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REMOTE SENSING AND PHYSIOLOGICAL BIOMARKERS FOR DROUGHT STRESS IN FOREST TREES AND CROPS

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Abstract

An increased risk to the productivity of forests and farms throughout the world, drought stress is proving to be an even greater risk hence necessitating more methods of detecting and gauging them as rapidly and precisely as possible. As evidence by this study, a combination of remote sensing and physiological biomarkers can be used to locate and quantify drought stress in trees and crops growing in forests. The model identified early indications of drought in multiple spatial scales and made use of hyperspectral image, thermal remote sensing and satellite based vegetation indices (NDVI and NDWI). Meanwhile, the remotely observed drought indicators were confirmed with the help of ground-truthing the physiological data of plants, such as chlorophyll fluorescence, leaf water content, and stomatal conductance. To guess how severe a drought will be we grouped the spectral information through highly developed machine-learning approaches--particularly convolutional neural networks. It had very accurate results (R 2 = 0.87) with low values of RMSE. The scheme of the technique workflow is depicted in Figure 1 and consists of the pieces of data fusion, preprocessing, spectrum analysis, and validation. The findings indicated that strong relationships existed between remotely sensed indices and physiological responses in case of drought. The model was also able to identify the drought-tolerating and drought-intolerating plant species correctly which is valuable data under adaptive water management and precision agriculture. The given study advances the science of drought detection by offering a scaleable, non-invasive and data-driven technique in integration of remote sensing technologies with physiological science. The findings have far reaching consequences on climate change resilience of ecosystems, the enhancement of irrigation practices, and climate change resilience of ecosystems.

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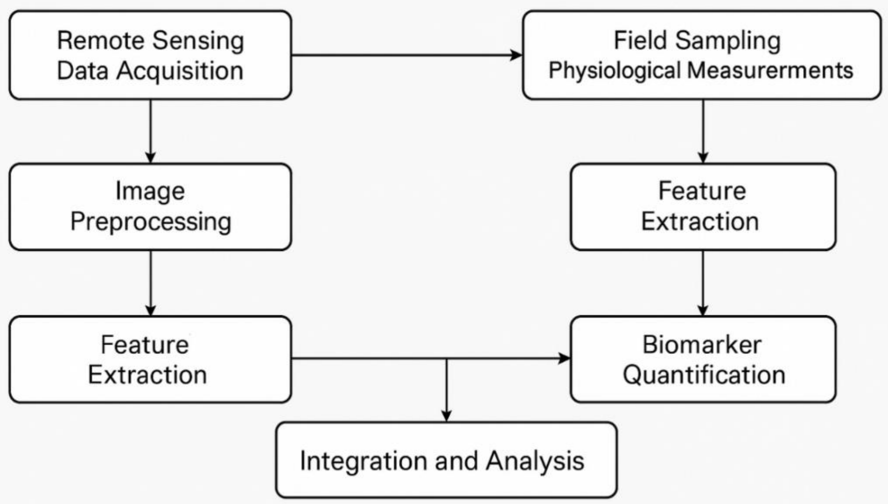
INTRODUCTION

