loan repayment and total money earned by the village from industry. Loan repayment was quicker for scenarios 1 and 3 compared to scenario 2. The village earnings from industry were maximum for scenario 3 compared to scenarios 1 and scenario, with the lowest earnings from scenario 1.

Overall, scenario 1 is good for the village as it increases village employment, reduces migration and helps repay loans quickly (attractive for money-lending institutions like banks). Scenario 2 is financially least attractive, while scenario 3, is the most attractive both financially and from a policy perspective as it helps repay loans quickly and uses cultivation as raw material source, but is least attractive for villagers as it will increase their migration.

The development of villages requires different forms of intervention ranging from policy to technology. The intervention success in a village depends on its ability to synchronize with functionality of the existing systems, both socially and economically. This study highlights that more successful interventions for a village are those that can generate overall development and revenue to the system. The system dynamics model of Khirvire village showed the ability of medicinal plants cultivation and industry to reduce village migration thereby strengthening the NMMP objectives. The study provides important insight into the policy objectives and financial plans to help realize the potential unaccounted external forces which can make a highly viable process unviable. Such a system dynamic models can be developed for different villages or regions to understand and determine future development status of the system and accordingly design interventions. These models can be used to evaluate the success of the proposed and implemented interventions in the field. Further, villagers will cultivate medicinal plants only when the income from this is lucrative compared to the commercial crops.

1. Van de Poel, E., O'Donnell, O. and Van Doorslaer, E., Are urban children really healthier? Evidence from 47 developing countries. *Soc. Sci. Med.*, 2007, **65**, 1986–2003.
2. Sen, A. and Himanshu, Poverty and inequality in India: getting closer to the truth. *Econ. Polit. Wkly.*, 2004, **39**, 4247–4263.
3. Government of Maharashtra, Maharashtra Human Development Report 2012, Mumbai, 2012, pp. 1–1028.
4. Registrar General of India, Census 2011: Population Enumeration Data, Ministry of Home Affairs, Government of India (GoI), 2011.
5. Datt, G. and Ravallion, M., Is India's economic growth leaving the poor behind ? *J. Econ. Perspect.*, 2002, **16**, 89–108.
6. Fan, S., Chan-Kang, C. and Mukherjee, A., *Rural and Urban Dynamics and Poverty: Evidence from China and India IFPRI*, Washington DC, USA, 2005.
7. Gautam, Y. and Andersen, P., Rural livelihood diversification and household well-being: insights from Humla, Nepal. *J. Rural Stud.*, 2016, **44**, 239–249.
8. Ellis, F., Household strategies and rural livelihood diversification. *J. Dev. Stud.*, 1998, **35**, 1–38.
9. National Medicinal Plants Board, *Centrally Sponsored Scheme of National Mission on Medicinal Plants: operational Guidelines* AYUSH, New Delhi, 2008.
10. Jain, R. and Rao, B., Critical analysis of India's National Mission on Medicinal Plants (NMMP) in providing access to quality botanical drugs to improve public health. *J. Ayurveda Integr. Med.*, 2015, **6**, 198–206.
11. Planning Commission of India, Report of Steering Committee on AYUSH for 12th Five Year Plan (2012–17), 2011.
12. Forrester, J. W., *Industrial Dynamics*, MIT Press, Cambridge, Massachusetts, USA, 1961.
13. Subbaraju, Understanding technology choice for region-specific planning–exploration through AHP and system dynamics, Indian Institue of Technology Bombay, 1995.
14. Jain, R. and Rao, B., Financial planning for small-scale herbal industries based on National Mission on Medicinal Plant scheme: a case study. In International Conference on Inter Disciplinary Research in Engineering and Technology, New Delhi, 2016.

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Forest biometric parameter extraction using unmanned aerial vehicle to aid in forest inventory data collection

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Frequent ground surveys and satellite-based information on tree height, canopy gaps and forest dynamics are limited by time, cost and spatial scales. In this study, an attempt has been made to derive forest biometric parameter on tree height by canopy height model and crown area projections using unmanned aerial vehicles (UAV)–RGB image. Sorensen's coefficient has been used as an index to compare between ground inventory and UAV-based species identification. The statistical paired *t*-test showed UAV RGB can be used for maximum tree height and tree crown extraction to aid in ground surveys.

