

1 Reviewer #1

2 *This manuscript presents a modelling study using the CliMA land surface model investigating the*
3 *effect of assumptions around tree recovery after drought at one site which experienced a severe*
4 *drought in 2012. The results show that including a mechanism for partial rather than full recovery*
5 *leads to a better fit to data in the post-drought period. This is an important topic as models still*
6 *frequently assume instantaneous responses to environmental conditions and there is no standard*
7 *framework for representing lagged responses.*

8 *In general, the analysis is scientifically sound but the paper itself need some edits to make it more*
9 *robust and easier to understand.*

10 [Response]

11 We thank the reviewer for their constructive feedback. Below, we provide a point-by-point
12 response. Reviewer comments are shown in *italics*, and our responses are provided in blue.

13

14 *Major comments*

15 *The methods are poorly written, with concepts that are not explained, variables that are not*
16 *defined and inconsistency between notations (detailed comments below). The whole section needs*
17 *to be re-written to allow the reader to understand what was actually done more easily*

18 [Response]

19 We thank the reviewer for pointing this out and apologize for the lack of clarity in the original
20 manuscript. To address this issue, we will (1) explicitly describe the calculation of key variables,
21 particularly those involved in the three recovery scenarios; (2) add descriptions of the additional
22 flux-tower sites used in the model simulations; and (3) ensure that notation is used consistently
23 throughout the manuscript.

24

25 *There is a lot of stress on the differences between the full and partial recovery representations,*
26 *which is interesting and relevant, but very little emphasis on the three different stomatal models*
27 *presented. In most cases there don't seem to be that many differences between the three, with the*
28 *exception of the model fit for the partial recovery (Fig. 5) some more explanations are needed*
29 *here.*

30 [Response]

31 We thank the reviewer for pointing this out. In the partial recovery (PR) scenario, the model
32 imposes an upper bound on hydraulic conductance, which subsequently propagates to the update
33 of leaf water potential. The stress factor β is computed from water potential, with more negative
34 leaf water potential corresponding to lower β (i.e., higher water stress). For the Medlyn-Vcmax
35 formulation, β is applied as a direct multiplicative modifier to Vcmax. For the Medlyn-g1
36 formulation, β is applied by directly modifying the term $(1 + \frac{g_1}{\sqrt{D}})$ in the Medlyn stomatal
37 conductance function. In contrast, in the optimality-based model, β does not directly affect
38 photosynthesis through modifying Vcmax or stomatal conductance. Instead, it influences
39 hydraulic conductance, which then affects water potential and vertical water flow (i.e.,
40 transpiration), and ultimately regulates stomatal conductance. We will incorporate this
41 clarification into the revised manuscript.

