Performance metrics

Team ID	PNT2022TMID41774
Project Name	Emerging Methods For Early Detection of Forest Fires
Maximum Marks	10 Marks

Forest fire detection performance metrics:

- The receiver operating characteristics (ROC) curve is one of the most important and widely used performance metrics for the evaluation of classification models in terms of their goodness-of-fit and generalizability.
- performance metrics, we investigated how well the different models used for the prediction of forest fire susceptibility captured the relationships between historical fires and different explanatory variables (i.e., goodness-of-fit with the training dataset) and made decisions when tested with the unseen validation dataset (i.e., generalization ability).

$$\mathrm{SPF} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$\mathrm{SST} = \frac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}}$$

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$\mathrm{Kappa} = \frac{(\mathrm{TP} + \mathrm{TN}) - ((\mathrm{TP} + \mathrm{FN})(\mathrm{TP} + \mathrm{FP}) + (\mathrm{FP} + \mathrm{TN})(\mathrm{FN} + \mathrm{TN}))}{1 - ((\mathrm{TP} + \mathrm{FN})(\mathrm{TP} + \mathrm{FP}) + (\mathrm{FP} + \mathrm{TN})(\mathrm{FN} + \mathrm{TN}))}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs} - X_{est})^2}{N}}$$

Metric Comparing table:

architecture	recall	IoU	accuracy	MSE	# parameters
FLAME U-Net	0.94	0.892	0.943	0.043	2M
DLV3+ w/ ResNet50	0.968	0.926	0.962	0.031	40M
DLV3+ w/ EfficientNetB4	0.967	0.93	0.964	0.028	22M
Squeeze U-Net	0.930	0.897	0.946	0.042	2.5M
ATT Squeeze U-Net	0.928	0.893	0.944	0.042	885K

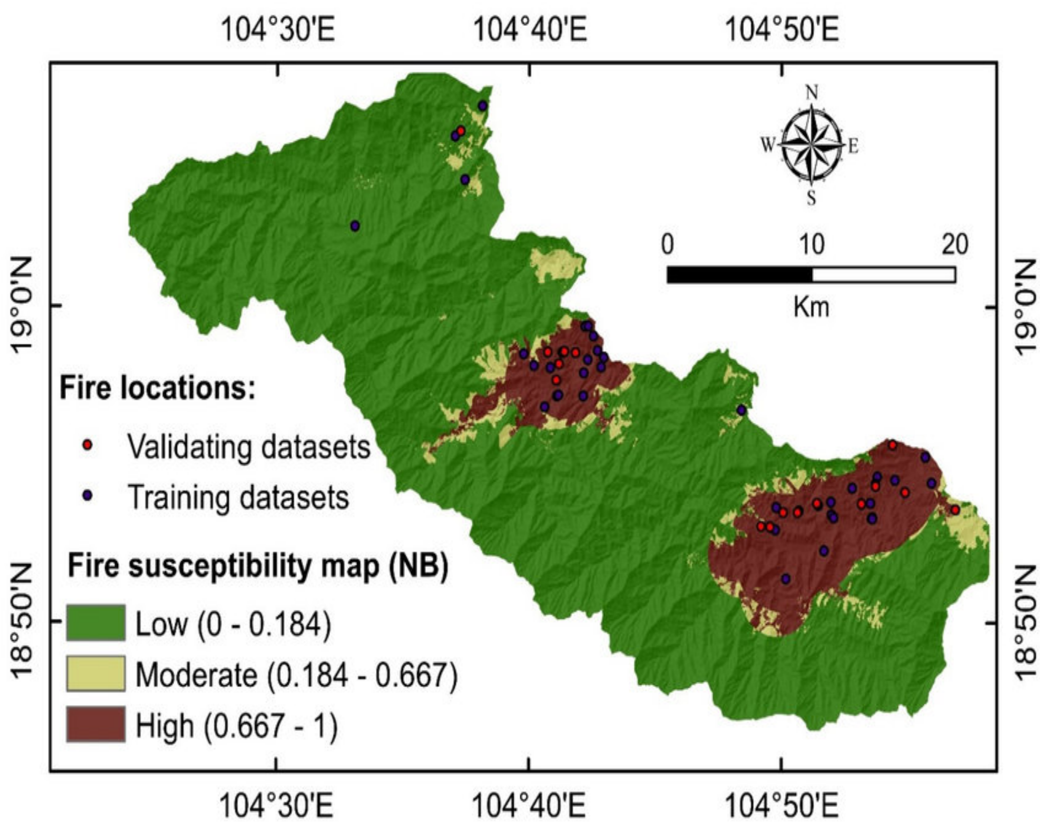
architecture	normalized recall	normalized IoU	normalized accuracy	normalized MSE	normalized # parameters
FLAME U-Net	1.013	0.999	0.943	1.023	2.3
DLV3+ w/ ResNet50	1.043	1.037	1.019	0.74	45.2
DLV3+ w/ EfficientNetB4	1.042	1.041	1.02	0.67	24.8
Squeeze U-Net	1.002	1.004	1.002	1	2.8

