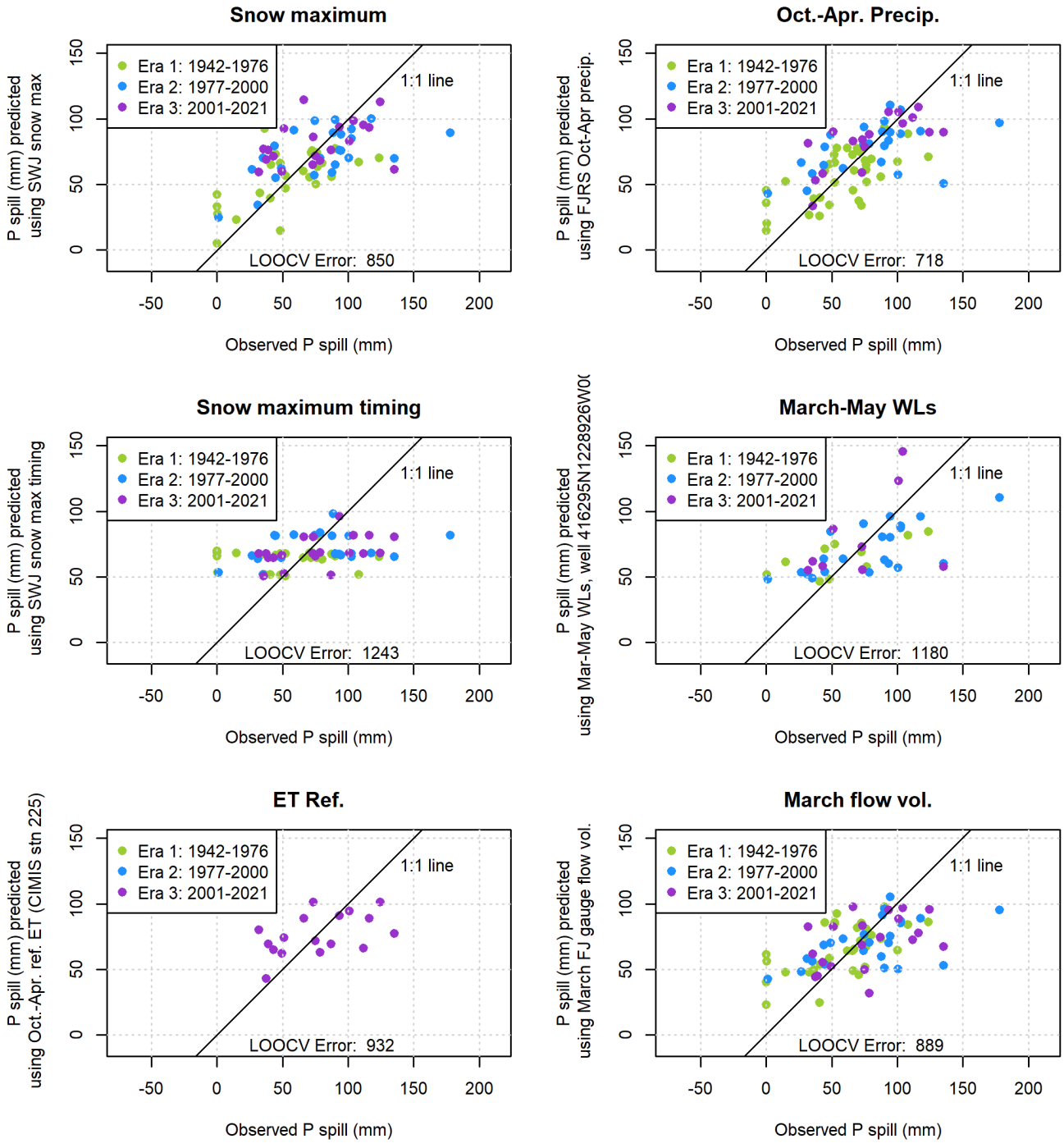



**Figure A6.** Single-predictor models of P spill, the cumulative precipitation after the dry season needed to generate 120 cfs of flow in the Scott River.

