Disentangling effects of rainfall and water management on water levels in Everglades National Park

November 15 2025

South Florida Natural Resources Center

University of California San Diego

Scripps Institution of Oceanography

Cooperative Ecosystem Studies Units, University of California San Diego

Cover picture rendering rainfall dominance in Everglades.

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EXECUTIVE SUMMARY

The First Biennial Review on Progress Toward Restoring the Everglades (2006) recognized adaptive management as a lynchpin of restoration success. Adaptive management is reliant on data to inform decisions, however, data sampling may be insufficient to adequately characterize the complex processes unfolding at management locations and remote natural areas. This is particularly true in the case of hydrological management where controls are applied at structures and canals surrounding the Everglades but the objective is to asses hydrological response in natural areas remote from the control. Another level of complexity arises since rainfall is the dominant hydrological forcing, while the integrated response of rainfall and water management are the observed result.

This report details efforts to disentangle rain–driven water levels from those induced by water management on the periphery of the Everglades. As these are state–dependent, nonlinear dynamics we employ appropriate data–driven nonlinear dynamical systems analysis to determine the relationships. As reported in Park & Paudel (2024) the stage/rain relationships were found to be invariant over the period of record indicating the mechanism by which stage responds to rain has not changed setting the stage to extend the analysis here with inclusion of water management flows.

On multiyear time scales spanning multiple wet/dry seasons the familiar dominance of rainfall in Everglades hydrology is expressed. Generally, the ratio of cumulative rain to flow components of stage at wilderness sites decreases over the progression of water management plans from IOP to COP suggesting that management flows are becoming increasingly important drivers of marsh water levels.

Two COP temporary deviations are also examined, one in 2020–2021, the second in 2023–2024 focusing on dry season discharges from S12A+B and response at NP-205. On short (daily) time scales rain components can dominate stage changes, while on longer time scales structure flow can dominate. Since structure flows operate continuously over extended periods their integrated contribution to NP-205 stage change over the deviation periods were 90% and 80% for the 2020–2021 and 2023–2024 deviations respectively. It should be emphasized these deviations spanned dry seasons where rain is typically sparse. Collectively the results accentuate the importance of time scale and model application period in estimation of stage components.

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1 Introduction

This work represents a collaboration within the Cooperative Ecosystems Studies Units (CESU) between the U.S. Department of the Interior South Florida Natural Resources Center (SFNRC) and the Sugihara Lab, Scripps Institution of Oceanography, UCSD. The project: *Disentangling the effects of rainfall and water management on the water levels and flows in Everglades National Park* seeks to separably quantify Everglades water level response into components of rainfall and water management actions. Figure 1 provides geographic overview of the study area, data monitoring sites and water control structures.

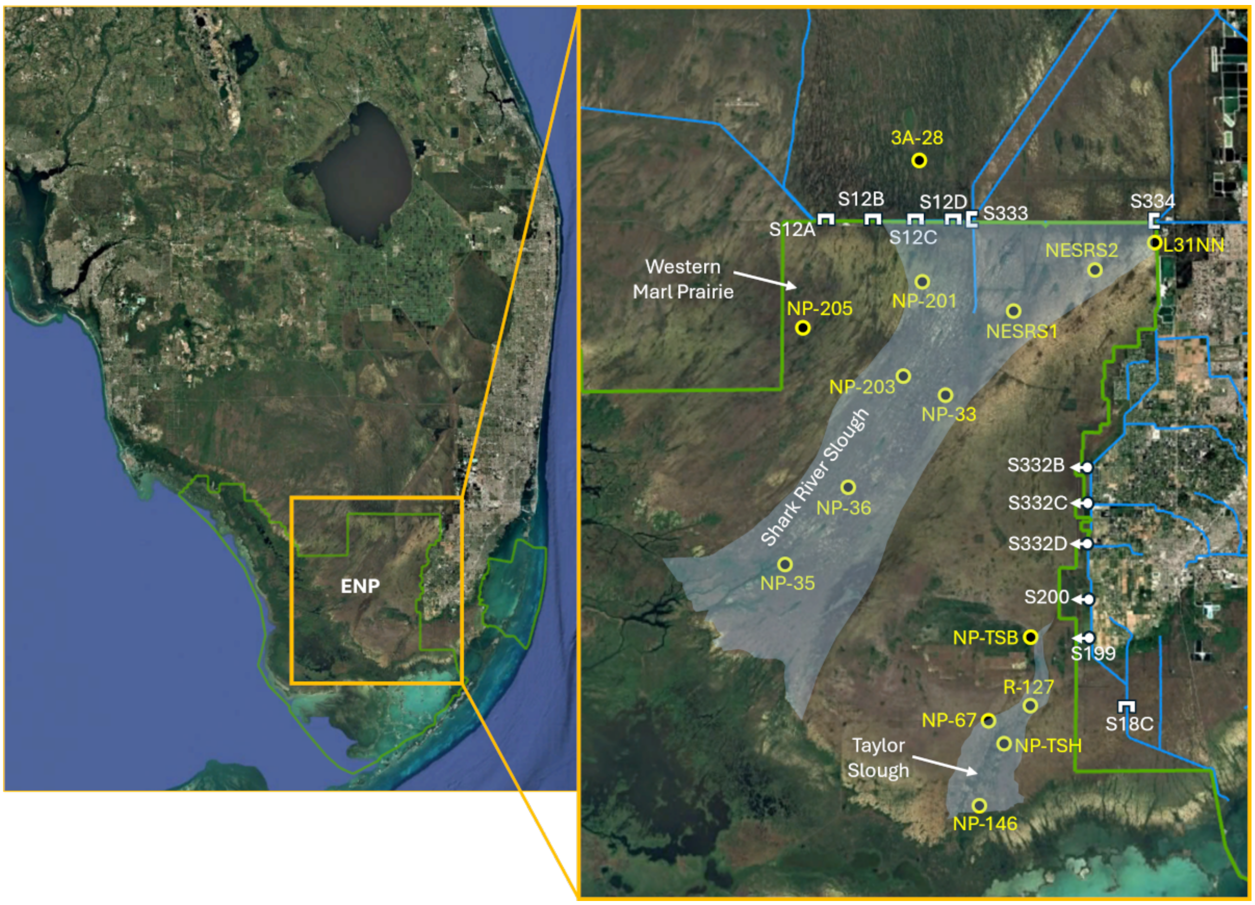

Figure 1. Satellite imagery highlighting Shark River Slough, Taylor Slough marsh station and water management control locations.

1.1 Previous Results

Previous work (Park & Paudel, 2024) explored fundamental aspects of the rain-stage response at marsh gauges finding:

1. The use of sequential globally weighted local linear maps (S-Map) in a multivariate embedding of rain and stage allows estimation the time varying rate at which rain (R) produces a change in stage (S): $\partial S/\partial R$

2. The rate at which stage changes from rain $\partial S/\partial R$ is a stage–dependent function reflecting local hydrogeological and topographical conditions

3. The stage–dependence of $\partial S/\partial R$ has not changed since 2000

4. The distribution of the component (fraction) of stage response attributed to rain has not changed from IFT to COP even though water levels and rainfall have increased and management infrastructure and operations have changed, indicating the mechanism by which stage responds to rain has not changed over the period of record.

1.2 Water Management Flows

The foregoing indicates that site–specific $\partial S/\partial R$ characterizing the stage/rain response can be considered an invariant across water management plans. Leveraging these results, we seek to apply them at marsh water level stations with incorporation of management–dependent flows to assess the relative contribution of rain and management to water level dynamics in the Everglades.

Here we extend the previous rain/stage models to include specified water management structure flows over six periods:

WMP	POR
ISOP/IOP USACE E (2006)	2000-01-01 - 2011-12-31
ERTP USACE (2016)	2012-01-01 - 2015-12-31
IFT	2016-01-01 - 2020-08-31
COP USACE (2020 a)	2020-09-01 - 2025-02-15
COP Deviation USACE (2020)	2020-10-15 - 2021-01-31
COP Deviation USACE (2023)	2023-11-05 - 2024-03-30

Table 1. Water management plan (WMP) and period of record (POR) over which rain and management flow components are estimated.

2 Data

Data were obtained at 33 monitoring stations from the water conservation areas to the southern Everglades as shown in figure 1. All data were downloaded from DBHydro and aggregated into daily values (mean water level, sum rainfall and flow) by DBHydro. All data were visually inspected to identify and remove invalid records. Data imputation details are provided in Park & Paudel (2024).

2.1 Water Level

Figure 2 plots key water level records in L-29, Shark River Slough, L-31 and Taylor Slough from 1990-01-01 through 2025-02-15. Stations P33 and G620 are not shown.

