

Modelling potential distribution of *Sapium sebiferum* – an invasive tree species in western Himalaya

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The use of species distribution models is gaining popularity in biological sciences. We used Maxent, a maximum entropy-based program, to predict distribution of *Sapium sebiferum* in western Himalaya. *Sapium sebiferum* is amongst the highly invasive species of the world and its spread in western Himalaya is a serious conservation issue. In order to model its distribution, we used field-collected coordinates of 177 presence locations of the species. Additionally, environmental data downloaded from the worldclim data portal were also used. Maxent was then run using default settings with 70% of the locations being used for training and the remaining 30% for testing the model. Area under curve for the receiving operator analyses measured at all possible threshold values training (0.993) and test (0.993) was close to 1, thereby showing the accuracy of the model.

Keywords: Mesic areas, plant invasion, *Sapium sebiferum*, species distribution models.

SPECIES distribution models (SDMs), also known as ecological niche models, are algorithmic tools that relate distribution and occurrence of a species to the environmental characteristics of the location(s) from where it has been recorded¹. These tools find use in predicting species distribution across landscapes² and have been used for prioritizing field surveys³. With the availability of high-resolution interpolated climate data for global land areas⁴ and continuously updated algorithms, SDMs are emerging as an important tool in ecological research^{5,6}. Bioclimatic variable (BIOCLIM), Domain (DOMAIN), Generalized Linear Model (GLMs), Multivariate Adaptive Regression Splines (MARS), Genetic Algorithm for Rule-set Production (GARP), Maximum Entropy Modelling (Maxent) and Boosted Regression Trees (BRT) are some of the popular and commonly used SDMs. The use of these models/algorithms is guided by the ultimate objective of the study. BIOCLIM is an envelope model that identifies locations where the climatic indices fall within the range that has been determined based on ground observations. The model treats each climatic axis independently, thus leading to unsound predictions⁷. The model does not per-

form well with respect to precipitation. DOMAIN, on the other hand, is a multivariate distance-based model. Though it uses presence only data, performance of the model is limited and sometimes additional information on absence locations is required³. GLM is a linear regression model that considers response variables that have other than normal distribution⁸. Compared to traditional models, such as DOMAIN, GLM performs well⁹. MARS provides an alternative regression-based method for fitting nonlinear responses using piece-wise linear fits⁹. It is faster than GLM, but highly sensitive to sample size¹⁰. BRT constructs a combination of trees and is quite effective. It is difficult to identify the significant predictor variable in BRT and it is relatively time-consuming³. Maxent is a comparatively popular model for accurately predicting species distribution and therefore it has been recommended¹⁰⁻¹³. As the name signifies, Maxent is a maximum entropy-based program in which relative entropy is minimized between the two probabilities of presence data and landscape¹⁴. It focuses on relating the environmental conditions of the area where a species is present to the environmental conditions across the area of interest^{15,16}. Thus, Maxent bypasses the requirement of absence data for a species and uses background environmental data for the area of interest.

On the biological front, owing to the ecological and economical ramifications of invasive alien species¹⁷⁻¹⁹, modelling potential distribution and mapping of invasive alien species in distinct biogeographical zones has been advocated²⁰. Consequently, SDMs have been used for documenting *Pinus* invasion in South America and Australia²¹, spread of invasive species in relation to changing climatic conditions in USA²² and invasion of habitats by *Bromus tectorum* and *Tamarix chinensis* in Grand Staircase-Escalante National Monument (GSENM), in south-central Utah USA²³. These studies have documented the utility of SDMs in conjugation with species ecology. *Sapium sebiferum* (family Euphorbiaceae), a native of China and hence commonly known as Chinese tallow tree, is amongst the highly invasive species of the world²⁴. It is a mid-sized deciduous tree that rarely attains a height of more than 15 m. The tree has a fast-growing potential and reproduces both sexually and by formation of root suckers. A mature tree produces more than 1 lakh seeds in a season²⁵ that have high germination rate and viability^{25,26}. Further, diverse modes of dispersal^{25,26} and its capability to survive in soils with pH ranging from 3.9 to 8.5 render the species highly invasive²⁷. *S. sebiferum* has led to habitat modifications²⁸ and loss of native biodiversity in many parts of USA²⁴ and Australia²⁹. Stands of *S. sebiferum* can also be seen in the Indian Himalayan state of Himachal Pradesh (HP)³⁰.