Keywords: Canopy height model, canopy area projection, forest biometry, unmanned aerial vehicles.

ADVANCES in unmanned aerial vehicles (UAV) with improved spatial, spectral and temporal resolution of

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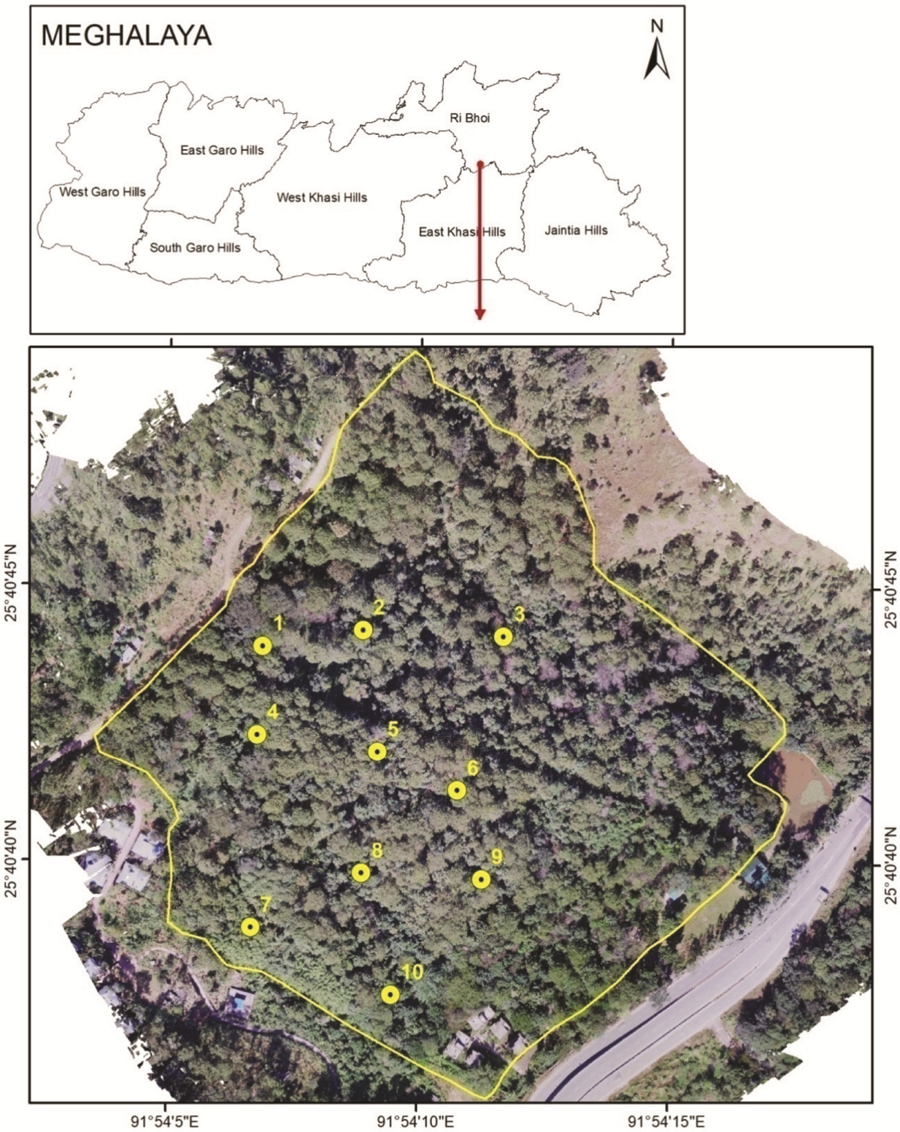

Figure 1. Location map of the study area with sample points.

sensors are driving improvement in forest mapping monitoring of tree crown/gap, forest stand mapping, volume estimations, infestation and harvest planning[1], biodiversity, precision forestry, sustainable forest management, canopy height, etc.[2]. Kaneko and Nohara[3] demonstrated UAV where field reconnaissance is difficult. UAV digital RGB camera due to its low cost, light weight and easy operability[4] is used for cost effective high accuracy forest inventory. UAV is 'forester's eye in the sky'[5] and trade-off between sensor and budget defines capability and usability[6].

