Machine learning for drainage flow prediction

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Background

- Previous drainage studies were mainly in complex terrain (mountain areas). A lack of such studies exists for areas of shallow terrain.
- The primary objective of this research is to develop AI models that can predict atmospheric parameters that can result in occurrence of nocturnal drainage flows in shallow terrain.

Method

- Stable Atmospheric Variablity And Transport (SAVANT) field campaign at shallow terrain (slope ratio:1.2%) was conducted during September, October, and November in 2018. Atmospheric data were measured during stable conditions (Hiscox et al., 2023).

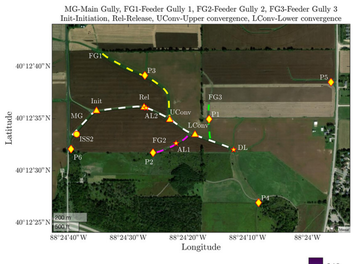


Figure 1. SAVANT field campaign at a shallow terrain at Mohomet, IL. Atmospheric data were measured mainly by 4 towers (Init 10 m tall, Rel 20 m, Uconv 10 m, and Lconv 20 m) (Hiscox et al., 2023).

Night time drainage flows were detected in the campaign based on atmospheric parameters (Table 1). The prediction of these atmospheric parameters can inform if a drainage flow will occur.

TABLE 1. Drainage-flow detection criteria for observations up to 4.5 m above ground (Bhimireddy et al., 2022). Profile calculation used 4.5 m and 20 m data.

Variable observed	Range or threshold value
Wind speed	<2 m s^{-1}
Wind direction	$290° \pm 10°$
Friction velocity	<0.1 m s^{-1}
Surface heat flux	$-30 < H < 0$ W m^{-2}
Wind direction profile	$\lvert\partial \mathrm{UDir}/\partial z\rvert > 0.1°$ m^{-1}
Temperature profile	$\partial\theta/\partial z > 0.2$ K m^{-1}

- Selected machine learning models to predict parameters in Table 1:

MTGNN, LSTNet, Informer, Dlinear, Crossformer, Autoformer

- Input variables:

The input variables are 5-minute atmospheric data from the SAVANT experiments.

- Output variables: Table 1 listed variables: 4.5 m wind speed, direction, friction velocity, surface heat flux, air temperature, and 20 m wind direction and air temperature. These are future 15 minutes to 240 minutes predictions.

Result

TABLE 2. Performance of six models with different number of input variables: mean square error (MSE) and mean absolute error (MAE).

Number of input variables	7	10	20	30	40	50	60
MSE	0.325	0.335	0.325	0.325	0.323	0.316	0.323
MAE	0.234	0.241	0.233	0.236	0.236	0.235	0.238

Table 2 shows that the models' performance with 7, 10, 20, 30, 40, 50, or 60 input variables was similar. Therefore, 7 input variables (least number of inputs) were chosen for the models. The 7 input variables are the same as the 7 output variables but input variables are historical and output are future predictions.

TABLE 3. Model performance

Prediction time (minutes)		15	30	60	120	240	Average
MSE	Informer	0.389	0.402	0.468	0.501	0.631	**0.478**
	Crossformer	0.285	0.291	0.299	0.312	0.330	**0.303**
	LSTNet	0.097	0.131	0.194	0.388	0.551	**0.272**
	MTGNN	0.097	0.128	0.176	0.272	0.454	**0.225**
	Autoformer	0.610	0.623	0.623	0.717	0.737	**0.662**
	Delinear	0.318	0.321	0.330	0.307	0.168	**0.289**
MAE	Informer	0.220	0.243	0.314	0.353	0.476	**0.321**
	Crossformer	0.121	0.127	0.154	0.173	0.194	**0.154**
	LSTNet	0.147	0.186	0.244	0.407	0.534	**0.304**
	MTGNN	0.146	0.175	0.218	0.303	0.438	**0.256**
	Autoformer	0.460	0.466	0.472	0.532	0.535	**0.493**
	Delinear	**0.318**	**0.321**	**0.330**	**0.307**	**0.168**	**0.289**

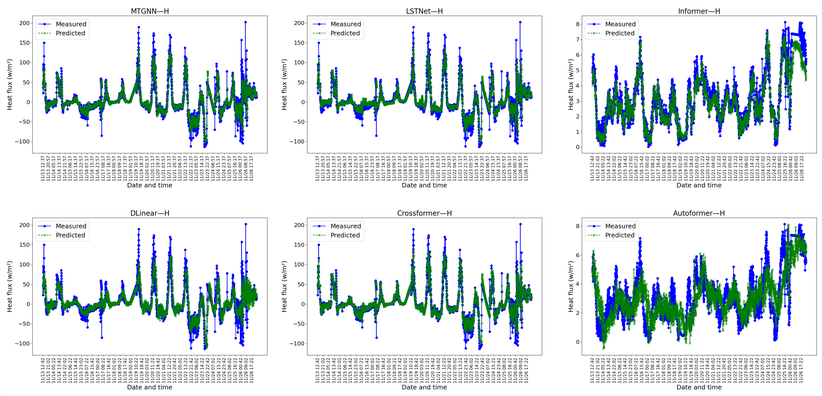


Figure 2. Predicted vs. year 2018 measured surface heat fluxes from six models. from left to right, top to bottom, MTGNN, LSTNet, Informer, Dlinear, Crossformer, Autoformer.

Summary

- Seven input variables are the optimal amount of variables for inputs (4.5 m wind speed, direction, friction velocity, surface heat flux, air temperature, and 20 m wind direction and air temperature).
- Two models of MTGNN and Crossformer have better performance than the other four models to predict atmospheric parameters for drainage flows.
- Future work will predict drainage flows from the model outputs.

References

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Acknowledgement

This study is funded by AGS-2203248, AGS-2220664, and AGS-2231229 for JS; 683 AGS-1733877 and AGS-2220663 for JW, SB, and DK; AGS-1733746, AGS-1843258, and 684 AGS-2220662 as well as the University of South Carolina Department of Geography for AH. SB was also partly supported by the NOAA cooperative agreement NA22OAR4320151 for the Cooperative Institute for Earth System Research and Data Science (CIESRDS). The statements, findings, conclusions, recommendations, and opinions expressed here are those of the authors and do not necessarily reflect the views of the NSF, NOAA, the U.S. Department of Commerce, the Illinois State Water Survey, the Prairie Research Institute, the University of Illinois, or the University of South Carolina. The authors would like to thank everyone involved in the SAVANT field campaign.