The Indian Himalayan region is divided into two distinct biogeographic zones, the western and the eastern Himalaya³¹. The western Himalaya comprises of Jammu & Kashmir (J&K), HP and Uttarakhand (UK). Recent

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studies have reported formation of close canopy woodlands by *S. sebiferum* in western Himalaya^{30,32}. *S. sebiferum* is a threat to the native flora and concerns regarding its possible spread^{32–34} to other areas are justified. SDMs find applicability in predicting areas vulnerable to plant invasion and thereby in prioritizing them for management^{6,35,36}. The present study, therefore, aimed at modelling the distribution of *S. sebiferum* in western Himalaya and for identifying areas vulnerable to invasion by *S. sebiferum*.

To identify sites bearing *S. sebiferum*, field surveys were conducted at different localities of HP during 2007–2012. HP was chosen for surveys as it lies at the centre of western Himalaya and is representative of the ecology of UK and J&K. Focusing on HP led to thorough and complete recording of *S. sebiferum* localities from a state^{32,34}. For this, the entire state of HP was gridded into 10 × 10 sq. km grids. Owing to the distribution limit of *S. sebiferum* up to 2000 m and based on our earlier surveys, all grids below 2000 m amsl were visited. A total of 177 sites having *S. sebiferum* populations were identified and their geographical coordinates were recorded using a Garmin etrex vista GPS handset^{32,34}. Later, the coordinates information of these 177 sites was converted into ‘CSV’ format. This was subsequently used as one of the inputs to Maxent.

In addition to species occurrence data, environmental data are a key input to Maxent. Therefore, information on 19 bioclimatic parameters was downloaded from the worldclim data portal (www.worldclim.org). Keeping in view the area of our interest, i.e. western Himalaya, we downloaded the bioclim tiles 18 and 28 that cover this region. These bioclimatic variables represent annual trends and seasonality such as mean temperature, precipitation, annual temperature range and limiting environmental factors such as temperature of coldest or hottest month and precipitation (Table 1). We used data of 30 s (0.86 sq. km at the equator) resolution, freely available from the worldclim database⁴. The native format of these files is ‘BIL’. In order to be compatible with Maxent, these files were converted to ‘ASC II’ using ArcGIS 9.3 version³⁷.

Autocorrelation among the predictor variables has been already identified as source of error; therefore, we checked for it before running the model³⁸. We did this using the ENM tools downloaded from the portal www.activestate.com. Based on the correlation ($r > 0.9$) and taking into consideration the species ecology and the importance of extreme environmental conditions, a total of 11 variables were ultimately selected for modelling (Table 2).

Maxent version 3.3.3, downloaded from the portal www.cs.princeton.edu, was used in the present study¹⁵. Thirty per cent of the data points was used for testing, and the remaining 70% was used for training the model. The model was then run with default settings. The output generated by Maxent predicts suitability of a habitat, for

a species, on the scale from 0 to 1 (ref. 39). Lowest suitability areas are represented by 0, while 1 represents areas with highest suitability. These numerical values generated by Maxent were converted into three probability classes, namely low, moderate and high. Such a classification has also been done by other workers². We converted the Maxent output in bmp format into ESRI grid format in ArcGIS 9.3 using import raster function⁴⁰. Here, areas that have values between 0.08 and 0.29 have been classified as low probability areas, whereas those that have values between 0.29 and 0.50 as well as 0.50 and 0.71 have been classified as moderate and high probability areas respectively.