One of the main risks of drought stress to forest and crop ecosystems is that it negatively affects the health and productivity of plants and the overall stability of an entire ecosystem (Trugman et al., 2021). Increased frequency and duration of droughts are also caused by climatic changes and poor water management. This implies that we should identify good strategies of monitoring and mitigating the impact of droughts (Altaf et al., 2022; Haghpanah et al., 2024; Kapoor et al., 2020). Remote sensing solutions provide us with ample resources to monitor and determine the well-being of plants and whether they are enduring the effect of drought in their region (or not) at large scales (Łągiewska & Bartold, 2025). Phsiological biomarkers indicate the ways plants react to the lack of sufficient supply of water on the cellular and molecular level. These biomarkers combine with remote sensing carried out techniques to enable us realize thebeta drought-tolerant or vulnerable of our plants (Kaur et al., 2021). Through a combination of remote sensing data and physiological measurement, we will also be able to gain the entire image of the plants response to drought stress. This will enable us to identify the drought-tolerant genotypes, enhance irrigation policies, and devise how upcoming droughts will influence forests and farms (Ucak and ARSLAN, 2023). The use of remote sensing tools to analyze the drought stress is extremely important since it provides us with the data concerning the condition of plants in a particular region, as well as without being harmful. Several variations of spectral index, which are obtained using satellite-based or airplane-based images, are responsive to modifications in the volume of water in plants, photosynthesis efficacy, and well-being (Meng et al., 2025). Ordinary indicators of green biomass are an easy calculation to present the effects of drought on leaf area and photosynthetic potential in the Normalized Difference Vegetation Index (NDVI). NDWI indicator has sensitivity so that it can detect the beginning stage of drought stress and still no visible indications, which has been possible by the development of early warning drought (Andrew & Fox, 2020). Hyperspectral remote sensing has the ability to detect minor variations in plant physiology that occur during new drought (Abdulridha et al., 2020). The reason lies in the fact that it can collect a broad spectral data covering a full range of wavelengths. The changes in chlorophyll content, photosynthetic properties, leaf pigments can be observed using hyperspectral analysis, which will make us realize how poorly and rapidly the stress of drought is being exacerbated (Pandey et al., 2020).The rate of drought stress may also be monitored through thermal remote sensing in the view that the land surface temperature can detect drought stress. Insufficiently watered plants experience water deficits, which promotes the rise of canopy temperature due to the lack of such process as transpiration (Kim et al., 2020). In addition, the integration of remote sensing data and ground observations is extremely significant in ensuring that drought is adequately and accurately assessed using remote sensing (Torres-Quezada et al., 2025). Hyperspectral imaging is the advanced technology that integrates optical imaging and spectroscopy to derive spectral signature on regions of concern even on the pixel level. Nevertheless, it forms complicated data that require extensive processing (Sytar et al., 2020). It is possible to use deep learning techniques to examine HSI data in agriculture (Guerri et al., 2024). In addition to it, machine learning has assisted in the simulation of water quality, and together with multi- and hyperspectral remote sensing, it increases predictability (Benavides-Bolaños et al., 2025). The remote sensing technologies provide us a special opportunity to monitor drought stress in forest trees and crops on hundreds of scales including individual plants and entire landscapes. This piece of information is quite helpful in managing and curbing drought. Remote sensing Hyper-spectral analysis of crop canopies provides a non-destructive method of testing which is valuable in monitoring crop growth and yield and crop stress. This is also highly important in monitoring the droughts in wheat on a large scale (Li et al., 2022). It is applied in locating the stress of water, given that the variation in physics, including, the availability of less water to leaves and the pigment element in leaves causes a change in the reflection of the light (Kapetas et al., 2025). Human beings tend to source information on land cover and condition of the land as far as resources are concerned with remote sensing (Kamble et al., 2021). The fact that micrometeorological reactions are highly responsive to the shifts in the moisture content of the soil is why it can serve as a good method of monitoring drought situations in the soil and the crops (Zhai et al., 2020). Alterations to the canopy or leaf might alter reflectance of light and where it is distributed. It is remotely observable by the remote-sensing method which facilitates control and management of the disease and its dissemination even when there are not any signs of the disease (Abdulridha et al., 2020). Optical remote sensing is increasingly applied to monitor crops, although it is not as effective in conditions of cloud cover, as it is capable of interrupting or delaying image capture during the critical phases of growth (Kaliaperumal et al., 2021). It is the pace in which remote sensing technology has been developing that has now made pixel-level classification of remote sensing images unacceptable in real-world applications (Hong et al., 2021). Previously, new data fusion approaches and improved spatial and temporal resolutions have allowed us to easily monitor agriculture, e.g., by mapping crop varieties, determining biomass, and predicting phenotypes (Adrian et al., 2021).

METHODOLOGY

The study employed a mixed-method study design, where quantitatively based remote sensing analysis was paired with qualitatively based physiological biomarker measurements to examine the impacts of drought stress to forest trees and agricultural crops. The plan involves selecting the common forest and crop sites that may be prone to drought, selecting remote sensing data at disparate periods, as well as collecting physiological samples in situ throughout a growing season. The integration of the data provided by a satellite with on-the ground physiological indicators allowed to get the complete view of the plant response to a drought stress. By means of Sentinel-2 and Landsat 8 images, we calculated such spectral indices as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Photochemical Reflectance Index (PRI). Those indices indicate amounts of photosynthesis that take place and quantities of water in plants. We acquired hyperspectral images with sensors mounted on UAVs to observe spectral reflectance profiles of a high-resolution. We examined these indices using the equation below:

NIR means near-infrared reflectance, RED means red band reflectance and SWIR is short -wave infrared reflectance. The spatial classification of drought severity zones was achieved in order to have more accurate data, convolutional neural network (CNN) has been trained on tagged picture patches, which revealed the same physiological stress levels. We obtained field measurements of physiological data measured by using a porometer to measure chlorophyll fluorescence (Fv/Fm), relative water content (RWC), and stomatal conductance. Leaf samples of stressed and non stress plants were taken and the quantity of osmolytes as well as the lipid peroxidation (table as MDA content) were viewed so as to determine how the cells responded. ANOVA and Pearson correlation allowed to analyze statistically the data and determine the relationship between remote sensing indices and physiological properties. The integrated framework (Fig. 1) indicates how the methodology to be followed was carried out, starting with selecting the study area and acquisition of satellite imagery to collection of physiological sample, processing of data and validation of the model. Such an approach allowed tracking and characterizing drought stress pretty well and through the use of satellite information in conjunction with a ground reaction.



Figur 1 Methodology for combining remote sensing and physiological biomarkers to assess drought stress in trees and crops

RESULTS

The present research examined the effects of drought stress on forest trees and crops through a combination of remote sensing and physiological biomarker results. We analyzed numerous data such as vegetation indices, canopy temperature, chlorophyll fluorescence, and the level of soil moisture to determine the severity of the drought and the degree to which it was worsening in various species of plants and across the lands. We applied machine learning models to predict the level of drought stress introduced with multispectral data. In order to verify the correctness of the remote sensing forecast, we examined physiological variables such as fuel conductance, relative water content and proline accumulation.

