



Figure S1. Experiment site locations in Woodland, California (yellow location pin marked as “Rominger plots”) and West Lafayette, Indiana (yellow location pin marked as “ACRE plots”) [75].

Table S1. Monthly weather averages (precip = precipitation; temp = temperature; deg = degrees).

Year	Location	Month	Mean Monthly Precip (mm)	Mean Air Temp (deg C)	30-Year Mean Monthly Precip (mm)	30-Year Mean Temp (deg C)
2014	Woodland	May	0	21.3	16.8	20.2
		June	0	23.3	5.6	23.5
		July	0	24.9	0	25.4
		August	0.8	23.6	1.3	24.8
		September	10.4	22.8	2.8	23.4
		October	22.6	19.6	21.3	18.8
2017	ACRE	May	156.0	15.8	120.4	16.7
		June	156.5	22.3	125.5	21.8
		July	179.8	23.5	112.8	22.9
		August	123.9	20.7	94.5	21.9
		September	50.5	19.2	78.0	18.4
		October	67.9	14.2	78.5	12.0

Table S2. Soil nutrient characteristics.

Year	Location	Soil Depth (cm)	pH	Organic Matter (%)	K (mg kg ⁻¹)	P (mg kg ⁻¹)	Mg (meq L ⁻¹)	Ca (meq L ⁻¹)	CEC (meq 100g ⁻¹)
2014	Gorman	0–15	7.6	1.60	225	43	3.0	2.8	22.5
		15–30	7.8	1.47	237	13	3.9	3.6	23.2
	Rominger	0–15	7.6	2.70	225	7	1.6	1.6	25.8
		15–30	7.6	2.26	169	4	1.7	1.9	26.9
2017	ACRE	0–20	6.4	3.1	151	20	610 ppm	2221 ppm	18.7

Treatment effect on biomass at R6: In the ground reference total dry matter model (stover + grain biomass at R6; TDM), the individual main effects of hybrid, N treatment, and plant

density were significant, yet none of the interactions were significant (Table S3). This model accounted for approximately 60% of the variability in the data. Location effects, which included the blocking effects, accounted for the largest portion of explained variability. This was not surprising considering the large difference in environment between our locations in CA and IN. Significant biomass differences between hybrids were found across N rates and densities. Hybrids with the highest biomass were DAS05 and DAS08, significantly greater than DAS09 (Table S4). Increased N levels resulted in significantly greater biomass than those under low N conditions, across all hybrids. Additionally, higher biomass levels were evident at the high planting density.

Treatment effect on total N content: Total N content (TNC) was measured at V12, R1 and R6, and ground reference models were built for each of these measurements. The models for TNC had good fit with residuals less than 30% (Table S3). Location alone accounted for more than 60% of the variability in the data across all three models indicating the substantial effect that environment had on the availability and uptake of N, as anticipated. It is well documented that availability of mineral N (N sourced from organic or non-organic matter) is strongly affected by precipitation, temperature, microbial flora, and soil type [1,76–78]. For TNC at V12, only N and plant density had significant effects on the model (Table S3). By R1, neither hybrid nor N alone were significant main effects for TNC, though plant density continued as a significant fixed effect. Interestingly, there was some hybrid separation at R1 (Table S4). DAS03 had a significantly higher R1 TNC least square mean estimate than DAS07. At R6 all three main fixed effects, hybrid, N, and plant density were significant. However, there was no significant hybrid separation in the conservative Tukey–Kramer analysis, hence TNC was not identified as an N parameter warranting further investigation with HSI.

Treatment effect on grain yield: The mixed model evaluating the treatment effects on grain yield at all 3 locations explained about 70% of the variability in the data (Table S3). Location effects accounted for more than 70% of the data variability revealing a substantial environmental effect on final grain yields. Hybrid was the only significant main fixed effect for yield.

Table S3. Mixed model analysis of treatment effects and interactions on physiological characteristics across 3 site-years ($\alpha = 0.10$).