To infer the spatial distribution of *S. sebiferum* in western Himalaya, the administrative boundary maps of J&K, HP and UK in ESRI shape format were overlaid on the above converted grid file in ArcGIS 9.3 (ref. 40). Further, this grid file was overlaid on the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) to generate information on the altitudinal range of *S. sebiferum* in the three states⁴⁰. The SRTM DEM was downloaded from the USGS website (<http://srtm.usgs.gov/index.php>) and has a resolution of 90 m. Additionally, Maxent generates response curves for each predictor variable (here the 11 bioclimatic variables) and uses jackknifing for highlighting the relative influence of each of the predictor variables^{41,42}.

A model has limited utility until it is tested and validated. It is the key to judging the performance of a model. Whether the results are by chance or true representation needs to be established. We therefore analysed the omission/commission rate, which is a threshold-dependent binomial test based on omission and predicted

Table 1. Codes and details of the 19 bioclimatic factors

Code	Parameter
BIO1*	Annual mean temperature
BIO2*	Mean diurnal range (mean of monthly (maximum temperature – minimum temperature))
BIO3*	Isothermality (BIO2/BIO7) (*100)
BIO4*	Temperature seasonality (standard deviation *100)
BIO5*	Maximum temperature of warmest month
BIO6	Minimum temperature of coldest month
BIO7*	Temperature annual range (BIO5–BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14*	Precipitation of driest month
BIO15*	Precipitation seasonality (coefficient of variation)
BIO16*	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18*	Precipitation of warmest quarter
BIO19*	Precipitation of coldest quarter

*Variables that were taken as inputs to the model.

Table 2. Correlation between different bioclimatic variables

Variable	BIO2	BIO3	BIO4	BIO5	BIO6	BIO7	BIO8	BIO9	BIO10	BIO11	BIO12	BIO13	BIO14	BIO15	BIO16	BIO17	BIO18	BIO19
BIO1	0.404																	
BIO2		0.682	-0.599	0.985	0.986	-0.271	0.934	0.975	0.994	0.995	0.411	0.490	0.018	0.513	0.487	0.130	0.404	0.144
BIO3			0.068	0.507	0.279	0.545	0.584	0.301	0.453	0.368	-0.412	-0.220	-0.651	0.712	-0.239	-0.650	-0.300	-0.610
BIO4				0.654	0.677	-0.246	0.776	0.630	0.647	0.718	0.263	0.391	-0.241	0.718	0.384	-0.042	0.377	-0.080
BIO5					-0.709	0.861	-0.549	-0.633	-0.506	-0.678	-0.799	-0.796	-0.329	-0.305	-0.801	-0.593	-0.828	-0.511
BIO6						-0.103	0.938	0.946	0.997	0.964	0.287	0.389	-0.083	0.548	0.383	-0.003	0.283	0.027
BIO7							-0.427	0.898	0.977	0.995	0.540	0.593	0.134	0.453	0.592	0.273	0.526	0.272
BIO8								-0.350	-0.169	-0.356	-0.837	-0.719	-0.628	0.135	-0.734	-0.828	-0.806	-0.742
BIO9									0.931	0.929	0.291	0.415	-0.163	0.643	0.404	-0.034	0.341	-0.028
BIO10										0.976	0.464	0.529	0.093	0.444	0.531	0.202	0.437	0.215
BIO11											0.329	0.416	-0.026	0.514	0.412	0.057	0.318	0.083
BIO12										0.977	0.477	0.550	0.057	0.512	0.548	0.194	0.476	0.196
BIO13												0.950	0.591	0.076	0.957	0.828	0.949	0.757
BIO14													0.341	0.316	0.997	0.630	0.930	0.541
BIO15														-0.553	0.357	0.908	0.456	0.932
BIO16															0.302	-0.371	0.161	-0.410
BIO17																0.644	0.930	0.555
BIO18																	0.733	0.973
																		0.647

area^{15,16} (Figure 1). Omission rate is the fraction of the test localities that fall into the pixels not predicted as suitable for the species and predicted area is the fraction of all the pixels that are predicted as suitable for the species¹⁵. In Figure 1, the red line indicates fraction of background predicted, black line indicates predicted omission, blue line indicates omission on training samples and the light blue line indicates omission on test samples. The omission rate is calculated both on the training presence records and on the test records^{41,43}. We also analysed the threshold-independent receiver operating characteristic (ROC). In ROC, the performance is measured on the basis of area under curve (AUC; Figure 2). ROC curve is

