Supplementary Material

This is the supplementary material that accompanies the Mathematical Geosciences paper "Contaminant Source Identification in Aquifers: A Critical View", by J. Jaime Gómez-Hernández (jgomez@upv.es, Universitat Politècnica de València, Spain) and Teng Xu (Hohai University, China)

Table 1: Paper highlights

	Reference	Highlights
1	Gorelick (1981)	The work that stated the problem and provided a solution. The details of the work are the same as the ones in the next paper .
2	Gorelick et al. (1983)	The first paper in the subject.
3	Hwang and Koerner (1983)	It could have started the way for a different approach to solve the problem using system sensitivity theory but failed to deliver two other papers on a real case study and on a three-dimensional one. The work also sketches a potential optimal network design.
4	Datta et al. (1989)	Very similar approach to Gorelick's, based on the use of response functions and optimization with the aid of an expert system for statistical pattern recognition.
5	Bagtzoglou et al. (1991)	It uses a random walk solution of the transport equation backward in time that can be interpreted as the source location probability. The authors perform the analysis assuming that the conductivity field is heterogeneous and that the covariance of the underlying random function is known. In this first implementation, it is necessary to know the time when the contaminant entered into the aquifer.
6	Ala and Domenico (1992)	The authors use a regression-like approach to fit observed concentration data to analytically-derived solutions for the transport equation. It is the first application to a field site, the Otis Air Force Base near Cape Cod (USA). Assuming all parameters homogeneous, the technique identifies the lateral extent of the source area, its position, the starting time and the concentration at the source, but also the parameters that control transport in the aquifer, such as dispersivities, decay rate or biodegradation rate.
7	Bagtzoglou et al. (1992)	Same concepts as in the previous paper by Bagtzoglou et al. (1991).
8	Wagner (1992)	For the first time, the parameters defining the source location (highly simplified to four unknowns corresponding to the mass fluxes at two locations and two stress periods) together with the parameters defining the aquifer model (all of them homogeneous in space: two conductivities, longitudinal and transversal dispersivities, porosity and lateral flux entering the aquifer) are estimated simultaneously.
9	Skaggs and Kabala (1994)	This is the first work that attempts to identify a time-dependent release history from measurements taken downgradient.
10	Wilson and Liu (1994)	The authors derived expressions for backward-in-time location and travel time probabilities using a heuristic approach.
11	Macdonald (1995)	The author proposes an approach for the location and strengths in a hypothetical one-dimensional domain in which a temperature pulse diffuses laterally. The impact of measurement errors is analyzed, since for an idealized medium, if the observations are error-free, the inversion is exact.

	Reference	Highlights
12	Skaggs and Kabala (1995)	The plume is traced back in time from a given snapshot by solving the diffusion equation with quasi-reversibility in a moving coordinate system. The estimation of the originating plume, not too far in time, from the observations is good, but it deteriorates when it gets closer to the source.
13	Aral and Guan (1996)	Simulation-optimization paper in which the response function is used to establish linear constraints for the optimization algorithm, which is solved using a genetic algorithm.
14	Sonnenborg et al. (1996)	Inverse modeling in the Vertskoven site (Denmark) containing a waste residue deposit. The geometry of the site and the location of the deposit are known, and the inversion focuses on identifying the flow and transport parameters in a zoned-conductivity aquifer, one of which is the contaminant concentration at the source.
15	Woodbury and Ulrych (1996)	The problem of contaminant source identification shifts from a deterministic inverse problem into a stochastic one.
16	Mahar and Datta (1997)	A standard weighted least-squares optimization using the embedding approach.
17	Snodgrass and Kitanidis (1997)	First paper using a Bayesian approach to solve the problem of source identification. Taking advantage of the response function solution, the problem can be solved using the geostatistical approach.
18	Sidauruk et al. (1998)	Curve fitting by least-squares to analytical solutions. Parameters fitted are location and strength of the source, but also the dispersivity coefficient.
19	Skaggs and Kabala (1998)	The authors perform an analysis of contaminant release function identification using a Monte-Carlo approach to test how the measurement errors hinder the optimization with Tikhonov regularization.
20	Woodbury et al. (1998)	First paper that addresses the problem in three dimensions.
21	Birchwood (1999)	Breakthrough curves and release function are expressed as Fourier series and a causality condition is imposed to determine the Fourier coefficients of the release function .
22	Liu and Ball (1999)	Using an analytical solution of the sorption-diffusion equation in a two-layer system, the authors infer the time function at which PCE has been crossing from an aquitard into an aquifer at the Dover Air Force Base in Delaware, USA.
23	Neupauer and Wilson (1999)	Improvement on the backward-in-time solution by Wilson and Liu (1994) based on the use of the adjoint equation of the advection dispersion equation.
24	Seibert and Stohl (1999)	This paper deals with dispersion in the atmosphere but it addresses the same problem: the identification of a pollution source and its time history.
25	Alapati and Kabala (2000)	The authors claim that there is no need to include a regularization term in the least-squares optimization process.
26	Mahar and Datta (2000)	Another simulation-optimization approach including a performance analysis of what happens if the solute concentration time series have missing data.
27	Morrison (2000)	Review paper of forensic techniques for age dating and source identification.
28	Neupauer et al. (2000)	Tikhonov regularization is less efficient in reproducing a step release function than minimum relative entropy.
29	Sciortino et al. (2000)	Application of least-squares optimization to identify the size and location of a pool of DNAPL being dissolved in a sandbox.