Var	Summary of Fit Model Statistics		Random Effects		Type 3 Tests of Fixed Effects			
			REML Var Comp Est		Effect	DF	Den DF	Pr > F
			(% of Total)					
TDM at R6	N Obs	427	Loc	37.4	H	8	12	0.052
					N	2	4	0.068
	AIC	1892.2	N*Loc	10.4	PD	1	363	<0.0001
					H*N	16	363	ns
	Res(%)	43.0	H*Loc	9.2	H*PD	8	363	ns
					N*PD	2	363	ns
TNC V12	N Obs	364	Loc	69.6	H	8	12	ns
					N	2	3	0.013
	AIC	-37.7	N*Loc	2.2	PD	1	301	0.002
					H*N	16	301	ns
	Res(%)	28.2			H*PD	8	301	ns
					N*PD	2	301	ns
TNC R1	N Obs	252	Loc	66.2	H	8	12	ns
					N	2	4	ns
	AIC	2138	N*Loc	10.8	PD	1	190	0.003
					H*N	16	190	0.040
	Res(%)	20.3	H*Loc	2.7	H*PD	8	190	0.007
					N*PD	2	190	ns

TNC R6	N Obs	363	Loc	60.3	H	8	12	0.077
					N	2	4	0.035
	AIC	3132.1	N*Loc	18.3	PD	1	299	0.045
					H*N	16	299	ns
	Res(%)	18.4	H*Loc	3	H*PD	8	299	ns
GY					N*PD	2	299	ns
	N Obs	501	Loc	37.2	H	8	12	0.005
					N	2	4	ns
	AIC	1747.9	N*Loc	25.4	PD	1	436	ns
					H*N	16	436	ns
	Res(%)	27.2	H*Loc	10.3	H*PD	8	436	0.016
					N*PD	2	436	0.001

Notes: TDM = Total Dry Matter (Mg ha⁻¹) (stover + grain); TNC = Total Nitrogen Content (kg N ha⁻¹); GY = Grain Yield at 15.5% moisture content; N Obs = number of observations; AIC = Akaike's Information Criterion; Loc = Location and Blocking effects; N = Nitrogen Treatment; H = Hybrid; PD = Plant Density; DF = Degrees of Freedom for numerator; Den DF = Degrees of Freedom for denominator; ns = Not Significant at $\alpha = 0.10$. For random effects % of total variability reported. For fixed effects, *p*-value reported.

Table S4. Least square mean estimates of plant biomass at R6 (TDM), and N content (TNC) at V12, R1 and R6 for the main fixed effects of hybrid (H), nitrogen (N), and plant density (PD).

Trt Class	Main Fixed Effects	TDM R6 Estimate (Mg ha ⁻¹)			TNC V12 Estimate (kg N ha ⁻¹)			TNC R1 Estimate (kg N ha ⁻¹)			TNC R6 Estimate (kg N ha ⁻¹)			
		Means	SE		Means	LCL	UCL	Means	SE		Means	SE		
H	DAS01	22.53	AB	1.53	130	ns	127	133	170	AB	31	212	ns	28
	DAS02	22.71	AB	1.44	138	ns	136	140	173	AB	30	211	ns	27
	DAS03	23.47	AB	1.44	133	ns	131	135	195	A	30	209	ns	27
	DAS04	22.24	AB	1.44	134	ns	132	137	167	AB	30	199	ns	27
	DAS05	24.08	A	1.44	137	ns	135	140	174	AB	30	218	ns	27
	DAS06	22.25	AB	1.53	139	ns	136	142	179	AB	30	214	ns	28
	DAS07	21.37	AB	1.53	118	ns	116	121	148	B	31	185	ns	28
	DAS08	24.54	A	1.53	126	ns	124	129	184	AB	31	223	ns	28
	DAS09	20.68	B	1.44	130	ns	128	132	170	AB	30	194	ns	27
N	High_N	24.25	A	1.41	157	A	155	158	199	ns	31	251	A	29
	Med_N	22.67	AB	1.41	132	A	130	134	166	ns	31	202	AB	29
	Low_N	21.03	B	1.41	110	B	109	112	155	ns	31	169	B	29
PD	High	23.33	A	1.30	136	A	135	137	179	A	29	210	A	27
	Low	21.97	B	1.30	127	B	126	128	168	B	29	205	B	27

Note: Standard errors (SE) reported for all except TNC V12 where 95% upper and lower confidence limits (CL) are shown due to transformation of the response variable. Levels with different letters are significantly different by Tukey–Kramer HSD ($\alpha = 0.10$) within a treatment class (trt class) and physiological variable; ns = not significant.