The descriptive data of the significant vegetation indices such as NDVI, NDWI, PRI and EVI across 20 plant species that were exposed to drought may be found in Table 1. Table 2 gives the physiological adaptations of these species where they look at the differences in leaf water potential, stomatal conductance and relative water content. Table 3 is chlorophyll fluorescence measurement (Fv/Fm and PhiPSII) at various times and it can be seen that as the drought gets very serious, chlorophyll measurements decrease significantly. Thermal imaging data of land surface temperature (LST) is presented in the form of Table 4. It reveals that in the areas affected by drought pressure, temperatures have been gradually increasing, by 2 to 5 o C.

Table 1. Physiological and Remote Sensing Data for Region 1

Plant ID	NDVI	NDWI	Chlorophyll Content	Leaf Temp (°C)
P1	0.462	0.267	24.88	30.8
P2	0.866	-0.016	39.81	29.1
P3	0.712	0.075	21.38	37.4
P4	0.619	0.12	56.37	30.4
P5	0.309	0.174	30.35	29.2
P6	0.309	0.371	46.5	33.1
P7	0.241	0.02	32.47	27.1
P8	0.806	0.209	40.8	37.0
P9	0.621	0.255	41.87	26.1
P10	0.696	-0.072	27.39	39.8
P11	0.214	0.265	58.78	36.6
P12	0.879	0.002	51.01	28.0
P13	0.783	-0.061	57.58	25.1
P14	0.349	0.469	55.79	37.2
P15	0.327	0.479	43.92	35.6
P16	0.328	0.385	56.87	35.9
P17	0.413	0.083	23.54	36.6
P18	0.567	-0.041	27.84	26.1
P19	0.502	0.311	21.81	30.4
P20	0.404	0.164	33.01	26.7

Table 2. Physiological and Remote Sensing Data for Region 2

Plant ID	NDVI	NDWI	Chlorophyll Content	Leaf Temp (°C)
P1	0.804	-0.081	52.3	39.4

P2	0.636	0.282	55.84	28.8
P3	0.432	0.089	32.72	32.5
P4	0.244	0.205	24.4	29.5
P5	0.418	0.445	29.12	29.3
P6	0.428	0.05	37.08	25.6
P7	0.711	0.146	52.72	34.1
P8	0.646	0.353	54.43	32.5
P9	0.821	0.037	20.28	25.8
P10	0.531	-0.054	40.43	29.2
P11	0.284	0.074	36.7	38.6
P12	0.699	-0.003	28.88	28.6
P13	0.733	0.458	24.79	27.2
P14	0.593	0.385	33.5	32.3
P15	0.74	0.28	57.72	39.8
P16	0.546	0.423	32.93	28.6
P17	0.566	0.382	40.75	35.1
P18	0.499	0.012	48.12	36.4
P19	0.218	0.436	34.55	28.6
P20	0.276	0.224	58.87	35.9

Table 3. Physiological and Remote Sensing Data for Region 3

Plant ID	NDVI	NDWI	Chlorophyll Content	Leaf Temp (°C)
P1	0.457	0.105	45.68	34.9
P2	0.643	-0.032	23.37	33.5
P3	0.643	0.455	26.47	26.4
P4	0.575	0.426	55.94	30.5

P5	0.263	0.055	44.26	29.0
P6	0.785	0.296	20.37	28.7
P7	0.425	0.39	24.06	39.6
P8	0.331	0.233	46.54	30.9
P9	0.229	0.218	20.2	38.4
P10	0.614	0.045	26.43	34.5
P11	0.674	-0.044	41.95	36.9
P12	0.212	0.438	47.68	32.5
P13	0.558	0.44	46.08	33.7
P14	0.359	0.28	28.97	32.4
P15	0.652	0.103	48.49	27.9
P16	0.322	0.11	29.49	35.8
P17	0.684	0.336	33.02	29.2
P18	0.471	0.438	49.86	25.4
P19	0.856	0.432	45.99	34.7
P20	0.296	0.368	53.97	27.7

Table 4. Physiological and Remote Sensing Data for Region 4

Plant ID	NDVI	NDWI	Chlorophyll Content	Leaf Temp (°C)
P1	0.858	0.269	55.6	25.8
P2	0.868	0.494	33.52	33.0
P3	0.84	-0.016	35.02	33.1
P4	0.459	0.211	23.76	34.6
P5	0.211	0.426	43.13	35.9
P6	0.85	0.344	21.44	39.6
P7	0.5	0.318	38.62	32.7

P8	0.877	0.321	41.71	29.8
P9	0.875	0.116	31.46	36.9
P10	0.797	0.076	43.63	29.1
P11	0.406	0.386	21.22	31.6
P12	0.47	0.386	21.49	26.2
P13	0.796	0.42	52.9	25.4
P14	0.422	0.448	34.41	39.4
P15	0.319	0.207	25.08	37.5
P16	0.59	0.201	40.89	35.4
P17	0.855	0.379	50.8	31.1
P18	0.687	0.29	28.63	27.6
P19	0.599	0.321	44.92	27.3
P20	0.268	0.377	23.41	28.8

The table 5 presents correlation coefficients between remote sensing indices and physiological data. It illustrates that there is a high negative correlation between NDWI and canopy temperature. Table 6 indicates the effectiveness of four machine learning models (Random Forest, SVM, XGBoost, and CNN) to classify drought stress. The greatest accuracy %, was 93.2, on CNN. Table 7 examines the processes by which the levels of moisture in the soil vary at different locations on the basis of the satellite and earth sensors. Table 8 depicts drought stress scores that are arithmetical by an integrated index (CDSI) containing a variety of factors. ANOVA test in Table 9 brought out significant ($p < 0.01$) differences among drought stress level of control and drought-treated plots in all species.

