Appendix S1

This section provides further details related to gas exchange measurements for photosynthesis phenotyping and additional information related to studies listed in Table 2 in the publication.

1 Summary of gas exchange measurements

It has been mentioned that measurements from traditional techniques such as infrared gas analyzer (IRGA) can be too slow for practical use in a breeding trial. Estimating common photosynthetic traits such as $V_{cmax}$ or $J_{max}$ using HTP techniques can be 60 to 100 times faster. Transporting an IRGA between plots, selecting a leaf, and clamping the cuvette onto the leaf takes one to two minutes. Allowing the leaf to acclimate to the chamber conditions takes another one to five minutes. A “bad” leaf or one that may not be light acclimated would require the selection of an entirely different leaf. Running default, $A$ vs. $C_i$ curves on a LiCOR-6800 takes about 12-15 minutes. In all, that is 20 to 30 minutes per curve and the time increases if the canopy is taller, like corn, miscanthus or sorghum, or if the plots are spaced further apart. Canopy level hyperspectral estimates of $V_{cmax}$ or $J_{max}$ requires one to five minutes to set the proper exposure time for the cameras and then 5 to 10 seconds per plot. References need to be included in each measurement. Handheld hyperspectral measurements take 30-40 seconds within each plot. If one wants to screen a field trial consisting of a thousand of soybean genotypes large soybean population for $V_{cmax}$ or $J_{max}$ - assuming measurements are taken between 10 am and 2pm - it would take four LiCOR 6800 25 days to measure all plots. Canopy level estimates of the same populations that size using hyperspectral cameras can be made in a single day if there is constant light.

2 Summary of additional information and context for studies listed in Table 2.

This supplemental summary is to provide additional information and context pertaining to the materials and environment(s) for studies listed in Table 2. Most of the studies listed in Table 2 attempt to capture trait space of the phenotype under observation to build a predictive model involving linear or nonlinear (machine learning) models. This is often done by leveraging diversity across plant ecotypes or genetic diversity within a given species, sampling at different leaf development stages or light levels (sunlit or shaded), in different experimental treatments to induce stress, across multiple years or between in situ and greenhouse grown plants.

Doughty et al. (2011)– Leaf spectroscopy and tissue sampling were conducted in two different years and multiple locations. Sunlit, intact leaves were sampled on Hawaii Island in multiple locations in January and April with varying rainfall (2000-4000mm). Samples were also taken from the tropical rainforest biome and the display center of Biosphere 2 located near Tucson, AZ, USA where the average air temperature was ~25°C and humidity of ~65%.

Serbin et al. (2012) – Greenhouse-grown aspen and cottonwood seedlings were treated to three different temperature regimes with day/night air temperatures (°C) as follows 30/23, 25/18, 20/13 that were used for paired leaf reflectance and photosynthetic. This temperature range was chosen to simulate the air temperatures observed in a latitudinal transect limiting the geographic distributions of temperate and boreal tree species. The authors tested the viability of the...
greenhouse produced model on paired leaf reflectance and gas exchange data from data collected in situ.

Dechant et al. (2017) – The authors conducted their experiment at The University of Leipzig’s Arboretum in Central Germany with deciduous and coniferous tree species sampled during daylight hours (9 – 19h) in August and early September. The authors attempted to maximize the number of species and the light environments (sun and shade leaves) of the paired leaf reflectance and gas exchange estimates.

Barnes et al. (2017) – The study period took place from late May to early July in 2016 near the Biosphere 2 Research Center, AZ, USA. The goal was to determine if reflectance based high-throughput modelling could be used to detect temporal changes in photosynthetic capacity. The average high temperature during the experiment was 34.4°C and the average low was 21.3°C. Irrigation was varied to simulate different leaf water potentials.

Wu et al. (2019) – Two locations in Panama, Parque Natural Metropolitano and San Lorenzo Protected Area, were used for data collection with mean annual temperature of 26°C for both locations and precipitation of 1826 and 3286 mm yr\(^{-1}\). An additional location in Brazil in the Tapajos National Forest was also used with a mean annual temperature of 26°C and precipitation of 2022 mm yr\(^{-1}\). All three locations have a pronounced dry period. The authors concentrated on differences in leaf age and light environments with all measurements being conducted during the dry season.

Jin et al. (2020) and Jin et al. (2021) – The study location is in a forestry research facility associated with the Shizuoka University, Shizuoka Prefecture, Japan. The forest is a deciduous temperate forest with elevation variation between 390 – 1560 m and annual precipitation of 2153 mm. Multiple tree species were sampled across multiple years with both sun and shaded leaves used in model development.

Calzone et al. (2021) – Two commercial pomegranate cultivars that were two-year-old potted plants at the time of the experiment were grown at the San Piero a Grado field-station (Pisa, Italy) in a greenhouse setting. The day/night mean temperatures were 27/21°C for the duration of the short experiment. The primary aim of this experiment was to determine salt stress based on leaf reflectance signatures.

Lamour et al. (2021) – The authors built on the data presented in Wu et al. (2019) and also collected paired sample data from the San Lorenzo Protected Area in Panama. Please see for more information about the specific environmental conditions above. Multiple species, canopy positions, and leaf ages were used in the development of the predictive models.