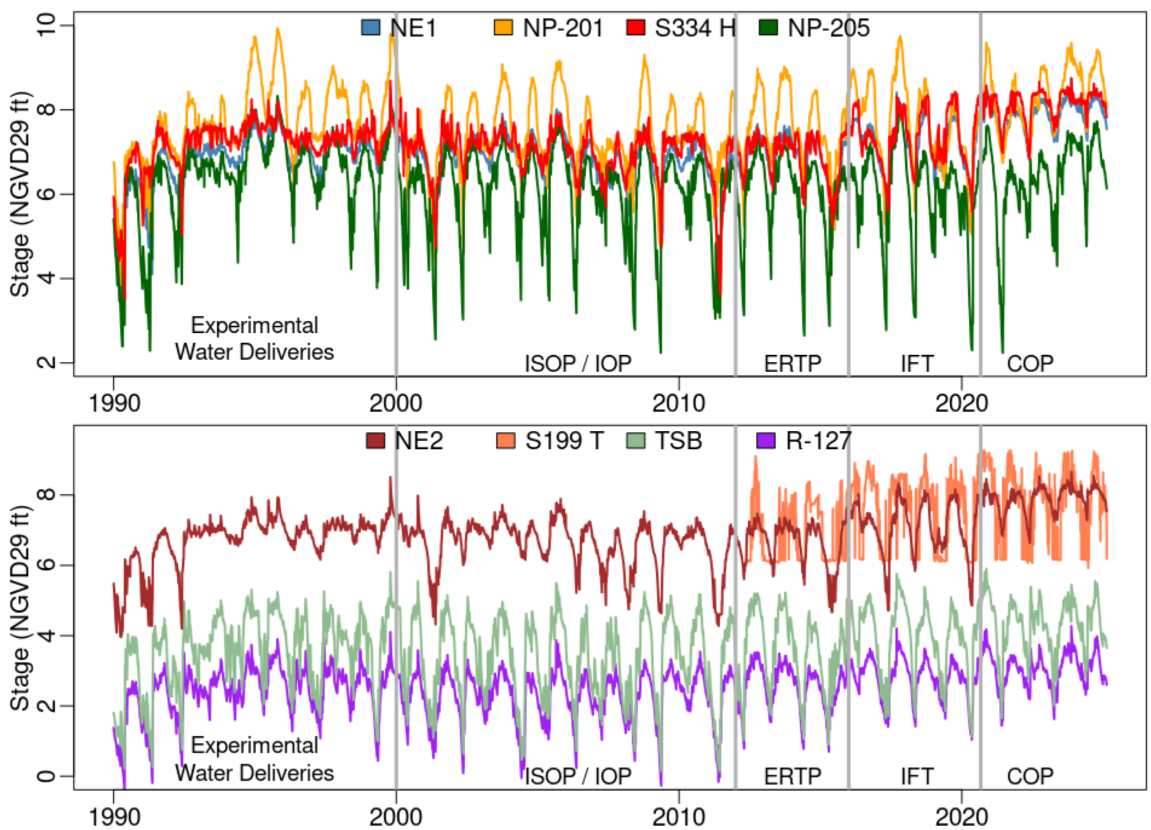

Figure 2. Key water level records examined in this report. ISOP: Interim Structural Operational Plan, IOP: Interim Operational Plan, ERTP: Everglades Restoration Transition Plan, IFT: Incremental Field Tests, COP: Combined Operational Plan. Stations P33 and G620 are not shown.

2.2 Rain

As we seek to unravel changes in marsh water levels in response to rainfall and management actions, it is important to assess the stationarity of regional rainfall. A study adopted by the South Florida Regional Climate Change Compact (S. FL Cli. Chng. Compact, 2020) found that South Florida rainfall can be considered stationary over 1892–2008.

On shorter time scales over which management plans are active, rainfall differences can be important. Table 2 lists mean yearly rainfall at the available rain stations suggesting the northern and central Everglades did not experience widely different rainfall averages between the IOP and COP regimes. S12D and Taylor Slough are found to have roughly an additional 6–7 inches of yearly rain during COP than IOP, however, one standard deviation of yearly rain at these stations ranges from 8 to 10 inches. Comparing conditions between IFT and COP, rain at NP-205 and TSB appear significantly higher during COP with approximately 12 and 14 additional inches of yearly rain during COP, the other stations not indicating a substantial difference.

Station	IOP	ERTP	IFT	COP	Std Dev	$\Delta R_{IOP:COP}$	$\Delta R_{IFT:COP}$
S-12D	48.6	52.2	54.0	55.9	8.0	7.3	1.9
NP-201	55.4	41.4	51.6	52.5	10.5	-2.9	0.9
NP-205	52.4	42.0	43.9	55.6	10.0	3.2	11.7
P33	56.9	47.6	54.8	55.6	11.0	-1.3	0.8
TSB	55.0	61.0	47.8	61.7	8.6	6.7	13.8
R-127	50.8	56.6	50.6	57.3	9.6	6.5	6.7

Table 2. Mean of yearly rain during water management plan periods, standard deviation over all years, differences between IOP and COP ($\Delta R_{IOP:COP}$), and IFT and COP ($\Delta R_{IFT:COP}$).

3 Rain & Flow Components

To identify the conjunctive response of marsh stage to rain, management flows and stage conditions, we invoke a 3–D model to predict current stage S(t) from the previous days rain R(t − 1), flow F(t − 1) and stage S(t − 1):

$$S(t) = C_0 + \frac{\partial S_t}{\partial R_{t-1}} R(t-1) + \frac{\partial S_t}{\partial F_{t-1}} F(t-1) + \frac{\partial S_t}{\partial S_{t-1}} S(t-1) \tag{1}$$

Since the terms in equation 1 sum to the total stage the second term $\frac{\partial S_t}{\partial R_{t-1}} R(t-1)$ represents the contribution of rain to the change in stage, the third term $\frac{\partial S_t}{\partial F_{t-1}} F(t-1)$ the contribution of flow to the change in stage and the fourth term $\frac{\partial S_t}{\partial S_{t-1}} S(t-1)$ the prexisting stage state dependence. Units are stage in feet (NGVD29), rain in inches, and flow in CFS. Stage and flow are daily averages, rain summed over one day.

To simplify nomenclature and emphasize the time dependence of the derivative coefficients, we use $\alpha(t) = \frac{\partial S_t}{\partial R_{t-1}}$, $\beta(t) = \frac{\partial S_t}{\partial F_{t-1}}$, $\gamma(t) = \frac{\partial S_t}{\partial S_{t-1}}$

$$S(t) = C_0 + \alpha(t)R(t-1) + \beta(t)F(t-1) + \gamma(t)S(t-1) \tag{2}$$

The coefficients $C_0, \alpha(t), \beta(t), \gamma(t)$ are found through sequential globally weighted local linear maps (Sugihara, 1994).

The degree of nonlinearity in S-Map is determined with a parameter θ. After exploring the range of θ from 0-15 we selected $\theta = 1.5$ for all models. Changing the value of θ changes the global weighting on nearest neighbors and for nonlinear systems can be expected to change the coefficients and model results.

Note: Inclusion of other variables might change the relative contributions found with the three component model. However, the finding that rain and flow are dominant drivers under different conditions is not expected to change.

3.1 Water Management Plans

The period over which equation 2 is applied reveals dynamics specific to the period. Previous work found that focusing on rain and flow contributions during the dry season emphasizes the time scale dependence of episodic rain events and continuous flow. Here we examine rain and flow contributions over management plan periods at seven marsh stations listed in table 3.

Stage	Rain	Flow
NP-205	NP-205	S12A + S12B
NP-201	NP-201	S12D
NESRS1	NP-201	S333 + S356
NESRS2	NP-201	S333 + S356
P33	P33	S12C + S12D + S333
G-620	P33	S12B + S12C + S12D
R-127	R-127	S199 + S200 + S332D

Table 3. Rain stations and water management flows used in equation 2 over water management plan periods. Other flow selections can be used to focus on specific management actions.

3.1.1 NP-205

Rain and S12A+B flow components of NP-205 stage over management plan periods are shown in figure 3 where multiple wet and dry seasons are recorded for each WMP. A notable result is the downward progression of cumulative rain–to-flow ratio over the management plans, from 4.4 during IOP, to 4.1 during ERTP, 3.8 over IFT and 3.6 over COP suggesting the relative influence of S12A+B flow is increasing over management plan periods.

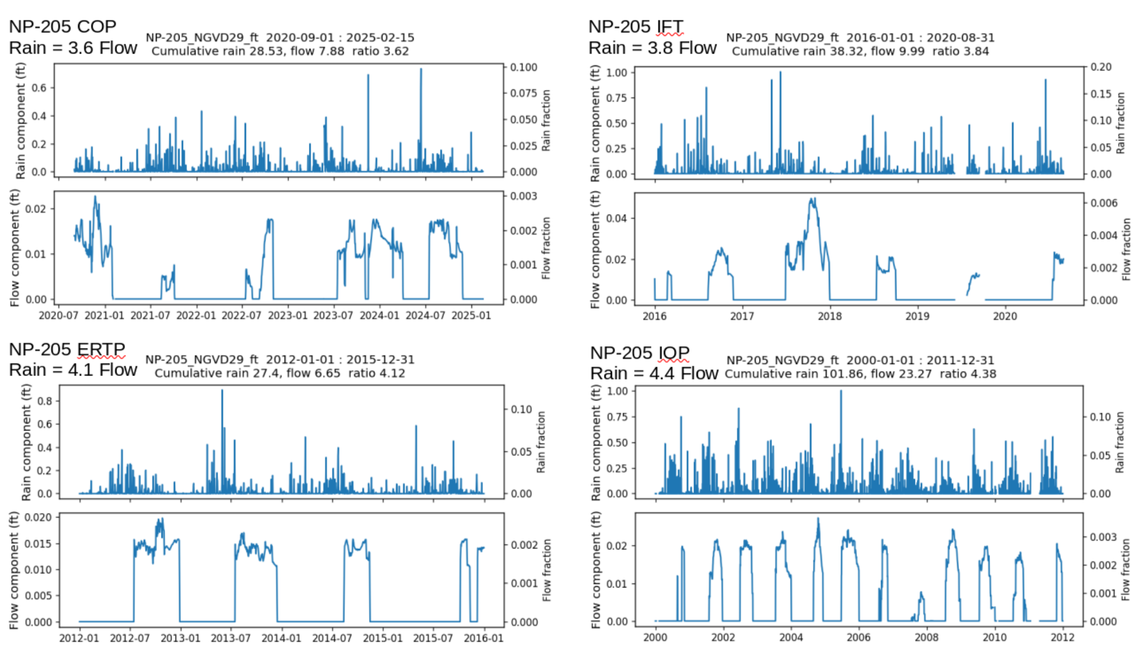

Figure 3. Estimates of rain and S12A + S12B flow components of NP-205 water level changes over COP, IFT, ERTP and IOP management plan periods.