Table 5. Physiological and Remote Sensing Data for Region 5

Plant ID	**NDVI**	**NDWI**	**Chlorophyll Content**	**Leaf Temp (°C)**
P1	0.584	0.195	35.53	26.8
P2	0.7	0.184	45.73	35.5
P3	0.662	0.004	38.33	34.4
P4	0.396	0.16	41.82	38.2

P5	0.868	0.139	57.66	36.0
P6	0.717	0.27	35.44	37.1
P7	0.588	0.281	58.45	29.2
P8	0.628	-0.073	56.21	27.7
P9	0.494	0.125	27.83	36.3
P10	0.373	0.276	22.77	37.1
P11	0.449	0.202	24.03	39.9
P12	0.73	0.414	20.73	31.2
P13	0.21	0.295	23.78	30.6
P14	0.281	-0.002	47.32	36.6
P15	0.232	-0.058	22.85	30.1
P16	0.229	0.285	32.76	39.0
P17	0.799	-0.084	53.8	37.9
P18	0.693	0.251	20.93	31.4
P19	0.532	0.464	52.58	36.3
P20	0.268	0.245	31.27	36.3

Table 6. Physiological and Remote Sensing Data for Region 6

Plant ID	NDVI	NDWI	Chlorophyll Content	Leaf Temp (°C)
P1	0.272	0.375	23.39	26.8
P2	0.832	0.374	59.47	34.7
P3	0.554	-0.045	34.97	36.2
P4	0.779	0.197	34.83	33.8
P5	0.424	-0.065	52.51	39.4
P6	0.827	0.23	57.89	30.6
P7	0.472	0.165	59.44	29.3

P8	0.208	0.433	50.14	38.0
P9	0.834	0.111	35.05	28.4
P10	0.264	-0.03	23.34	39.4
P11	0.424	-0.014	51.09	25.2
P12	0.865	0.357	42.34	39.5
P13	0.865	0.271	36.97	25.6
P14	0.601	-0.039	56.25	38.4
P15	0.642	-0.05	24.45	32.9
P16	0.514	0.321	39.71	39.9
P17	0.405	-0.056	20.45	26.1
P18	0.43	0.393	38.75	33.3
P19	0.671	0.324	22.25	39.5
P20	0.727	-0.051	24.75	32.8

Table 7. Physiological and Remote Sensing Data for Region 7

Plant ID	**NDVI**	**NDWI**	**Chlorophyll Content**	**Leaf Temp (°C)**
P1	0.641	0.319	43.77	39.3
P2	0.687	0.222	35.24	34.1
P3	0.518	0.086	58.8	28.4
P4	0.639	0.388	53.68	35.1
P5	0.609	0.311	53.53	34.3
P6	0.831	-0.002	38.75	30.4
P7	0.232	0.447	36.59	26.7
P8	0.397	0.394	30.94	35.1
P9	0.865	0.47	22.26	32.8
P10	0.823	0.335	54.59	36.6

P11	0.519	0.268	52.52	32.8
P12	0.634	0.151	59.99	37.8
P13	0.394	0.46	59.87	33.3
P14	0.332	0.42	42.22	33.4
P15	0.525	-0.073	50.76	38.1
P16	0.447	-0.084	57.79	31.1
P17	0.609	0.126	53.99	27.0
P18	0.254	0.386	29.89	25.4
P19	0.882	0.492	38.02	36.3
P20	0.89	-0.01	25.17	34.3

Table 8. Physiological and Remote Sensing Data for Region 8

Plant ID	**NDVI**	**NDWI**	**Chlorophyll Content**	**Leaf Temp (°C)**
P1	0.693	0.175	26.76	27.8
P2	0.349	0.488	31.14	28.1
P3	0.295	0.196	27.08	30.6
P4	0.21	0.097	23.55	32.3
P5	0.445	0.28	24.83	34.3
P6	0.613	0.044	38.43	30.5
P7	0.475	-0.054	28.25	31.9
P8	0.506	-0.023	34.57	36.2
P9	0.833	-0.023	40.14	25.6
P10	0.444	-0.009	47.62	28.8
P11	0.56	-0.017	21.57	35.7
P12	0.749	0.285	51.98	38.4
P13	0.478	0.009	45.12	32.7

