Supplementary Data

Table S1: Drone acquired data VIs used in literature.

UAV Data Vegetation indices	**References**
Normalized difference vegetation index (NDVI)	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]
Normalized difference red edge index (NDRE)	[6], [8], [9], [11]
Renormalized difference vegetation index (RDVI)	[8], [11]
Normalized difference water index (NDWI)	[8]
Maximum difference water index (MDWI)	[8]
Excess green index (EGI)	[1], [4], [13]
Enhanced vegetation index (EVI2)	[2], [15]
green difference vegetation index (GDVI)	[10], [11], [14]
Difference Vegetation Index	[11]
Green normalized difference vegetation index (GNDVI)	[2], [9], [10], [11], [16], [14]
Normalized Green red difference index (NGRDI)	[8]
Simple ratio (SR)	[2], [10], [11], [14]
Modified Simple Ratio Index (MSRI)	[10], [11]
Modified SAVI 2	[11]
Soil-adjusted Vegetation Index (SAVI)	[11]
Optimized Soil-adjusted Vegetation Index (OSAVI)	[15], [8]
Green and Red ratio Vegetation Index (GRVI)	[9]
Red-Edge Simple Ratio (SRre)	[10]
Normalized difference photosynthetic vigor ratio	[5]
TCARI	[8]
Nutritional nitrogen index (NNI)	[17]
Crop water stress index	[8]
Chlorophyll Vegetation Index	[11]
Green Chlorophyll Index	[11]
Chlorophyll concentration index	[18]
Chlorophyll reflectance red-edge index	[12]
Modified Chlorophyll Absorption Index	[11]
Crop water stress index (CWSI).	[19]
Moisture stress index	[8]
Photochemical reflectance index	[8]
canopy difference	[19]
B1/B2	[10]
Green leaf index	[13]
Visible atmospherically resistant index	[13]

Table S2: Satellite data acquired VI's used in literature

Satellite (Vegetation indices)	References
NDVI	[20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31]
DEV NDVI	[20]
normalized difference red edge index	[21]
enhanced vegetation index (EVI2)	[30], [32], [33]
Difference Vegetation Index	[24]
green normalized difference vegetation index (GNDVI)	[25], [26], [31]
simple ratio (SR)	[21]
Ratio Vegetation Index (RVI)	[24]
Soil-adjusted Vegetation Index (SAVI)	[23], [25], [26], [28]
Vegetation Condition Index (VCI)	[20]
Simple ratio red edge	[21]
TCARI	[21]
nutritional nitrogen index (NNI)	[17]
Chlorophyll Vegetation Index	[21]
Green Chlorophyll Index	[21]
chlorophyll reflectance red-edge index	[21]
Modified Chlorophyll Absorption Index	[21]
Triangular vegetation index (TVI)	[21]
modified triangular index 2	[21]
Normalized Difference Water Index	[30] ,[31]

Table S3: Drone platforms used in mapping specific NUS crop attributes other than stomatall conductance.

Drone sensor type	Crop Type	Research domain	Reference
DJI Phantom 4 Pro, M600 Pro	Palmer amaranth	Modelling, Phenology/growth, Monitoring, Regression and prediction	[1]
DJI Phantom 4 Pro	Bambara groundnut	Modelling, Production/crop yield, Phenology/growth, Regression and prediction	[2]
MikroKopter JR11X	Sorghum & Amaranth	Modelling, Phenology/growth, Regression and prediction	[3]
DJI S1000 UAV, DJI Phantom 4 Pro	Amaranthus	Classification, Phenology/growth	[34]
DJI Phantom 4 Pro	Cotton & Palmer amaranth	Classification, Land suitability, Production/crop yield, Phenology/growth,	[4]
Quadcopter G-Q45	Ruzi grass & Millet	Modelling, Production/crop yield, Phenology/growth, Regression and prediction	[17]
Hexacopter UAV, M600 Pro	Tumeric	Modelling, Physiology, Phenology/growth, Regression and prediction	[18]

	Sorghum	Phenotyping, growth, production	[35]
DJI Phantom 4 Pro	Bambara groundnut	Modelling, Phenotyping/crop genetics, Physiology, Phenology/growth, Regression and prediction	[36]
DJI 100	Alfalfa	Phenotyping/crop genetics, Phenology/growth	[9]
Parrot Bebop 2 Pro,	Chickpea & Lentil	Classification, Physiology and crop vigour, Phenology/growth	[10]
Sensefly eBee RTK	Red clover	Land suitability, Modelling, Phenology/growth	[14]
DJI Phantom 4 Pro	Legumes	Modelling, Climate adaptation, Production/crop yield, Physiology, Phenology/growth.	[11]
Octocopter	Dry bean	Phenotyping/crop genetics, Production/crop yield, Phenology/growth	[16]
DJI Inspire 1	Sweet potato	Phenotyping/crop genetics, Climate adaptation, Production/crop yield, Physiology, Phenology/growth	[12]
Cessna	Taro	Classification, Land suitability, Production/crop yield	[37]
DJI S1000 UAV	Sweet potato	Modelling, Production/crop yield, Physiology, Phenology/growth	[38]
Mavic Mini	Chickpea	Modelling, Climate adaptation, Physiology, Phenology/growth, Regression and prediction	[13]

Table S4: Drone platforms used to map the spatial distribution of various NUS crops.