3.1.2 All Stations

The ratio of cumulative rain to stage components at all stations listed in table 3 are shown in figure 4 with site–specific results provided in Appendix A. A consistent feature of the cumulative Rain/Flow component ratio is a decrease over the progression of management plans. This suggests the influence of management flows on water level changes are becoming increasingly important. We note the decreasing influence of rain cannot be explained by a reduction in rainfall between water management plans as rainfall recorded during COP is generally higher than preceeding WMP (table 2).

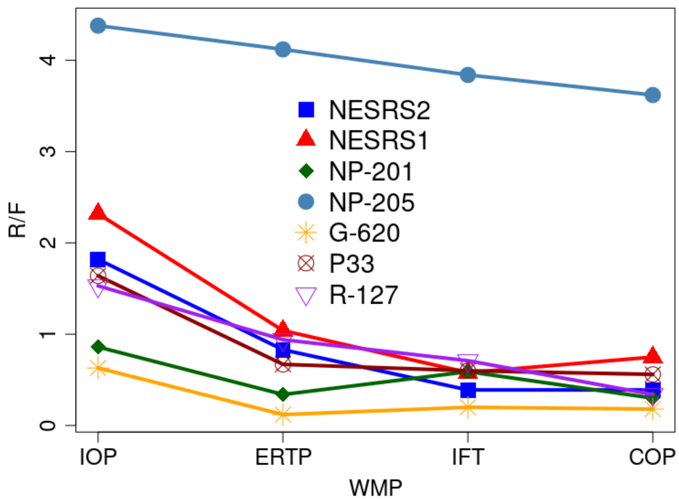

Figure 4. Ratio of cumulative estimated rain (R) and flow (F) components of water level changes over IOP, ERTP, IFT and COP water management plan (WMP) periods.

Examination of figure 4 raises the question: Why is the Rain/Flow ratio at NP-205 higher than other stations? Examination of NP-205 stage data in figure 2 shows that in relation to other stations dry season minimums are much deeper indicating subterranean stage changes at NP-205 are significantly greater than other stations. This is consistent with the ∂S/∂R stage dependence identified in Park & Paudel (2024) and shown in figure 5 where NP-205 subterranean stage response is generally larger than other stations. This indicates the increased importance of rain at NP-205 is a result of subsurface hydrogeology with heightened stage response to rain.

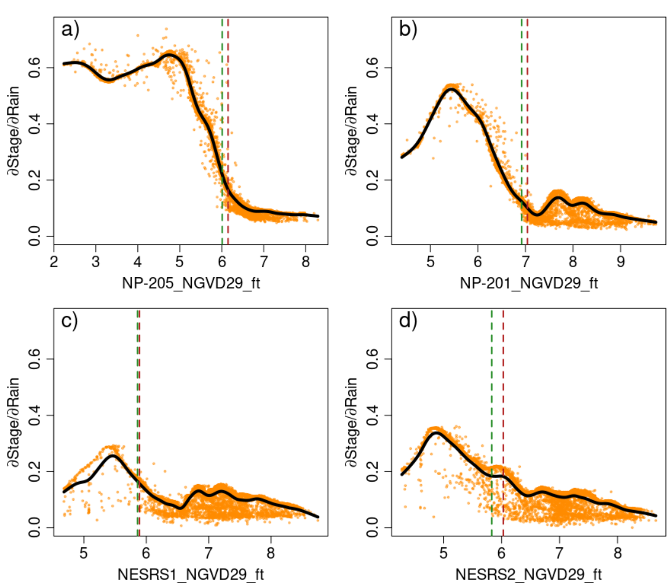

Figure 5. ∂S/∂R **as a function of stage at a) NP-205 b) NP-201 c) NESRS1 d) NESRS2. Vertical dashed lines indicate land surface elevation of dominant and secondary vegetation.**

3.2 COP Deviations

Since the COP implementation in September 2020 two temporary water management deviations allowing S12A, S12B and S343 flows during seasonal closures have occurred:

1. November 4, 2020 – January 31, 2021 (USACE, 2020)
2. November 16, 2023 – March 31, 2024 (USACE, 2023)

Here, we quantify contributions of rainfall and S12A + S12B flow to changes in NP-205 stage during these two management deviations. Figure 6 plots observations of NP-205 rain, stage, and S12A flow during the deviations. The 2020–2021 deviation is characterized by significant rainfall during the October to mid–November 2020 time frame. S12A flow was significant with increasing flow through much of November, with continued large flows through January. S12B flow was essentially the same as S12A over the period, thus combined flow during mid–November to mid–December exceeded 2000 CFS with peak values of 2710 CFS on November 23. NP-205 stage response reflects both the rainfall and flow contributions with short time scale spikes corresponding to rain events, and longer time scale variation consistent with the flow profile. The 2023–2024 deviation was qualitatively different with an isolated, large mid-November rain event and significantly lower flows.

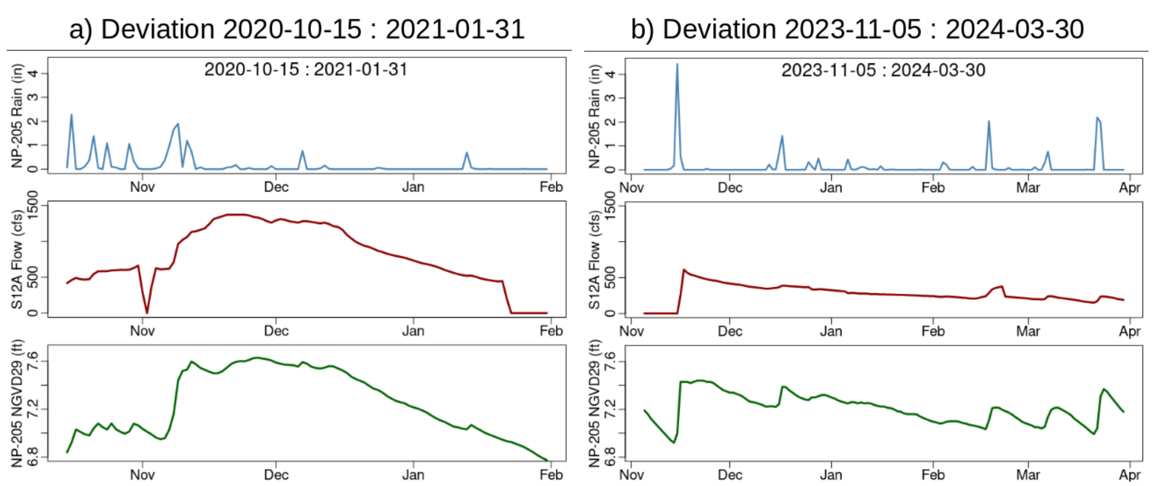

Figure 6. Observed rain (top), S12A flow (middle) and NP-205 stage (bottom) for a) 2020 COP Deviation, b) 2023 COP Deviation.

Coefficients of equation 2 are presented in figure 7. Horizontal dashed lines are linear model coefficients, thus the linear model provides a static representation of the stage dependencies rather than a dynamic, state–dependent one. Owing to the significant inertia (autocorrelation) in marsh water levels, the dominant component is $\gamma(t)$ representing the effect of the state of preceding water level. The rain ($\alpha(t)$) and flow ($\beta(t)$) coefficients capture the internal interplay between rain, flow and stage, and should be noted these are not values of rain or stage, but internal derivatives of the dynamic relationships.

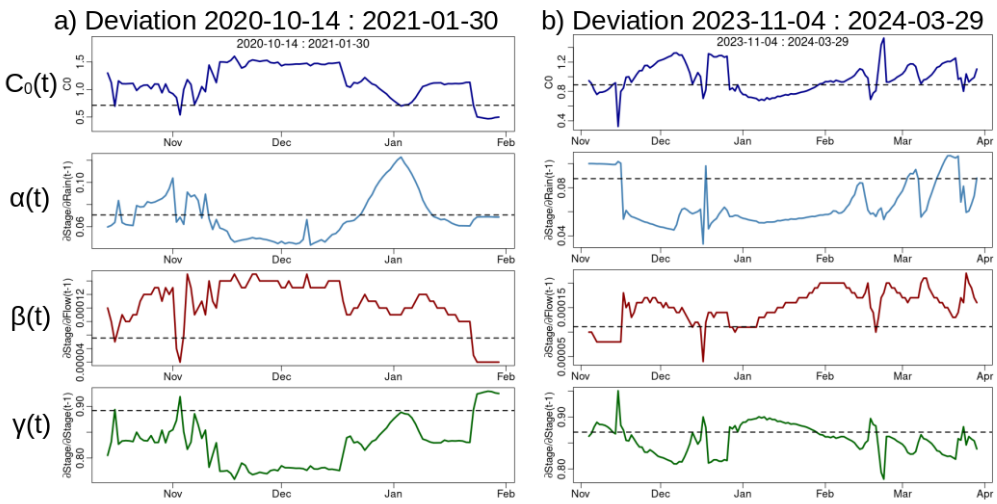

Figure 7. Coefficients $\mathrm{C_0(t)}, \alpha(\mathrm{t}), \beta(\mathrm{t}), \gamma(\mathrm{t})$ **for a) 2020 b) 2023 COP deviations.**

Figure 8 shows the projection of model coefficients onto the data representing the rain and flow terms in equation 2.