42

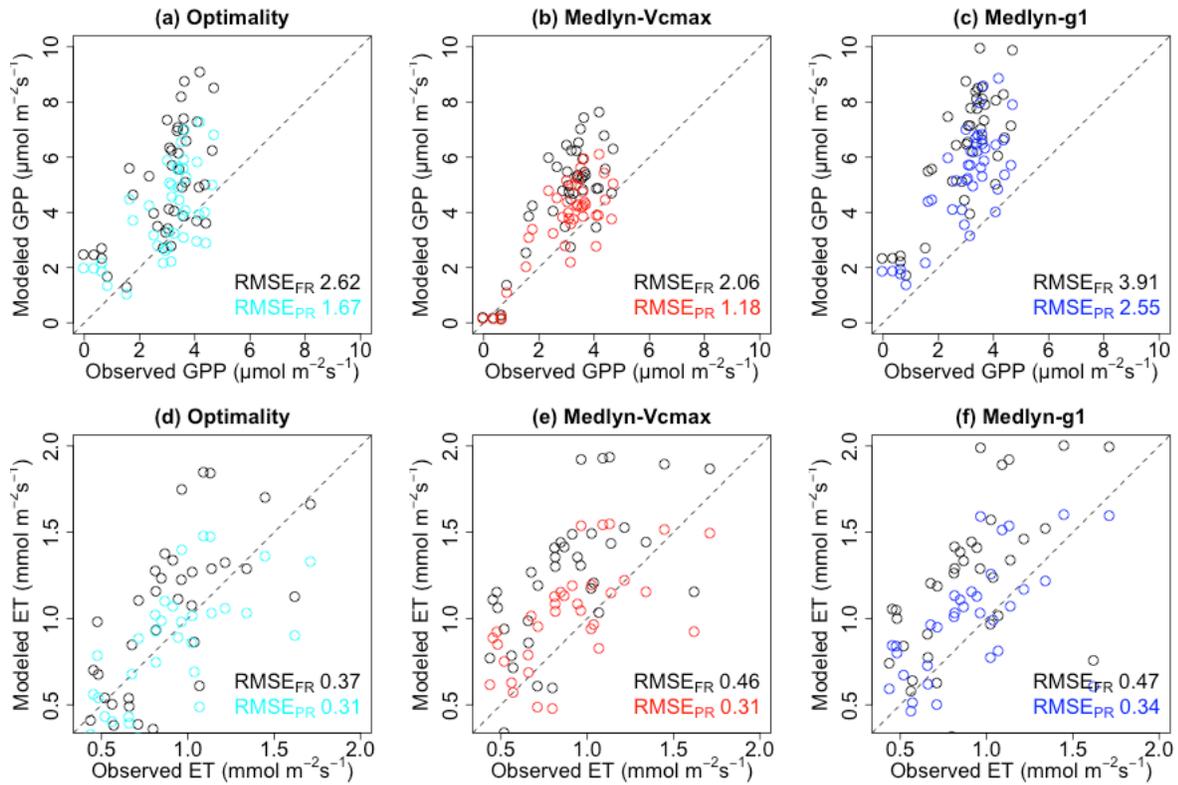
43 *The partial recovery is implemented by fitting the model to observations rather than through a*
44 *process based representation. This raises two questions. First – how general is this method? Can*
45 *the model make predictions at sites where there is no eddy covariance data? Second – how much*
46 *is the improvement in fit after the introduction of partial recovery to do with partial recovery itself*
47 *and how much is it to do with the fact that the model is brought closer to observations via data*
48 *assimilation?*

49 [Response]

50 We thank the reviewer for pointing this out. Regarding generalizability, the proposed method can
51 be applied at sites with eddy-covariance observations to derive general constraints on vegetation
52 recovery processes, which can then be transferred to sites lacking eddy-covariance measurements.
53 For example, key recovery characteristics, such as the time required for the release of accumulated
54 water deficit and the upper bound of hydraulic conductance recovery, can be derived from existing
55 eddy-covariance observations. These features can then be related to commonly available
56 environmental variables using nonlinear regression or machine-learning approaches, enabling their
57 prediction at sites without eddy-covariance data. We will add this clarification to the Discussion
58 section.