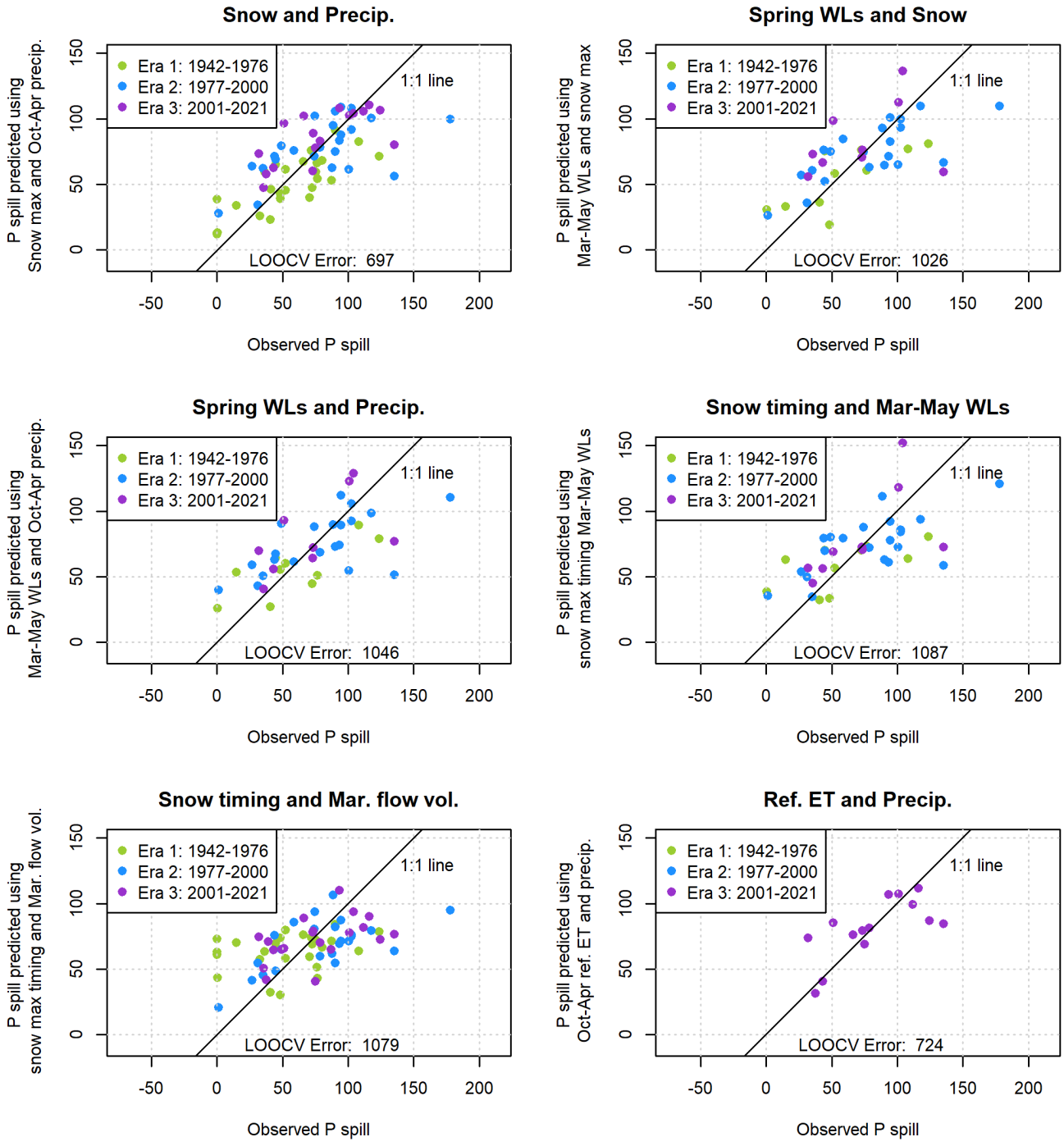



**Figure A7.** Two-predictor models of P spill, the cumulative precipitation after the dry season needed to generate 120 cfs of flow in the Scott River.