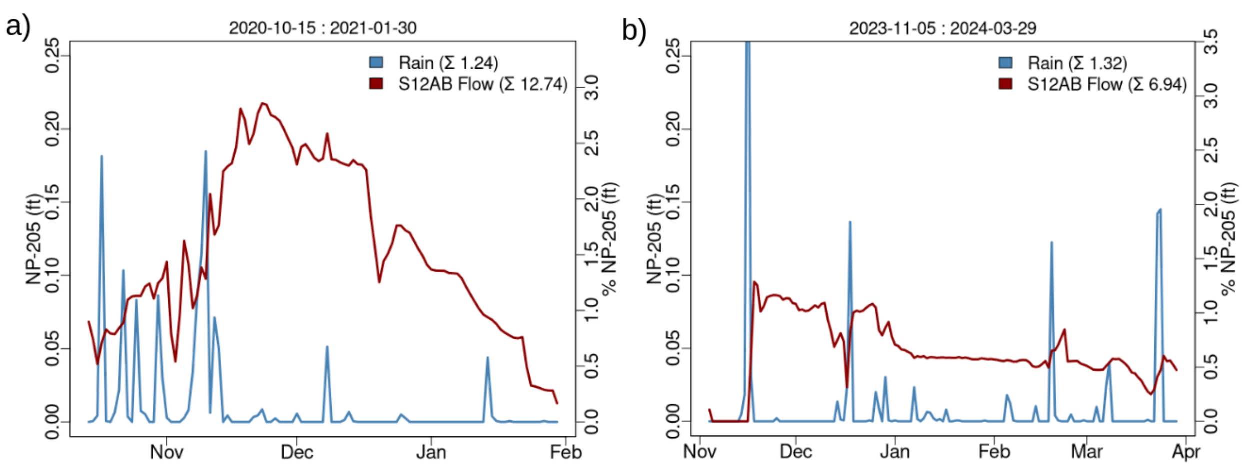

Figure 8. Rain and S12A+B flow components of changes in NP-205 stage during a) 2020 COP Deviation, b) 2023 COP Deviation.

As a general inference, when significant rain events occur (rain $>$ 1 in/day) rain can be the dominant contributor to NP-205 stage change on short time scales. This is evident in the first month of the 2020–2021 deviation and throughout the 2023–2024 deviation. When S12A & S12B are flowing, flow can be the dominant contributor to NP-205 stage change over longer time scales resulting in larger cumulative contributions. For example, over the entire 2020–2021 deviation the cumulative change in NP-205 stage from rain is estimated at 1.24 feet, while the flow component is 12.74 feet suggesting rain influence was $\approx$10% that of flow. Over the 2023–2024 deviation cumulative changes in stage from rain and flow are estimated at 1.32 and 6.94 feet, indicating a roughly 20% contribution from rain.

This suggests the relative contribution of rainfall and S12A/B flow to changes in NP-205 dry season stage are complex acting over different time scales with dependence on antecedent conditions.

4 Discussion

Water management in large-scale ecosystem restoration projects such as the Everglades represent not only an operational water management challenge, but also a balancing act between ecological resilience and societal needs. Our findings underscore that state-dependent empirical modeling can reveal when and where water management actions influence hydrological conditions in sensitive habitats, such as marl prairies inhabited by the endangered Cape Sable Seaside Sparrow. In this context our findings support long-standing calls for explicitly integrating ecosystem needs into water management operations of multi-stakeholder landscapes such as the Everglades Sklar et al. (2005).

From a broader natural resource management perspective, the methods demonstrated here provide a scalable, data-driven tool for adaptive management informing decision frameworks responsive to new information and changing conditions. For example, the current COP can be dynamically adjusted in response to climatic and infrastructural conditions discovered here.

As climate variability intensifies and restoration goals evolve, empirical dynamical methods can serve as early-warning indicators of management effectiveness, offering actionable insights without sole reliance on computationally intensive numerical models. Such approaches are inline with adaptive management strategies previously identified as essential for large ecosystem restorations under uncertainty Gunderson (2006). Furthermore, by empirically estimating hydrogeological response functions and their relation to hydrologic targets, the method supports development of more effective water management strategies that help achieve ecologically appropriate water levels for Everglades restoration - an essential step toward restoring pre-drainage hydroperiods and wetland function NRC (2012).

5 Conclusion

How effective are water management actions in producing targeted hydrologic responses in the Everglades? To what extent can such responses be attributed to water management actions and the dominant hydrological driver, rainfall? These questions are central to design and assessment of water management actions, yet are difficult to answer at marsh locations remote from management action sites. This work investigates whether data–driven analysis can identify interdependent components of marsh water level response to rainfall and management actions.

The initial phase of this project identified sequential globally weighted local linear maps (S-Map) estimate the rate at which rain produces a change in stage: $\partial S/\partial R$. This rate is both time and stage dependent. It was found that site-specific functions of $\partial S/\partial R$ were invariant over water management plans, with no discernible change in the ratio of the rainfall component to stage over time. The present work adds management flows to assess site-specific marsh response to rainfall and management flows.

The analysis was applied over different water management plan time periods (table 1) highlighting the importance of time scale in assessment of hydrological response. When applied to NP-205 stage with respect to S12A+B flows during 2020–2021 and 2023–2024 dry season

COP temporary deviations, results indicate that on short time scales rain can dominate stage response in relation to flow. Over longer time scales continuous flow contributes substantially more to stage response. For example, over the entire 2020–2021 deviation rain contributed roughly 10% of the stage response, while over the 2023–2024 deviation rain contributed roughly 20% of the stage response.

When assessed over multiyear periods encapsulating multiple wet/dry seasons the anticipated rain dominance is found at most stations. Over the progression of water management plans from IOP to COP most stations exhibit a decrease in the ratio of rain/flow components suggesting that flows are providing increasingly greater contributions to marsh stage response.

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Appendix A Rain & Flow Component Results

Equation 2 is applied over the period of each management plan to estimate the rain and flow components of stage change. The flow considered in the $\beta(t)F(t-1)$ term of equation 2 is a user–defined set of flow data. Results shown here use flows listed in 3. Flows at S-333 include contributions from S-333N, a nearby structure that has been in operation since November 15, 2020. Other selections can be used to focus on specific management flows.

Table 4 lists the ratio of cumulative rain to flow components over management plan periods, depicted in figure 4.

Station	Flow	IOP	ERTP	IFT	COP
NESRS2	S-333 + S-356	1.8	0.8	0.4	0.4
NESRS1	S-333 + S-356	2.3	1.0	0.6	0.8
NP-201	S-12D	0.9	0.3	0.6	0.3
NP-205	S-12A + S-12B	4.4	4.1	3.8	3.6
G-620	S-12B + S-12C + S-12D	0.6	0.1	0.2	0.2
P33	S-12C + S-12D + S-333	1.6	0.7	0.6	0.6
R-127	S-199 + S-200 + S-332D	1.5	0.9	0.7	0.3

Table 4. Ratio of cumulative rain to flow components (R/F) over management plan periods.

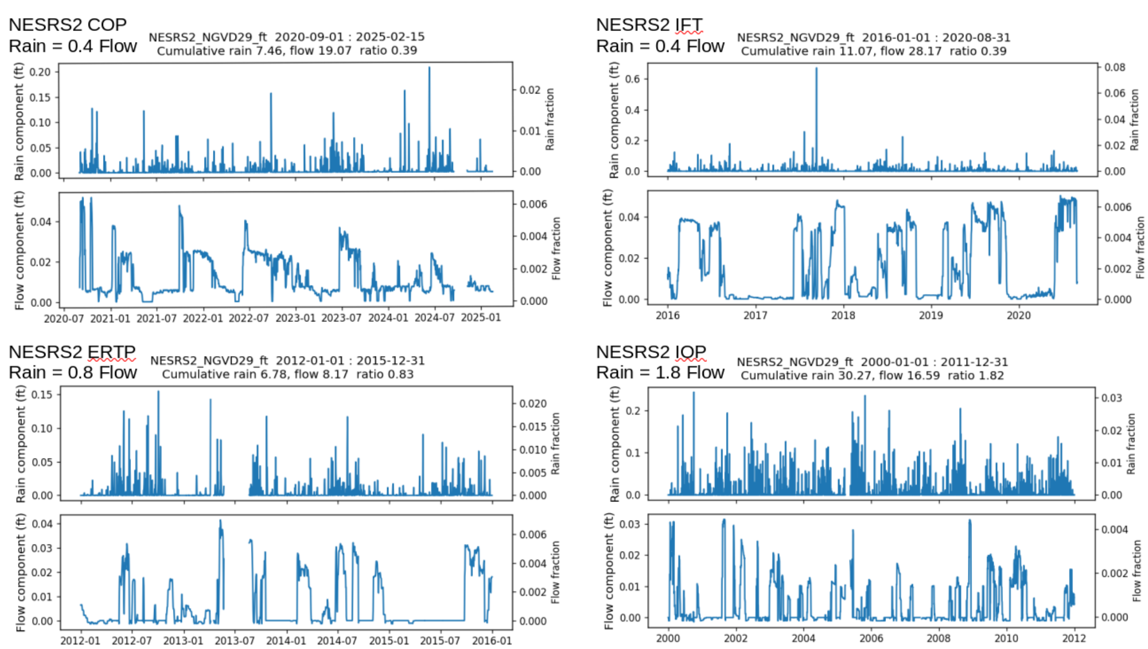


Figure 9. Estimates of rain and flow components of NESRS2 changes over COP, IFT, ERTP and IOP management plan periods.

