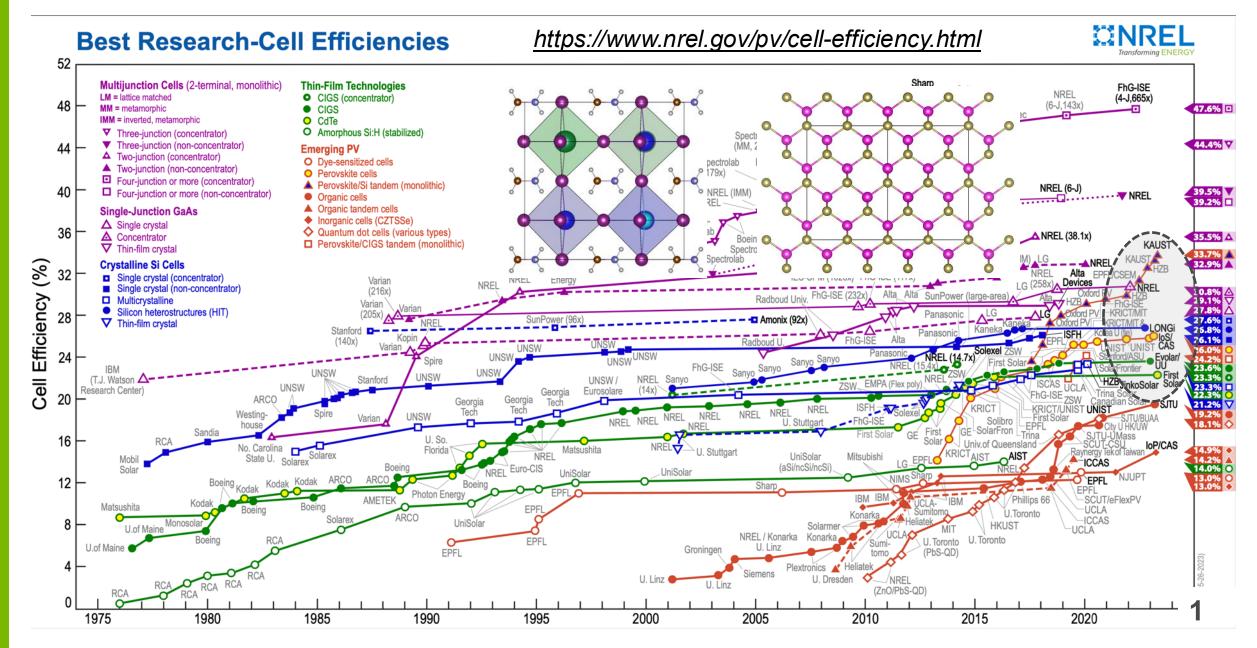
Designing Halide Perovskites for Solar Absorption using Machine Learning

Arun Mannodi Kanakkithodi

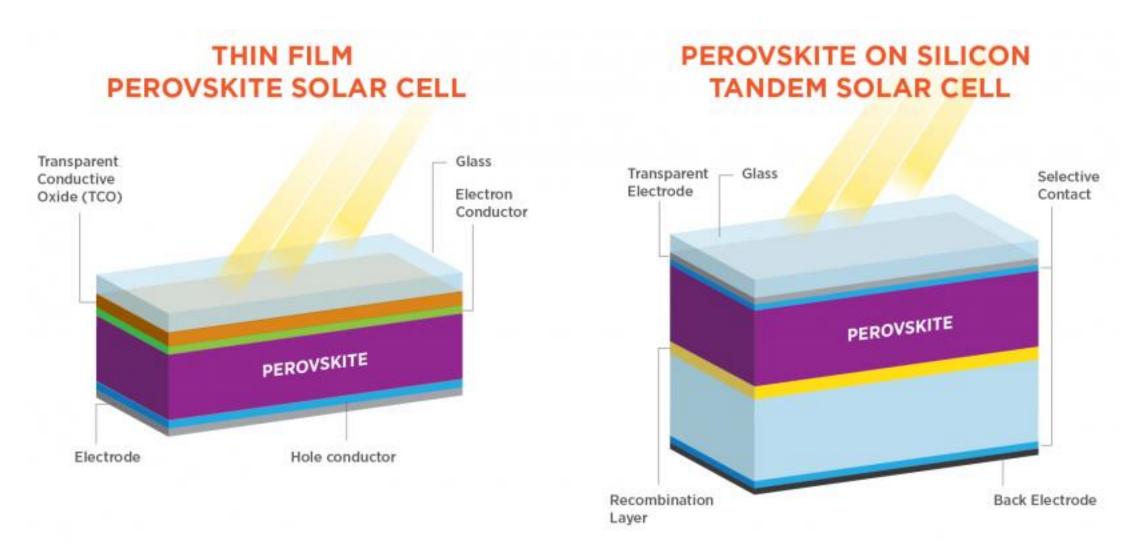
Assistant Professor, School of Materials Engineering Purdue University, West Lafayette, IN