Drone used in study	**Crop assessed**
Octocopter	Dry bean [16]
Hexacopter UAV	Tumeric [18]
Cessna	Taro [37]
Parrot Bebop 2 Pro	Chickpea and Lentil [10]
DJI Inspire 1	Sweet potato [12]
DJI 100	Alfalfa (Medicago sativa L) [9]
DJI S1000 UAV	Amaranthus [34], Sweet potato[38]
DJI Phantom 4 Pro	Palmer amaranth [1], Bamara groundut [2], Amaranthus [34], Palmer amaranth (Amaranthus palmeri S. Watson) [4] , Bamara groundut [7] Legume [11].
M600 Pro	Palmer amaranth [1], Tumeric [18]
Mavic Mini	Chickpea [13]
quadcopter G-Q45	Ruzi grass and Millet [17]
Sensefly eBee RTK	Red clover [14]
MikroKopter JR11X	sorghum and amaranth *[3]*

Table S5: Satellite borne sensors used to assess NUS crops.

Reference	**Satellite Sensor**	**Crop type**	**Research domain**
[28]	Landsat Thematic mapper	Chickpea, lentil, vetch	Classification, Regression and prediction, Climate adaptation, Production/crop yield, Phenology/growth, Regression and prediction
[22]	Landsat 7	Sorghum	Regression and prediction, Land suiitability, Climate adaptation, Physiology and crop vigour, Phenology
[20]	MODIS	Teff, haricot beans, sweet potato (Ipomoea batatas) and taro (Colocasia esculenta).	Land suiitability, Modelling, Climate adaptation, Production/crop yield, Phenology, Regression and prediction
[33]	MODIS	C3 and C4 crops	Regression and prediction, Land suiitability, Modelling, Climate adaptation, Production
[17]	Planet	Ruzi grass & Millet	Modelling, Production/crop yield, Phenology/growth, regression
[17]	Sentinel-2	Ruzi grass & Millet	Modelling, Production/crop yield, Phenology/growth, regression
[21]	Sentinel-2	Cotton & Sugar beet	Modelling, Production/crop yield, Physiology, Phenology/growth, regression
[23]	Sentinel-2	Sorghum, alfalfa,	Land suiitability, Modelling, Climate adaptation, Production/crop yield, Phenology, Regression and prediction
[39]	Sentinel-2	Chickpea, faba bean, field pea, lentil, vetch	Classification, land suitability, Phenology/growth
[25]	Sentinel-2	Sweet potato	Phenotyping, Climate adaptation, Phenology/growth, Regression, and prediction
[26]	Sentinel-2	Sweet potato	Classification, Regression and prediction, Climate adaptation, Production/crop yield, Phenology
[27]	Sentinel-2	Legumes	Modelling, Climate adaptation, Physiology, Phenology/growth, regression
[30]	Sentinel-2	Sorghum, Alfalfa, and dry beans	Classification, land suitability, Climate adaptation,Phenology/growth
[29]	Worldview 2	Sweet potato	Classification, land suitability, Climate adaptation,Phenology/growth
[24]	LiDAR	Sorghum	Phenotyping/crop genetics, Phenology
[40]	LiDAR	Cassava	Regression and prediction,Phenotyping/crop genetics, Physiology, Phenology,

[41]	LiDAR	Sweet potato	Regression and prediction, Physiology, Phenology,
[33]	Global Ozone Monitoring Experiment-2 satellite	C3 and C4 crops	Regression and prediction, Land suitability, Modelling, Climate adaptation, Production
[31]	Landsat 8	Alfalfa	Classification,, Land suitability, Production/crop yield, Climate adaptation, Phenology

Table S6: Satellites Datasets used by different institution to assess various research domains of NUS.