The objective of this study is to derive forest biometric parameter on tree height and canopy projection area (CPA) along with species identification, using UAV-borne RGB camera in a mixed dense forests. The study was conducted in 10-hectares area in the experimental garden of Botanical Survey of India (BSI) in Umroi, Ri-Bhoi district of Meghalaya, North East India. The extent of the study area is 25°40′31.87″–25°40′51.89″N and 91°53′59.773″–91°54′21.84″E. The study area and the sample plot locations are shown in Figure 1.

The aerial survey was conducted with UAV (Hex Copter, DJI Matrice 600) RGB camera (DJI Zenmuse X3, 12 MP) in a single flight. A total of 250 images were processed in Pix4D software for generation of 3D point clouds, ortho-mosaic image and digital surface model (DSM). The spatial resolution of the ortho-image is 4.6 cm posting. From the 3D point clouds, digital terrain model (DTM) was generated with ground sampling distance (GSD) (cm/pixel) of 23 cm posting. The UAV camera is calibrated by using 'checker board' method[7,8] in Matlab. Camera-only specification was chosen for radiometric correction to avoid atmospheric and vignetting effects[9]. Report on geometric corrections showed

Table 1. Number of trees grouped under tree height category in each sample plot

Field inventory sites	05–10 m	11–15 m	16–20 m	21–25 m	Total number of trees
Site 1	22	11	9	2	44
Site 2	16	36	10	8	70
Site 3	36	37	6	7	86
Site 4	7	20	18	3	48
Site 5	11	43	16	4	74
Site 6	17	25	13	8	63
Site 7	0	5	5	3	13
Site 8	28	30	12	3	73
Site 9	35	13	12	0	60
Site 10	3	27	13	7	50

Table 2. Number of species identified

	Number of species		Similarity
Field inventory sites	Field inventory	Observed from UAV image	Field inventory versus UAV image
Site 1	11	5	0.625
Site 2	11	6	0.706
Site 3	16	7	0.609
Site 4	3	3	1.00
Site 5	11	7	0.779
Site 6	11	6	0.706
Site 7	4	4	1.00
Site 8	14	5	0.526
Site 9	14	6	0.6
Site 10	23	10	0.606

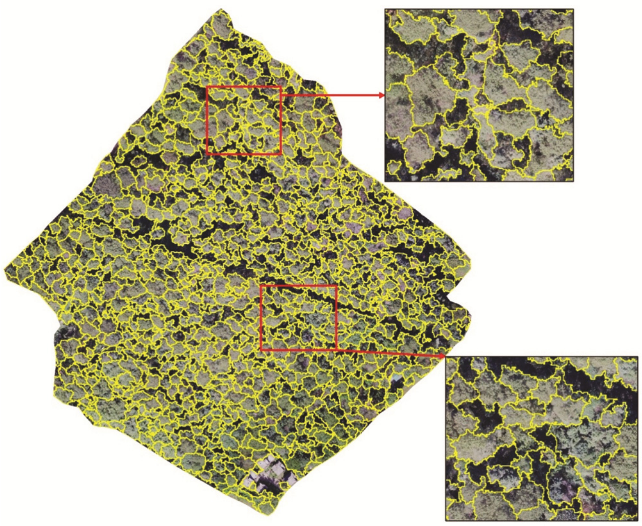

Figure 2. Tree crown delineation by automatic segmentation method.

mean projection error to be 0.201 and difference between initial and optimized camera parameters to be 1.97%.