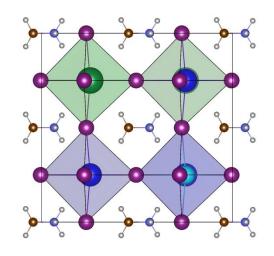
Research: Absorbers for Next-Gen Solar Cells



Perovskite Solar Cells



Halide Perovskites

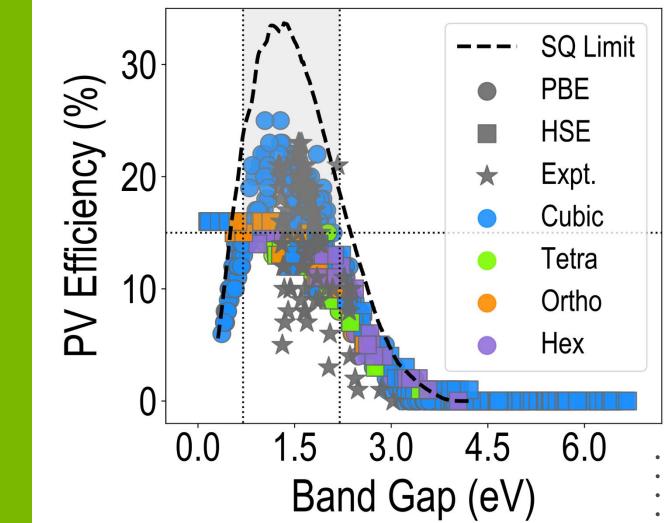


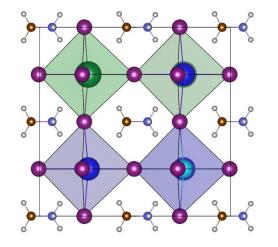
General formula: ABX₃

Α	В	X
MA	Pb	I
FA	Sn	Br
Cs	Ge	CI
Rb	Ва	
K	Sr	
	Ca	

- ABX₃ perovskites, both purely inorganic (e.g., CsPbl₃) and hybrid organic-inorganic (e.g., MAPbBr₃, MA = methylammonium), are sought after for photovoltaic (PV) applications (PCE > 25%).
- Other applications: photodiodes, infrared sensors, electronics, LEDs, lasers, transistors, quantum information sciences.
- Issues: inherent instability, toxicity of Pb, defects.
- Stability and electronic, optical, and defect properties of ABX₃ compounds can be tailored by changing atoms, composition, structure, octahedral arrangements, point defects, interfaces, etc.
- Atom-composition-structure space is combinatorial → data-driven design based on high-throughput density functional theory (HT-DFT) and machine learning (ML).