Model performance in the training and validation datasets:

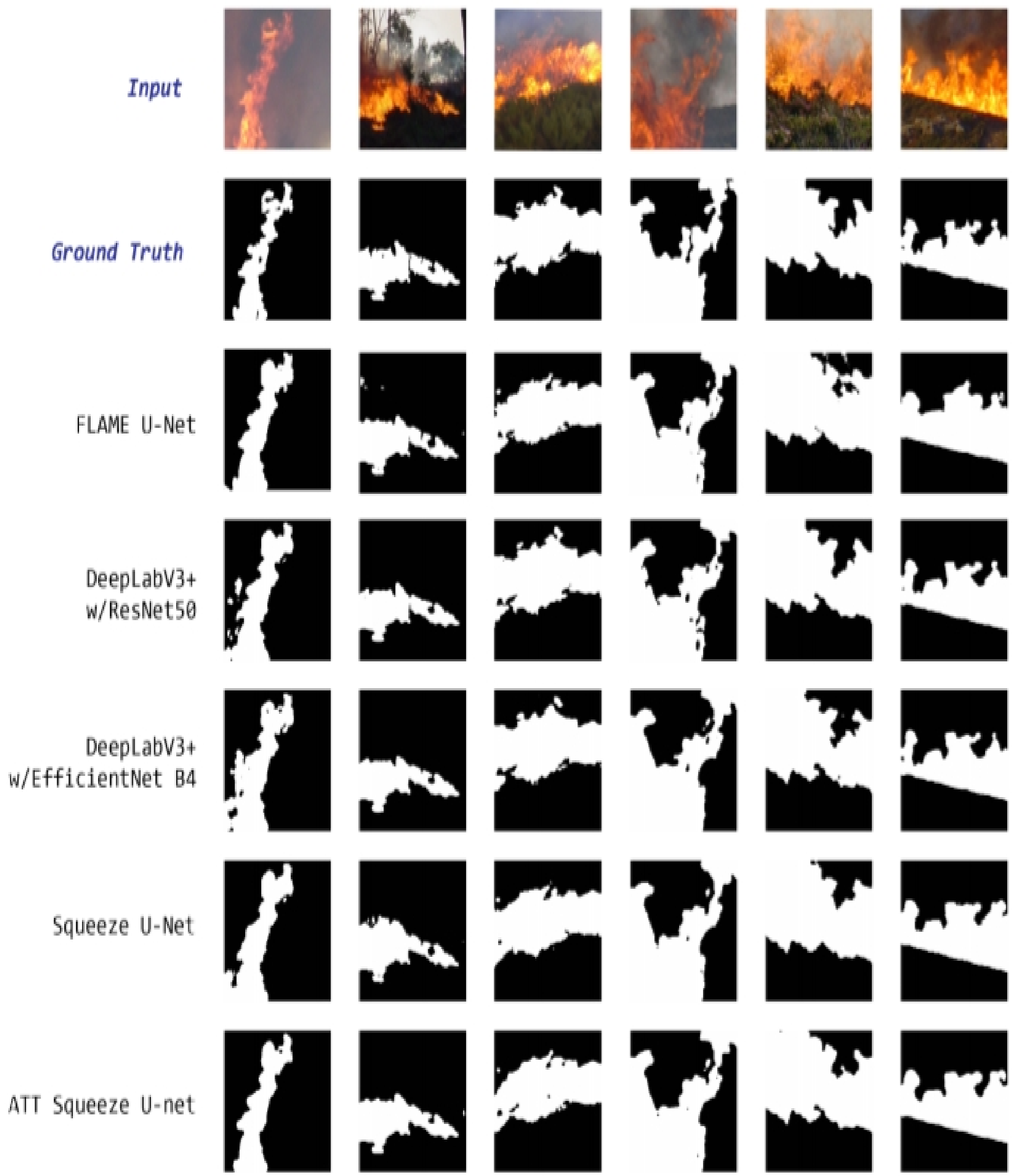
Metric	Training Dataset				Validation Dataset			
	BN	DT	MLR	NB	BN	DT	MLR	NB
PPV (%)	89.74	82.05	84.62	87.18	100.00	64.71	76.47	94.12
NPV (%)	87.18	100.00	100.00	87.18	88.24	100.00	100.00	94.12
SST (%)	87.50	100.00	100.00	87.18	89.47	100.00	100.00	94.12
SPF (%)	89.47	84.78	86.67	87.18	100.00	73.91	80.95	94.12
ACC (%)	88.46	91.03	92.31	87.18	94.12	82.35	88.24	94.12
Kappa	0.769	0.821	0.846	0.744	0.884	0.647	0.765	0.882