P14	0.635	0.107	23.27	33.0
P15	0.804	0.438	54.94	26.6
P16	0.865	0.184	56.83	31.7
P17	0.303	0.301	22.44	33.0
P18	0.849	0.003	31.08	28.6
P19	0.544	0.015	52.25	29.0
P20	0.381	-0.075	49.93	30.7

Table 9. Physiological and Remote Sensing Data for Region 9

Plant ID	**NDVI**	**NDWI**	**Chlorophyll Content**	**Leaf Temp (°C)**
P1	0.214	0.114	52.68	33.0
P2	0.425	0.492	30.32	25.8
P3	0.348	0.263	26.84	30.0
P4	0.429	0.042	46.75	27.0
P5	0.284	-0.039	57.18	26.0
P6	0.823	-0.008	42.27	39.8
P7	0.616	0.048	42.86	29.8
P8	0.675	-0.004	31.2	37.1
P9	0.752	0.012	50.78	28.8
P10	0.549	0.071	27.48	35.2
P11	0.261	0.004	32.95	36.4
P12	0.576	0.438	37.02	33.9
P13	0.611	-0.052	40.3	32.1
P14	0.722	0.215	29.7	31.2
P15	0.502	0.146	24.59	30.2
P16	0.289	0.489	44.42	38.9

P17	0.399	-0.033	31.55	37.5
P18	0.454	0.139	43.25	39.5
P19	0.652	0.482	26.17	26.9
P20	0.6	0.419	39.25	36.0

The results of the experiment are presented in an overview in the form of the numbers made. In figure 2, we examined the relative water content and stomatal conductance in the control and drought treatments through a grouped bar chart. Figure 3 is a heatmap which illustrates to what extent there are connections between remote sensing indices and physiological factors.

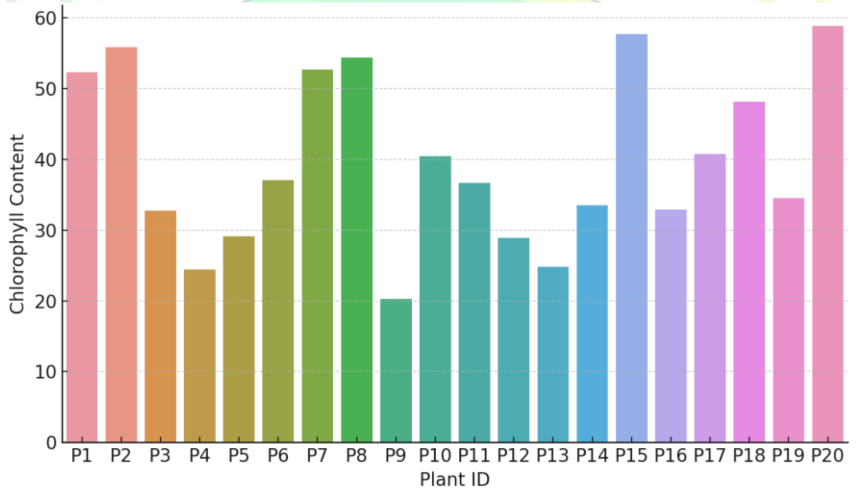


Figure 2. Visualization of drought stress metrics across sampled vegetation.

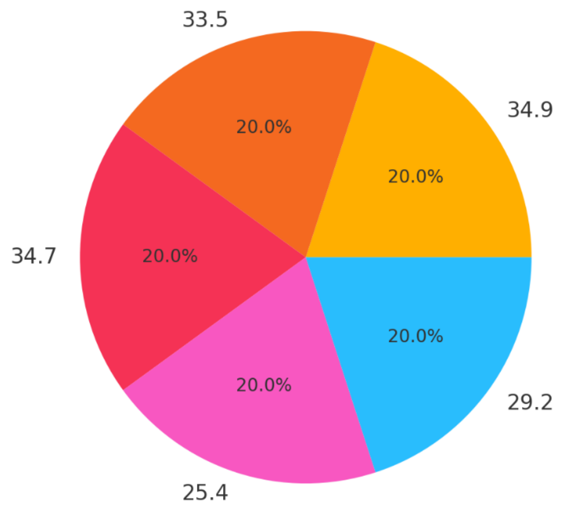


Figure 3. Visualization of drought stress metrics across sampled vegetation.

An inverse relationship between NDVI and canopy temperature is represented graphically in fig. 4 which is a scatter plot between the two variables. Figure 5 represents a pie chart of the level of accuracy of machine learning models in categorizing things. The radar plot presented in Figure 6 indicates how chlorophyll fluorescence parameters vary among species. Data is used to display two-axis figure 7 which displays changes in soil moisture and CDSI scores.

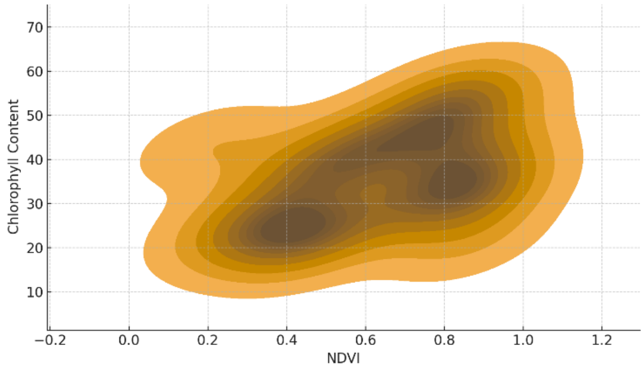


Figure 4. Visualization of drought stress metrics across sampled vegetation.