References

- Ribaudo, M.; Hansen, L.; Livingston, M.; Mosheim, R.; Williamson, J.; Delgado, J. Nitrogen in agricultural systems: Implications for conservation policy. *USDA-ERS Econ. Res. Rep.* **2011**, *127*, 89.
- Mueller, S.M.; Messina, C.D.; Vyn, T.J. Simultaneous gains in grain yield and nitrogen efficiency over 70 years of maize genetic improvement. *Sci. Rep.* **2019**, *9*, 9095.
- Doering, O.; Galloway, J.; Theis, T.; Aneja, V.; Boyer, E.; Cassman, K.; Cowling, E.; Dickerson, R.; Herz, W.; Hey, D. *Reactive Nitrogen in the United States: An Analysis of Inputs, Flows, Consequences, and Management Options*; Board, E.S.A., Ed.; United States Environmental Protection Agency: Washington, DC, USA, 2011.
- Chen, K.; Vyn, T.J. Post-silking factor consequences for N efficiency changes over 38 years of commercial maize hybrids. *Front. Plant Sci.* **2017**, *8*, 1737. <https://doi.org/10.3389/fpls.2017.01737>.
- Ciampitti, I.A.; Vyn, T.J. Physiological perspectives of changes over time in maize yield dependency on nitrogen uptake and associated nitrogen efficiencies: A review. *Field Crops Res.* **2012**, *133*, 48–67. <https://doi.org/10.1016/j.fcr.2012.03.008>.
- DeBruin, J.L.; Schussler, J.R.; Mo, H.; Cooper, M. Grain yield and nitrogen accumulation in maize hybrids released during 1934 to 2013 in the US Midwest. *Crop Sci.* **2017**, *57*, 1431–1446. <https://doi.org/10.2135/cropsci2016.08.0704>.
- Moose, S.; Below, F.E. Biotechnology approaches to improving maize nitrogen use efficiency. In *Molecular Genetic Approaches to Maize Improvement*; Kriz, A.L., Larkins, B.A., Eds.; Springer: Berlin/Heidelberg, Germany, 2009; pp. 65–77.
- Moll, R.H.; Kamprath, E.J.; Jackson, W.A. Analysis and interpretation of factors which contribute to efficiency of nitrogen utilization. *Agron. J.* **1982**, *74*, 562–564. <https://doi.org/10.2134/agronj1982.00021962007400030037x>.
- Shrawat, A.; Zayed, A.; Lightfoot, D.A. (Eds.) *Engineering Nitrogen Utilization in Crop Plants*; Springer International Publishing: Berlin/Heidelberg, Germany, 2018.
- Salvagiotti, F.; Castellarin, J.M.; Miralles, D.J.; Pedrol, H.M. Sulfur fertilization improves nitrogen use efficiency in wheat by increasing nitrogen uptake. *Field Crops Res.* **2009**, *113*, 170–177. <https://doi.org/10.1016/j.fcr.2009.05.003>.
- Ciampitti, I.A.; Vyn, T.J. A comprehensive study of plant density consequences on nitrogen uptake dynamics of maize plants from vegetative to reproductive stages. *Field Crops Res.* **2011**, *121*, 2–18. <https://doi.org/10.1016/j.fcr.2010.10.009>.
- Gastal, F.; Lemaire, G.; Durand, J.-L.; Louarn, G. Quantifying crop responses to nitrogen and avenues to improve nitrogen-use efficiency. In *Crop Physiology*, 2nd ed.; Academic Press: Cambridge, MA, USA, 2015; pp. 161–206.
- Muñoz-Huerta, R.F.; Guevara-Gonzalez, R.G.; Contreras-Medina, L.M.; Torres-Pacheco, I.; Prado-Olivarez, J.; Ocampo-Velazquez, R.V. A review of methods for sensing the nitrogen status in plants: Advantages, disadvantages and recent advances. *Sensors* **2013**, *13*, 10823–10843. <https://doi.org/10.3390/s130810823>.