The ground inventory consists information on tree species, tree height (using laser hypsometer) and individual tree crown measurement in 10 sample sites of 0.1 hectare plots. Han *et al.*[10] used eye judgement of a vegetation expert for community naming. UAV image was used to identify dominant trees (top canopy trees) by expert knowledge. The community commonality between ground survey and UAV-based identification was compared with Sorenson's coefficient[11] as given below. The coefficient value ranges between 0 and 1. Higher the commonality, closer is the value to 1.

$$\text{Sorenson's coefficient (CC)} = (2C/S1 + S2),$$

where C is the number of species the two communities have in common, $S1$ and $S2$ are the total number of species found in community 1 (field inventory) and community 2 (UAV image identification) respectively.

The CPA during field survey was estimated for individual tree crown based on the following formula[12]

$$\text{Canopy area} = \pi\,[(\text{CD}_\text{W} \times \text{CD}_\text{P})/4],$$

where CD_W is the widest canopy diameter, CD_P the perpendicular canopy diameter and π is 3.147.

Canopy height model (CHM) was generated by subtracting the DTM from the DSM. The focal statistics identified highest value with circular kernels for tree

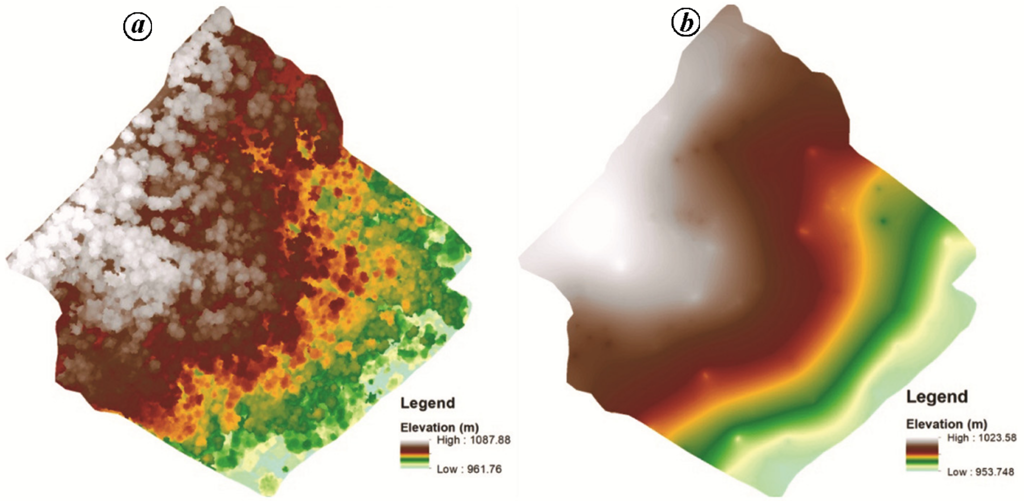

Figure 3. Digital surface model (***a***) and digital terrain model (***b***) of the study area.

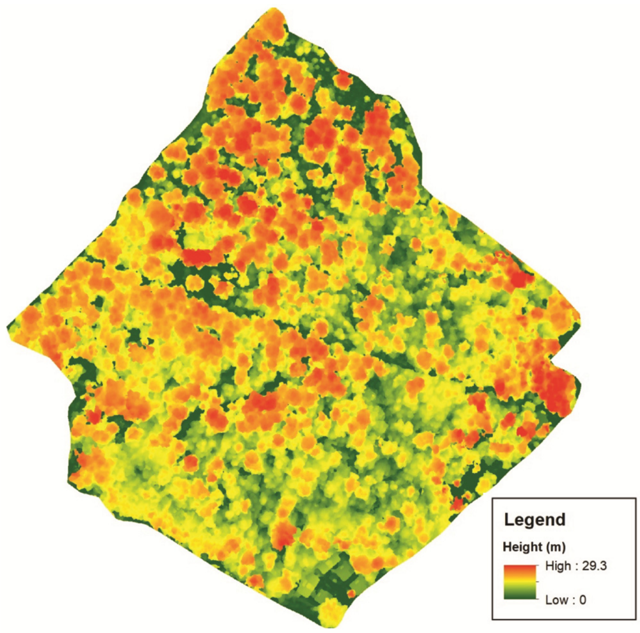

Figure 4. Canopy height model.