	Reference	Highlights
30	Aral et al. (2001)	Introduction of a variant of genetic algorithm combined with an iterative approach to reduce the number of forward model evaluations typically needed by heuristic algorithms such as genetic ones.
31	Atmadja and Bagtzoglou (2001a)	The authors develop a new approach for the backward-in-time solution of the transport equation. Once the observed plume has been traced back in time, deducing the release function is a much harder problem solved with relative success.
32	Atmadja and Bagtzoglou (2001b)	Very good review paper at the time it was written.
33	Duffy and Brandes (2001)	In a contaminated site in the Midwestern US, 184 observations are taken on 116 chemical species. Principal component analysis help in reducing the dimensionality of the problem and identifying potential sources.
34	Mahar and Datta (2001)	Simultaneous estimation of homogeneous aquifer parameters (conductivity, porosity and dispersivities) and source locations and strengths.
35	Michalak and Kitanidis (2002)	Application of the geostatistical approach to the analysis of 136 measurements taken at the Gloucester landfill in Ontario, Canada. The forward model used is an analytical solution with homogeneous coefficients in a semi-infinite layer of given thickness.
36	Sohn et al. (2002a)	Bayesian approach to determine the room at which an air pollution event started in a three-story building.
37	Sohn et al. (2002b)	Similar to the previous paper applied to a synthetic single-story building.
38	Akçelik et al. (2003)	The authors use a variational finite-element method for source inversion of convective-diffusive transport.
39	Butera and Tanda (2003)	Extension of the geostatistical approach in two dimensions. Demonstration for point, non-point and multiple sources, the locations of which are known.
40	Bagtzoglou and Atmadja (2003)	The paper focuses on heterogeneous conductivity distributions in one dimension and shows that marching-jury works better that quasi-reversibility for these cases.
41	Michalak and Kitanidis (2003)	Application of the geostatistical approach enforcing parameter non-negativity to a diffusion problem from a two-layer aquifer onto an aquitard at the Dover Air Force Base in Delaware, USA.
42	Michalak and Kitanidis (2004b)	Coupling the geostatistical approach and the adjoint state method allows the identification of the spatial distribution of the contaminant at a given instant back in time.
43	Michalak and Kitanidis (2004a)	Application of the geostatistical approach for source contaminant identification at the Dover Air Force Base in Delaware. The problem solved is a diffusion one using two-layers overlaying an aquitard.
44	Singh and Datta (2004)	After training an artificial neural network, homogeneous aquifer parameters, such as conductivity, porosity and dispersivity, as well as the source strengths at two given locations are identified.
45	Singh et al. (2004)	Same approach as previous one.
46	Bagtzoglou and Atmadja (2005)	Best review paper published until then.
47	Boano et al. (2005)	Given the conceptual similarity between source contaminant detection in aquifers and rivers, the geostatistical approach is used to identify the release function by Skaggs and Kabala (1994) in a river contamination event.

	Reference	Highlights
48	Mahinthakumar and Sayeed (2005)	The authors perform a comparison of many optimization approaches, concluding that the hybrid ones work best.
49	Mahinthakumar and Sayeed (2006)	Similar to the previous paper, now with a three dimensional parallelepiped source.
50	Neupauer and Lin (2006)	Extension of the work by Neupauer and Wilson (1999) but now conditioning on measured concentrations. The aquifer is heterogeneous but the transmissivity distribution is perfectly known.
51	Newman et al. (2006)	Laboratory experiment with a DNAPL source zone. The inverse flux plane model coupled with a hybrid simulated annealing-minimum relative entropy is used to identify the source and also to quantify the uncertainty on the estimates.
52	Singh and Datta (2006)	Same as Singh and Datta (2004) and Singh et al. (2004) but different case studies.
53	Sun et al. (2006a)	Model uncertainty is considered thanks to the use of constrained robust least squares optimization.
54	Sun et al. (2006b)	In this paper, in addition to the release function, the source location is also identified.
55	Wang and Zabaras (2006)	The hierarchical Bayesian method is used to reconstruct contaminant history backward in time until the time of an instantaneous release. The authors analyze several cases with homogeneous conductivities and one with heterogeneous, but known, uncorrelated values.
56	Liu and Zhai (2007)	Although in the field of air pollution, the paper includes an extensive review of groundwater literature plus a few references from air pollution.
57	Milnes and Perrochet (2007)	Backtracking a predicted concentration contour line until its point of disappearance. The underlying conductivity field is binary and heterogeneous.
58	Sun (2007)	Conductivity is only known in some statistical sense, the robust geostatistical method incorporates this uncertainty. The conductivity field is not subject to identification, though.
59	Yeh et al. (2007)	Tabu search is used to detect trial source locations, then simulated annealing is used to identify strength and release period. In one of the case studies, conductivity is considered heterogeneous and unknown. Several realizations are generated to conclude that only in 50% of them it was possible to identify the source. No attempt to identify conductivities.
60	Sun (2008)	CONSID, a program that implements nonnegative least squares, constrained robust least squares and robust geostatistical inversion.
61	Datta et al. (2009)	Simultaneous identification of aquifer and source parameters. However, aquifer parameters are homogeneous except for a case in which the aquifer is divided in two homogeneous known zones.
62	Dokou and Pinder (2009)	A stochastic flow and transport model is used to generate multiple realizations of the plume evolution. These realizations are averaged to obtain mean plumes that are then used to decide on the potential source location using an iterative approach.
63	Jin et al. (2009)	An application at the Canadian Force Base Borden site, near Toronto, of a simulation-optimization method to identify, with reasonable accuracy, a contaminant source under field conditions. A heterogeneous conductivity field that had been previously used elsewhere is used here and assumed known.
64	Liu and Zhai (2009)	Another application from a groundwater solution to the field of indoor airborne contaminant source locations.