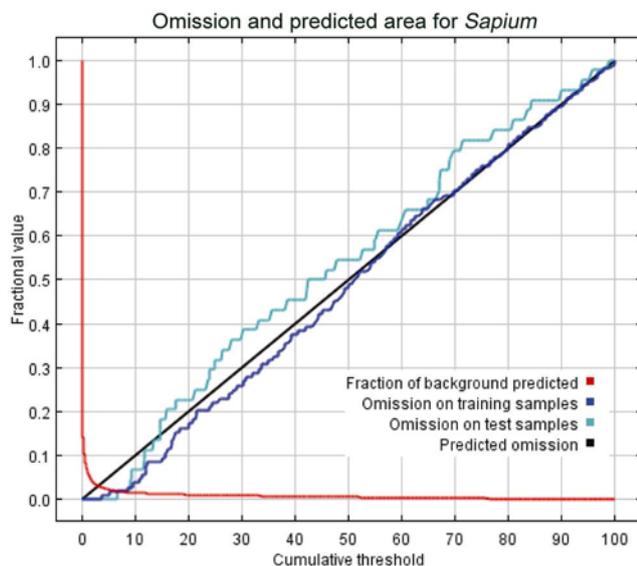


Figure 1. Omission versus predicted area.

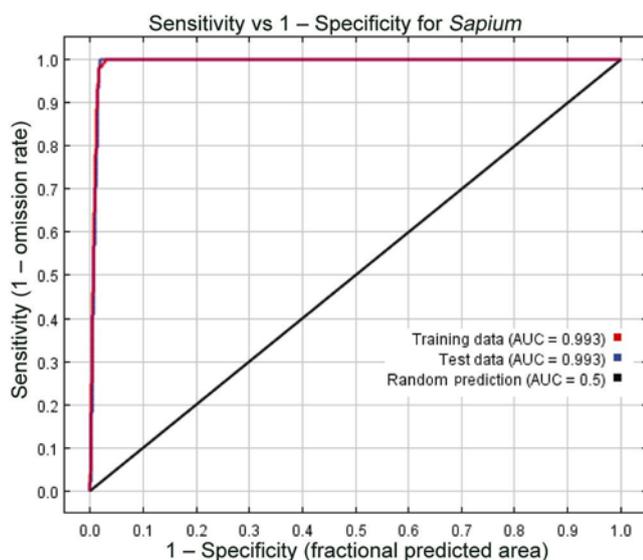


Figure 2. Receiver operating characteristic curve with area under curve (AUC).

a plot between sensitivity (true positive fraction), i.e. absence of omission error and the proportion of incorrectly predicted observed absences (1-specificity) or false positive fraction, i.e. commission error. The specificity is defined using predicted area, rather than true commission. AUC value of 0.50 indicates that the model is close to random and is a poor indicator, whereas a value of 1 indicates best run⁴⁴. Rigorous evaluation has been advocated specially for invasive species, as the species ecological niche is invariably higher than the geographical range of a species and the uninhabited suitable areas are in disjunct regions⁴⁵. Use of maximum possible information on the distribution of a species and variables directly linked to species distribution has been advocated⁴⁶. Owing to this, we surveyed the entire landscape of HP, which is representative of western Himalaya, for recording locations of *S. sebiferum*. Further, ground validation of the results, specially predicted presences, is much desired⁴⁶. We thereby checked the results on ground.

The output of the model is shown in Figure 3. In this figure, the white dots represent *S. sebiferum* locations used for training the model and the violet dots represent the test locations. We choose the logistic output format of Maxent as it is easy to conceptualize and interpret³⁹.

