List of Publications by Year in descending order

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HENC XIAO

#	Article	IF	CITATIONS
1	Turbulence Modeling in the Age of Data. Annual Review of Fluid Mechanics, 2019, 51, 357-377.	25.0	755
2	Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data. Physical Review Fluids, 2017, 2, .	2.5	403
3	Physics-informed machine learning approach for augmenting turbulence models: A comprehensive framework. Physical Review Fluids, 2018, 3, .	2.5	309
4	Quantification of model uncertainty in RANS simulations: A review. Progress in Aerospace Sciences, 2019, 108, 1-31.	12.1	228
5	Quantifying and reducing model-form uncertainties in Reynolds-averaged Navier–Stokes simulations: A data-driven, physics-informed Bayesian approach. Journal of Computational Physics, 2016, 324, 115-136.	3.8	209
6	Physics-informed machine learning: case studies for weather and climate modelling. Philosophical Transactions Series A, Mathematical, Physical, and Engineering Sciences, 2021, 379, 20200093.	3.4	167
7	Predictive large-eddy-simulation wall modeling via physics-informed neural networks. Physical Review Fluids, 2019, 4, .	2.5	149
8	Seeing permeability from images: fast prediction with convolutional neural networks. Science Bulletin, 2018, 63, 1215-1222.	9.0	125
9	SediFoam: A general-purpose, open-source CFD–DEM solver for particle-laden flow with emphasis on sediment transport. Computers and Geosciences, 2016, 89, 207-219.	4.2	112
10	Reynolds-averaged Navier–Stokes equations with explicit data-driven Reynolds stress closure can be ill-conditioned. Journal of Fluid Mechanics, 2019, 869, 553-586.	3.4	109
11	Diffusion-based coarse graining in hybrid continuum–discrete solvers: Theoretical formulation and a priori tests. International Journal of Multiphase Flow, 2015, 77, 142-157.	3.4	93
12	Algorithms in a Robust Hybrid CFD-DEM Solver for Particle-Laden Flows. Communications in Computational Physics, 2011, 9, 297-323.	1.7	81
13	Enforcing statistical constraints in generative adversarial networks for modeling chaotic dynamical systems. Journal of Computational Physics, 2020, 406, 109209.	3.8	77
14	Diffusion-based coarse graining in hybrid continuum–discrete solvers: Applications in CFD–DEM. International Journal of Multiphase Flow, 2015, 72, 233-247.	3.4	69
15	Flows over periodic hills of parameterized geometries: A dataset for data-driven turbulence modeling from direct simulations. Computers and Fluids, 2020, 200, 104431.	2.5	67
16	A Priori Assessment of Prediction Confidence for Data-Driven Turbulence Modeling. Flow, Turbulence and Combustion, 2017, 99, 25-46.	2.6	51
17	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part I: Experimental study. Marine Geology, 2010, 269, 107-118.	2.1	50
18	A consistent dual-mesh framework for hybrid LES/RANS modeling. Journal of Computational Physics, 2012, 231, 1848-1865.	3.8	50

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19	Liquefaction potential of coastal slopes induced by solitary waves. Acta Geotechnica, 2009, 4, 17-34.	5.7	49
20	CFD–DEM simulations of current-induced dune formation and morphological evolution. Advances in Water Resources, 2016, 92, 228-239.	3.8	47
21	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part II: Numerical simulation. Marine Geology, 2010, 269, 119-131.	2.1	46
22	A Bayesian Calibration–Prediction Method for Reducing Model-Form Uncertainties with Application in RANS Simulations. Flow, Turbulence and Combustion, 2016, 97, 761-786.	2.6	42
23	Prediction of Reynolds stresses in high-Mach-number turbulent boundary layers using physics-informed machine learning. Theoretical and Computational Fluid Dynamics, 2019, 33, 1-19.	2.2	33
24	Investigating the settling dynamics of cohesive silt particles with particle-resolving simulations. Advances in Water Resources, 2018, 111, 406-422.	3.8	31
25	Representation of stress tensor perturbations with application in machine-learning-assisted turbulence modeling. Computer Methods in Applied Mechanics and Engineering, 2019, 346, 707-726.	6.6	31
26	A random matrix approach for quantifying model-form uncertainties in turbulence modeling. Computer Methods in Applied Mechanics and Engineering, 2017, 313, 941-965.	6.6	29
27	Regularized ensemble Kalman methods for inverse problems. Journal of Computational Physics, 2020, 416, 109517.	3.8	29
28	Data-driven CFD modeling of turbulent flows through complex structures. International Journal of Heat and Fluid Flow, 2016, 62, 138-149.	2.4	25
29	Realistic representation of grain shapes in CFD–DEM simulations of sediment transport with a bonded-sphere approach. Advances in Water Resources, 2017, 107, 421-438.	3.8	24
30	Recent progress in augmenting turbulence models with physics-informed machine learning. Journal of Hydrodynamics, 2019, 31, 1153-1158.	3.2	23
31	Numerical study of segregation using multiscale models. International Journal of Computational Fluid Dynamics, 2009, 23, 81-92.	1.2	20
32	Visualization of High Dimensional Turbulence Simulation Data using t-SNE. , 2017, , .		20
33	Learning nonlocal constitutive models with neural networks. Computer Methods in Applied Mechanics and Engineering, 2021, 384, 113927.	6.6	20
34	Convolutional neural network for transition modeling based on linear stability theory. Physical Review Fluids, 2020, 5, .	2.5	20
35	Analysis of four-dimensional Mie imaging using fiber-based endoscopes. Applied Optics, 2014, 53, 6389.	1.8	19
36	Parametric study of breaking solitary wave induced liquefaction of coastal sandyslopes. Ocean Engineering, 2010, 37, 1546-1553.	4.3	18