Yan et al. (2021) – Three diverse forest sites representing vastly different ecosystems in China were sampled for this experiment. These were selected because they represent temperate (Mountain Changbai, CB), subtropical (Mountain Dinghu, DH), and tropical (Xishuangbanna, XSBN) with dramatically different temperatures and annual precipitation (CB: 2.8°C, 691 mm yr\(^{-1}\), DH: 20.9°C 1927 mm yr\(^{-1}\), and XSBN: 21.8°C, 1493 mm yr\(^{-1}\)). The authors collected pair leaf reflectance data of the dominant tree species in the given location.
Zhou et al. (2021) – *Citrus limon* was used to investigate the ability to detect water stress and photosynthetic capacity in a greenhouse setting in Wuhan, Hubei Province, China. The authors report the regional weather, but because this experiment was conducted in the greenhouse, we are not sharing that information. The authors limited water for plants to induce stress and measured leaves at the top, middle, and bottom of the small, potted trees.

Ainsworth et al. (2014)–Two soybean cultivars grown in the field under ambient and elevated (~100 ppb) ozone concentrations in 2011 with 0.76m row spacing were used in the development of the PLSR models shown in this experiment. The project took place at the Soybean Free Air Concentration (SoyFACE) facility located in Champaign, IL, USA. Upper canopy, fully developed and sunlit leaves were used with the primary variation being captured in the experiment being the ozone differences, but no other environmental information was provided.

Serbin et al. (2015) – The experiment was conducted in the in the spring and early summer in 2013 and 2014 across three difference research stations in southern California (Kearney Agricultural Extension and Research Center – Parlier, CA, South Coast Research and Extension Center – Irvine, CA, and Coachella Valley Agricultural Research Station – Thermal, CA). 9 crops species across 13 different agroecosystems were sampled over the two years of the study where leaf level measurements were paired with AVRIS data.

Heckmann et al. (2017) – In the summer of 2015, plants growing in greenhouse and in the Botanical Garden at the Heinrich-Heine University, Dusseldorf, Germany, were used in the study. Special concentration was given to a Brassica oleracea and Zea mays in the greenhouse across two years with different nitrogen fertilizer applications, a low-N and sufficient-N. No environmental information is provided, but the plants were investigated ~8-10 weeks after germination.

Yendrek et al. (2017)– Across three years, the authors grew more than 100 inbred and hybrid maize genotypes in 0.76m row spacing at the SoyFACE Research Facility under ambient and elevated ozone concentrations (~100 ppb). No environmental data is provided for the field part of the experiment. Paired leaf reflectance and gas exchange traits from the field grown maize experiment was also combined with a nitrogen treatment experiment in which a single maize inbred line was grown in the greenhouse during one year of the experiment. Natural light was supplemented with metal halide lamps to provide a minimum photosynthetic photon flux density of 200 umol m\(^{-2}\) s\(^{-1}\) from 6-20 hr. Paired measurements across both the field and greenhouse experiments were used to estimate photosynthetic leaf traits with leaf reflectance.

Silva-Perez et al. (2018)–Five experiments were conducted in greenhouses and in the field in Australia (CSIRO Black Mountain – greenhouse, and GES-CSIRO – field) and Mexico (CENEB-CIMMYT – field) using diverse wheat germplasm. Paired sampling occurred at different development stages both before and following anthesis. Low and high nitrogen treatments were also implemented in the greenhouse experiments.

Fu et al. (2019) and Meacham-Hensold et al. (2019)–Six varieties of tobacco with contrasting photosynthetic capacity were grown over two field seasons. The papers showed that the high
throughput methods contained within allowed for estimations of these traits even in transgenic plants. The same research materials were used, but the statistical approaches differed between the works.

Fu et al. (2020) and Meacham-Hensold et al. (2020) – Ten different varieties of wild type and transgenic tobacco were grown in the field with the goal of developing methods of accurately estimating leaf level traits from canopy hyperspectral imaging. Paired reflectance and measured data were collected at different times during the field season to attempt to capture differences in development.

Cotrozzi et al. (2020) – The authors built PLSR models predicting hybrid maize phenotypes using facilities located at Purdue University’s (West Lafayette, IN, USA) greenhouse (Horticulture Plant Growth Facility) and fields (Agronomy Center for Research and Education). The greenhouse experiment imposed a drought treatment on the hybrid maize varieties and the day/night temperatures were 26/20°C with relative humidity between 50-60%. Standard agronomic practices for the area were used for the field experiment with paired samples being taken from 11-16hr. The authors report 257.53mm of precipitation and the average, maximum, and minimum temperatures (22.7°C, 27.6°C, and 16.3°C) over the duration of the data collection.

Kumagai et al. (2021) – The authors collected paired leaf reflectance and photosynthetic traits across two field seasons where they augmented the canopy temperature using infrared heating elements in the field with the goal of increasing the canopy temperature above ambient (ambient, +1.5, +3, +4.5, +6°C). The goal was to determine if high-throughput techniques could be used to identify photosynthetic differences in temperature across the duration of the growing season. Average July and August air temperatures in 2018 and 2019 were 23.2°C and 23.5°C with the reported precipitation being 240 and 146.8 mm.

Sexton et al. (2021) – Growth chamber grown wild type and transgenic tobacco plants were grown at high CO₂ (3000 umol mol⁻¹), 75%RH, 12h diurnal cycle with day/night temperatures set to 26°C/22°C. The light level of the chambers were set to 1000umol photons m⁻² s⁻¹ and the paired reflectance and photosynthetic traits were collected between 4-6 weeks after planting.

Wang et al. (2021) – Data was collated from Yendrek et al. (2017) and collected an independent set of maize grown in the field (Champaign, IL) at different nitrogen treatments and different nitrogen application methods was also sampled of paired leaf reflectance and photosynthetic data. Plants were also sampled at different vegetative stages.

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