High-Throughput DFT Dataset of Perovskite Properties



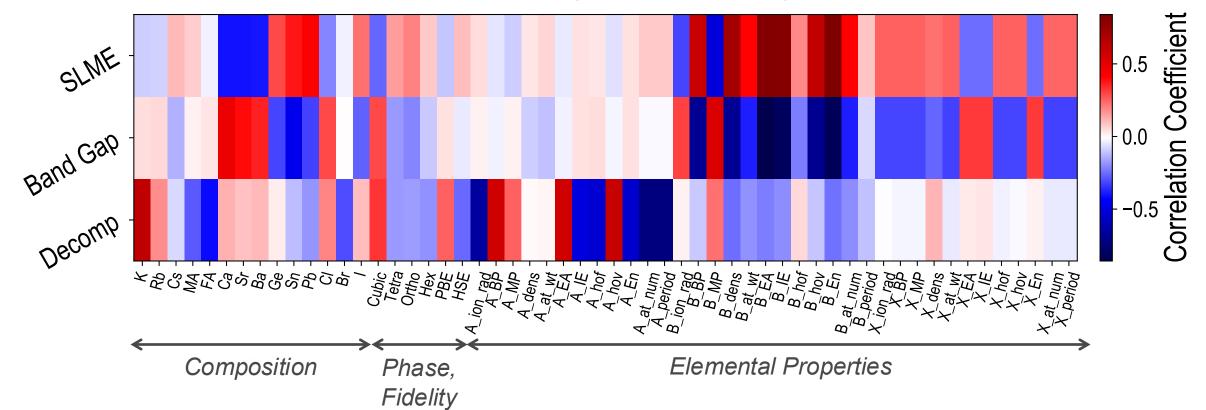


Α	В	Х
MA	Pb	I
FA	Sn	Br
Cs	Ge	Cl
Rb	Ва	
K	Sr	
	Ca	

- DFT dataset: > 1000 compounds, multiple functionals and properties.
- Descriptors for ML: composition & elemental properties of A/B/X species.
- A.M.K. et al., Energy Environ. Sci., 15 (5), 1930-1949 (2022).
- J. Yang et al., Digital Discovery, 2, 856-870 (2023).
- J. Yang et al., J. Chem. Phys. 160, 064114 (2024).
- M. Biswas et al., Phys. Chem. Chem. Phys. 26, 23177-23188 (2024).

Linear Correlation between DFT Properties and Input Descriptors

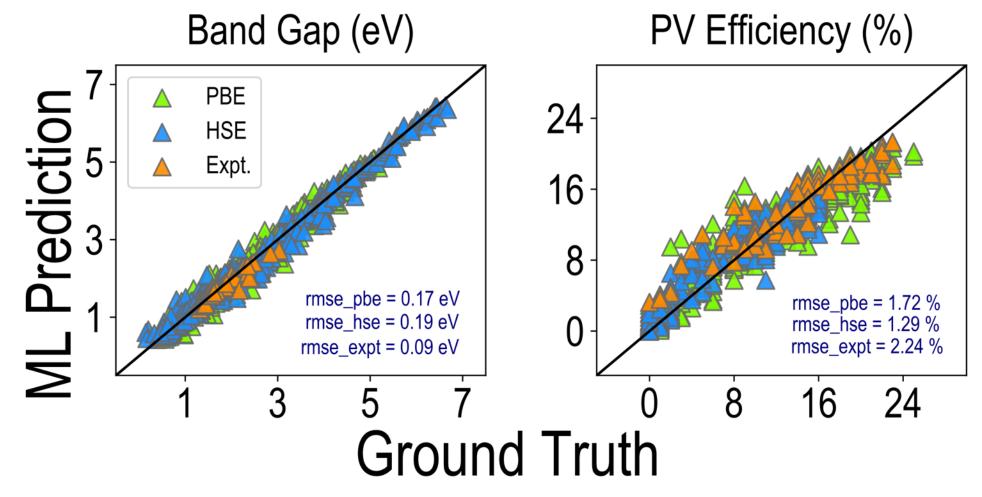
Correlation: Descriptors vs DFT Properties