Table 3. Canopy area (sq. m) from UAV imagery

Site no.	Canopy area (sq. m) Field	UAV	Difference (sq. m)
1	907.07	933.26	–26.19
2	864.9	871.83	–6.93
3	852.13	904.74	–52.61
4	932.84	938.8	–5.96
5	1008.0	978.27	29.76
6	890.82	828.97	61.85
7	857.4	938.48	–81.08
8	874.24	887.44	–13.2
9	870.16	872.4	–2.24
10	765.49	809.0	–43.51

tops. Local maxima points were considered to be tree tops for tree count and height estimations. For automatic individual tree crown delineation, image segmentation technique was used in Ecognition Developer software by multi-resolution segmentation[13] using the RGB image, CHM and slope of the study area. Segmentation parameters were adjusted by trial and error method with weights of image layers (R-1, G-1, B-1, CHM-2, slope-3), scale (150), shape (0.6) and compactness (0.2).

Maximum tree height and CPA are for top canopy trees, whereas approximation of minimum height could be done from the canopy gaps subtracting the terrain. The estimates of the tree height and CPA were compared with field data by linear regression before other statistical tests were performed. The statistical significance of the two means (ground versus UAV), viz. maximum height, minimum height and CPA was observed by paired t-test method and confidence interval calculated for the limits of the mean difference. Null hypotheses assumed that the mean differences between paired observations are equal. The confidence interval provided the limits of the mean difference when null hypotheses are rejected. The hypothesis was evaluated at 95% significance level. The following equation was used for paired samples t-test

$$t = \frac{\bar{d}}{\sqrt{s^2 \div n}},$$

where t is paired sample t-test with $n - 1$ degrees of freedom, d the mean difference between two samples, S^2 the sample variance and n is the sample size.

At 95% confidence interval mean difference has been calculated as

$$\bar{d} \pm t \times SE(\bar{d})),$$

where t is the t value at $n - 1$ degrees of freedom.

Table 4. *t*-Value at 95% significance level is 2.262

Tree parameters	*t*-Test	*R*-Squared	Confidence interval
Average maximum tree height	0.058	0.683	
Average minimum tree height	2.324	0.528	0.773, 0.006
Average canopy area	1.09	0.578	43.15, –15.12

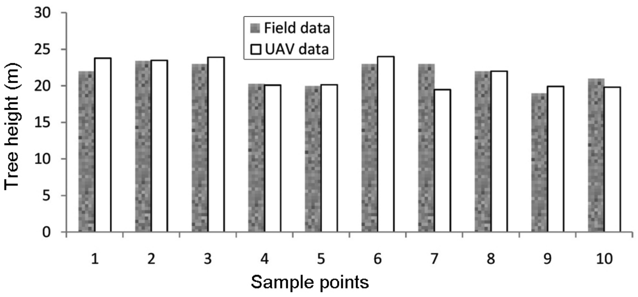

Figure 5. Maximum tree height.

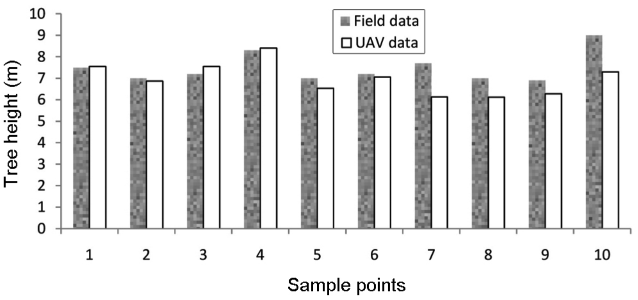

Figure 6. Minimum tree height.

The trees in each sample plot were grouped into different height classes (Table 1). Trees in the study area vary in height from 5 to 25 m.