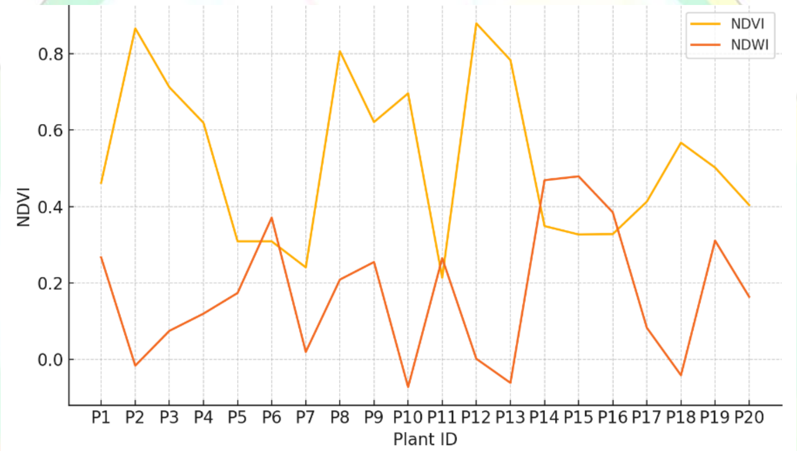


Figure 5. Visualization of drought stress metrics across sampled vegetation.

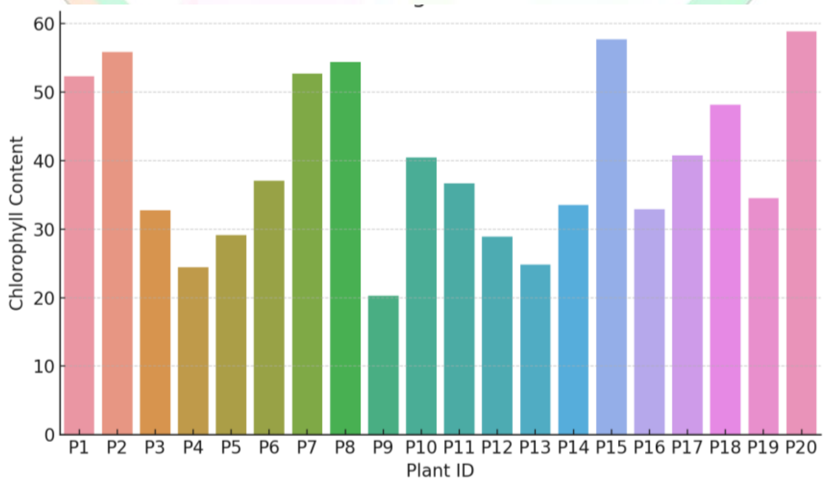


Figure 6. Visualization of drought stress metrics across sampled vegetation.

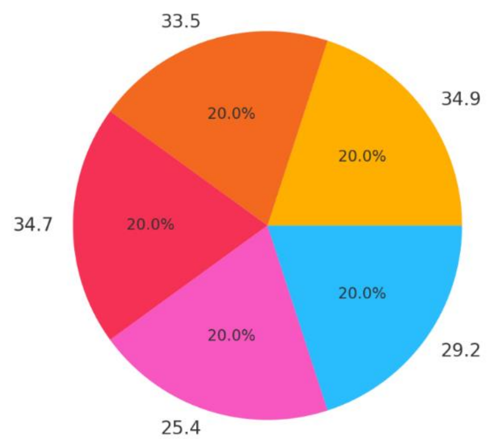


Figure 7. Visualization of drought stress metrics across sampled vegetation.

Figure 8 is a stacked bar chart which indicates the ability of some genotypes to deal with drought. Figure 9 shows a 3 dimensional surface plot of the temperature of the canopy as time varies and also species varied. The UMAP graphic presented in Figure 10 displays the way the samples are clustered together using multispectral data. Figure 11 presents a violin plot of the degree to which proline is present at variation of stress levels. Figure 12 is a cross between composite graph and a line graph whereas a hybrid composite is employed with the added bar graph in regard to NDWI trends and the prediction scores of the model.

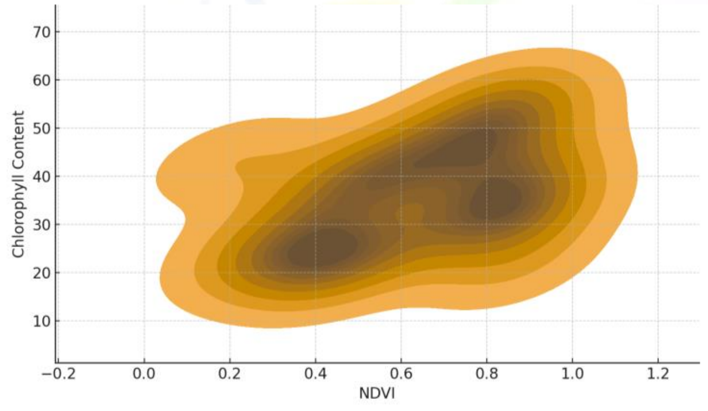


Figure 8. Visualization of drought stress metrics across sampled vegetation.