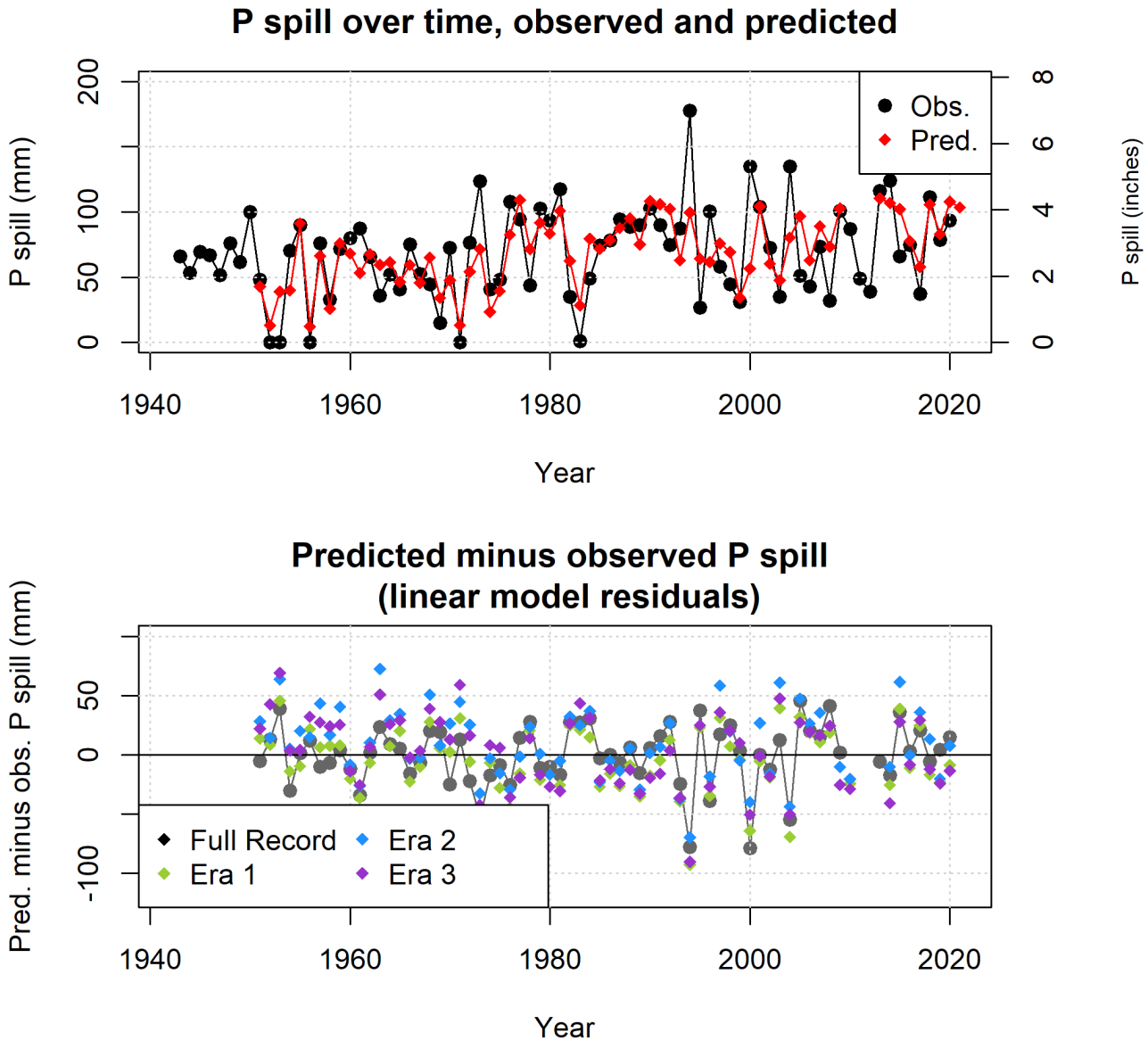



**Figure A8.** Observed and predicted values of P spill (panel A) indicate a worse model fit for the P spill prediction than for minimum 30-day dry season baseflows. Serious overprediction in Era 1 is followed by more mixed over- and under-prediction in Eras 2 and 3 (bottom panel). The overall P spill model is based on observations from the full record, but three additional models were generated based on only the observations from Eras 1, 2, and 3. Residuals based on Era 1 data are generally lower than those from Eras 2 or 3 or from the full record.

**Table A5.** Linear model diagnostics for two-predictor models of P spill. See table of one-predictor models for description of predictor IDs. Reference ET was not included in two- and three-predictor models due to an insufficient sample size.

| Predictor 1 | Predictor 2 | n | Log Likelihood | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | 67 | -312 | 631 | 697 | 0.51 |
| SWJ_max_wc_mm | SWJ_jday_of_max | 70 | -333 | 674 | 870 | 0.39 |
| SWJ_max_wc_mm | springWL_415635N1228315W001 | 50 | -240 | 487 | 951 | 0.38 |
| SWJ_max_wc_mm | mar_flow | 70 | -333 | 674 | 853 | 0.39 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | 67 | -315 | 637 | 760 | 0.47 |
| USC00043182_oct_apr_mm | springWL_415635N1228315W001 | 47 | -224 | 457 | 920 | 0.43 |
| USC00043182_oct_apr_mm | mar_flow | 75 | -351 | 709 | 728 | 0.44 |
| SWJ_jday_of_max | springWL_415635N1228315W001 | 50 | -243 | 493 | 1068 | 0.30 |
| SWJ_jday_of_max | mar_flow | 70 | -341 | 690 | 1079 | 0.23 |
| springWL_415635N1228315W001 | mar_flow | 50 | -242 | 493 | 1067 | 0.31 |