In the model, the lines of omission from both the training and test data are very close to predicted omission (Figure 1). Also, the value of AUC in case of training (0.993) and test (0.993) is close to 1, which shows that the model performed better than random and therefore points to the accuracy of the model (Figure 2).

The predicted spatial extent of *S. sebiferum* in western Himalaya is between 30°14'43"–32°50'40"N and 74°52'25"–79°23'28"E over an altitudinal range of 349 to 2390 m. The total predicted area is 11,920 sq. km (Figure 4). In Figure 4, the areas in red depict localities that have high probability of harbouring *S. sebiferum*, while those in blue represent low probability areas. Moderate probability areas are shown in green (Figure 4). Here our

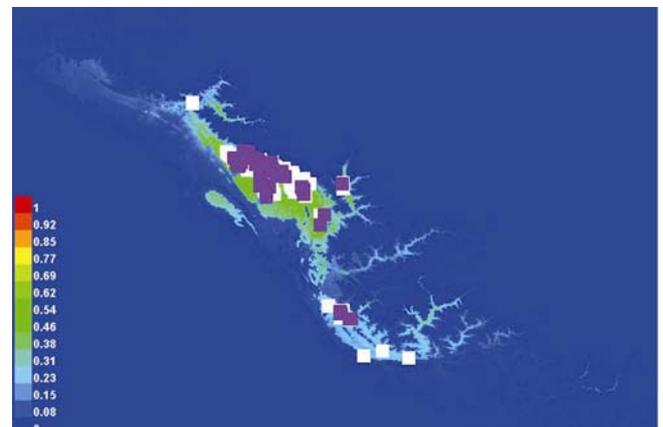


Figure 3. Model output showing the presence locations used for training (in white) and the test locations (in violet).

GPS points depicted in black show that the species is growing in the high probability areas (Figure 4). Of the total 11,920 sq. km area, 15% area (1802 sq. km) has high probability of having *S. sebiferum*, 2881 sq. km has moderate probability and 7237 sq. km has low probability of *S. sebiferum*.

If we analyse the three western Himalayan states individually, maximum predicted area under *S. sebiferum* is for HP (9794 sq. km). This area lies between the altitudinal limit 452 to 2390 m and extends from 30°30'25" to 32°50'40"N and 75°43'46" to 78°00'49"E. The predicted area for J&K is 1233 sq. km within altitudinal limits of 349 to 1895 m and coordinates 32°05'09"–32°20'21"N and 74°52'25"–75°54'02"E. For UK, 892 sq. km is the total predicted area. This lies between the coordinates 30°14'43"–31°06'32"N and 77°47'59"–79°23'28"E within altitudinal limits of 503 to 2144 m. In HP, the chances of spread of *S. sebiferum* are high in Chamba, Hamirpur, Kangra, Kullu, Solan, Shimla and Sirmaur districts, while in UK high probability of *S. sebiferum* spread is in Dehradun and Uttarkashi districts. On the other hand, Rudraprayag, Tehri, Pauri, Chamoli (UK), Bilaspur, Mandi and Una (HP), and Kathua, Jammu, and Udhampur (J&K) have moderate probability of harbouring *S. sebiferum*. The jackknifing plots, comparing the environmental variables in the model prediction are depicted