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37	Assimilation of disparate data for enhanced reconstruction of turbulent mean flows. Computers and Fluids, 2021, 224, 104962.	2.5	17
38	Toward a Practical Method for Hypersonic Transition Prediction Based on Stability Correlations. AIAA Journal, 2020, 58, 4475-4484.	2.6	16
39	Evaluation of ensemble methods for quantifying uncertainties in steady-state CFD applications with small ensemble sizes. Computers and Fluids, 2020, 203, 104530.	2.5	15
40	TSUFLIND-EnKF: Inversion of tsunami flow depth and flow speed from deposits with quantified uncertainties. Marine Geology, 2018, 396, 16-25.	2.1	13
41	End-to-end differentiable learning of turbulence models from indirect observations. Theoretical and Applied Mechanics Letters, 2021, 11, 100280.	2.8	13
42	Recurrent neural network for end-to-end modeling of laminar-turbulent transition. Data-Centric Engineering, 2021, 2, .	2.3	13
43	Neural network–based pore flow field prediction in porous media using super resolution. Physical Review Fluids, 2022, 7, .	2.5	13
44	Physics-informed covariance kernel for model-form uncertainty quantification with application to turbulent flows. Computers and Fluids, 2019, 193, 104292.	2.5	12
45	Frame-independent vector-cloud neural network for nonlocal constitutive modeling on arbitrary grids. Computer Methods in Applied Mechanics and Engineering, 2022, 388, 114211.	6.6	12
46	An Implicitly Consistent Formulation of a Dual-Mesh Hybrid LES/RANS Method. Communications in Computational Physics, 2017, 21, 570-599.	1.7	11
47	Quantification of uncertainties in turbulence modeling: A comparison of physics-based and random matrix theoretic approaches. International Journal of Heat and Fluid Flow, 2016, 62, 577-592.	2.4	10
48	Dynamic Evaluation of Mesh Resolution and Its Application in Hybrid LES/RANS Methods. Flow, Turbulence and Combustion, 2014, 93, 141-170.	2.6	9
49	INCORPORATING PRIOR KNOWLEDGE FOR QUANTIFYING AND REDUCING MODEL-FORM UNCERTAINTY IN RANS SIMULATIONS. , 2016, 6, 109-126.		9
50	Propagation of Input Uncertainty in Presence of Model-Form Uncertainty: A Multifidelity Approach for Computational Fluid Dynamics Applications. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering, 2018, 4, .	1.1	8
51	A Physics-Informed Machine Learning Approach of Improving RANS Predicted Reynolds Stresses. , 2017, ,		6
52	Coupling of solvers with non-conforming computational domains in a dual-mesh hybrid LES/RANS framework. Computers and Fluids, 2013, 88, 653-662.	2.5	5
53	Sediment micromechanics in sheet flows induced by asymmetric waves: A CFD–DEM study. Computers and Geosciences, 2016, 96, 35-46.	4.2	5
54	Inferring tsunami flow depth and flow speed from sediment deposits based on Ensemble Kalman Filtering. Geophysical Journal International, 2018, 212, 646-658.	2.4	5

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55	Enforcing boundary conditions on physical fields in Bayesian inversion. Computer Methods in Applied Mechanics and Engineering, 2020, 367, 113097.	6.6	4
56	Timeâ€scale analysis in unsaturated porous media under external wave loads. International Journal for Numerical and Analytical Methods in Geomechanics, 2010, 34, 1935-1959.	3.3	3
57	High-Mach-Number Turbulence Modeling using Machine Learning and Direct Numerical Simulation Database. , 2017, , .		3
58	Acoustic Inversion for Uncertainty Reduction in Reynolds-Averaged Navier–Stokes-Based Jet Noise Prediction. AIAA Journal, 2022, 60, 2407-2422.	2.6	3
59	Preliminary Evaluation and Applications of a Consistent Hybrid LES/RANS Method. Notes on Numerical Fluid Mechanics and Multidisciplinary Design, 2012, , 91-100.	0.3	2
60	Scaling of transient wave–soil interaction problems. International Journal for Numerical and Analytical Methods in Geomechanics, 2010, 34, 839-858.	3.3	1
61	Toward Transition Modeling in a Hypersonic Boundary Layer at Flight Conditions. , 2020, , .		1
62	Assessment of Regularized Ensemble Kalman Method for Inversion of Turbulence Quantity Fields. AIAA Journal, O, , 1-11.	2.6	1
63	Dynamic Interactions Between the Vadose and Phreatic Zones During Breaking Solitary Wave Runup and Drawdown Over a Fine Sand Beach. , 2009, , .		Ο