Getzin *et al.*[14] observed sub-meter spatial resolution from low altitude flights and Oldeland *et al.*[15] presented potential of UAV–RGB image in mapping of tree species. Table 2 shows a comparison of the number of species with Sorensen's coefficient (>0.6) values indicating its applicability in tree species identification.

The automatic delineation of tree canopy by segmentation is shown in Figure 2 and its comparison with field based data (top canopy) is shown in Table 3.

Figure 3 *a* and *b* shows the DSM and DTM generated from UAV images respectively. Surface elevation of the study area ranges from approximately 962 to 1088 m.

The CHM (Figure 4) is used for tree height estimations. The maximum and minimum tree heights in each sample plot are compared in Figures 5 and 6.

The statistical analysis of the data from all the sample locations is given in Table 4.

The number of identified species from UAV–RGB depends on tree heights (top canopy), tree density, number of species and canopy dimension in the respective plots. The CPA showed $r^2 = 0.578$ and paired *t*-test of 1.09 (critical *t* value = 2.262) indicating assumption of equal means. The canopy cover in a mixed dense forest limits the crown delineation with decrease in tree detection accuracy[16]. Linear regression showed $r^2 = 0.683$ between UAV and ground inventory derived maximum tree height. The paired *t*-test at 95% significance level showed a lower range of value than the critical value, thereby leading to acceptance of the null hypothesis. However, the minimum tree heights estimate failed to qualify the null hypothesis of equal mean. The *t*-value was found to be 2.324 (*t*-critical value = 2.262) with confidence interval ranging between 0.006 and 0.773. UAV remote sensing focuses on adoption of advanced sensor payloads like hyperspectral, LiDAR and SAR[17] for more accurate estimates.

UAV–RGB can be an important tool for forest staff due to simplicity of image interpretation, to design forest inventory and management plans. However, with integration of advanced sensors, more biometric parameters can be retrieved with improved accuracy. Low flying UAV survey with local ground knowledge can prove to be a reliable technology in vegetation studies.

1. Gálvez, P. J., McCall, M. K., Napoletano, B. M., Wich, S. A. and Koh Pin, L., Small drones for community-based forest monitoring: an assessment of their feasibility and potential in tropical areas. *Forests*, 2014, **5**, 1481–1507.
2. Banu, P. T., Borlea, F. G. and Banu, C., The use of drones in forestry. *J. Environ. Sci. Eng.*, 2016, **B5**, 557–562.
3. Kaneko, K. and Nohara, S., Review of effective vegetation mapping using the UAV (unmanned aerial vehicle) method. *J. Geogr. Inf. Syst.*, 2014, **6**, 733–742.
4. Lu, B. and He, Y., Species classification using unmanned aerial vehicle (UAV)-acquired high spatial resolution imagery in heterogeneous grassland. *ISPRS J. Photogramm. Remote Sensing*, 2017, **128**, 73–85.
5. Zarco-Tejada, P. J., Diaz-Varela, R., Angileri, V. and Loudjani, P., Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods. *Eur. J. Agron.*, 2014, **55**, 89–99.
6. Padua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J. J., Peres, E. and Morais, R., UAS, sensors, and data processing in agroforestry: a review towards practical applications. *Int. J. Remote Sensing*, 2017, **38**(8–10), 2349–2391.
7. Fryskowska, A., Kedzierski, M., Grochala, A. and Braula, A., Calibration of low cost RGB and NIR UAV cameras. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXIII ISPRS 2016 Congress Prague, Czech Republic, 2016, XLI-B1.