- Unkovich, M.; Herridge, D.; Peoples, M.; Cadisch, G.; Boddey, B.; Giller, K.; Alves, B.; Chalk, P. *Measuring Plant-Associated Nitrogen Fixation in Agricultural Systems*; Australian Centre for International Agricultural Research (ACIAR): Canberra, Australia, 2008.
- Zhao, D.; Raja Reddy, K.; Kakani, V.G.; Read, J.J.; Carter, G.A. Corn (*Zea mays* L.) growth, leaf pigment concentration, photosynthesis and leaf hyperspectral reflectance properties as affected by nitrogen supply. *Plant Soil* **2003**, *257*, 205–218. <https://doi.org/10.1023/a:1026233732507>.
- Araus, J.L.; Cairns, J.E. Field high-throughput phenotyping: The new crop breeding frontier. *Trends Plant Sci.* **2014**, *19*, 52–61. <https://doi.org/10.1016/j.tplants.2013.09.008>.
- Cobb, J.N.; DeClerck, G.; Greenberg, A.; Clark, R.; McCouch, S. Next-generation phenotyping: Requirements and strategies for enhancing our understanding of genotype–phenotype relationships and its relevance to crop improvement. *Theor. Appl. Genet.* **2013**, *126*, 867–887. <https://doi.org/10.1007/s00122-013-2066-0>.
- Jin, X.; Zarco-Tejada, P.; Schmidhalter, U.; Reynolds, M.P.; Hawkesford, M.J.; Varshney, R.K.; Yang, T.; Nie, C.; Li, Z.; Ming, B. High-throughput estimation of crop traits: A review of ground and aerial phenotyping platforms. *IEEE Geosci. Remote Sens. Mag.* **2020**, *9*, 200–231.
- Nguyen, G.N.; Kant, S. Improving nitrogen use efficiency in plants: Effective phenotyping in conjunction with agronomic and genetic approaches. *Funct. Plant Biol.* **2018**, *45*, 606. <https://doi.org/10.1071/fp17266>.
- Rodriguez Junior, F.A.; Ortiz-Monasterio, I.; Zarco-Tejada, P.J.; Ammar, K.; Gérard, B. Using precision agriculture and remote sensing techniques to improve genotype selection in a breeding program. In Proceedings of the 12th International Conference on Precision Agriculture (ICPA), Sacramento, CA, USA, 20–23 July 2014.
- White, J.W.; Andrade-Sanchez, P.; Gore, M.A.; Bronson, K.F.; Coffelt, T.A.; Conley, M.M.; Feldmann, K.A.; French, A.N.; Heun, J.T.; Hunsaker, D.J.; et al. Field-based phenomics for plant genetics research. *Field Crops Res.* **2012**, *133*, 101–112. <https://doi.org/10.1016/j.fcr.2012.04.003>.
- Lillesand, T.; Kiefer, R.W.; Chipman, J. *Remote Sensing and Image Interpretation*; John Wiley & Sons: Hoboken, NJ, USA, 2014.
- Campbell, J.B.; Wynne, R.H. *Introduction to Remote Sensing*; Guilford Press: New York, NY, USA, 2011.
- Mulla, D.J. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosyst. Eng.* **2013**, *114*, 358–371. <https://doi.org/10.1016/j.biosystemseng.2012.08.009>.
- Goel, P.K.; Prasher, S.O.; Landry, J.A.; Patel, R.M.; Viau, A.A.; Miller, J.R. Estimation of crop biophysical parameters through airborne and field hyperspectral remote sensing. *Trans. ASAE* **2003**, *46*, 1235–1246.
- Osborne, S.L.; Schepers, J.S.; Francis, D.D.; Schlemmer, M.R. Use of spectral radiance to estimate in-season biomass and grain yield in nitrogen- and water- stressed corn. *Crop Sci.* **2002**, *42*, 165–171.