Robustness Analysis:

- The analysis of the model robustness based on the five different datasets (Fold 1–5) and three performance metrics (ACC, RMSE, and AUC) showed that the models were very stable, and their performance changed in a narrow range.
- For example, the training phase of the BN model ranged ACC from 87.17% to 88.46% (mean = 87.44% and standard deviation = 0.57%), ranged RMSE from 0.279 to 0.301 (mean = 0.29 and standard deviation = 0.01), and ranged AUC from 0.98 to 0.99 (mean = 0.98 and standard deviation = 0.00).

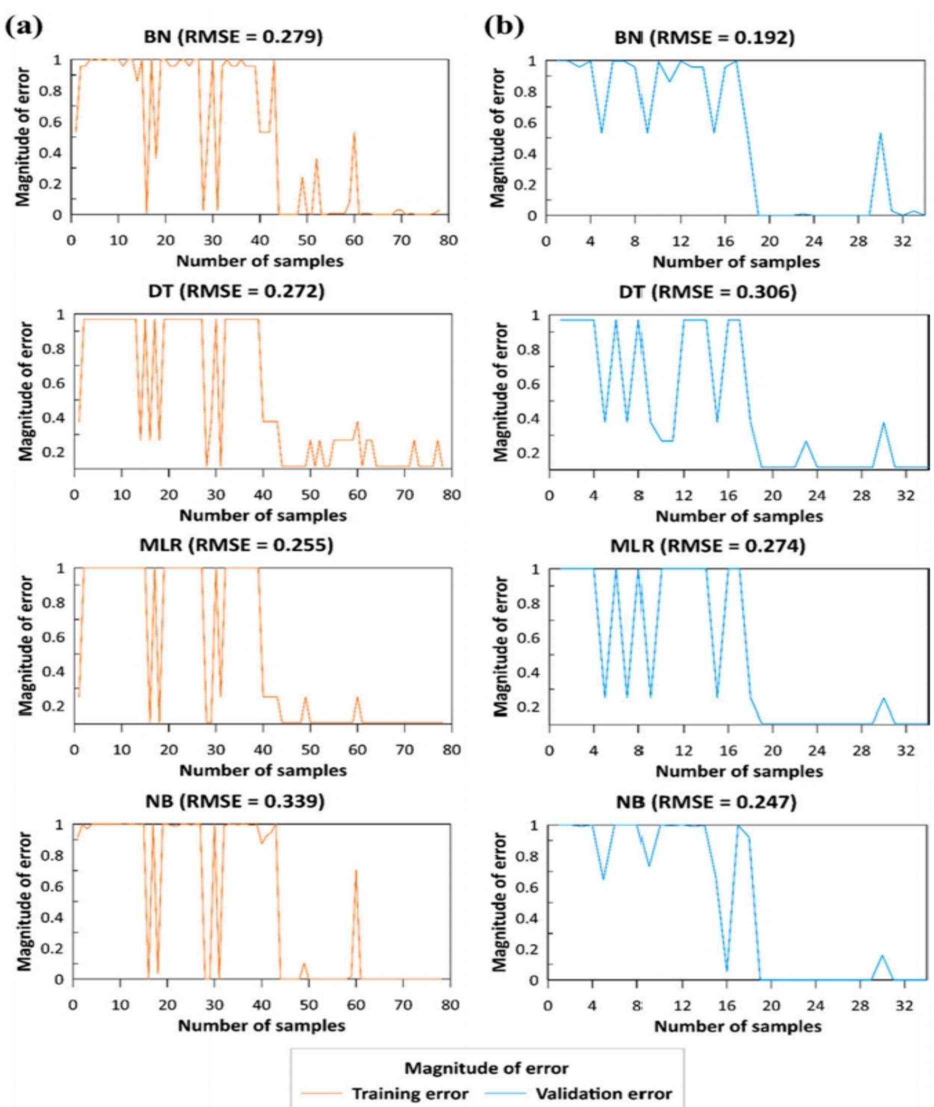


Model	Phase	Metric	Fold 1	2	3	4	5	Mean	SD
BN	Training	ACC	88.46	87.18	87.18	87.18	87.18	87.44	0.57
		RMSE	0.279	0.287	0.285	0.299	0.301	0.29	0.01
		AUC	0.99	0.984	0.98	0.98	0.98	0.98	0.00
	Validation	ACC	100	99.88	99.88	99.88	99.85	99.90	0.06
		RMSE	0.192	0.31	0.291	0.296	0.286	0.28	0.05
		AUC	0.96	0.954	0.965	0.941	0.956	0.96	0.01
DT	Training	ACC	91.03	89.99	90.87	89.62	89.9	90.28	0.63
		RMSE	0.272	0.306	0.267	0.325	0.321	0.30	0.03
		AUC	0.969	0.953	0.958	0.947	0.949	0.96	0.01
	Validation	ACC	94.12	94.12	93.18	93.01	93.18	93.52	0.55
		RMSE	0.306	0.307	0.296	0.302	0.298	0.30	0.00
		AUC	0.94	0.94	0.94	0.934	0.94	0.94	0.00
MLR	Training	ACC	92.31	91.9	92.9	89.9	89.18	91.24	1.61
		RMSE	0.255	0.35	0.344	0.352	0.34	0.33	0.04
		AUC	0.986	0.96	0.97	0.974	0.959	0.97	0.01
	Validation	ACC	88.24	87.06	90.18	88.14	88.14	88.35	1.13
		RMSE	0.274	0.203	0.295	0.306	0.299	0.28	0.04
		AUC	0.937	0.935	0.93	0.933	0.938	0.93	0.00
NB	Training	ACC	87.18	87.18	87.18	87.18	87.18	87.18	0.00
		RMSE	0.339	0.339	0.335	0.351	0.347	0.34	0.01
		AUC	0.983	0.983	0.979	0.979	0.979	0.98	0.00
	Validation	ACC	94.12	93.18	93.24	93.18	93.18	93.38	0.41
		RMSE	0.274	0.299	0.315	0.297	0.256	0.29	0.02
		AUC	0.939	0.937	0.932	0.933	0.932	0.93	0.00