**Table A6.** Linear model diagnostics for three-predictor models of P spill. See table of one-predictor models for description of predictor IDs. Reference ET was not included in two- and three-predictor models due to an insufficient sample size.

| Predictor 1 | Predictor 2 | Predictor 3 | n | Log Like. | AIC | LOOCV | R squared |
|---|---|---|---|---|---|---|---|
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | SWJ_jday_of_max | 67 | -311 | 633 | 712 | 0.52 |
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | springWL_415635N1228315W001 | 47 | -222 | 455 | 874 | 0.47 |
| SWJ_max_wc_mm | USC00043182_oct_apr_mm | mar_flow | 67 | -312 | 633 | 714 | 0.51 |
| SWJ_max_wc_mm | SWJ_jday_of_max | springWL_415635N1228315W001 | 50 | -239 | 488 | 973 | 0.39 |
| SWJ_max_wc_mm | SWJ_jday_of_max | mar_flow | 70 | -332 | 675 | 872 | 0.40 |
| SWJ_max_wc_mm | springWL_415635N1228315W001 | mar_flow | 50 | -239 | 488 | 955 | 0.40 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | springWL_415635N1228315W001 | 47 | -224 | 457 | 936 | 0.44 |
| USC00043182_oct_apr_mm | SWJ_jday_of_max | mar_flow | 67 | -314 | 638 | 768 | 0.48 |
| USC00043182_oct_apr_mm | springWL_415635N1228315W001 | mar_flow | 47 | -223 | 457 | 923 | 0.45 |
| SWJ_jday_of_max | springWL_415635N1228315W001 | mar_flow | 50 | -240 | 490 | 1008 | 0.37 |

### A.5 Diagnostic plots for selected models

Standard diagnostic plots for the selected predictive models for $V_{min}$ and $P_{spill}$. For $V_{min}$, these diagnostic plots highlight outlier record 42, which corresponds to the year 1983, when an early September storm followed a wet year. For $P_{spill}$, three lesser outliers are highlighted, corresponding to water years 1994, 2000 and 2004, in which the three highest values of $P_{spill}$ were observed. These outliers represent the basin in extreme hydrologic conditions, so are retained in the dataset even though they exert disproportionate leverage over the predictive models.