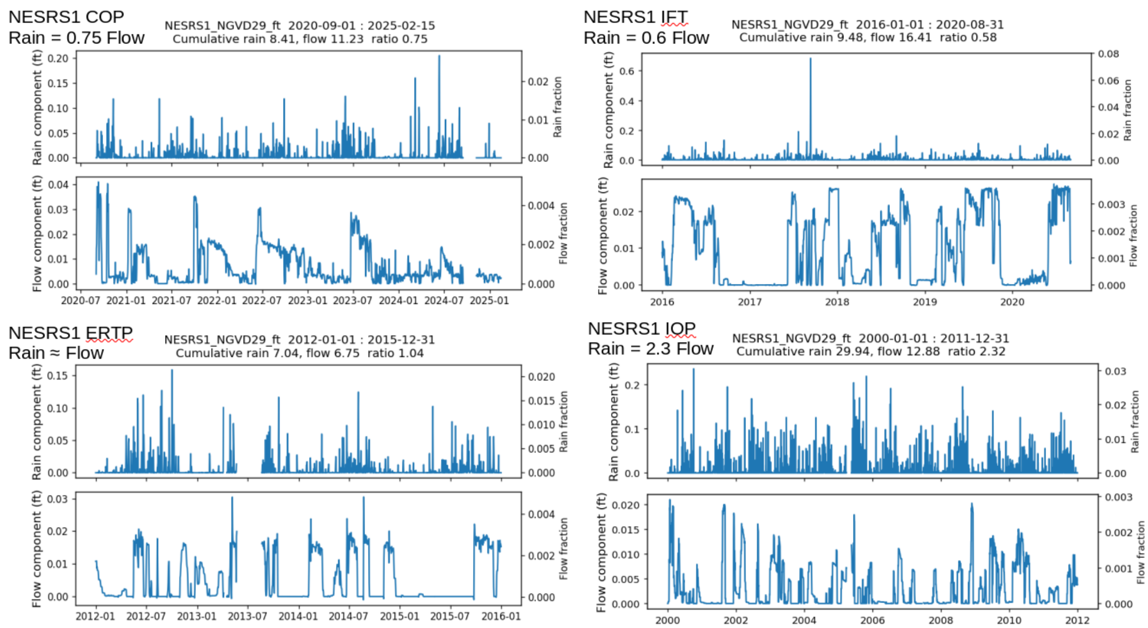


Figure 10. Estimates of rain and flow components of NESRS1 changes over COP, IFT, ERTP and IOP management plan periods.

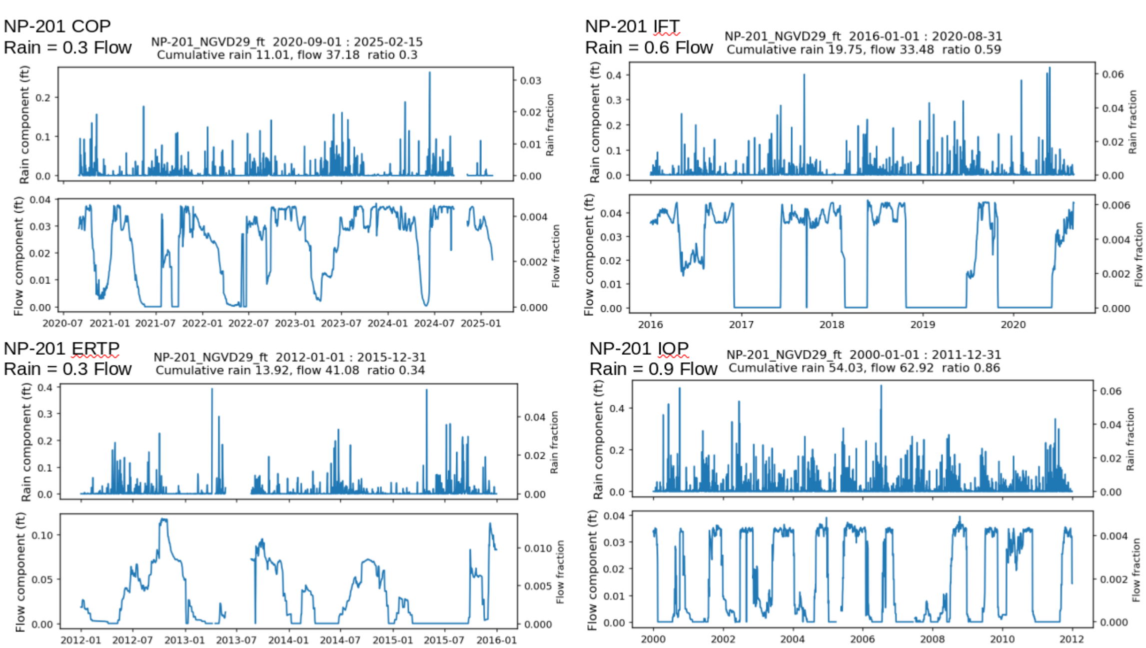


Figure 11. Estimates of rain and flow components of NP-201 changes over COP, IFT, ERTP and IOP management plan periods.

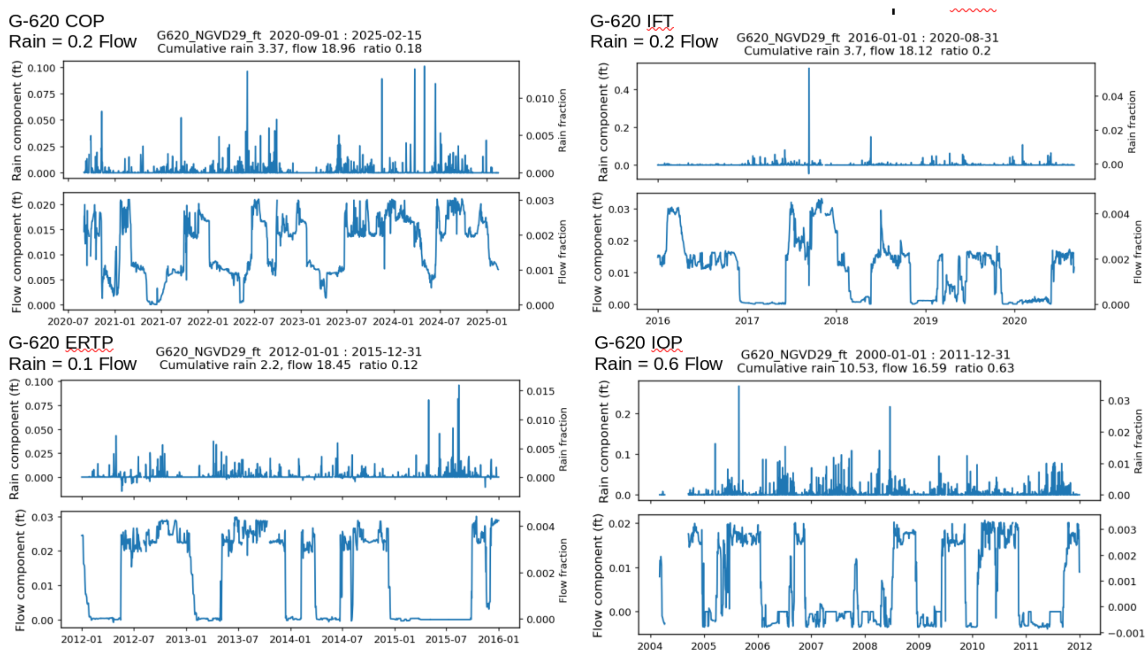


Figure 12. Estimates of rain and flow components of G-620 changes over COP, IFT, ERTP and IOP management plan periods.

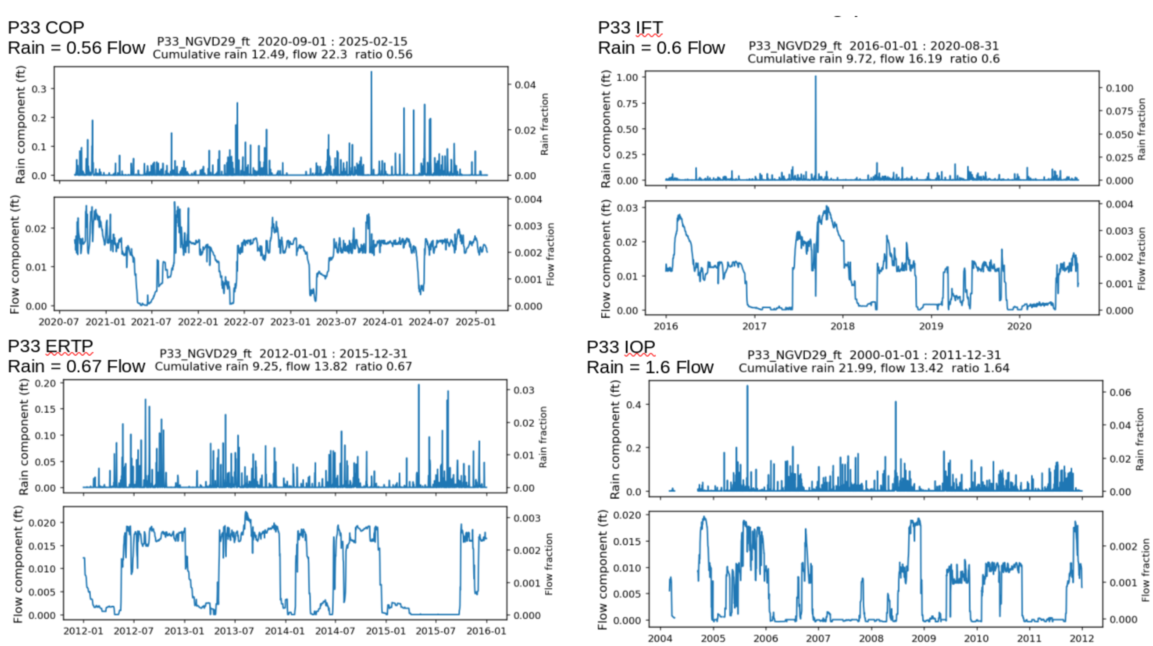


Figure 13. Estimates of rain and flow components of P33 changes over COP, IFT, ERTP and IOP management plan periods.