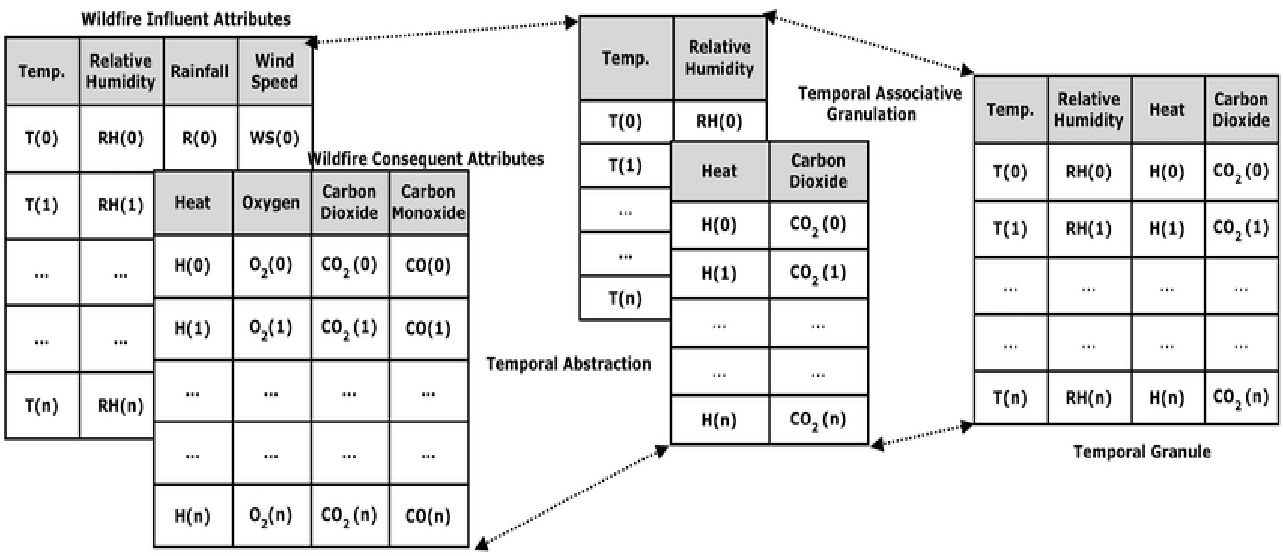

Input
Ground Truth
FLAME U-Net
DeepLabV3+
w/ResNet50
DeepLabV3+
w/EfficientNet B4
Squeeze U-Net
ATT Squeeze U-net

Model verification and comparison:

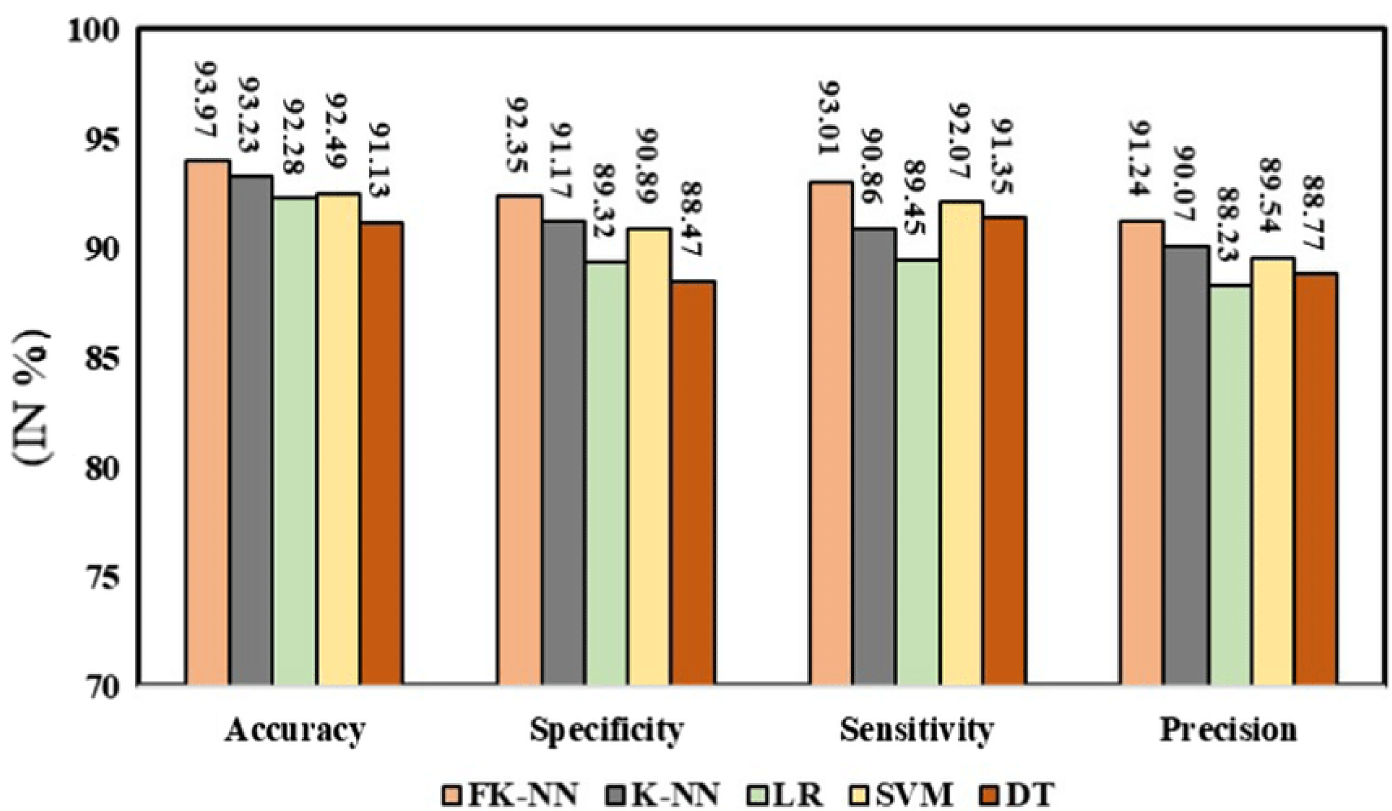
- In the matter of the magnitude of the modeling error, the four models exhibited training error that ranged from 0.255 (MLR) to 0.339 (NB) and validation error that ranged from 0.192 (BN) to 0.306 (DT).
- Again, we are inclined to attribute these asymmetric performances of a model in training and validation phases to its computational algorithm when tested with different datasets.