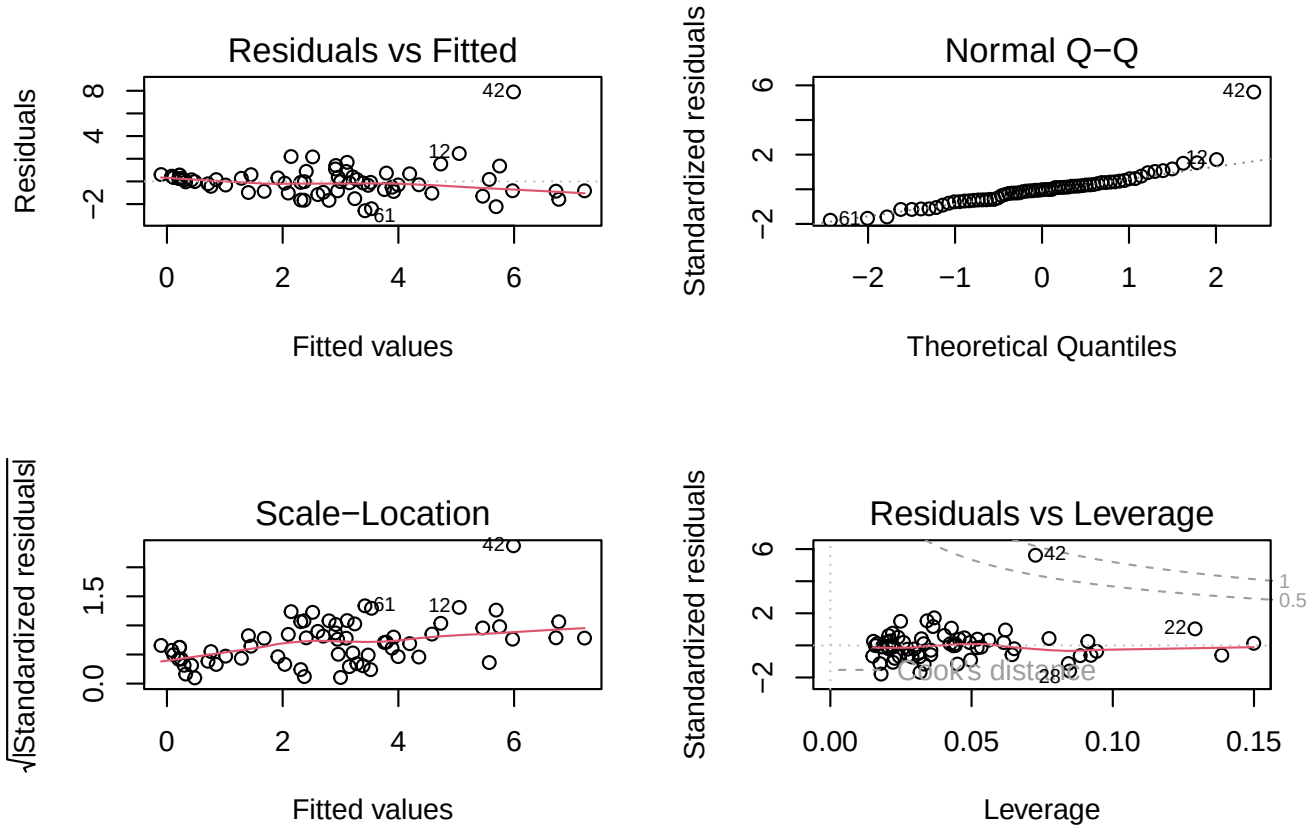



**Figure A9.** Diagnostic plots for the selected predictive models of V min.

. Analyses and figures in this manuscript were drafted in RMarkdown. The RMarkdown scripts are available on the corresponding author's GitHub page. All data used in this manuscript are publicly available on local, state or federal data portals.