Satellite sensor articles and Institutions					
Author	**Article title**	**Publication**	**Area**	**Crop Type**	**Institutions**
[20]	Assessing the spatio-temporal variability of NDVI and VCI as indices of crops productivity in Ethiopia: a remote sensing approach	2021	Ethiopia	Teff, haricot beans, sweet potato (Ipomoea batatas) and taro (Colocasia esculenta).	Copperbelt University, Kitwe, Zambia; b Institute of Climate and Society, Mekelle University, Mekelle, Ethiopia. University of Nigeria, Nsukka, Enugu, Nigeria. Ghent University, Ghent, Belgium.
[17]	Nitrogen variability assessment of pasture fields under an integrated crop-livestock system using UAV, PlanetScope, and Sentinel-2 data	2022	Brazil	Ruzi grass & Millet	Federal Institute of Education, Science and Technology of Alagoas, 57120-000 Satuba, Alagoas, Brazil.. University of Campinas, 13083-896 Campinas, Sao Paulo, Brazil.
[21]	Remotely sensed vegetation indices for crop nutrition mapping	2020	Iran	Cotton & Sugar beet	Shahid Rajaee Teacher Training University, Tehran, 16785-136, Iran. E-mail: a_sharifi@sru.ac.ir
[23]	Optimized land use through integrated land suitability and gis approach in west el-minia governorate, upper Egypt	2021	Egypt	Sorghum & alfalfa,	Ain-Shams University, Cairo 11241, Egypt. National Authority for Remote Sensing and Space Sciences, Cairo 11769, Egypt; National Authority for Remote Sensing and Space Sciences (NARSS),
[22]	Water requirement and crop coefficients of sorghum in apodi plateau [Necessidade hídrica e coeficientes de cultivo do sorgo nas condições da chapada do apodi]	2021	Brazil	Sorghum	Research developed at Empresa de Pesquisa Agropecuária do Rio Grande do Norte, Apodi, RN, Brazil Faculdade UNINASSAU, Caruaru, PE, Brazil Universidade Federal Rural do Semi-Árido/Centro de Ciências Agrárias/Departamento de Ciências Agronômicas e Florestais, Mossoró, RN, Brazil
[39]	Needle in a haystack: Mapping rare and infrequent crops using satellite imagery and data balancing methods	2019	Australia	Chickpea, faba bean, field pea, lentil, vetch	CSIRO Agriculture & Food, St Lucia, QLD 4067, Australia CSIRO Data61, Docklands, VIC 3008, Australia CSIRO Agriculture & Food, Floreat, WA 6014, Australia

[24]	Crop 3D—a LiDAR based platform for 3D high-throughput crop phenotyping	2018	China	Sorghum	University of Chinese Academy of Sciences, Beijing China. Beijing Normal University, Beijing 100875, China.
[33]	Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence	2016	USA	C3 and C4 crops	Stanford University, Stanford, CA 94305,USA Nanjing University, Nanjing 210023, China, German Research Center for Geosciences (GFZ), Telegrafenberg A17, 14473 Potsdam, Germany, National Aeronautics and Space Administration Goddard Space Flight Center, Greenbelt, MD 20771, USA
[25]	Use of remote sensing to characterize the phenological development and to predict sweet potato yield in two growing seasons	2021	Brazil	Sweet potato	São Paulo State University. Federal University Lavras, Brazil. Taquaritinguense Institute of Higher Education, Brazil
[26]	Predicting on multi-target regression for the yield of sweet potato by the market class of its roots upon vegetation indices	2021	Brazil	Sweet potato	São Paulo State University.
[40]	Prediction of aboveground biomass of three cassava (manihot esculenta) genotypes using a terrestrial laser scann	2021	Colombia	Cassava	Texas A&M University, College Station, TX, USA International Center for Tropical Agriculture, Santiago de Cali 6713, Colombia
[27]	Application of Sentinel-2A data for pasture biomass monitoring using a physically based radiative transfer model	2018	England	Legumes	University of Reading, Reading RG6 6UR, UK
[28]	Biophysical and yield information for precision farming from near-real-time and historical Landsat TM images	2003	Syria	Chickpea, lentil, vetch	Yale University, New Haven.
[41]	Estimating Leaf Water Content through Low-Cost LiDAR	2022	Japan	Sweet potato	Chiba University, 648, Matsudo, Matsudo-shi 271-8510, Japan.
[29]	Parcel-level mapping of crops in a smallholder agricultural area: A case of central China using single-temporal VHSR imagery	2020	China	Sweet potato,	China University of Geosciences (CUG), Wuhan 430074, PR China. University of Connecticut, Storrs, CT 06269, USA. Key Laboratory of Rule of Law Research, Ministry of Natural Resources, Wuhan 430074, PR China
[31]	Crop type detection using an object-based classification method and multi-temporal Landsat satellite images,Paddy and Water Environment	2022	Iran	Alfalfa	Department of Water Resources Study and Research, Water Research Institute, Tehran, Iran
[30]	Exploring machine learning algorithms for mapping crop types in a heterogeneous agriculture landscape using Sentinel-2 data. A case study of	2020	South Africa	Sorghum, Alfalfa and dry beans	Geo-information Division, Institute for soil water and climate, Agricultural Research Council.

	Free State Province, South Africa				University of Witwatersrand. Private Bag x3, Wits 2050, Johannesburg, South Africa.

Table S7: Institutions that utilized UAV borne sensors to assess NUS crops.