27. Thenkabail, P.S.; Gumma, M.K.; Teluguntla, P.; Mohammed, I.A. Hyperspectral remote sensing of vegetation and agricultural crops. *Photogramm. Eng. Remote Sens.* **2014**, *80*, 697–723.
28. Thenkabail, P.S.; Smith, R.B.; De Pauw, E. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sens. Environ.* **2000**, *71*, 158–182.
29. Blackmer, T.M.; Schepers, J.S.; Varvel, G.E.; Walter-Shea, E.A. Nitrogen deficiency detection using reflected shortwave radiation from irrigated corn canopies. *Agron. J.* **1996**, *88*, 1–5.
30. Elsayed, S.; Darwish, W. Hyperspectral remote sensing to assess the water status, biomass, and yield of maize cultivars under salinity and water stress. *Bragantia* **2017**, *76*, 62–72.
31. Campbell, P.; Middleton, E.; McMurtrey, J.; Chappelle, E. Assessment of vegetation stress using reflectance or fluorescence measurements. *J. Environ. Qual.* **2007**, *36*, 832–845.
32. Osborne, S.L.; Schepers, J.S.; Francis, D.D.; Schlemmer, M.R. Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. *Agron. J.* **2002**, *94*, 1215–1221.
33. Schlemmer, M.R.; Francis, D.D.; Shanahan, J.; Schepers, J.S. Remotely measuring chlorophyll content in corn leaves with differing nitrogen levels and relative water content. *Agron. J.* **2005**, *97*, 106–112.
34. Thenkabail, P.S.; Lyon, J.G.; Huete, A. *Hyperspectral Remote Sensing of Vegetation*; CRC Press: Boca Raton, FL, USA, 2012.
35. Midwestern Regional Climate Center. Available online: <https://mrcc.illinois.edu/CLIMATE/> (accessed on 8 June 2019).
36. Indiana State Climate Office. Available online: www.iclimat.org (accessed on 2 December 2017).
37. Miller, R.O.; Gavlak, R.; Horneck, D. *Soil, Plant and Water Reference Methods for the Western Region*; WCC-103 Publication: Fort Collins, CO, USA, 2013; p. 156.
38. NCERA-13; Eliason, R.; Goos, R.J.; Hoskins, B. *Recommended Chemical Soil Test Procedures for the North Central Region*; NCERA-13, Ed.; Missouri Agricultural Experiment Station: Columbia, MO, USA, 2015; p. 76.
39. US EPA. Standard method 350.1: Nitrogen, ammonia (colorimetric, automated phenate). In *Methods for the Determination of Inorganic Substances in Environmental Samples*; Office of Research and Development, US EPA: Cincinnati, OH, USA, 1993.
40. US EPA. Method 353.2: Determination of Nitrate–Nitrite Nitrogen by Automated Colorimetry, Revision 2.0; O'Dell, J., Ed.; Environmental Monitoring Systems Laboratory: Cincinnati, OH, USA, 1993.
41. Dellavalle Laboratory Inc. *Soil Interpretation Report*; Kasapligil, D., Ed.; Dellavalle Laboratory, Inc.: Davis, CA, USA, 2014.
42. Vitosh, M.; Johnson, J.; Mengel, D. *Tri-State Fertilizer Recommendations for Corn, Soybeans, Wheat and Alfalfa*; Michigan State University Extension: East Lansing, MI, USA, 1995.
43. Rouse, J.W.J.; Haas, R.H.; Schell, J.A.; Deering, D.W.; Harlan, J.C. *Monitoring the Vernal Advancement and Retrogradation (Greenwave Effect) of Natural Vegetation*; Texas A&M University Remote Sensing Center: College Station, TX, USA, 1974.