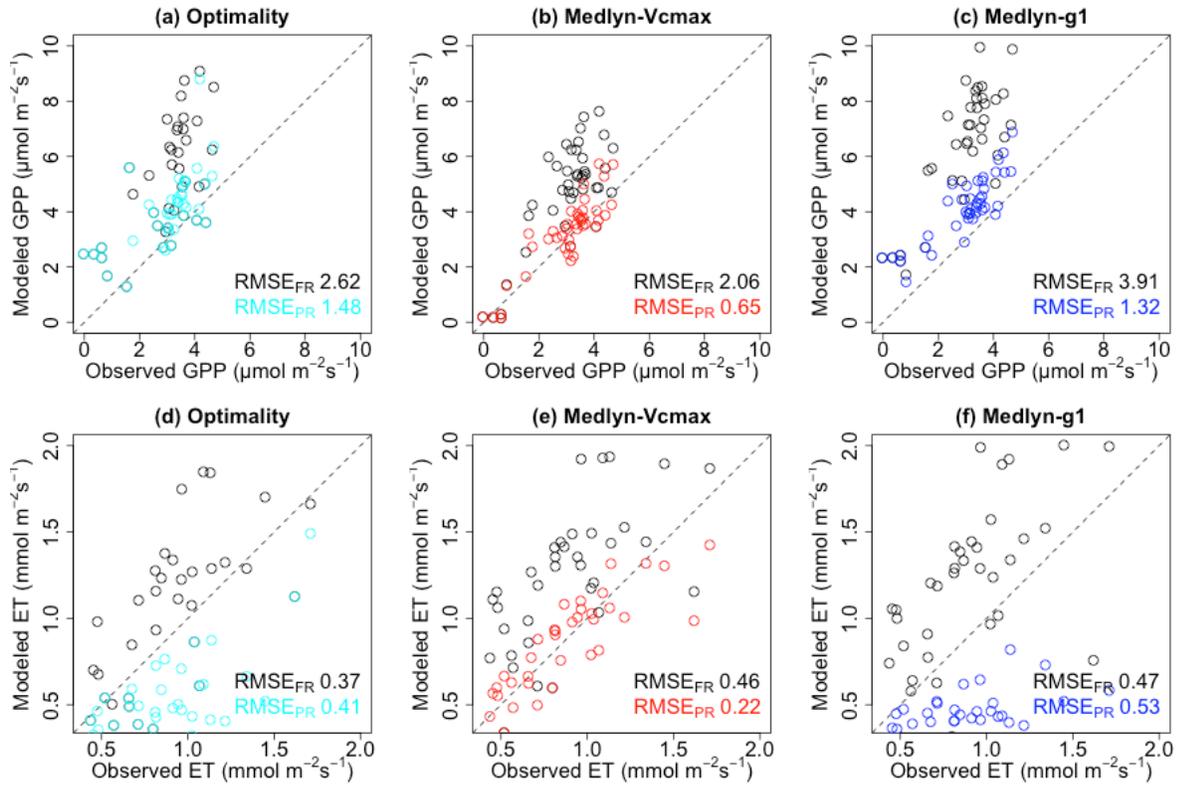
59 In this framework, partial recovery involves two components: (1) the introduction of a partial
60 recovery process in the model, and (2) data assimilation to infer the upper bound to which the

61 hydraulic system can recover. To disentangle the contributions of these two components, we
 62 impose a constraint whereby vegetation is allowed to recover only to 80% of the full-recovery
 63 condition, which is treated as A1 (partial recovery alone), and compare it with A2, which
 64 additionally includes data assimilation. By comparing model performance between A1 and A2
 65 (Figure R1 and R2), we find that the improvement associated with partial recovery is primarily
 66 driven by the data assimilation component.



67
 68 **Figure R1** Change in model performance after accounting for drought legacy effects by setting
 69 recovery upper boundary to 80% of the full-recovery condition (recovery period only).

70



71
 72 **Figure R2** Change in model performance after accounting for drought legacy effects by data
 73 assimilation (recovery period only).

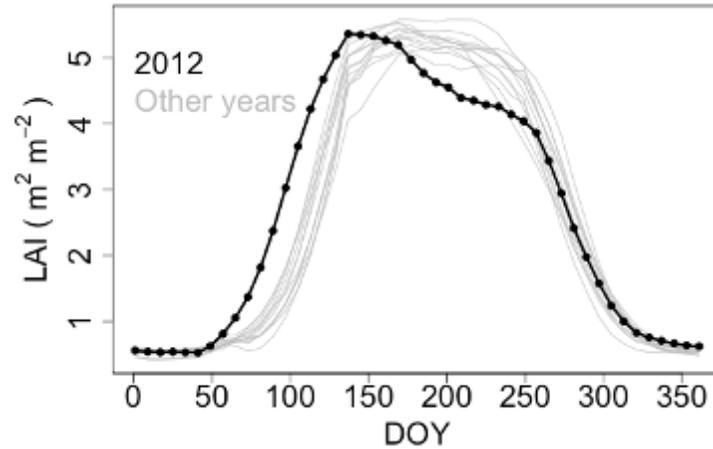
74
 75 *Minor comments*

76 *L 135 does the MODIS LAI respond to drought at the site? Does having this as an input partially*
 77 *represent the effects of drought already?*

78 **[Response]**

79 **Yes, MODIS LAI decreased in response to the 2012 drought (Figure R3). We therefore consider**
 80 **that using MODIS LAI as an input already captures canopy structural responses to drought.**

81



82

83 **Figure R3** LAI time series in 2012 extracted from MODIS LAI products using GriddingMachine
 84 package (Wang et al., 2022; Yuan et al., 2011).