UAV articles and Institutions					
Author	**Article title**	**Publication**	**Area**	**Crop Type**	**Institutions**
[1]	Seed rain potential in late-season weed escapes can be estimated using remote sensing	2021	United States	Palmer amaranth	Texas A&M University, College Station, TX, USA;
[2]	The feasibility of using a low-cost near-infrared, sensitive, consumer-grade digital camera mounted on a commercial UAV to assess Bambara groundnut yield	2022	Malaysia	Bamara groundut	University of Nottingham Malaysia Campus, Semenyih, Malaysia. The University of Adelaide, Glen Osmond, Australia. Charles Darwin University, Casuarina, Australia. University of Nottingham, Nottingham, UK.
[3]	Assessment of Weed Classification Using Hyperspectral Reflectance and Optimal Multispectral UAV Imagery	2021	Australia	sorghum and amaranth	The University of Queensland, Gatton Campus, QLD 4343, Australia. University Putra Malaysia, Serdang 43400, Selangor, Malaysia
[34]	Field identification of weed species and glyphosate-resistant weeds using high resolution imagery in early growing season	2020	USA	Amaranth	Shiraz University, Shiraz, Iran. North Dakota State University, Fargo, ND, USA. Montana State University, Bozeman, MT, USA. Yazd University, Yazd, Iran
[4]	Mapping and Estimating Weeds in Cotton Using Unmanned Aerial Systems-Borne Imagery	2020	United States	Cotton, Palmer amaranth (Amaranthus palmeri S. Watson)	Texas A&M University, College Station, TX 77843, USA.
[17]	Nitrogen variability assessment of pasture fields under an integrated crop-livestock system using UAV, PlanetScope, and Sentinel-2 data	2022	Brazil	Ruzi grass & Millet	Federal Institute of Education, Science and Technology of Alagoas, 57120-000 Satuba, Alagoas, Brazil. University of Campinas, 13083-896 Campinas, Sao Paulo, Brazil.
[35]	Corn and sorghum phenotyping using a fixed-wing UAV-based remote sensing system	2016	United States	Sorghum	

[7]	Use of Unmanned Aerial Vehicles (UAVs) Imagery in Phenotyping of Bambara Groundnut	2020	Selangor	Bambara groundnut	Semenyih, Selangor, Malaysia. University of Nottingham Malaysia. University of Reading, Early Gate, Reading, UK
[9]	Phenomics-Assisted Selection for Herbage Accumulation in Alfalfa (Medicago sativa L.)	2021	United States	Alfalfa (Medicago sativa L)	University of Florida, Gainesville, FL, United States. EMBRAPA-ACRE, Rio Branco, Brazil.
[10]	Drone RGB Images as a Reliable Information Source to Determine Legumes Establishment Success	2021	Spain	Chickpea & Lentil	Universitat Politècnica de València. Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA), Finca "El Encin". Areaverde MG Projects SL. C/Oña, 43, 28933 Madrid, Spain.
[14]	The Application of an Unmanned Aerial System and Machine Learning Techniques for Red Clover-Grass Mixture Yield Estimation under Variety Performance Trials	2021	Estonia	Red clover	Estonian University of Life Sciences, Kreutzwaldi 5, EE-51006 Tartu, Estonia. University of Brighton, Lewes Road, Brighton BN2 4JG, UK. Agricultural Research Center, 4/6 Teaduse St., 75501 Saku, Estonia. National Chung Hsing University, Taichung 402, Taiwan.
[11]	Prediction of Biomass and N Fixation of Legume-Grass Mixtures Using Sensor Fusion	2021	Germany	Legume	Universität Kassel, Witzenhausen, Germany
[16]	High-throughput field phenotyping in dry bean using small unmanned aerial vehicle based multispectral imagery	2018	United States	Dry bean	Washington State University, United States. University of Missouri, 211 Agricultural Engineering Building, Columbia, MO, United States. USDA–ARS, Grain Legume Genetics and Physiology Research Unit, 24106 N. Bunn Rd., Prosser, WA, United States
[12]	Phenotyping of productivity and resilience in sweetpotato under water stress through UAV-based multispectral and thermal imagery in Mozambique	2021	Mozambique	Sweet potato	International Potato Center (CIP), Lima, Peru Universidad Nacional Agraria La Molina (UNALM), Lima, Peru. International Potato Center (CIP), Maputo, Mozambique.

					International Potato Center (CIP), Nairobi, Kenya.
[37]	Mapping wild taro with color-infrared aerial photography and image processing	2007	United States	Taro	USDA-ARS, Integrated Farming and Natural Resources Research Unit, 2413 E. Highway 83, Weslaco.
[38]	Estimation of ground surface and accuracy assessments of growth parameters for a sweet potato community in ridge cultition	2019	Japan	Sweet potato	The University of Tokyo, Graduate School of Agricultural and Life Sciences,1-1-1 Yayoi, Bunkyo, Tokyo 113-8657, Japan. National Institute for Environmental Studies, 16. Takasaki University of Health and Welfare, 54 Nakaorui-machi, Takasaki, Gunma 370-0033, Japan.
[13]	Uav-Based Imaging for Prediction of Chickpea Crop Biophysical Parameters and Yield	2022	Israel	Chickpea	Newe Ya'ar Research Center, Agricultural Research Organization (ARO) - Volcani Center, Ramat Yishay 30095, Israel. The Hebrew University of Jerusalem, Rehovot 7610001, Israel. Field Crops and Natural Resources Department, Agricultural Research Organization (ARO) – Gilat Research Center, Gilat 8531100, Israel
[42]	Classifying Breadfruit Tree using Artificial Neural Networks	2018	China	Breadfruit	Technological Institute of the Philippines, Manila Philippines.