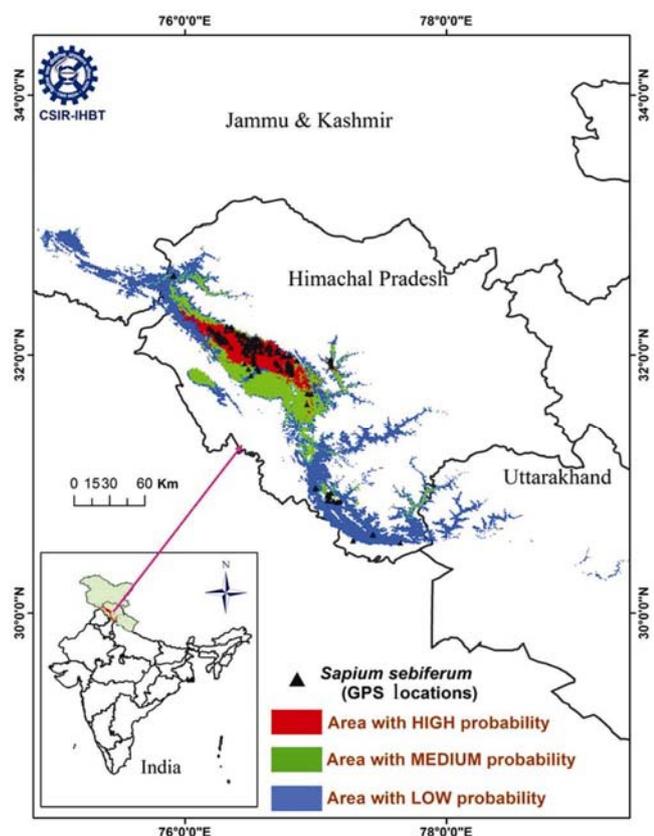


Figure 4. Probability distribution of *Sapium sebiferum* in Western Himalaya.

in Figure 5. Here BIO 16, which is precipitation of the wettest quarter, produces the highest gain while BIO 15, which is precipitation seasonality, achieves little gain. This clearly shows that high precipitation has a bearing on the distribution and future spread of *S. sebiferum*.

On the basis of its occurrence in HP, it is revealed that almost 3% area of western Himalaya has the probability of being invaded by *S. sebiferum*. Of this, the maximum area lies in the state of HP, followed by J&K and UK. This could be attributed to the fact that few localities in HP have comparatively higher rainfall than J&K and UK. The affinity of *S. sebiferum* to mesic conditions has been documented⁴⁷. Also, the jackknife plots showed affinity of *S. sebiferum* to rainfall (Figure 5 a and b).

In terms of per cent coverage in the respective states, UK displaces J&K from the second position. Almost 1.7% (892 of the total 53,483 sq. km) of the state's area has environmental conditions favourable to invasion by *S. sebiferum*, whereas this is only 0.6% in case of J&K (1233 of the total 222,236 sq. km). This could be attributed to the fact that a substantial area in J&K is under cold desert⁴⁸. For HP the total vulnerable area is 17% (9794 of the total 55,673 sq. km). This is almost twice the area that is presently under *S. sebiferum* in the state. Recent reports have documented that *S. sebiferum* occupies 8% geographical of the state³⁴. In J&K, the model predicted the occurrence of *S. sebiferum* in Jammu and Kathua. These areas were found to have *S. sebiferum*^{26,49}. Similarly, the model predicted the occurrence of *S. sebiferum* in Dehradun (UK) and the same has been reported

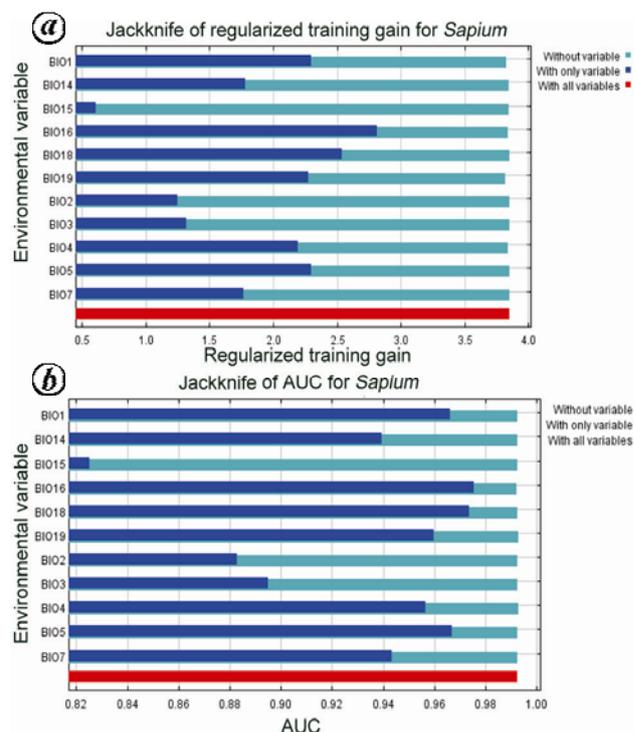


Figure 5. Jackknife plot for (a) training gain and (b) AUC.