85

86 *L 150 unclear why, given the research questions, it is necessary to evaluate canopy spectra*

87 [Response]

88 We now remove the evaluation of canopy spectra.

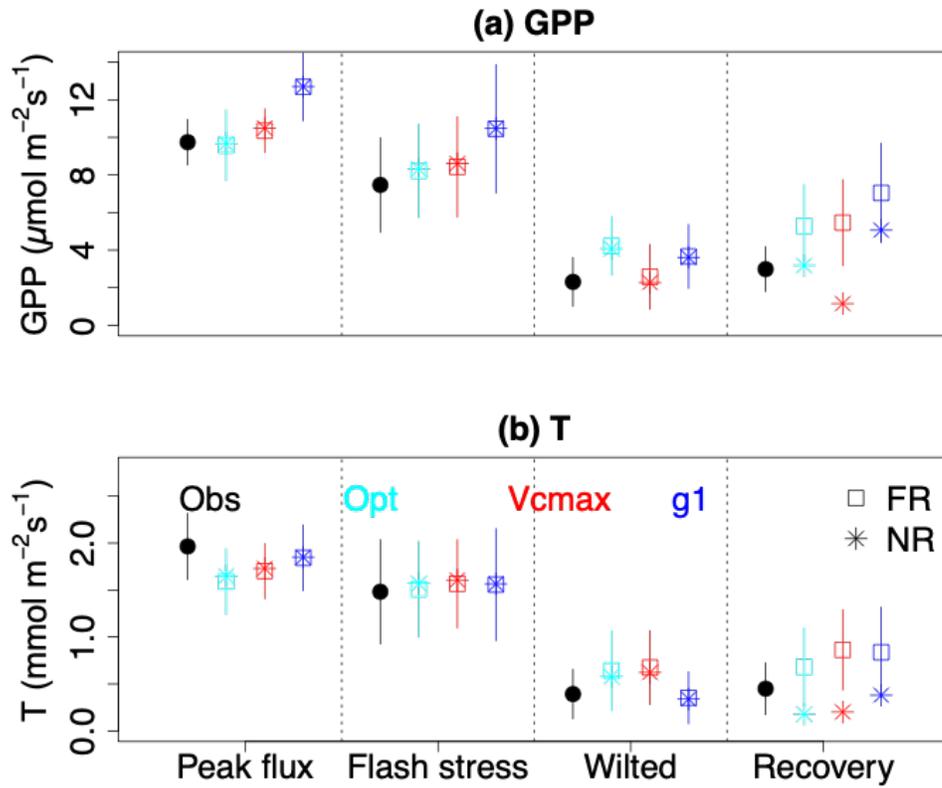
89

90 *L 167 “Changing this T/ET ratio does not impact our results.” Some evidence is needed here*

91 [Response]

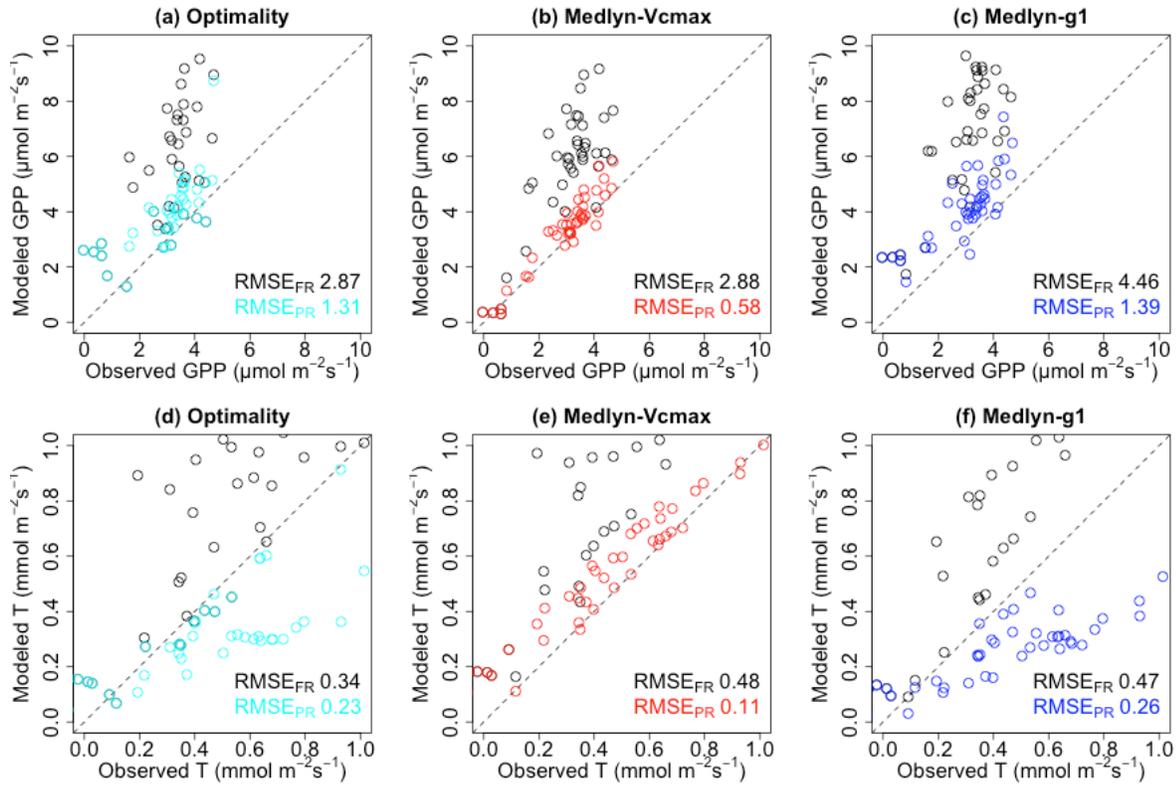
92 To avoid potential evaluation bias associated with assuming a fixed T/ET ratio, we applied the ET
 93 partitioning method of Nelson et al. (2020) to directly compare modeled transpiration with
 94 observation-based partitioned transpiration. This partitioning approach allows the T/ET ratio to
 95 vary dynamically. We find that using either a fixed T/ET ratio or observation-based partitioned
 96 transpiration does not alter our conclusions, namely, that biochemical limitations delay the
 97 recovery of both carbon and water fluxes (Figures R4 and R5). The corresponding figures will be
 98 added to the Supplementary Information.

99



100
 101 **Figure R4** Model performance for GPP and T across four periods in 2012. Curves show the
 102 optimality-based stomatal model (cyan) and the Medlyn model with the water-stress factor applied
 103 to Vcmax (red) or to g1 (blue). FR, full recovery; NR, no recovery. Error bars indicate variability
 104 within each period.

105



106

107 **Figure R5** Improvement in model performance after accounting for drought legacy effects
 108 (recovery period only). Scatterplots compare RMSE under the partial-recovery scenario (RMSE_{PR})
 109 against the full-recovery baseline (RMSE_{FR}) for GPP and T. Symbols denote simulations assuming
 110 full recovery (black circles) and partial recovery using the optimality-based model (cyan) or the
 111 Medlyn model with the water-stress factor applied to Vcmax (red) or g1 (blue). RMSEs are
 112 computed against flux observations; lower values indicate better fit.

113

114 *L 167 “The CliMA Land model was employed to reproduce the dynamics of carbon and water*
 115 *fluxes during the drought period.” This statement feels superfluous here.*

116 [Response]

117 We will remove this sentence.

118

119 *L 171 “several stomatal optimality models” sever feels very vague here*

120 [Response]

121 We will list other stomatal optimality models here, including Eller et al. (2018) and Sperry et al.
 122 (2017).

123

124 *L 189 table 1 – this table has only 1 line, but above you say you also used an optimal model*

125 [Response]

126 Because the β factor does not directly affect V_{cmax} or stomatal conductance in the optimality-
127 based stomatal model, it was not included in Table 1. To clarify this point, we will revise the table
128 caption to indicate that Table 1 summarizes the parameter settings for the empirical Medlyn
129 stomatal models only.

130

131 *Section 2.4 – many more details are needed here, preferably in the form of equations. It is not*
132 *enough to say that vulnerability curves or the data assimilation method is taken from another*
133 *paper*

134 [Response]

135 We apologize for the unclear description. The equations describing the three recovery scenarios
136 are provided below and will be added to the revised version.

137 In the full recovery scenario (FR), $K^{FR}(t)$ is updated according to the water stress factor β (Eqs.1-
138 2).

139 $K^{FR}(t) = K_{max} \cdot \beta(\psi(t))$ Eq. (1)

140 $\psi(t)$ is leaf water potential at time t. $K^{FR}(t)$ is hydraulic conductance under FR at time t.

141 $K^{FR}(t + 1) - K^{FR}(t) = K_{max} \cdot [\beta(\psi(t + 1)) - \beta(\psi(t))]$ Eq. (2)

142 In the partial recovery scenario (PR), β is estimated by minimizing the model-observation
143 mismatch (Eqs. 3-5), where β represents the degree of recovery. $K^{PR}(t)$ is then updated using the
144 inverted β (Eq. 6).

145 $F_{mod}(t; \beta(t)) = \begin{bmatrix} GPP_{mod}(t; \beta(t)) \\ ET_{mod}(t; \beta(t)) \end{bmatrix}$ Eq. (3)

146 $F_{obs}(t) = \begin{bmatrix} GPP_{obs}(t) \\ ET_{obs}(t) \end{bmatrix}$ Eq. (4)

147 $\beta^*(t) = \arg \min_{\beta \in [\beta_{min}, 1]} \left(F_{mod}(t; \beta^*(t)) - F_{obs}(t) \right)^T \left(F_{mod}(t; \beta^*(t)) - F_{obs}(t) \right)$ Eq. (5)

148 $K^{PR}(t) = K_{max} \cdot \beta^*(t)$ Eq. (6)

149 $K^{PR}(t)$ is hydraulic conductance under PR at time t.

150

151 In the no-recovery scenario (NR), $K^{NR}(t)$ is constrained to be non-increasing (Eqs. 7-8). When
152 drought causes $\psi(t)$ to become more negative, instantaneous hydraulic conductance K^{inst} drops and
153 K^{NR} drops. After drought, $\psi(t)$ becomes less negative and K^{inst} increases. However, the minimum
154 operator in Eq. (8) prevents recovery of K^{NR} (Eq. 8).

155 $K^{inst}(t) = K_{max} \cdot \beta(\psi(t))$ Eq. (7)

156 $K^{NR}(t) = \min(K^{NR}(t-1), K^{inst}(t))$ Eq. (8)

157 $K^{NR}(t)$ is hydraulic conductance under NR at time t.

158 All scenarios share the same initial condition corresponding to the pre-drought state (Eq. 9).

159 $K^{FR}(t_0) = K_{max} \cdot \beta(\psi(t_0))$ Eq. (9)

160

161 *L 215 Table 2 – unclear what information this table add as everything is just a tick. The notations*
162 *for the two options for the Medlyn model also do not match those in Table 1*

163 [Response]

164 In the previous version, this table was included to indicate that a total of nine scenarios were
165 considered, arising from three stomatal model configurations combined with three recovery
166 scenarios. As the table provides limited additional information, we will remove it from the revised
167 manuscript.

168

169 *L 231 what is Kmax? Seems like an important parameter but it is the first time it's mentioned I*
170 *think*

171 [Response]

172 We apologize for the missing description. Kmax denotes the maximum hydraulic conductance.
173 We will ensure that all variables are defined at their first occurrence in the revised manuscript.

174

175 *L 257 is this the same method as the data assimilation for the partial recovery scenario above or*
176 *something else?*

177 [Response]

178 Yes. We use this equation as an error function during data assimilation.

179

180 *L 335 But the model overestimates the coupling during the wilted period as well, so the issue here*
181 *is not just the full recovery assumption*

182 [Response]

183 Yes, the model overestimates the coupling strength during both the wilted and recovery period,
184 which indicates the biochemical limitations. We will further clarify it in the revised version.

185

186 *L 338 this looks like a repetition of the methods here*

187 [Response]

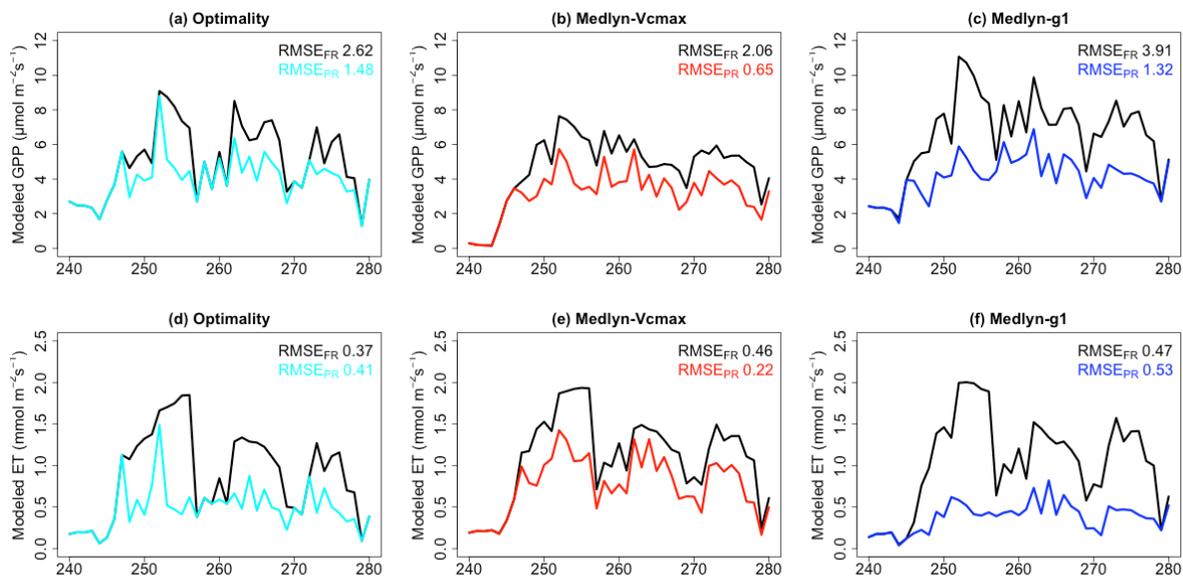
188 We will remove this paragraph.

189

190 *L 346 it might help here to show a timeseries of model GPP and ET to understand the evolution*
191 *of recovery*

192 [Response]

193 We agree with this suggestion. Below we show the time series of modeled GPP and ET. This will
194 be added to the revised version.



195

196 **Figure R6** Time series of GPP and ET during recovery period between model simulations and
197 observations.

198

199 *L 421 it feels odd to mention simulations at other sites in the discussion for the first time when this*
200 *was not mentioned in the methods*

201 [Response]

202 To address this issue, we will add descriptions of the additional validation sites in the Methods
203 section, as shown below.

204 2.2 Other flux sites used for model validation

205 We conducted model simulations at several flux-tower sites that experienced the 2012 drought,
206 including US-MMS, US-GLE, US-UMB, US-NR1, and US-UMd. The US-MMS site is located in
207 Morgan-Monroe State Forest, Indiana, within a temperate deciduous broadleaf forest dominated
208 by a maple–beech–oak–hickory transition community representing secondary successional stands
209 approximately 60–80 years old (Novick and Phillips, 2022). The US-GLE site is located in
210 northern Michigan and consists of a mixed forest composed of aspen, maple, pine, and northern
211 hardwood species (Frank et al., 2022). The US-UMB site, also located in northern lower Michigan,
212 is an aspen-dominated northern hardwood forest (FLUXNET2015). The US-NR1 site is located in
213 the Rocky Mountains of Colorado within a subalpine evergreen needleleaf forest dominated by
214 *Abies lasiocarpa*, *Picea engelmannii*, and *Pinus contorta* (FLUXNET2015). The US-UMd site,
215 located in northern lower Michigan, represents a temperate deciduous broadleaf forest (Gough et
216 al., 2024).

217

218 **References**

219 Frank John, Valentine George, Massman Bill (2022), AmeriFlux FLUXNET-1F US-GLE GLEES,
220 Ver. 3-5, AmeriFlux AMP, (Dataset). <https://doi.org/10.17190/AMF/1871136>

221 Gough Christopher, Bohrer Gil, Curtis Peter (2024), AmeriFlux FLUXNET-1F US-UMd UMBS
222 Disturbance, Ver. 4-6, AmeriFlux AMP, (Dataset). <https://doi.org/10.17190/AMF/1881597>

223 Novick Kim and Phillips Rich (2022). AmeriFlux FLUXNET-1F US-MMS Morgan Monroe State
224 Forest. (Dataset) <https://doi.org/10.17190/AMF/1854369>

225

226

227