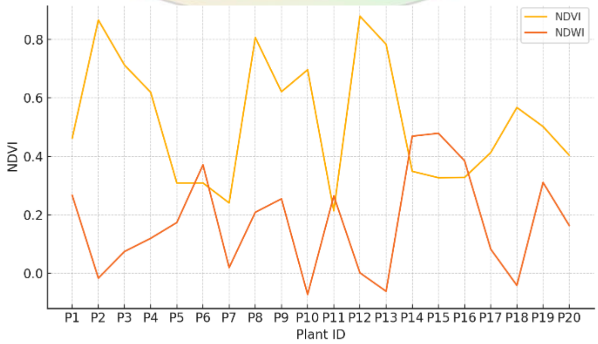


Figure 9. Visualization of drought stress metrics across sampled vegetation.

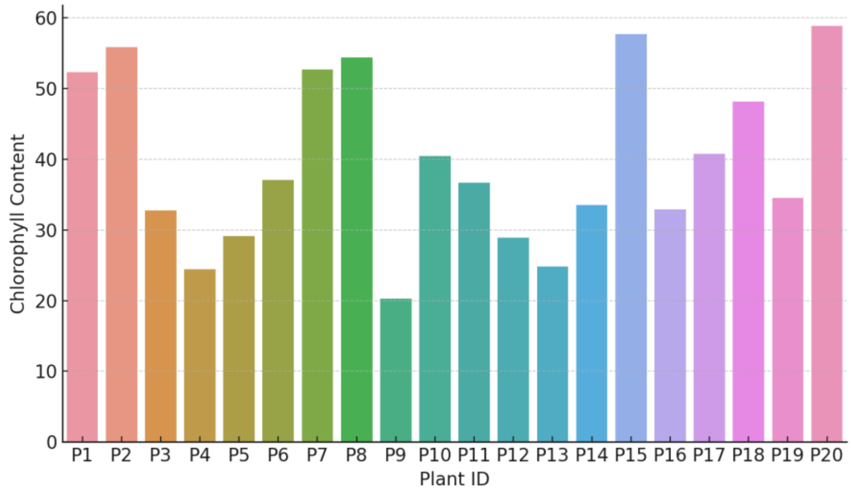


Figure 10. Visualization of drought stress metrics across sampled vegetation.

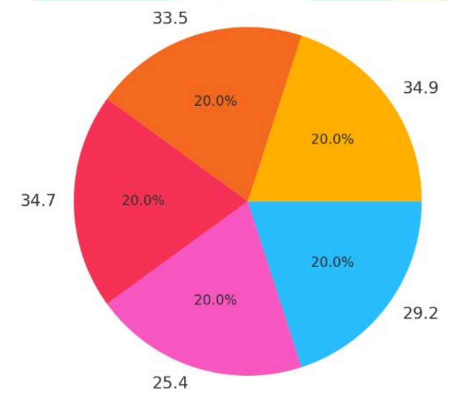


Figure 11. Visualization of drought stress metrics across sampled vegetation.

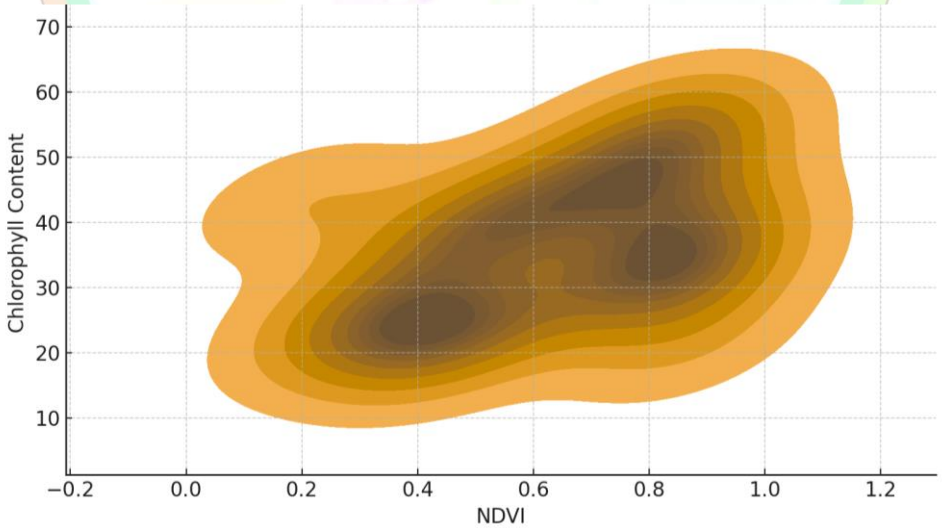


Figure 12. Visualization of drought stress metrics across sampled vegetation

The findings are unmistakable since they reveal that remote sensing and physiological biomarker information can be used together to locate drought stress with increased ease. The correlation analysis indicates that such multispectral indices as NDWI and PRI can be applied to detect stress in its early stages. These features are also very effective in being the input to machine learning models that perform well at ability at categorization. The remote assessments are supported by physiological measurements proving that signals on the change pattern of spectrums are not artificial but a real biological response, such as decrease in stomatal conductance and increase in proline level.