- A.M.K. et al., Energy Environ. Sci., 15 (5), 1930-1949 (2022).
- J. Yang et al., MRS Bulletin., 47, 940–948 (2022).
- J. Yang et al., Digital Discovery, 2, 856-870 (2023).
- J. Yang et al., J. Chem. Phys. 160, 064114 (2024)

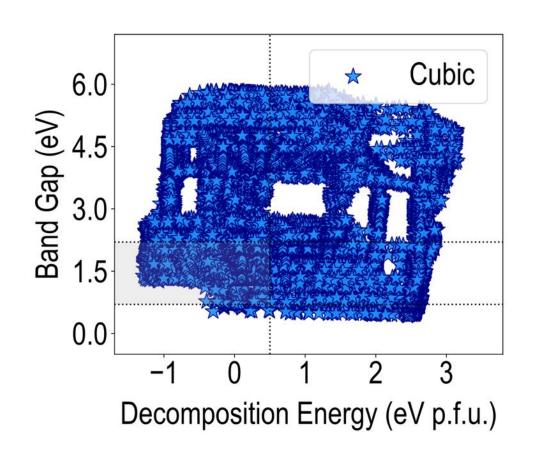
Descriptor-Based Multi-Fidelity Random Forest Regression Models

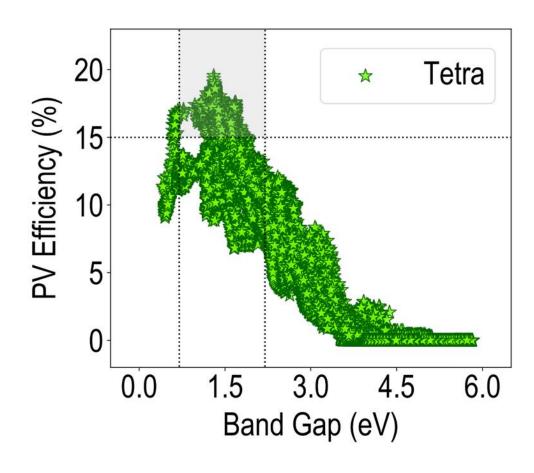




School of Materials Engineering

Enumeration \rightarrow Expt. Prediction \rightarrow Screening

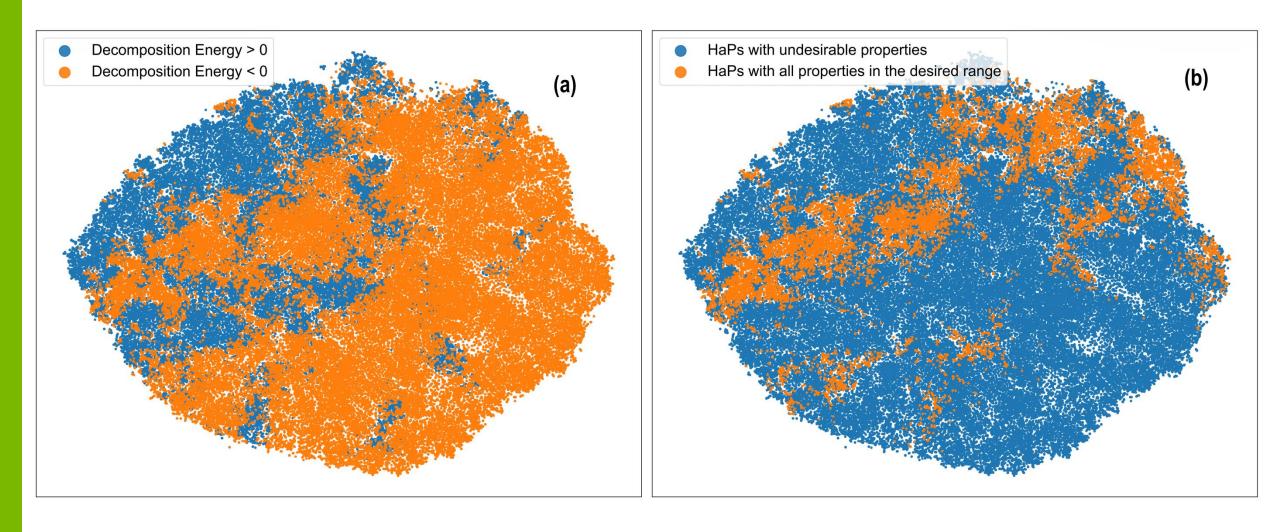




37,775 compositions in n/8 mixing fractions \rightarrow 4 phases each = ~ 151,000 compounds \rightarrow 3610 compounds with low ΔH , E_{gap} between 1 and 2 eV, PCE > 15%



2D Projection example: t-SNE

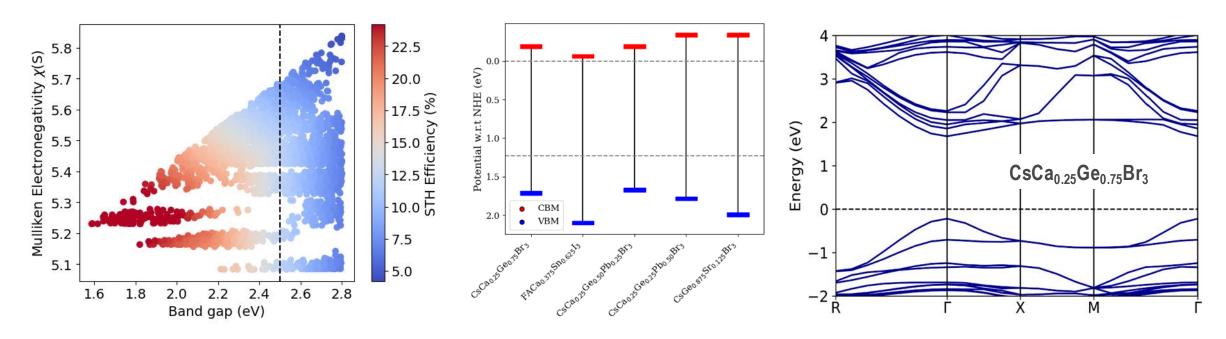


I. Agrawal, M. Biswas, and A. Mannodi-Kanakkithodi*, "Discovering Novel Halide Perovskites using Generative Adversarial Networks and Random Forest Regression", accepted, Computational Materials Science. (2025).