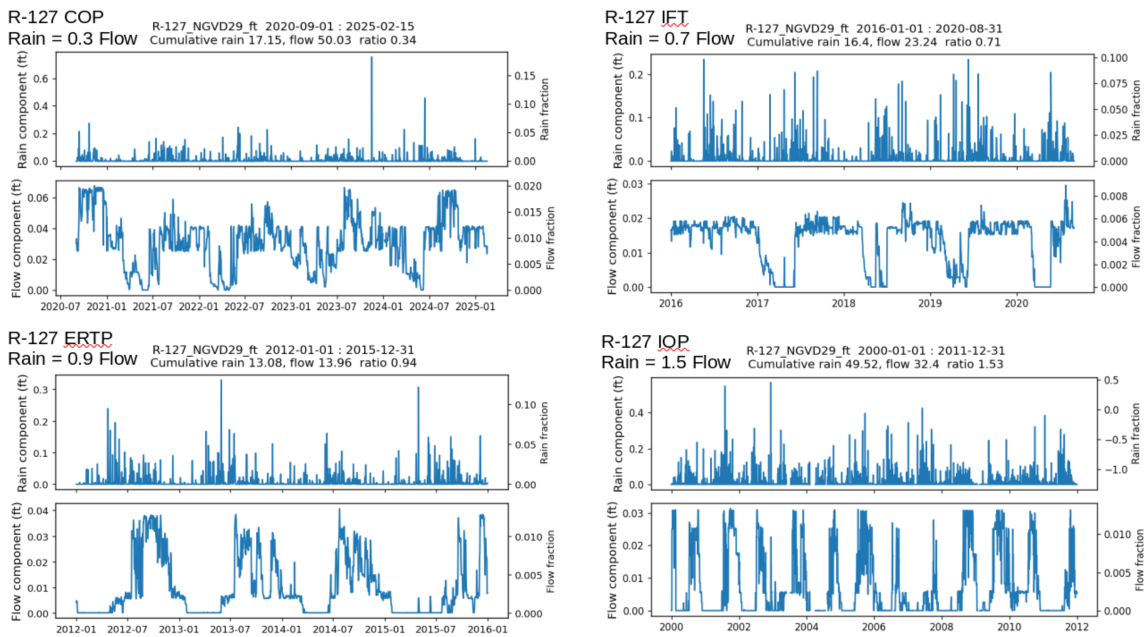


Figure 14. Estimates of rain and flow components of R-127 changes over COP, IFT, ERTP and IOP management plan periods.

Appendix B Python

Here we present Jupyter notebook pages documenting the methods and code.

Components of stage predicted from SMap

A 3 component model predicts Stage $S(t)$ from previous timestep Rain $R(t-1)$, Flow $F(t-1)$ and Stage $S(t-1)$:

$$S(t) \ = \ C_0(t) + \alpha(t)R(t-1) + \beta(t)F(t-1) + \gamma(t)S(t-1)$$

$C_0(t), \alpha(t),\ \beta(t),\ \gamma(t)$ are time dependent coefficients determined by Sequential Locally Weighted Global Linear Maps (SMap, Sugihara 1994).

The `param` dictionary holds dictionaries of parameters for each station. For example `param['NP-205']` is a dictionary with keys `['rain','stage','flow','elevation','Tp','theta']` where `param['NP-205']['flow']` is a list of flow variables summed into a single flow variable.

The model coefficients are multiplied by the respective data ($R(t-1), F(t-1)$) to quantify the contribution of rain and flow to stage. The fraction of each component to the total stage is plotted and stored in a DataFrame.

2-D models of rain and flow are computed to isolate changes in stage from rain ($\partial S/\partial R$) and flow ($\partial S/\partial F$).

Import modules

In [1]:
```
from numpy  import arange, where
from pandas import concat, DataFrame, read_csv, Series
from pyEDM  import SMap, Embed

from matplotlib import pyplot as plt
%matplotlib ipympl
```

Read Data

In [2]:
```
df = read_csv('../Data/Data_r2_1990-01-01_2025-02-15.csv')
print( f'shape: {df.shape}' )
```

```
shape: (12830, 29)
```

Parameters

```
Rain & flow drivers for SMap rain, flow

Stage    Rain    Flow
NP-205   NP-205  S12A + S12B
```

```
NP-201   NP-201  S12D
NESRS1   NP-201  S333 + S356  # S12D + S355A + S355B + S356
NESRS2   NP-201  S333 + S356  # S355A + S355B + S356
P33      P33     S12C + S12D + S333
G-620    P33     S12B + S12C + S12D
R-127    R-127   S199 + S200 + S332D
```

In [3]:
```
param = {'NP-205':{'rain':'NP_205_Rain_in', 'stage':'NP-205_NGVD29_ft', 'elevation':[6.01, 6.15],
                   'flow':['S12A_Flow_cfs', 'S12B_Flow_cfs'], 'Tp':0, 'theta':3 },

         'NP-201':{'rain':'NP-201_Rain_in', 'stage':'NP-201_NGVD29_ft', 'elevation':[6.92,7.04],
                   'flow':['S12D_Flow_cfs'],'Tp':0, 'theta':1.5 },

         'NESRS1':{'rain':'NP-201_Rain_in', 'stage':'NESRS1_NGVD29_ft', 'elevation':[5.86,5.89],
                   'flow':['S333_Flow_cfs', 'S356_Flow_cfs'], 'Tp':0, 'theta':1.5 },

         'NESRS2':{'rain':'NP-201_Rain_in', 'stage':'NESRS2_NGVD29_ft', 'elevation':[5.83,6.03],
                   'flow':['S333_Flow_cfs', 'S356_Flow_cfs'], 'Tp':0, 'theta':1.5 },

         'P33'   :{'rain':'P33_Rain_in', 'stage':'P33_NGVD29_ft', 'elevation':[5.43,5.55],
                   'flow':['S12C_Flow_cfs', 'S12D_Flow_cfs', 'S333_Flow_cfs'], 'Tp':0, 'theta':1.5 },

         'G-620' :{'rain':'P33_Rain_in', 'stage':'G620_NGVD29_ft', 'elevation':[6.8,6.8],
                   'flow':['S12C_Flow_cfs', 'S12D_Flow_cfs', 'S333_Flow_cfs'], 'Tp':0, 'theta':1.5 },

         'R-127' :{'rain':'R-127_Rain_in', 'stage':'R-127_NGVD29_ft', 'elevation':[1.65,1.68],
                   'flow':['S199_Flow_cfs', 'S200_Flow_cfs', 'S332D_Flow_cfs'], 'Tp':0, 'theta':1.5 }
        }
```

Function to return indices from Date match

In [4]:
```
def DateRowIndices ( df, var = 'Date', start = '2000-01-01', end = '2020-12-31' ) :
    '''Return df row indices of var equals start, end'''
    i_start = where( df.loc[:,var] == start )
    i_end   = where( df.loc[:,var] == end )
    return [i_start[0][0], i_end[0][0]]
```

start : end row indices for IOP / ERTP / IFT / COP

Note these are 0-offset

In [5]:
```
dev1 = DateRowIndices(df, start = '2020-10-15', end = '2021-01-31') # COP Deviation 1
dev2 = DateRowIndices(df, start = '2023-11-05', end = '2024-03-30') # COP Deviation 2
COP  = DateRowIndices(df, start = '2020-09-01', end = '2025-02-15')
IFT  = DateRowIndices(df, start = '2016-01-01', end = '2020-08-31')
ERTP = DateRowIndices(df, start = '2012-01-01', end = '2015-12-31')
```

```
IOP  = DateRowIndices(df, start = '2000-01-01', end = '2011-12-31')

dev1_i = arange( dev1[0], dev1[1] + 1 )
dev2_i = arange( dev2[0], dev2[1] + 1 )
COP_i  = arange( COP[0],  COP[1]  + 1 )
IFT_i  = arange( IFT[0],  IFT[1]  + 1 )
ERTP_i = arange( ERTP[0], ERTP[1] + 1 )
IOP_i  = arange( IOP[0],  IOP[1]  + 1 )
```