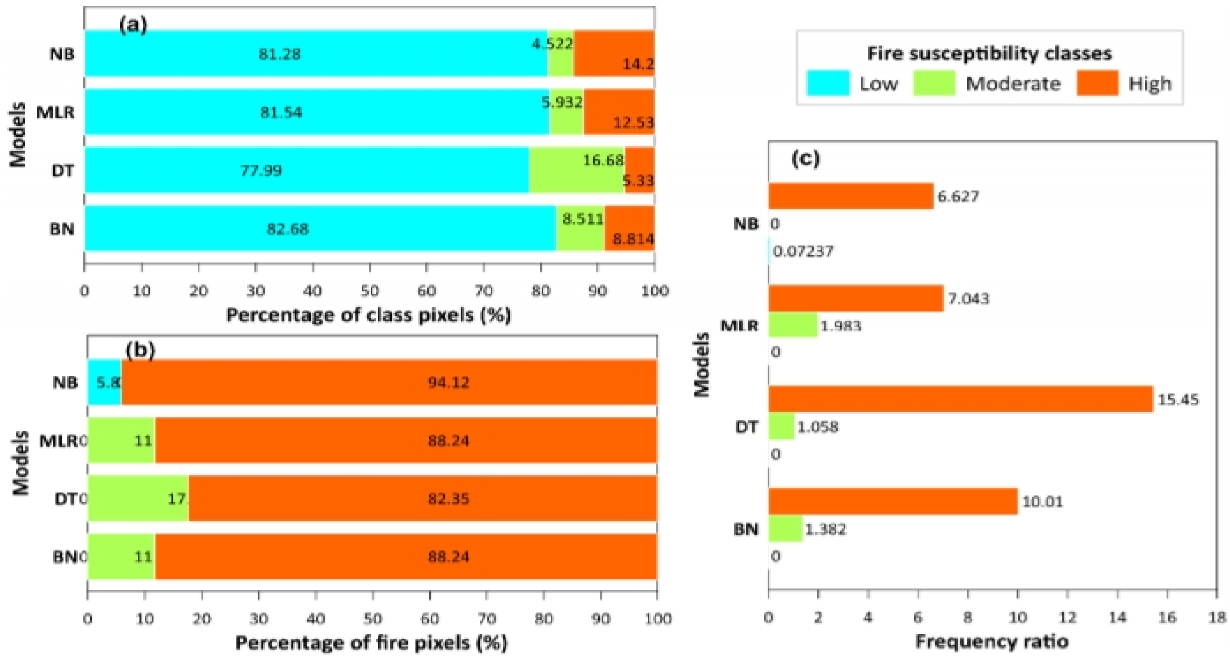


Temporal mining:



Comparative analysis of performance metrics:





Quantitative analysis of the fire susceptibility maps: (a) Percentage of class pixels; (b)Percentage of fire pixels; (c) Frequency ratio analysis

Conclusion:

The accurate prediction of fire probability aids forest managers in drafting more efficient fire-fighting strategies and also helps to reorganize policies for sustainable management of forest resources. To achieve these, we evaluated and compared four fire predictive models derived from the BN, NB, DT, and MLR machine learning methods for predicting and mapping fire susceptibility in the Pu Mat National Park, Vietnam.