from Dehradun⁵⁰. Thus, apart from the statistical accuracy of the model, field accuracy also exists. Considering that *S. sebiferum* has wide ecological amplitude, i.e. it is capable of occurring on varied soil types and in diverse habitats^{27,51}, there is possibility of its further spread in the western Himalayan region. Other studies on the species have also modelled its spread in USA³⁵ and reported considerable area to be vulnerable to it.

During our field surveys in HP, we have observed *S. sebiferum* on stream banks, along roads, on hill slopes and on the bunds of agriculture lands^{32,34}. At few places in mesic areas, *S. sebiferum* is forming close-canopy woodlands. Global observations on the species have revealed its dominance in mesic areas^{29,51,52}. Reports that *S. sebiferum* prefers mesic areas for initial establishment are available^{47,52}. It is from these areas that it spreads to new localities⁵². Thus, among habitats, mesic areas are most vulnerable to invasion by *S. sebiferum*. Though we have not looked into the impacts of *S. sebiferum* on native habitat and species, studies done elsewhere have reported modification of wetlands⁵³ and loss of native biodiversity⁵⁴. Therefore, mesic areas should be prioritized for management and monitoring.

Also, during our field surveys, good populations of *S. sebiferum* were seen around agricultural bunds and human settlements³². Interactions with the local people revealed that they hardly use the plant and are not aware how and when it came to their locality. Thus, awareness creation among the local people is desired. Villages that fall in the high probable areas for invasion by *S. sebiferum* may be taken up as starting points.

S. sebiferum occurs in the Himalayan region and the model predicted its potential to occupy 11,920 sq. km area in the western Himalaya. Of this, 15% area has high probability of harbouring *S. sebiferum*. Apart from the statistical accuracy of the model, some of the localities predicted by it were reported to have populations of *S. sebiferum*. Mesic areas appear to be most vulnerable. Thus, the outputs of the study would guide informed management programmes.

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ACKNOWLEDGEMENTS. We thank the Director CSIR-IHBT, Palampur for providing facilities and encouragement, and the staff and faculty of CSIR-IHBT herbarium for fruitful discussions. V.J. thanks the Council of Scientific and Industrial Research, New Delhi for Senior Research Fellowship. We acknowledge the constructive comments of the editor and the two anonymous reviewers that helped improve the manuscript. This is IHBT communication number 3410.

Received 26 March 2013; revised accepted 28 August 2013

Crevasses detection in Himalayan glaciers using ground-penetrating radar

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Identification and mapping of crevasses in glaciated regions is important for safe movement. However, the remote and rugged glacial terrain in the Himalaya poses greater challenges for field data collection. In the present study crevasse signatures were collected from Siachen and Samudra Tapu glaciers in the Indian Himalaya using ground-penetrating radar (GPR). The surveys were conducted using the antennas of 250 MHz frequency in ground mode and 350 MHz in airborne mode. The identified signatures of open and hidden crevasses in GPR profiles collected in ground mode were validated by ground truthing. The crevasse zones and buried boulder areas in a glacier were identified using a combination of airborne GPR profiles and SAR data, and the same have been validated with the high-resolution optical satellite imagery (Cartosat-1) and Survey of India mapsheet. Using multi-sensor data, a crevasse map for Samudra Tapu glacier was prepared. The present methodology can also be used for mapping the crevasse zones in other glaciers in the Himalaya.

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