ML Predictions over 150,000 compounds → screening of promising compounds

_	ML-HSE Δ H	ML-Expt.	ML-Expt. PV
Compound	(eV p.f.u.)	E_{gap}	efficiency (%)
$FA_{0.75}MA_{0.25}PbI_3$	-1.07	1.65	20
$Cs_{0.625}FA_{0.125}Rb_{0.25}PbI_3$	-0.55	1.66	19
$Cs_{0.5}FA_{0.375}Rb_{0.125}PbI_3$	-0.23	1.66	19
$Cs_{0.875}Rb_{0.125}PbI_3$	-0.38	1.38	19
$Cs_{0.625}MA_{0.25}Rb_{0.125}PbI_3$	-0.35	1.68	18
$FABa_{0.125}Ge_{0.875}I_{3}$	-0.99	1.52	20
$FAGe_{0.875}Sr_{0.125}I_3$	-0.98	1.57	19
$FACa_{0.125}Ge_{0.75}Sn_{0.125}I_3$	-0.98	1.54	19
$FACa_{0.125}Ge_{0.875}I_3$	-0.98	1.56	19
$FABa_{0.125}Ge_{0.75}Sn_{0.125}I_{3}$	-0.99	1.50	19

Using the same framework to discover materials for photocatalytic water splitting



Predictions on enumerated compositions → suitable decomposition energies and band gaps → empirical band edges to straddle the H₂O redox potentials → high solar-to-hydrogen conversion efficiency → validation DFT



Interface with the data and models