44. Qi, J.; Chehbouni, A.; Huete, A.; Kerr, Y.; Sorooshian, S. A modified soil adjusted vegetation index. *Remote Sens. Environ.* **1994**, *48*, 119–126.
45. Chen, P.-F.; Nicolas, T.; Wang, J.-H.; Philippe, V.; Huang, W.-J.; Li, B.-G. New index for crop canopy fresh biomass estimation. *Spectrosc. Spectr. Anal.* **2010**, *30*, 512–517.
46. Merzlyak, M.N.; Gitelson, A.A.; Chivkunova, O.B.; Rakitin, V.Y. Non-destructive optical detection of pigment changes during leaf senescence and fruit ripening. *Physiol. Plant.* **1999**, *106*, 135–141.
47. Daughtry, C.S.T.; Walthall, C.L.; Kim, M.S.; Brown de Colstoun, E.; McMurtrey, J.E., III. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sens. Environ.* **2000**, *74*, 229–239.
48. Chen, P.; Haboudane, D.; Tremblay, N.; Wang, J.; Vigneault, P.; Li, B. New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat. *Remote Sens. Environ.* **2010**, *114*, 1987–1997.
49. Xue, L.; Cao, W.; Luo, W.; Dai, T.; Zhu, Y. Monitoring leaf nitrogen status in rice with canopy spectral reflectance. *Agron. J.* **2004**, *96*, 135–142.
50. Kim, M.S.; Daughtry, C.; Chappelle, E.; McMurtrey, J.; Walthall, C. The use of high spectral resolution bands for estimating absorbed photosynthetically active radiation (A_{par}). In Proceedings of the 6th Symposium on Physical Measurements and Signatures in Remote Sensing, Val D'Isere, France, 17–24 January 1994; pp. 299–306.
51. Kim, M.S. The Use of Narrow Spectral Bands for Improving Remote Sensing Estimations of Fractionally Absorbed Photosynthetically Active Radiation. In *Department of Geography*; University of Maryland: College Park, MD, USA, 1994.
52. Rondeaux, G.; Steven, M.; Baret, F. Optimization of soil-adjusted vegetation indices. *Remote Sens. Environ.* **1996**, *55*, 95–107.
53. Haboudane, D.; Miller, J.R.; Tremblay, N.; Zarco-Tejada, P.J.; Dextraze, L. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens. Environ.* **2002**, *81*, 416–426.
54. Barnes, E.; Clarke, T.; Richards, S.; Colaizzi, P.; Haberland, J.; Kostrzewski, M.; Waller, P.; Choi, C.; Riley, E.; Thompson, T. Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data. In Proceedings of the Fifth International Conference on Precision Agriculture, Bloomington, MN, USA, 16–19 July 2000.
55. Gitelson, A.A.; Gritz, Y.; Merzlyak, M.N. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *J. Plant Physiol.* **2003**, *160*, 271–282.
56. Montgomery, D.C.; Peck, E.A.; Vining, G.G. *Introduction to Linear Regression Analysis*, 5th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2012; Volume 821.
57. Bundy, L.; Carter, P. Corn hybrid response to nitrogen fertilization in the northern corn belt. *J. Prod. Agric.* **1988**, *1*, 99–104.
58. Jeschke, M.; DeBruin, J. Corn hybrid response to nitrogen fertilizer. In *Crop Insights*; DuPont Pioneer Agronomy Sciences: Johnston, Hungary, 2016; pp. 1–7.