. The authors declare no competing interests.

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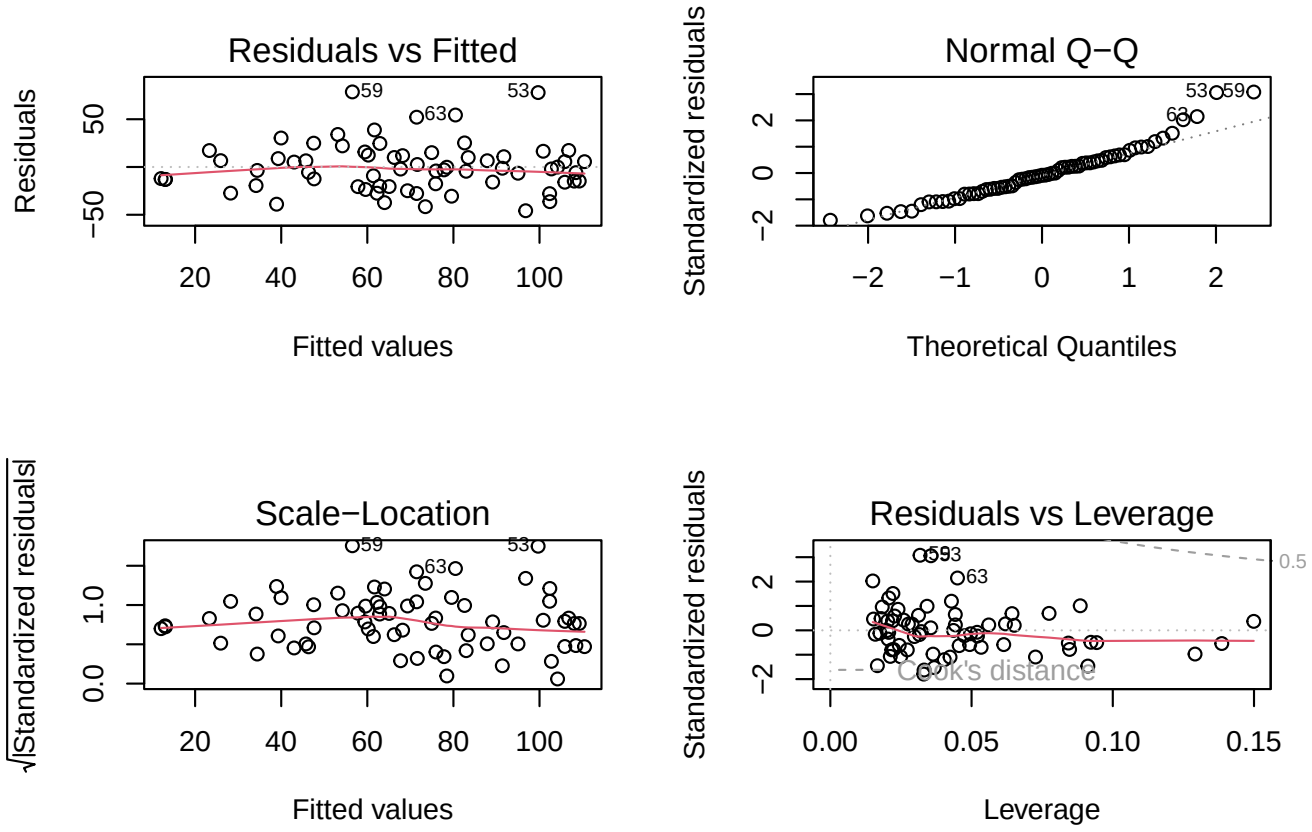


**Figure A10.** Diagnostic plots for the selected predictive models of P spill.

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