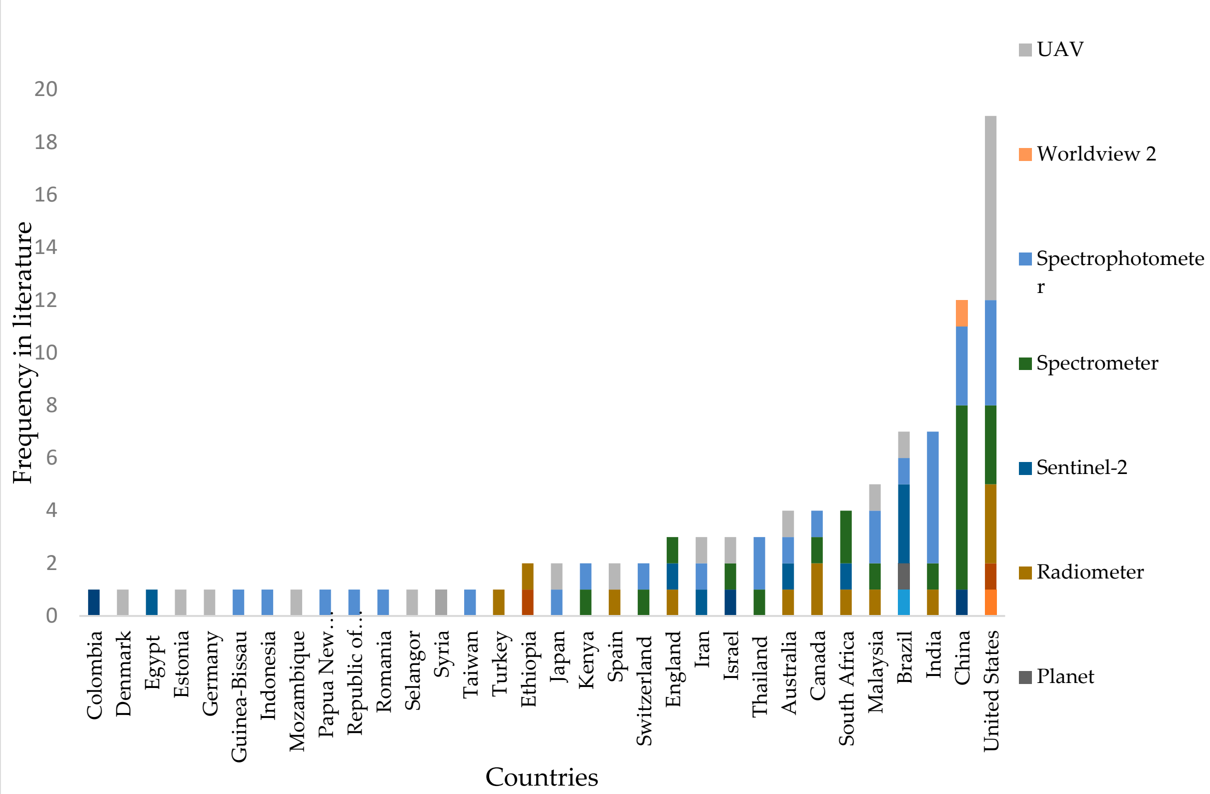

Figure S1: Countries and various sensors they used to assess NUS.