In [6]:

```
_i = dev1_i;print(f'dev1 n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
_i = dev2_i;print(f'dev2 n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
_i = COP_i; print(f'COP  n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
_i = IFT_i; print(f'IFT  n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
_i = ERTP_i;print(f'ERTP n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
_i = IOP_i; print(f'IOP  n={len(_i):4}  {int(_i[0]):5}-{int(_i[-1]):5}  {df["Date"][_i[0]]} {df["Date"][_i[-1]]}' )
```

```
dev1 n= 109  11245-11353  2020-10-15 2021-01-31
dev2 n= 147  12361-12507  2023-11-05 2024-03-30
COP  n=1629  11201-12829  2020-09-01 2025-02-15
IFT  n=1705   9496-11200  2016-01-01 2020-08-31
ERTP n=1461   8035- 9495  2012-01-01 2015-12-31
IOP  n=4383   3652- 8034  2000-01-01 2011-12-31
```

Chose site from param and management plan

Note index from DateRowIndices are 0-offset, EDM lib param is not, ergo + 1

In [7]:

```
#site = param['G-620']
#site = param['P33']
#site = param['NESRS1']
#site = param['NESRS2']
site = param['NP-205']
#site = param['NP-201']
#site = param['R-127']

plan, plan_i = COP,  COP_i
#plan, plan_i = IFT,  IFT_i
#plan, plan_i = ERTP, ERTP_i
#plan, plan_i = IOP,  IOP_i
#plan, plan_i = dev1, dev1_i
#plan, plan_i = dev2, dev2_i
```

Assign EDM lib indices and lib_i from plan

In [8]:

```
lib   = [ plan_i[0] + 1, plan_i[-1] + 1 ] # 1-offset for EDM
lib_i = plan_i                            # 0-offset for data access/plot
```

Sanity check : head & tail of site data during plan from df

In [9]:
```
_ = ['Date'] + [site['stage']] + [site['rain']] + site['flow']
concat( [ df.loc[lib_i[:2],_], df.loc[lib_i[-2:],_] ] )
```

Out[9]:

	Date	NP-205_NGVD29_ft	NP_205_Rain_in	S12A_Flow_cfs	S12B_Flow_cfs
11201	2020-09-01	6.700	0.00	294.0	231.0
11202	2020-09-02	6.730	0.00	287.0	226.0
12828	2025-02-14	6.159	0.01	0.0	0.0
12829	2025-02-15	6.133	0.00	0.0	0.0

Sum site flows into single variable `flowCFS`

In [10]:
```
flowCFS = df.loc[:,site['flow']].sum( skipna = True, axis = 1 )
```

New DataFrame with flowCFS

In [11]:
```
dfFlow = df.assign( flowCFS = flowCFS )
print( f'shape: {dfFlow.shape}' )
```

```
shape: (12830, 30)
```

Create multivariate embedding for SMap

Use `E = 2` to create (t-1) time delay

In [12]:
```
embedColumns = [ site['stage'], site['rain'], 'flowCFS' ]
embed = Embed( dataFrame = dfFlow, columns = embedColumns, E = 2, includeTime = True )
```

Remove '(t-0)' from column names

In [13]:
```
embed.columns = [ s.replace('(t-0)','') for s in embed.columns]
```

In [14]:
```
print( f'embed shape {embed.shape}' )
print( embed.columns.values )
```

```
embed shape (12830, 7)
['Date' 'NP-205_NGVD29_ft' 'NP_205_Rain_in' 'flowCFS'
 'NP-205_NGVD29_ft(t-1)' 'NP_205_Rain_in(t-1)' 'flowCFS(t-1)']
```

Subset embedding to library to concat data with SMap results

In [15]:
```
embed_lib = embed.loc[ lib_i, : ]

# pandas is PITA : have to reset index for downstream use
embed_lib = embed_lib.reset_index( drop = True )
print( f'embed_lib shape {embed_lib.shape}' )
embed_lib.head(3)
```

```
embed_lib shape (1629, 7)
```

Out[15]:

	Date	NP-205_NGVD29_ft	NP_205_Rain_in	flowCFS	NP-205_NGVD29_ft(t-1)	NP_205_Rain_in(t-1)	flowCFS(t-1)
0	2020-09-01	6.70	0.00	525.0	6.68	0.22	513.0
1	2020-09-02	6.73	0.00	513.0	6.70	0.00	525.0
2	2020-09-03	6.73	0.01	503.0	6.73	0.00	513.0

SMap

Explicit list of variables for SMap

In [16]:
```
columns = [ site['rain']+'(t-1)', 'flowCFS(t-1)', site['stage']+'(t-1)' ]
```

In [17]:
```
print( columns )
print( site['stage'] )
```

```
['NP_205_Rain_in(t-1)', 'flowCFS(t-1)', 'NP-205_NGVD29_ft(t-1)']
NP-205_NGVD29_ft
```

In [18]:
```
SM = SMap( dataFrame = embed, lib = lib, pred = lib, Tp = site['Tp'],
           theta = site['theta'], columns = columns, target = site['stage'],
           embedded = True, showPlot = False )
```

In [19]:
```
PR = SM['predictions']
SC = SM['coefficients']
SV = SM['singularValues']
print( f'SC shape {SC.shape}' )
```

```
SC shape (1629, 5)
```

Get coefficient names

In [20]:
```
Time, C0, rainCoef, flowCoef, stageCoef = list(SC.keys())
print(f'Time      {Time}\nC0        {C0}\nrainCoef  {rainCoef}\nflowCoef  {flowCoef}\nstageCoef {stageCoef}')
```

```
Time      Time
C0        C0
rainCoef  ∂NP-205_NGVD29_ft/∂NP_205_Rain_in(t-1)
flowCoef  ∂NP-205_NGVD29_ft/∂flowCFS(t-1)
stageCoef ∂NP-205_NGVD29_ft/∂NP-205_NGVD29_ft(t-1)
```

Create DataFrame with prediction & coefficients

Drop trailing Tp rows to maintain coherence with embed_lib

In [21]:
```
dfSM = DataFrame( { 'Date'         : PR['Time'],
                    'Observations' : PR['Observations'],
                    'Predictions'  : PR['Predictions'],
                    'C0'           : SC['C0'],
                    'stageCoef'    : SC[stageCoef],
                    'rainCoef'     : SC[rainCoef],
                    'flowCoef'     : SC[flowCoef]  } )
if site['Tp'] > 0 :
    dfSM = dfSM.iloc[ :-site['Tp'], : ]
```

In [22]:
```
print(dfSM.shape)
```

```
(1629, 7)
```

Add rain and flowCFS from embed_lib

In [23]:
```
dfSM = concat( [ dfSM, embed_lib.iloc[:,1:] ], axis = 1 )
dfSM.head(3)
```

Out[23]:

	Date	Observations	Predictions	C0	stageCoef	rainCoef	flowCoef	NP-205_NGVD29_ft	NP_205_Rain_in	flowCFS	NP-205_NGVD29_ft(t-1)
0	2020-09-01	6.70	6.692150	0.101643	0.982079	0.061498	0.000033	6.70	0.00	525.0	6.68
1	2020-09-02	6.73	6.698204	0.097787	0.982590	0.061910	0.000033	6.73	0.00	513.0	6.70
2	2020-09-03	6.73	6.727865	0.103666	0.981774	0.061527	0.000033	6.73	0.01	503.0	6.73

Rain & flow data for components

Note `columns = [ site['rain']+'(t-1)', 'flowCFS(t-1)', site['stage']+'(t-1)' ]`

In [24]:
```
rainData = embed_lib[ columns[0] ]
flowData = embed_lib[ columns[1] ]
```

Rain & Flow components of stage

In [25]:
```
rainCoefPred  = rainData * dfSM['rainCoef'].values
flowCoefPred  = flowData * dfSM['flowCoef'].values
stageCoefPred = dfSM['Observations'].values * dfSM['stageCoef'].values
sumRainFlowStageC0 = dfSM['C0'].to_numpy() + rainCoefPred + flowCoefPred + stageCoefPred

rainFraction  = rainCoefPred  / dfSM['Predictions'].values
flowFraction  = flowCoefPred  / dfSM['Predictions'].values
stageFraction = stageCoefPred / dfSM['Predictions'].values
```

Ratio of cumulative components over plan period

In [26]:
```
sumRain = rainCoefPred.sum().round(2)
sumFlow = flowCoefPred.sum().round(2)
rainToFlow = round( sumRain / sumFlow, 2 )
infoString = f'Cumulative rain {sumRain}, flow {sumFlow}  ratio {rainToFlow}'
print( infoString )
```

```
Cumulative rain 27.14, flow 8.41  ratio 3.23
```