8. Geiger, A., Moosmann, F., Car, O. and Schuster, B., Automatic camera and range sensor calibration using a single shot. In Proceedings – IEEE International Conference on Robotics and Automation, 2012.
9. Lebourgeois, V., Bégué, A., Labbé, S., Mallavan, B., Prevot, L. and Roux, B., Can commercial digital cameras be used as multispectral? A crop monitoring test. *Sensors*, 2008, **8**(11), 7300–7322.
10. Han, G. Y., Jung, H. S. and Kwon, O., How to utilize vegetation survey using drone image and image analysis software. *J. Ecol. Environ.*, 2017, **41**(18).
11. Sorensen, T., A method of establishing groups of equal amplitude in plant sociology based on similarity of species content and its application to analyses of the vegetation on Danish commons. Kongelige Danske Videnskabernes Selskab. *Biologiske Skrifier*, 1948, **5**, 1–34.
12. Gara, T. W., Murwira, A., Chivhenge, E., Dube, T. and Bangira, T., Estimating wood volume from canopy area in deciduous woodlands of Zimbabwe. *South Forests: J. For. Sci.*, 2014, **76**(4), 237–244.
13. Baatz, M. and Schape, A., Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation. In *Angewandte Geographische Informations – Verarbeitung*, *XII* (eds Strobl, J., Blaschke, T. and Griesbner, G.), Wichmann Verlag, Karlsruhe, Germany, 2000, pp. 12–23.
14. Getzin, S., Wiegand, K. and Schöning, I., Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. *Methods Ecol. Evol.*, 2012, **3**, 397–404.
15. Oldeland, J., Stoltenberg, G. A., Naftal, L. and Strohbach, J. B., The potential of UAV derived image features for discriminating savannah tree species. In *The Roles of Remote Sensing in Nature Conservation* (eds Díaz-Delgado, R., Lucas, R. and Hurford, C.), Springer, Germany, 2017, pp. 183–201.
16. Yu, X., Hyyppä, J., Vastaranta, M., Holopainen, M. and Viitala, R., Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. *ISPRS J. Photogramm.*, 2011, **66**, 28–37.
17. Whitehead, K. and Hugenholtz, C. H., Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: a review of progress and challenges. *J. Unmanned Veh. Syst.*, 2014, **2**(3), 69–85.

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Imidacloprid efficacy against brown planthopper, *Nilaparvata lugens* under elevated carbon dioxide and temperature

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Influence of elevated CO_2 and temperature (elevated condition (EC)) vis-à-vis ambient CO_2 and temperature (ambient condition (AC)) on plant (rice) growth, insect *Nilaparvata lugens* (brown planthopper (BPH)) population and insecticide (Imidacloprid) efficacy was evaluated under open top chamber conditions. EC had a positive effect on rice crop through increase in tillers numbers (18.4%), reproductive tillers (20.5%) but inflicted negative effect on 1000-grain weight (11.7%) and grain yield (11.9%). Likewise, higher canopy cover of the plant was noticed under EC (16.1 cm) when compared to AC (12.9 cm). With respect to BPH population during 2013 and 2014, EC exhibited positive effect by enhancing its mean population to 66.1 and 49.4 hoppers hill^{-1} respectively, compared to corresponding 36.8 and 29.5 hoppers hill^{-1} under AC. With respect to Imidacloprid efficacy against BPH, LC_{50} was significantly lower under EC (0.044%) in comparison to AC (0.065). Similarly, in 2013 under AC, 500, 600, 700 l ha^{-1} spray volume caused >50% BPH mortality than 400 l ha^{-1} at 5 day after spray. However, during the same exposure period under EC, only 700 and 600 l ha^{-1} produced more than 50% mortality compared to 500 and 400 l ha^{-1}. Positive influence of EC on BPH population resulted in significantly higher yield loss (41.1%) compared to ambient (26.5%) in untreated check. Though LC_{50} under EC was less, higher canopy size and more BPH population resulted in increase in spray volume to cause similar mortality as of AC. The present results indicated that spray volumes of 400 and 500 l ha^{-1} was found insufficient to manage BPH population under EC; hence the current management strategies for BPH needs to be redefined under changing climatic conditions.

Keywords: Basmati rice, brown planthopper, climate change, elevated CO_2, insecticide.

ATMOSPHERIC CO_2 level has increased from 280 ppm during pre-industrial period to 400 ppm at present and Intergovernmental Panel on Climate Change (IPCC) projected it to reach 550 ppm by 2050 (ref. 1). Further by 2100, atmospheric CO_2 would reach 730–1020 ppm in the

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