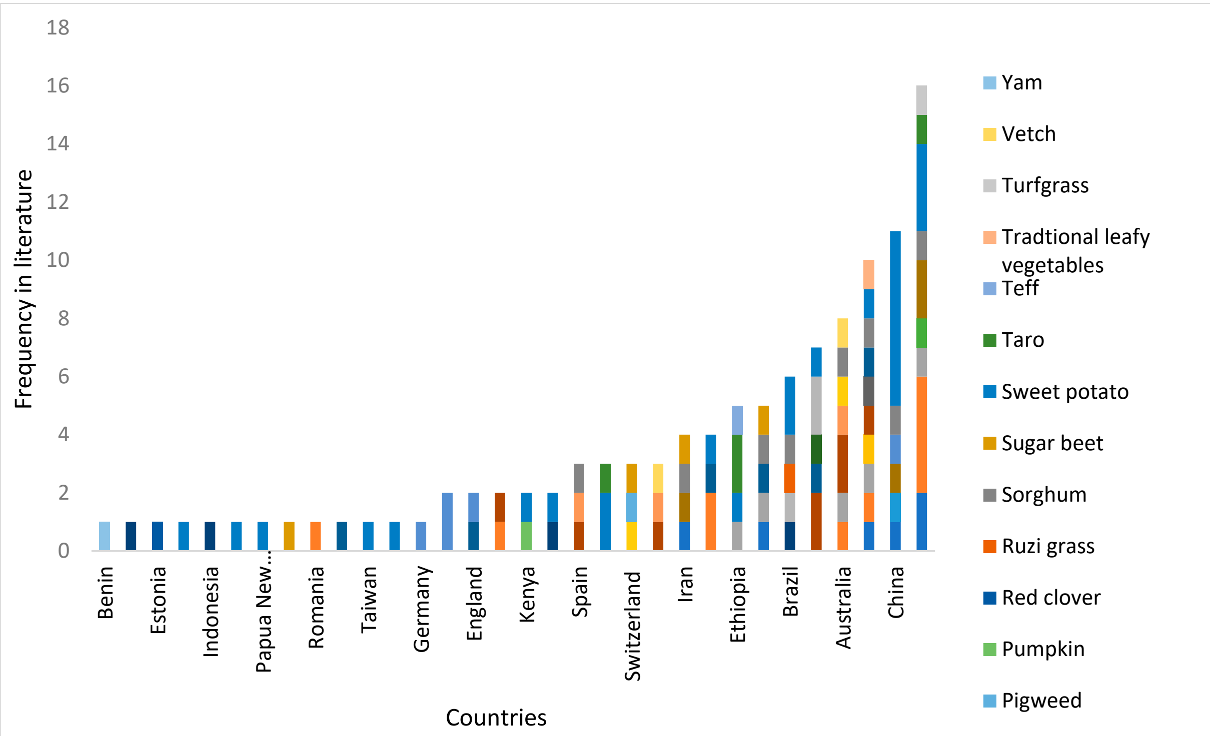

Figure:S2 Countries which assessed various NUS crops.

References

1. Kutugata, M.; Hu, C.; Sapkota, B.; Bagavathiannan, M. Seed rain potential in late-season weed escapes can be estimated using remote sensing. *Weed Sci.* **2021**, *69*, 653–659.
2. Jewan, S.Y.Y.; Pagay, V.; Billa, L.; Tyerman, S.D.; Gautam, D.; Sparkes, D.; Chai, H.H.; Singh, A. The feasibility of using a low-cost near-infrared, sensitive, consumer-grade digital camera mounted on a commercial UAV to assess Bambara groundnut yield. *Int. J. Remote Sens.* **2022**, *43*, 393–423. https://doi.org/10.1080/01431161.2021.1974116.
3. Che'Ya, N.N.; Dunwoody, E.; Gupta, M. Assessment of Weed Classification Using Hyperspectral Reflectance and Optimal Multispectral UAV Imagery. *Agronomy* **2021**, *11*, 1435. https://doi.org/10.3390/agronomy11071435.
4. Sapkota, B.; Singh, V.; Cope, D.; Valasek, J.; Bagavathiannan, M. Mapping and Estimating Weeds in Cotton Using Unmanned Aerial Systems-Borne Imagery. *Agriengineering* **2020**, *2*, 24. https://doi.org/10.3390/agriengineering2020024.
5. Huang, Y.B.; Reddy, K.N.; Fletcher, R.S.; Pennington, D. UAV Low-Altitude Remote Sensing for Precision Weed Management. *Weed Technol.* **2018**, *32*, 2–6. https://doi.org/10.1017/wet.2017.89.
6. Li, L.; Zheng, X.; Zhao, K.; Li, X.; Meng, Z.; Su, C. Potential Evaluation of High Spatial Resolution Multi-Spectral Images Based on Unmanned Aerial Vehicle in Accurate Recognition of Crop Types. *J. Indian Soc. Remote Sens.* **2020**, *48*, 1471–1478.
7. Suhairi, T.A.S.T.M.; Sinin, S.S.M.; Wimalasiri, E.M.; Nizar, N.M.M.; Tharmandran, A.S.; Jahanshiri, E.; Gregory, P.J.; Azam-Ali, S.N. Use of Unmanned Aerial Vehicles (UAVs) Imagery in Phenotyping of Bambara Groundnut. *J. Agric. Sci.* **2020**, *12*. https://doi.org/10.5539/jas.v12n6p12
8. Awais, M.; Li, W.; Cheema, M.; Zaman, Q.; Shaheen, A.; Aslam, B.; Zhu, W.; Ajmal, M.; Faheem, M.; Hussain, S. UAV-based remote sensing in plant stress imagine using high-resolution thermal sensor for digital agriculture practices: A meta-review. *Int. J. Environ. Sci. Technol.* **2022**, *20*, 1135–1152.
9. Biswas, A.; Andrade, M.H.M.L.; Acharya, J.P.; de Souza, C.L.; Lopez, Y.; De Assis, G.; Shirbhate, S.; Singh, A.; Munoz, P.; Rios, E.F. Phenomics-Assisted Selection for Herbage Accumulation in Alfalfa (Medicago sativa L.). *Front. Plant Sci.* **2021**, *12*, 756768.