Plot stage components

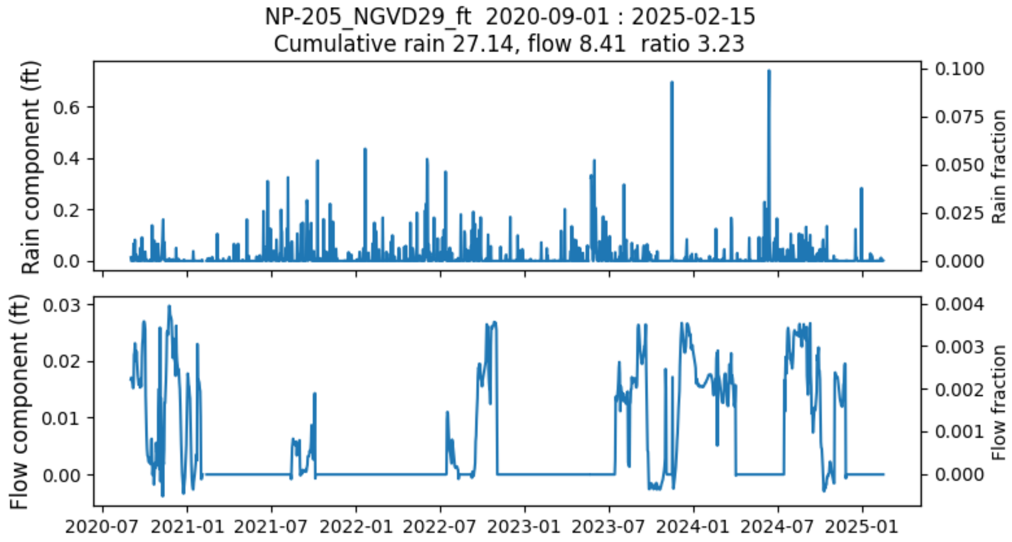
In [27]:
```
fig1, ax1 = plt.subplots(nrows=2, ncols=1, sharex=True, sharey=False, figsize = [8,4.5] )

ax1[0].plot( dfSM['Date'], rainCoefPred ) #rainFraction )
ax1[0].set_ylabel( 'Rain component (ft)',size=12)
ax1[1].plot( dfSM['Date'], flowCoefPred ) #flowFraction )
ax1[1].set_ylabel( 'Flow component (ft)',size=12)

# matplotlib is Rube-Goldberg to add a y-axis of rain fraction
ax1_0_right = ax1[0].twinx()
ax1_0_right.set_ylabel( 'Rain fraction' )
ax1_0_right.plot( dfSM['Date'], rainFraction, lw = 0 )
ax1_1_right = ax1[1].twinx()
ax1_1_right.set_ylabel( 'Flow fraction' )
ax1_1_right.plot( dfSM['Date'], flowFraction, lw = 0 )
```

```
dateTitle = f'{site['stage']}  {df["Date"][plan_i[0]]} : {df["Date"][plan_i[-1]]}'
fig1.suptitle( dateTitle + '\n' + infoString,  y = 0.94, fontsize = 12)
fig1.tight_layout()
```

Figure



Output DataFrame of data, predictions, coefficients, components

In [28]:
```
df_ = DataFrame( { 'stageCoefPred' : stageCoefPred, 'rainCoefPred' : rainCoefPred,
                   'flowCoefPred' : flowCoefPred, 'sumRainFlowStageC0' : sumRainFlowStageC0 } )

# Pandas is PITA, reset dataframe indexes so concat aligns column rows properly
dfSM.reset_index( drop = True, inplace = True )
df_.reset_index(  drop = True, inplace = True )

dfOut = concat( [ dfSM, df_ ], axis = 1 )
dfOut.set_index( 'Date' )

names = dfSM.columns.to_list()
names = names + [ 'StagePred', 'RainPred', 'FlowPred', 'sumRainFlowStageC0' ]
dfOut.columns = names
```

```
#dfOut.round(5).to_csv('NP205_SMap_S12AB_Deviation_1.csv',index=False)
```

In [29]:
```
dfOut.head(3)
```

Out[29]:

	Date	Observations	Predictions	C0	stageCoef	rainCoef	flowCoef	NP-205_NGVD29_ft	NP_205_Rain_in	flowCFS	NP-205_NGVD29_ft(t-1)
0	2020-09-01	6.70	6.692150	0.101643	0.982079	0.061498	0.000033	6.70	0.00	525.0	6.68
1	2020-09-02	6.73	6.698204	0.097787	0.982590	0.061910	0.000033	6.73	0.00	513.0	6.70
2	2020-09-03	6.73	6.727865	0.103666	0.981774	0.061527	0.000033	6.73	0.01	503.0	6.73

2-D models for isolated influence of rain & flow

SMap Stage : Rain

Note higher theta is used for increased resolution

In [30]:
```
columns = [ site['stage'], site['rain'] ]
theta2D = 5
Tp2D    = 1
```

In [31]:
```
SM_rain = SMap( dataFrame = embed, lib = lib, pred = lib, Tp = Tp2D,
                theta = theta2D, columns = columns, target = site['stage'],
                embedded = True, showPlot = False )
```

In [32]:
```
PR_rain = SM_rain['predictions']
SC_rain = SM_rain['coefficients']
SV_rain = SM_rain['singularValues']

print( f'SC_rain shape {SC_rain.shape}' )
print( f'SC_rain coeff: {list(SC_rain.keys())}' )
```

```
SC_rain shape (1630, 4)
SC_rain coeff: ['Time', 'C0', '∂NP-205_NGVD29_ft/∂NP-205_NGVD29_ft', '∂NP-205_NGVD29_ft/∂NP_205_Rain_in']
```

SMap Stage : Flow

In [33]:
```
columns = [ site['stage'], 'flowCFS' ]
```

In [34]:
```
SM_flow = SMap( dataFrame = embed, lib = lib, pred = lib, Tp = Tp2D,
                theta = theta2D, columns = columns, target = site['stage'],
                embedded = True, showPlot = False )
```

In [35]:
```
PR_flow = SM_flow['predictions']
```

```
SC_flow = SM_flow['coefficients']
SV_flow = SM_flow['singularValues']

print( f'SC_flow shape {SC_flow.shape}' )
print( f'SC_flow coeff: {list(SC_flow.keys())}' )
```

```
SC_flow shape (1630, 4)
SC_flow coeff: ['Time', 'C0', '∂NP-205_NGVD29_ft/∂NP-205_NGVD29_ft', '∂NP-205_NGVD29_ft/∂flowCFS']
```

Get coefficient names for plots

In [36]:
```
rainCoef, flowCoef = list(SC_rain.keys())[3], list(SC_flow.keys())[3]
###Time, C0, stageCoef, flowCoef = list(SC_flow.keys())
print(f'rainCoef  {rainCoef}\nflowCoef  {flowCoef}')
```

```
rainCoef  ∂NP-205_NGVD29_ft/∂NP_205_Rain_in
flowCoef  ∂NP-205_NGVD29_ft/∂flowCFS
```

Plot ∂S/∂R, ∂S/∂F vs S

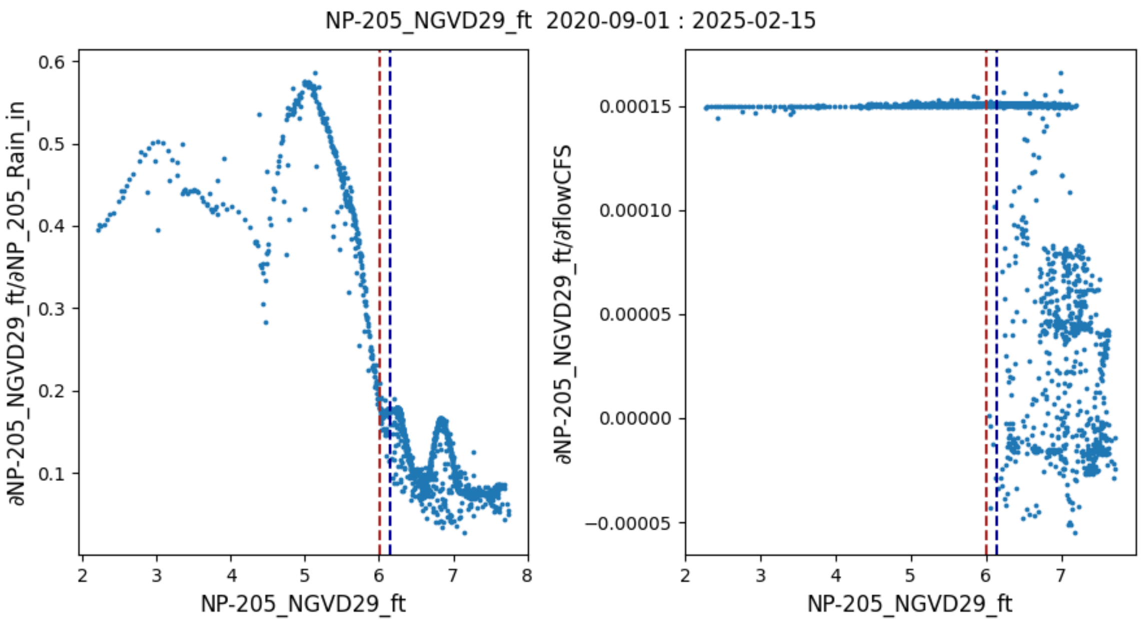
In [37]:
```
fig2, ax2 = plt.subplots(nrows=1, ncols=2, sharex=False, sharey=False, figsize = [9,5] )

ax2[0].scatter( PR_rain['Predictions'], SC_rain[rainCoef], s = 3 )
ax2[0].set_xlabel(site['stage'],size=12)
ax2[0].set_ylabel(rainCoef,size=12)
#ax2[0].set_ylim((0,0.7))
ax2[0].axvline( site['elevation'][0], linestyle = 'dashed', c = 'brown' )
ax2[0].axvline( site['elevation'][1], linestyle = 'dashed', c = 'darkblue' )

ax2[1].scatter( PR_flow['Predictions'], SC_flow[flowCoef], s = 3 )
ax2[1].axvline( site['elevation'][0], linestyle = 'dashed', c = 'brown' )
ax2[1].axvline( site['elevation'][1], linestyle = 'dashed', c = 'darkblue' )
ax2[1].set_xlabel(site['stage'],size=12)
ax2[1].set_ylabel(flowCoef,size=12)

fig2.suptitle( dateTitle, y = 0.965, fontsize = 12)
fig2.tight_layout()
```

Figure


NP-205_NGVD29_ft 2020-09-01 : 2025-02-15
∂NP-205_NGVD29_ft/∂NP_205_Rain_in
NP-205_NGVD29_ft
∂NP-205_NGVD29_ft/∂flowCFS
NP-205_NGVD29_ft

In [ ]: