**Table S1. Spectra sample sizes in each weekly dataset.** Symptomatic leaf sample numbers were low in weeks prior to week 6 and were not included in analyses. In all analyses, sample sizes (oak wilt vs. not oak wilt) were randomly sampled to balance sample sizes.



**Table S2. Pairwise differences in instantaneous photosynthesis and stomatal conductance declines (difference from control) by treatment and leaf symptom status.** Values are the mean difference (units are photosynthesis = µmolCO2 m-2 s-1 and stomatal conductance = molH2O m-2 s-1) between columns and rows, followed by lower and upper limits of a 95% CI and significance of pairwise difference (\* *P* < 0.05, \*\* *P* < 0.01, \*\*\* *P* < 0.001) from a post-hoc Tukey test (α = 0.05).



**Table S3. Oak wilt specific spectral regions.** Wavelengths and indices at which oak wilt inoculated individuals have significantly different reflectance values, including commonly used indices or reflectance values (at top, from Pontius et al. ( 2005)). Reflectance percent values are mean difference between oak wilt and all other treatments. The minimum difference (min. diff %) in reflectance between the mean value of the oak wilt reflectance and the most similar treatment at that wavelength. \* = oak wilt reflectance values are significantly different from all other treatment reflectance values (*P* < 0.001). wk = interactive effect of treatment and experimental timing was significant (*P* <0.001). Species oak wilt reflectance values are mean difference between oak wilt and all other treatments (*ellip* OW % or *macro* OW %) and are only shown if species is a significant predictor of reflectance. Annotations included when available (Blackburn, 1998; Carter, 1993; Cotrozzi et al., 2017; Curran, 1989; Elvidge, 1990; Govender, Dye, Weiersbye, Witkowski, & Ahmed, 2009; Kumar, 2007; Lehmann, Große-Stoltenberg, Römer, & Oldeland, 2015; Penuelas et al., 1997; Pontius et al., 2005; Serbin, Dillaway, Kruger, & Townsend, 2012; Tucker, 1980).



**Table S4. PLS-DA oak wilt classification summary, all experimental times aggregated.**

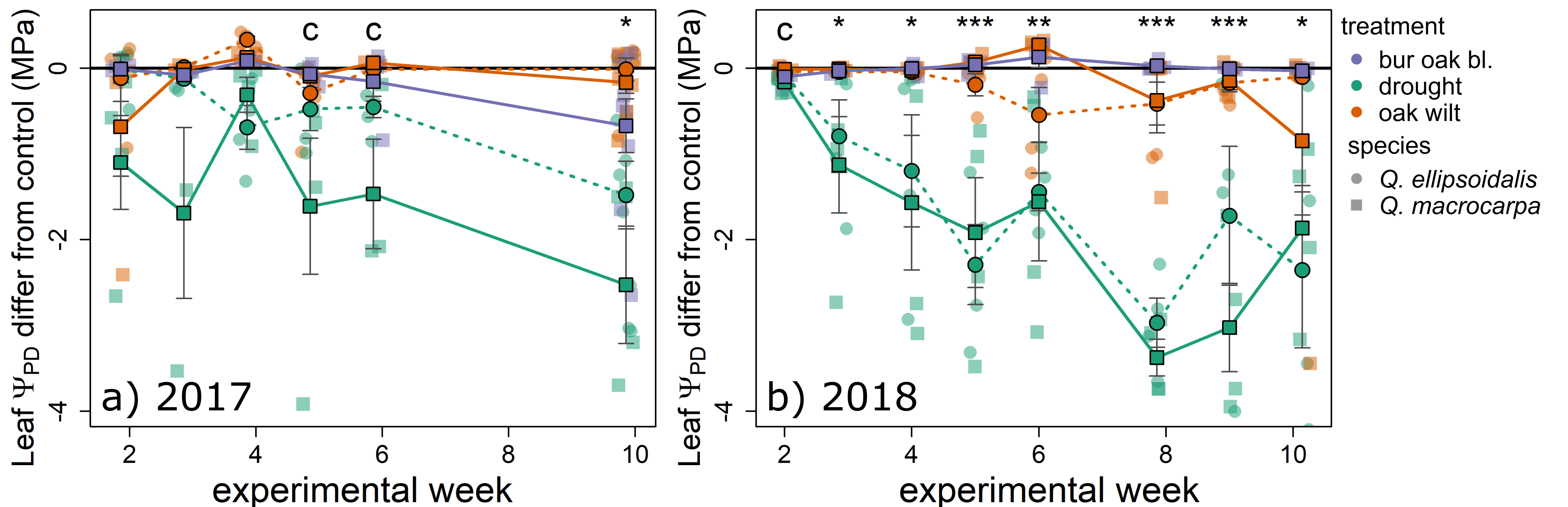


**Table S5. PLS-DA oak wilt classification summary, time explicit and comparisons oak wilt or “not oak wilt”.**

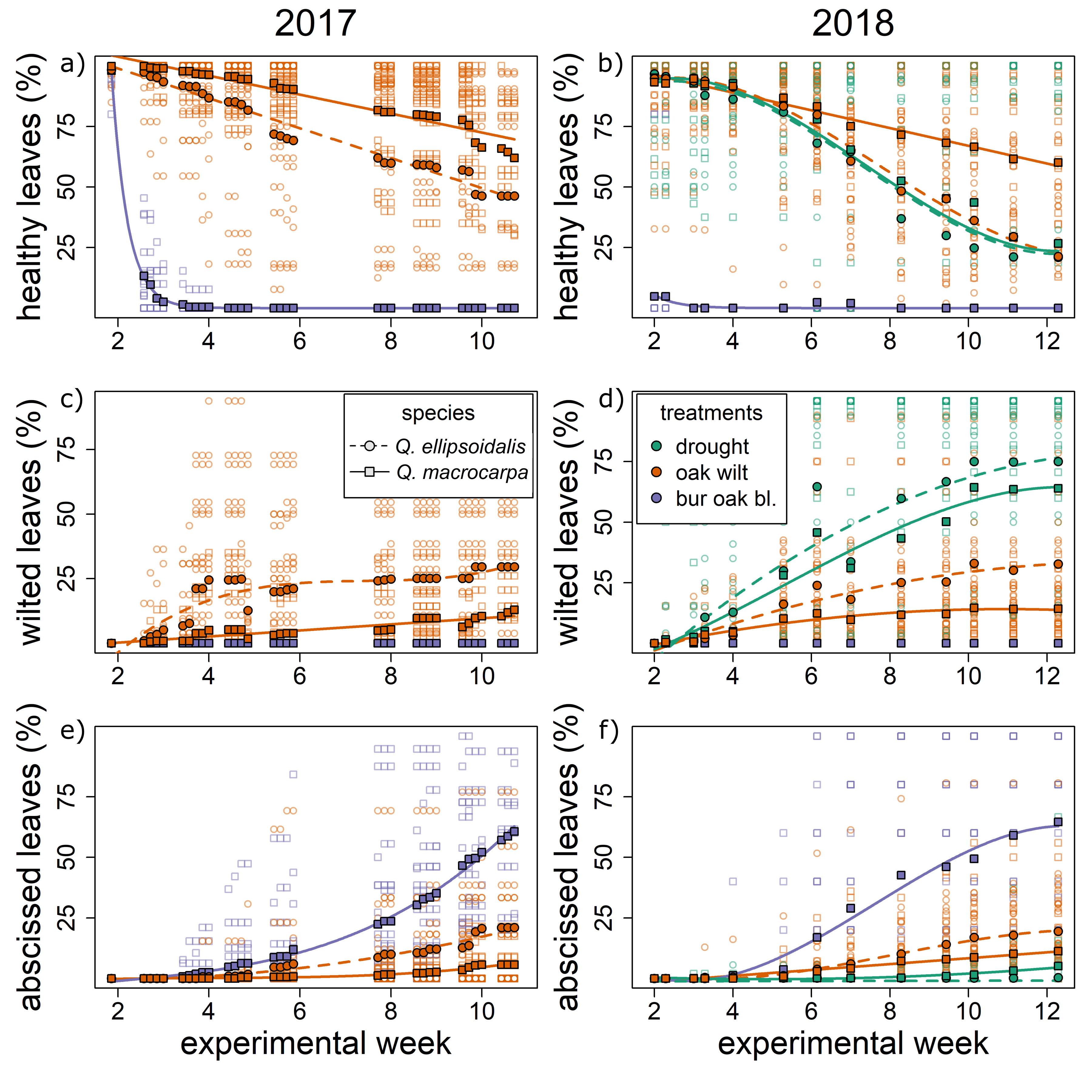


**Table S6. PLS-DA species classification summary, all experimental times aggregated.**

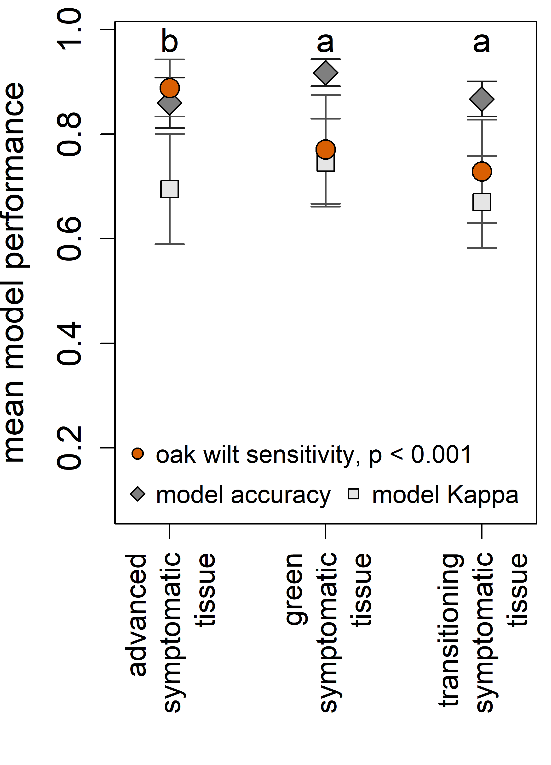




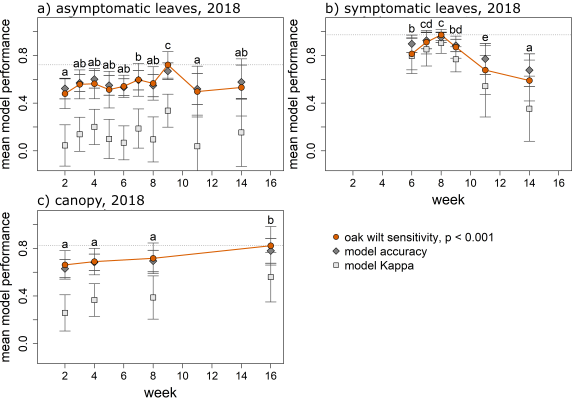
**Figure S1. Pre-dawn water potentials**. Difference between mean control treatments of each species and treatments. **a)** 2017 experimental data, **b)** 2018 experimental data. Error bars show one standard error around the mean differences. Asterisks denote significant pairwise differences between drought and all other treatments (\* P < 0.05, \*\* P < 0.01, \*\*\* P < 0.001), significant differences from control, when all other pairwise differences are not significant, are denoted by “c”.



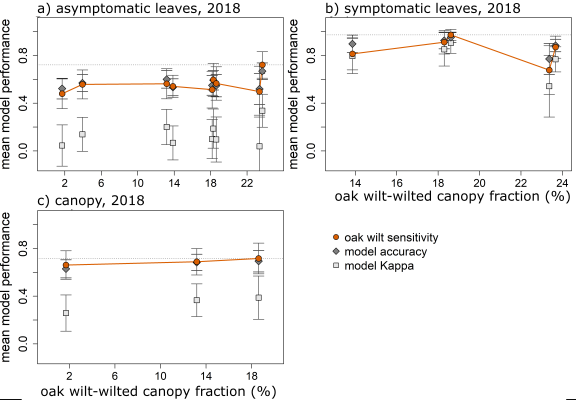
**Figure S2. Symptom appearance by week of experiment**, 2017 and 2018 experiments. 2017 does not include data for drought symptoms. **a,b)** Percent of healthy leaves remaining. **c,d)** Percent of leaves showing signs of wilting (browning, curling, and/or desiccation). **e,f)** Percent of leaves lost during the experiment. Bur oak blight percentages are calculated from the total of inoculated leaves, not total canopy.



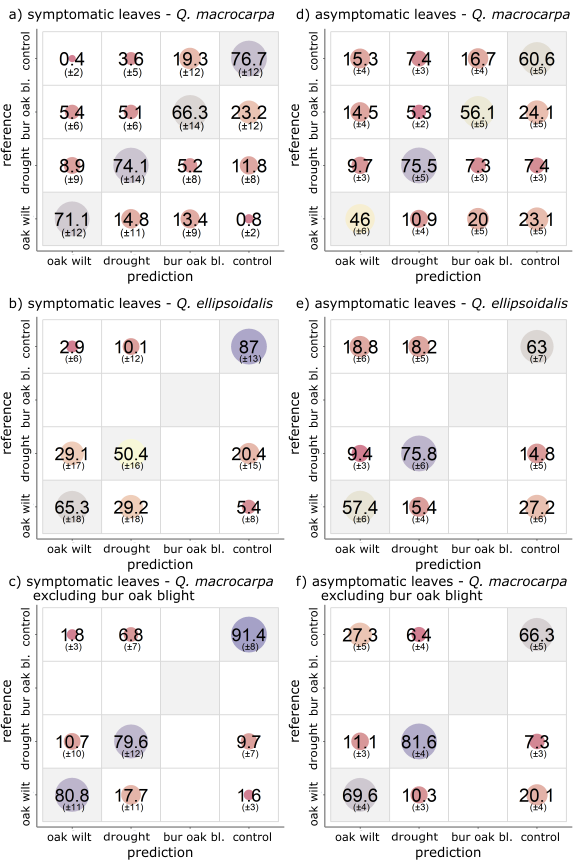
**Figure S3. PLS-DA Model performance by symptomatic leaf status.** Letters denote significant differences in oak wilt sensitivity between models, error bars are one standard deviation in model summary statistics from 100 model fitting iterations.



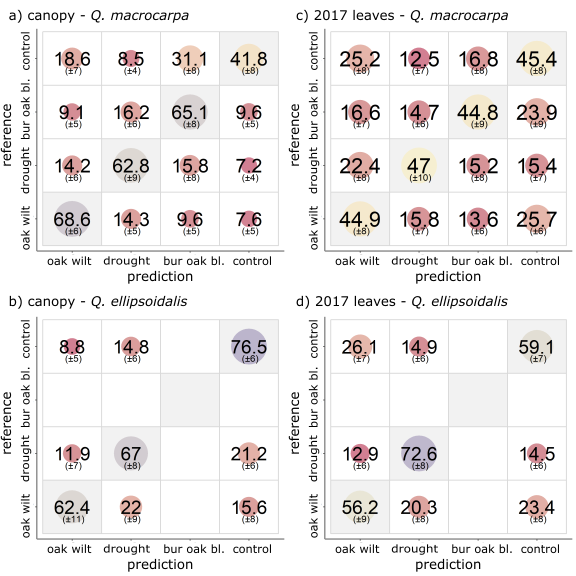
**Figure S4. PLS-DA model accuracy, Kappa, and sensitivity to oak wilt by week of experiment.** Model performance statistics from PLS-DA classifications of data into oak wilt or not oak wilt (all other treatments grouped) in spectral reflectance weekly datasets of **a)** asymptomatic leaves **b)** symptomatic leaves, and c**)** seedling canopies. Letters denote significant comparisons (post hoc Tukey test, P < 0.001) between oak wilt sensitivities of each week’s models and error bars are one SD (100 iterations of model fitting).



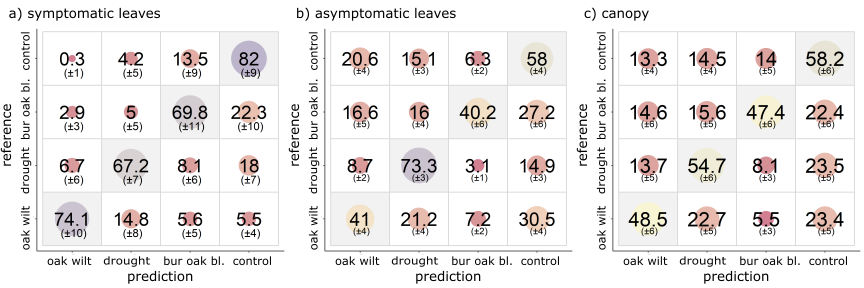
**Figure S5. PLS-DA model accuracy, Kappa, and sensitivity to oak wilt by oak wilt-treatments wilted canopy fractions.** Model performance statistics from PLS-DA classifications of data into oak wilt or not oak wilt (all other treatments grouped) in spectral reflectance weekly datasets plotted against mean canopy fraction of wilted leaves among oak wilt-inoculated plants. **a)** asymptomatic leaves **b)** symptomatic leaves, and c**)** seedling canopies. Letters denote significant comparisons (post hoc Tukey test, P < 0.001) between oak wilt sensitivities of each week’s models and error bars are one SD (100 iterations of model fitting).



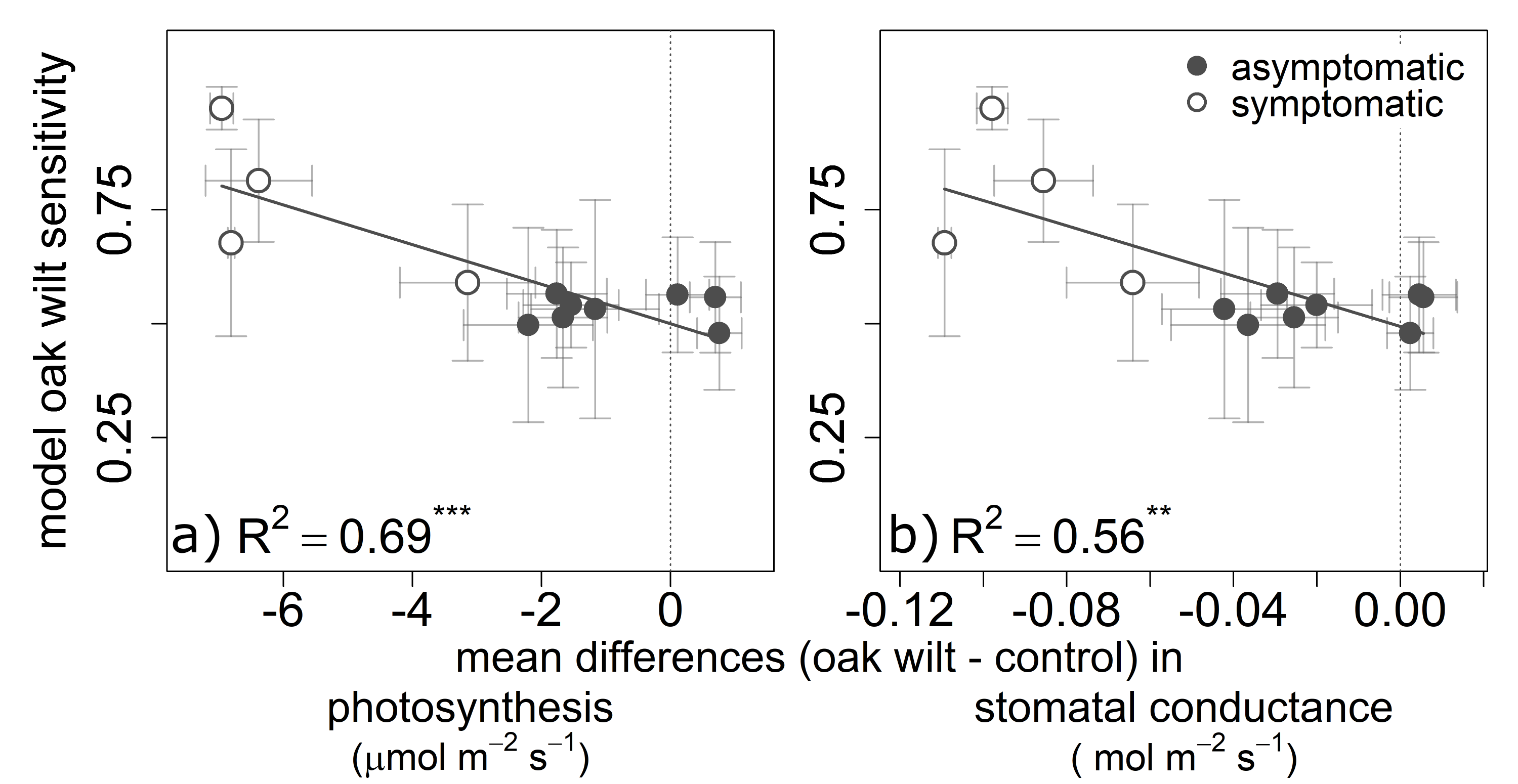
**Figure S6. Confusion matrices of PLS-DA classification to treatment in leaf level, symptom status data sets subset to species.** Average percentage of treatment individuals classified in PLS-DA models (100 iterations for each dataset) of subsets of: symptomatic leaves **a)** *Q. macrocarpa*, **b)** *Q. ellipsoidalis*, **c)** *Q. macrocarpa* when bur oak blight individuals are excluded from the analysis; and asymptomatic leaves **d)** *Q. macrocarpa*, **e)** *Q. ellipsoidalis*, and **f)** *Q. macrocarpa* when bur oak blight individuals are excluded from the analysis. Vertical axis is applied treatments and horizontal axis is predicted classification.



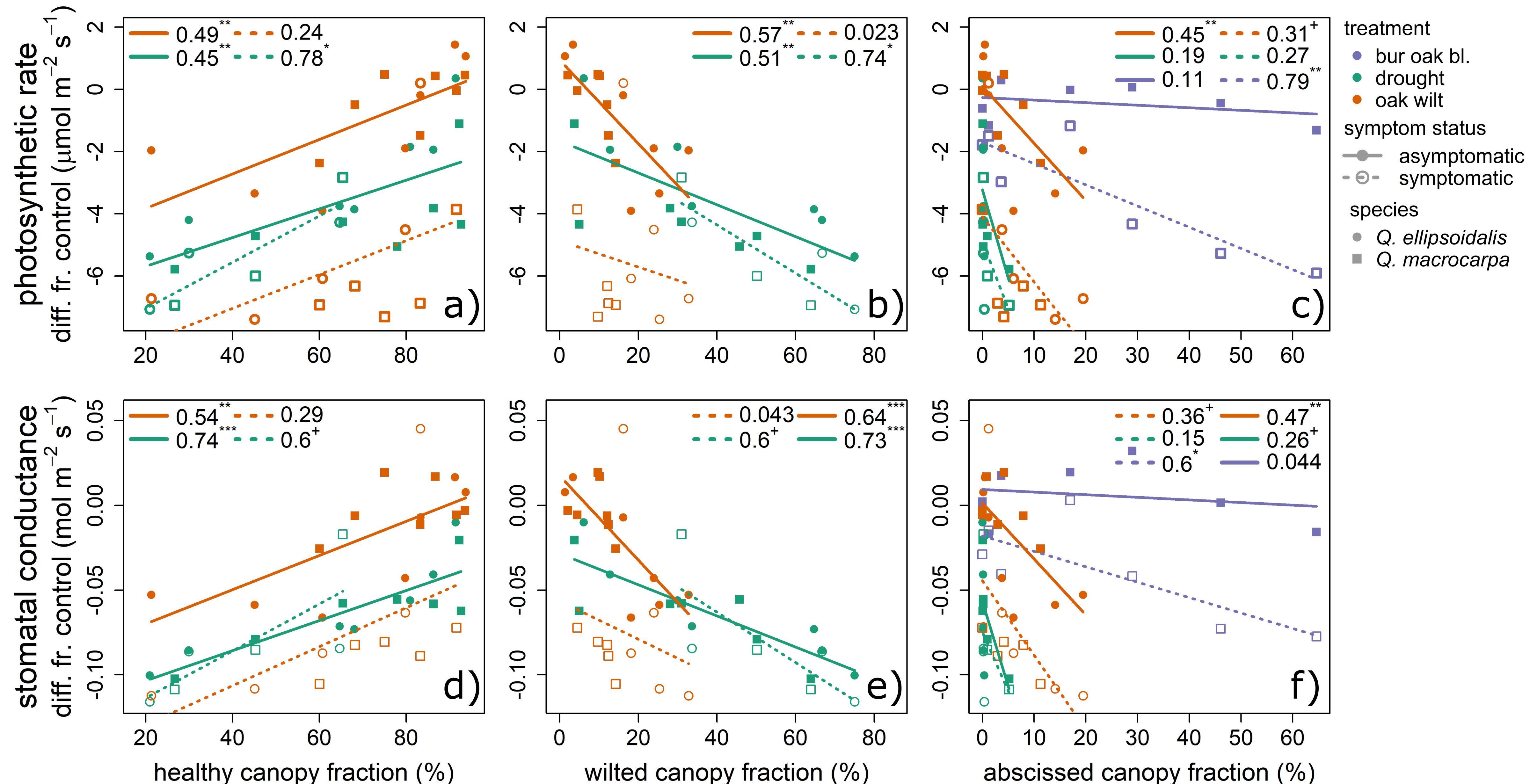
**Figure S7. Confusion matrices of PLS-DA classification to treatment whole plant and leaf aggregated data sets.** Average percentage of treatment individuals classified in PLS-DA models (100 iterations for each dataset) of subsets of: canopy reflectance **a)** *Q. macrocarpa*, **b)** *Q. ellipsoidalis*; and leaf reflectance (2017) **c)** *Q. macrocarpa*, d**)** *Q. ellipsoidalis*. Vertical axis is applied treatments and horizontal axis is predicted classification.