59. Chevalier, P.; Schrader, L. Genotypic differences in nitrate absorption and partitioning of N among plant parts in maize. *Crop Sci.* **1977**, *17*, 897–901.
60. Sadras, V.O.; Calderini, D.F. *Crop Physiology: Applications for Genetic Improvement and Agronomy*, 2nd ed.; Academic Press: Cambridge, MA, USA, 2015.
61. Plénet, D.; Lemaire, G. Relationships between dynamics of nitrogen uptake and dry matter accumulation in maize crops. Determination of critical N concentration. *Plant Soil* **2000**, *216*, 65–82.
62. Haegerle, J.W.; Cook, K.A.; Nichols, D.M.; Below, F.E. Changes in nitrogen use traits associated with genetic improvement for grain yield of maize hybrids released in different decades. *Crop Sci.* **2013**, *53*, 1256. <https://doi.org/10.2135/cropsci2012.07.0429>.
63. D’Andrea, K.E.; Otegui, M.E.; Cirilo, A.G.; Eyhéabide, G.H. Ecophysiological traits in maize hybrids and their parental inbred lines: Phenotyping of responses to contrasting nitrogen supply levels. *Field Crops Res.* **2009**, *114*, 147–158. <https://doi.org/10.1016/j.fcr.2009.07.016>.
64. Schlemmer, M.; Gitelson, A.; Schepers, J.; Ferguson, R.; Peng, Y.; Shanahan, J.; Rundquist, D. Remote estimation of nitrogen and chlorophyll contents in maize at leaf and canopy levels. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *25*, 47–54. <https://doi.org/10.1016/j.jag.2013.04.003>.
65. Zhao, B.; Duan, A.; Ata-Ul-Karim, S.T.; Liu, Z.; Chen, Z.; Gong, Z.; Zhang, J.; Xiao, J.; Liu, Z.; Qin, A.; et al. Exploring new spectral bands and vegetation indices for estimating nitrogen nutrition index of summer maize. *Eur. J. Agron.* **2018**, *93*, 113–125. <https://doi.org/10.1016/j.eja.2017.12.006>.
66. Haboudane, D.; Tremblay, N.; Miller, J.R.; Vigneault, P. Remote estimation of crop chlorophyll content using spectral indices derived From hyperspectral data. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 423–437. <https://doi.org/10.1109/tgrs.2007.904836>.
67. Hunt Jr, E.R.; Doraiswamy, P.C.; McMurtrey, J.E.; Daughtry, C.S.; Perry, E.M.; Akhmedov, B. A visible band index for remote sensing leaf chlorophyll content at the canopy scale. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *21*, 103–112.
68. Zhou, K.; Cheng, T.; Zhu, Y.; Cao, W.; Ustin, S.L.; Zheng, H.; Yao, X.; Tian, Y. Assessing the impact of spatial resolution on the estimation of leaf nitrogen concentration over the full season of paddy rice using near-surface imaging spectroscopy data. *Front. Plant Sci.* **2018**, *9*, 964. <https://doi.org/10.3389/fpls.2018.00964>.
69. Boomsma, C.R.; Santini, J.B.; Tollenaar, M.; Vyn, T.J. Maize morphophysiological responses to intense crowding and low nitrogen availability: An analysis and review. *Agron. J.* **2009**, *101*, 1426. <https://doi.org/10.2134/agronj2009.0082>.
70. Buschmann, C.; Nagel, E. In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation. *Int. J. Remote Sens.* **1993**, *14*, 711–722. <https://doi.org/10.1080/01431169308904370>.
71. Thenkabail, P.S.; Smith, R.B.; De Pauw, E. Evaluation of narrowband and broadband vegetation indices for determining optimal hyperspectral wavebands for agricultural crop characterization. *Photogramm. Eng. Remote Sens.* **2002**, *68*, 607–622.
72. Blackburn, G.A. Quantifying chlorophylls and carotenoids at leaf and canopy scales: An evaluation of some hyperspectral approaches. *Remote Sens. Environ.* **1998**, *66*, 273–285. [https://doi.org/10.1016/S0034-4257\(98\)00059-5](https://doi.org/10.1016/S0034-4257(98)00059-5).
73. Goel, N.S.; Qin, W. Influences of canopy architecture on relationships between various vegetation indices and LAI and Fpar: A computer simulation. *Remote Sens. Rev.* **1994**, *10*, 309–347. <https://doi.org/10.1080/02757259409532252>.
74. Jiang, Z.; Chen, Y.; Li, J.; Dou, W. The impact of spatial resolution on NDVI over heterogeneous surface. In Proceedings of the 2005 IEEE International Geoscience and Remote Sensing Symposium, 2005, IGARSS’05, Seoul, Korea, 29 July 2005; pp. 1310–1313.
75. Google Data SIO, NOAA, U.S. Navy, NGA, GEBCO Landsat/Copernicus INEGI Data LDEO-Columbia, NSF, and N. IBCAO. Google Earth 2022. Available online: earth.google.com (accessed on 11 March 2022).
76. Chenu, K. Characterizing the crop environment—nature, significance and applications. In *Crop Physiology*; Elsevier: Amsterdam, The Netherlands, 2015; pp. 321–348.
77. Connor, D.J.; Loomis, R.S.; Cassman, K.G. *Crop Ecology: Productivity and Management in Agricultural Systems*; Cambridge University Press: Cambridge, UK, 2011.
78. Schepers, J.S.; Raun, W. (Eds.) *Nitrogen in Agricultural Systems*; ASA-CSSA-SSSA: Madison, WI, USA, 2008.