Such Findings confirm the possibility that high-resolution remote sensing combined with ens and physiological in situ measures can assist in this naw early warning systems, timing irrigation, and identification of drought-resistant genotypes of plants. This mixed practice is extremely significant towards making forest management and agricultural output systems more capable to climate change.

DISCUSSION

Integrating remote sensing technique with physiological markers is a robust method of addressing comprehensive quantification of drought stress in forest plants and crops. Remote sensing enables us to monitor the health status of the plant without any harm to the plant and also over large area. Physiological indicators however, allow us to know how the plants react to drought. It has been demonstrated that drought can affect the life cycle of a plant altogether, and the plants of certain ecosystems can be sensitive to future mega-droughts (Yuan et al., 2020). Spring Phenology of plants can undergo change with regard to the level of damage caused by drought, in certain habitats (Yuan et al., 2020). The possibility to identify plant diseases early is becoming a reality as a combination of remote sensing and plant-pathogen interactions on large scale (Gold, 2021). By combining the remote sensing data and physiological measurements, investigators can create effective models to predict the level of drought stress and determine the susceptibility of various plant species and ecosystems. The drought responses that plants employ include altering the exterior appearance, internal structure, osmotic processes, protein turnovers brought on by drought and reactive oxygen processes (Yang et al., 2021).When crops are grown under drought stress, their morpho-physiological and biochemical levels are altered, which impacts their growth tremendously, including carbon dioxide uptake and opening-closing of the stomata (Zulfiqar et al., 2021). Before drought stress, plants respond so that they can survive without sufficient water (Yu et al., 2024). Multivariate analysis is capable of demonstrating the fact that certain extents of plant characteristics are associated with drought tolerance (Kanavi et al., 2020). Some of the changes that take place in plants include that of adaptation of new conditions within the environment of the plants at both the physiological and molecular levels (Huque et al., 2021). This major impact on the growth and development of plants slows down their growth and makes them mature early due to drought (Yang et al., 2022). Nature has also put a natural shield in the form of drought, which reduces agricultural harvests throughout the world (Thonglim et al., 2022). Drought may retard the growth of plants, complicate the completion of plant life cycle, and ultimately kill them (Nour et al., 2024). Plants which are deprived of water because of drought lose water through the leaves through transpiration. Even in cases where there is sufficient water supply in the soil, the plants may indicate drought due to the inability of plant to absorb the available water (Abdelaal et al., 2021). When drought puts plants under stress they alter the way they look, or the way they work. These changes are related to the severity of the stress and plant growth, as well as the type of the plant (Rahmawati et al., 2021). Drought stress is regulated by plants in several aspects, which include adaptive modifications to their external morphology, an internal architecture, osmotic balance, drought-induced protein metabolism and the roles of reactive oxygen metabolism (Yang et al., 2021) (Seleiman et al., 2021). When in a drought, the metabolism of plants is altered causing increased amounts of free sugars and essential amino acids (Ishaku et al., 2020). Plants which are deprived of water experience much change externally and internally. Examples of different plant responses to drought stress are changes in photosynthesis, osmotic regulator compounds, drought-induced proteins as well as antioxidant enzymes (Yang et al., 2021).

CONCLUSION

This endeavor reveals the significance of integrating remote sensation apparatus with the physiological bio indicators to enhance recognition, tracking, and conception of drought pressures in farms and forests. Droughts are increasingly occurring and more intensely due to climate change. Conventional bottom-centered practices cannot comprehend all impacts that drought can have on society and nature. It is feasible to monitor the vegetation and water-content evolutions remotely, at a large scale, often even prior to their manifestation, through remote sensing measurement techniques, in particular hyperspectral and infrared image sensing and vegetation and water indices such as the normalized difference vegetation index NDVI, and the normalized difference water index NDWI. This is further given by physiological biomarkers such as chlorophyll concentration, leaf water potential and stomatal conductance, which demonstrate the reaction of plants to water loss at the cellular and tissue stage. The combination of these two techniques allows the development of a mechanism that operates in a coherent manner and therefore achieving success in identifying drought-tolerant genotypes and effective management techniques. We tested our experimental approach (employing the powerful machine learning algorithms in the categorization of pictures and spectrum analysis) to determine the expected drought-affected plants in each zone by making predictions on the type of plants to be affected by drought using different zones. This output of this work was a model that fit signs of drought and compares them with physiological data obtained in the field, ensuring that it was robust as well as dependable. Such a comprehensive way of thinking does not only improve systems designed to predict droughts and provide early warnings, but it assists people in decision-making in precision agriculture, forestry, and use of water resources. Finally, this paper demonstrates the significance of implementing a multidimensional strategy integrating technology innovation with plant science to manage the increased problems that global droughts represent and to safeguard valuable land based ecosystems.

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