**Figure S8. Oak wilt diagnostic wavelengths only as predictors perform classifications as well in symptomatic leaves, but not in asymptomatic leaves or canopy reflectance datasets.** Using 30 wavelengths found to be significantly different in oak wilt reflectance spectra from other treatments, the average percentage of treatment individuals classified in PLS-DA models (100 iterations for each dataset) in **a)** symptomatic leaves, **b)** asymptomatic leaves, and **c)** canopy reflectances. Vertical axis is applied treatments and horizontal axis is predicted classification.



**Figure S9. PLS-DA model oak wilt sensitivity increases as photosynthesis and stomatal conductance decline in oak wilt-inoculated plants.** Mean PLS-DA oak wilt sensitivity by differences between oak wilt-inoculated individual leaf gas exchange rates and controls. Error bars are standard error of oak wilt sensitivity and standard error of the mean in gas exchange. \*\*\* = *P* < 0.001, \*\* = *P* < 0.01. **a)** instantaneous photosynthetic assimilation rate declines (R2 = 0.69, *P* < 0.001, F1,10 = 22) and **b)** instantaneous stomatal conductance rate declines (R2 = 0.56, *P* = 0.005, F1,10 = 12.9).



**Figure S10. Gas exchange rate declines correlated with symptom progression in canopies.** Mean weekly treatment differences from control by mean symptom prevalence in canopy and leaf symptom type. Species are shown by squares (*Q.* ellipsoidalis) and circles (*Q. macrocarpa)*. Values are R2 followed by significance (+ = *P* < 0.1, \* = *P* < 0.05, \*\* = *P* < 0.01, \*\*\* = *P* < 0.001). Instantaneous photosynthetic rate difference from control (**a,b,c**) or mean stomatal conductance difference from control (**d,e,f**) by mean canopy fraction of healthy, wilted, and abscissed leaves.



**Figure S11. Differences from mean control gas exchange rates by experimental week, species, and treatment**. Difference between mean control treatments of each species and week, instantaneous photosynthetic and stomatal conductance rates. **a & b)** Measurements on asymptomatic leaves in 2018 seedling experiment, **c & d)** Measurements of symptomatic leaves in 2018 seedling experiment, **e & f)** Measurements of leaves, without symptom status considered in 2017 seedling experiment. Error bars show one standard error around the mean differences.

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