10. Parra, L.; Mostaza-Colado, D.; Yousfi, S.; Marin, J.F.; Mauri, P.V.; Lloret, J. Drone RGB images as a reliable information source to determine legumes establishment success. *Drones* **2021**, *5*, 79.
11. Grüner, E.; Astor, T.; Wachendorf, M. Prediction of biomass and N fixation of legume–grass mixtures using sensor fusion. *Front. Plant Sci.* **2021**, *11*, 603921.
12. Ramírez, D.A.; Grüneberg, W.; Andrade, M.I.; De Boeck, B.; Loayza, H.; Makunde, G.S.; Ninanya, J.; Rinza, J.; Heck, S.; Campos, H. Phenotyping of productivity and resilience in sweetpotato under water stress through UAV-based multispectral and thermal imagery in Mozambique. *J. Agron. Crop Sci.* **2023**, *209*, 41–55.
13. Lati, R.; Avneri, A.; Aharon, S.; Atsmon, G.; Smirnov, E.; Sadeh, R.; Abbo, S.; Peleg, Z.; Herrmann, I.; Bonfil, D.J. Uav-Based Imaging for Prediction of Chickpea Crop Biophysical Parameters and Yield. *Available at SSRN 4123863*.
14. Li, K.-Y.; Burnside, N.G.; Sampaio de Lima, R.; Villoslada Peciña, M.; Sepp, K.; Yang, M.-D.; Raet, J.; Vain, A.; Selge, A.; Sepp, K. The application of an unmanned aerial system and machine learning techniques for red clover-grass mixture yield estimation under variety performance trials. *Remote Sens.* **2021**, *13*, 1994.
15. Sobejano-Paz, V.; Mikkelsen, T.N.; Baum, A.; Mo, X.; Liu, S.; Köppl, C.J.; Johnson, M.S.; Gulyas, L.; García, M. Hyperspectral and thermal sensing of stomatal conductance, transpiration, and photosynthesis for soybean and maize under drought. *Remote Sens.* **2020**, *12*, 3182.
16. Sankaran, S.; Zhou, J.; Khot, L.R.; Trapp, J.J.; Mndolwa, E.; Miklas, P.N. High-throughput field phenotyping in dry bean using small unmanned aerial vehicle based multispectral imagery. *Comput. Electron. Agric.* **2018**, *151*, 84–92.
17. Pereira, F.d.S.; de Lima, J.; Freitas, R.; Dos Reis, A.A.; do Amaral, L.R.; Figueiredo, G.K.D.A.; Lamparelli, R.A.; Magalhães, P.S.G. Nitrogen variability assessment of pasture fields under an integrated crop-livestock system using UAV, PlanetScope, and Sentinel-2 data. *Comput. Electron. Agric.* **2022**, *193*, 106645.
18. Singhal, G.; Bansod, B.; Mathew, L.; Goswami, J.; Choudhury, B.; Raju, P. Estimation of leaf chlorophyll concentration in turmeric (Curcuma longa) using high-resolution unmanned aerial vehicle imagery based on kernel ridge regression. *J. Indian Soc. Remote Sens.* **2019**, *47*, 1111–1122.

19. Awais, M.; Li, W.; Cheema, M.; Hussain, S.; Shaheen, A.; Aslam, B.; Liu, C.; Ali, A. Assessment of optimal flying height and timing using high-resolution unmanned aerial vehicle images in precision agriculture. *Int. J. Environ. Sci. Technol.* **2022**, *19*, 2703–2720.
20. Kourouma, J.M.; Eze, E.; Negash, E.; Phiri, D.; Vinya, R.; Girma, A.; Zenebe, A. Assessing the spatio-temporal variability of NDVI and VCI as indices of crops productivity in Ethiopia: A remote sensing approach. *Geomat. Nat. Hazards Risk* **2021**, *12*, 2880–2903. https://doi.org/10.1080/19475705.2021.1976849.
21. Sharifi, A. Remotely sensed vegetation indices for crop nutrition mapping. *J. Sci. Food Agric.* **2020**, *100*, 5191–5196. https://doi.org/10.1002/jsfa.10568.
22. Lima, J.G.; Espínola, J.; Medeiros, J.F.d.; Viana, P.C.; Maniçoba, R.M. Water requirement and crop coefficients of sorghum in Apodi Plateau. *Rev. Bras. De Eng. Agrícola E Ambient.* **2021**, *25*, 684–688.
23. Zakarya, Y.M.; Metwaly, M.M.; AbdelRahman, M.A.; Metwalli, M.R.; Koubouris, G. Optimized land use through integrated land suitability and GIS approach in West El-Minia Governorate, Upper Egypt. *Sustainability* **2021**, *13*, 12236.
24. Guo, Q.; Wu, F.; Pang, S.; Zhao, X.; Chen, L.; Liu, J.; Xue, B.; Xu, G.; Li, L.; Jing, H. Crop 3D—A LiDAR based platform for 3D high-throughput crop phenotyping. *Sci. China Life Sci.* **2018**, *61*, 328–339.
25. Tedesco, D.; de Oliveira, M.F.; dos Santos, A.F.; Silva, E.H.C.; de Souza Rolim, G.; da Silva, R.P. Use of remote sensing to characterize the phenological development and to predict sweet potato yield in two growing seasons. *Eur. J. Agron.* **2021**, *129*, 126337.
26. Tedesco, D.; de Almeida Moreira, B.R.; Júnior, M.R.B.; Papa, J.P.; da Silva, R.P. Predicting on multi-target regression for the yield of sweet potato by the market class of its roots upon vegetation indices. *Comput. Electron. Agric.* **2021**, *191*, 106544.
27. Punalekar, S.M.; Verhoef, A.; Quaife, T.; Humphries, D.; Bermingham, L.; Reynolds, C. Application of Sentinel-2A data for pasture biomass monitoring using a physically based radiative transfer model. *Remote Sens. Environ.* **2018**, *218*, 207–220.
28. Thenkabail, P. Biophysical and yield information for precision farming from near-real-time and historical Landsat TM images. *Int. J. Remote Sens.* **2003**, *24*, 2879–2904.
29. Zhang, P.; Hu, S.; Li, W.; Zhang, C. Parcel-level mapping of crops in a smallholder agricultural area: A case of central China using single-temporal VHSR imagery. *Comput. Electron. Agric.* **2020**, *175*, 105581.
30. Mazarire, T.T.; Ratshiedana, P.E.; Nyamugama, A.; Adam, E.; Chirima, G. Exploring machine learning algorithms for mapping crop types in a heterogeneous agriculture landscape using Sentinel-2 data. A case study of Free State Province, South Africa. *S. Afr. J. Geomat.* **2020**, *9*, 333–347.
31. Karimi, N.; Sheshangosht, S.; Eftekhari, M. Crop type detection using an object-based classification method and multi-temporal Landsat satellite images. *Paddy Water Environ.* **2022**, *20*, 395–412.
32. Karlson, M.; Ostwald, M.; Bayala, J.; Bazié, H.R.; Ouedraogo, A.S.; Soro, B.; Sanou, J.; Reese, H. The potential of Sentinel-2 for crop production estimation in a smallholder agroforestry landscape, Burkina Faso. *Front. Environ. Sci.* **2020**, *8*, 85.
33. Guan, K.; Berry, J.A.; Zhang, Y.; Joiner, J.; Guanter, L.; Badgley, G.; Lobell, D.B. Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence. *Glob. Change Biol.* **2016**, *22*, 716–726.
34. Shirzadifar, A.; Bajwa, S.; Nowatzki, J.; Bazrafkan, A. Field identification of weed species and glyphosate-resistant weeds using high resolution imagery in early growing season. *Biosyst. Eng.* **2020**, *200*, 200–214.
35. Shi, Y.; Murray, S.C.; Rooney, W.L.; Valasek, J.; Olsenholler, J.; Pugh, N.A.; Henrickson, J.; Bowden, E.; Zhang, D.; Thomasson, J.A. Corn and sorghum phenotyping using a fixed-wing UAV-based remote sensing system. In *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping*; SPIE: Bellingham, WA, USA, 2016; pp. 46–53.
36. Wimalasiri, E.M.; Jahanshiri, E.; Suhairi, T.; Udayangani, H.; Mapa, R.B.; Karunaratne, A.S.; Vidhanarachchi, L.P.; Azam-Ali, S.N. Basic Soil Data Requirements for Process-Based Crop Models as a Basis for Crop Diversification. *Sustainability* **2020**, *12*, 7781. https://doi.org/10.3390/su12187781.
37. Everitt, J.; Yang, C.; Davis, M.; Everitt, J.; Davis, M. Mapping wild taro with color-infrared aerial photography and image processing. *J. Aquat. Plant Manag.* **2007**, *45*, 106–110.
38. Teng, P.; Ono, E.; Zhang, Y.; Aono, M.; Shimizu, Y.; Hosoi, F.; Omasa, K. Estimation of ground surface and accuracy assessments of growth parameters for a sweet potato community in ridge cultivation. *Remote Sens.* **2019**, *11*, 1487.
39. Waldner, F.; Chen, Y.; Lawes, R.; Hochman, Z. Needle in a haystack: Mapping rare and infrequent crops using satellite imagery and data balancing methods. *Remote Sens. Environ.* **2019**, *233*, 111375.
40. Adams, T.; Bruton, R.; Ruiz, H.; Barrios-Perez, I.; Selvaraj, M.G.; Hays, D.B. Prediction of Aboveground Biomass of Three Cassava (Manihot esculenta) Genotypes Using a Terrestrial Laser Scanner. *Remote Sens.* **2021**, *13*, 1272.

41. Hama, A.; Matsumoto, Y.; Matsuoka, N. Estimating Leaf Water Content through Low-Cost LiDAR. *Agronomy* **2022**, *12*, 1183.
42. Malinao, R.M.L.; Hernandez, A.A. Classifying Breadfruit Tree using Artificial Neural Networks. In Proceedings of Proceedings of the 6th ACM/ACIS International Conference on Applied Computing and Information Technology, Kunming, China, 13–15 June 2018; pp. 27–31.