	Reference	Highlights
65	Mirghani et al. (2009)	A simulation-optimization approach with emphasis in the parallelization of the computations. A heterogeneous conductivity field is used but it is assumed known.
66	Ayvaz (2010)	A new heuristic approach comes into play. Conductivity is, at most, zoned, but with known values. Source locations are known.
67	Cheng and Jia (2010)	Another extension of the adjoint method by Neupauer and Wilson (1999), in this case, to a point contamination in an open-surface water body.
68	Datta et al. (2011)	The authors claim that gradient-based optimization approaches can beat heuristic ones, which need too many evaluations of the forward problem.
69	Hosseini et al. (2011)	The paper focuses in determining the geometry of a DNAPL pool using wells inside and outside the pool. In the process, heterogeneous conductivity fields are calibrated, as well as other homogeneous transport parameters.
70	Jha and Datta (2011)	The authors claim that simulated annealing is better than genetic algorithms for source identification.
71	Li and zhong Mao (2011)	The novelty of the paper is the use of a new way to solve for concentrations using the global space-time multiquadric.
72	Telci and Aral (2011)	A paper dealing with identification of multiple instantaneous spills in a river network from a large set of potential locations. It is demonstrated in the Althamah river in Georgia, USA.
73	Chadalavada et al. (2012)	The novelty of the paper is the use of feedback information obtained from sequentially-designed monitoring networks. An application to a contaminated farmland in South Australia is shown.
74	Zeng et al. (2012)	First paper to use a surrogate model to speed up forward model evaluation.
75	Aghasi et al. (2013)	Multi-objective optimization combined with level set functions to determine a DNAPL pool. Conductivity is heterogeneous and known.
76	Amirabdollahian and Datta (2014)	Good review paper.
77	Butera et al. (2013)	For the first time, the geostatistical approach was applied to the identification of the release function and the source location in a known heterogeneous aquifer.
78	Jha and Datta (2013)	Comparison between genetic algorithm and simulated annealing.
79	Wang and Jin (2013)	A synthetic case based on the Borden site using a heterogeneous known distribution of conductivities.
80	Amirabdollahian and Datta (2014)	Another simulation-optimization approach. Conductivities are interpolated from spare data using inverse-distance weighting.
81	Gzyl et al. (2014)	A combination of integral pumping tests to identify the sources, then the release history is recovered by the geostatistical approach. The method is applied in a chemical plant at southern Poland in the city of Jaworzno in the valley of the Wawolnic river that has been contaminated with lindane. The aquifer model had been calibrated with homogeneous parameters.
82	Jha and Datta (2014)	Multi-step approach involving an intelligent network design.
83	Jin et al. (2014)	The authors focus in determining the best monitoring network for the purposes of source identification.
84	Srivastava and Singh (2014)	An artificial neural network is trained by running many contamination scenarios originating in one or two potential sources.
85	Yeh et al. (2014)	Demonstration of a hybrid heuristic approach. The aquifer is divided in three zones of known parameters.

	Reference	Highlights
86	Cupola et al. (2015)	The minimum entropy approach works equally well for source identification in two-dimensional homogeneous and heterogeneous conductivity fields.
87	Gurarslan and Karahan (2015)	Application of the differential evolution algorithm as the best genetic algorithm for source identification.
88	Jha and Datta (2015)	Adaptive simulated annealing is used for contaminant source identification including surface-subsurface water interaction. The flow model had been previously calibrated with PEST using a zoned conductivity. The method is applied to the upper Macquarie Groundwater Management Area in New South Wales, Australia.
89	Ngamsritrakul et al. (2015)	Simulation-optimization approach.
90	Prakash and Datta (2015)	Application at the Macquarie Groundwater Management Area, the authors claim that the feedback provided by the new monitoring wells drilled as a result of the optimal network design improves the final results.
91	Srivastava and Singh (2015)	Simultaneous identification of aquifer and source parameters. However, aquifer parameters are homogeneous.
92	Zhang et al. (2015)	Coupling experimental design and source identification for the optimal placement of observation wells. In the final case study, the authors show a joint identification problem of heterogeneous conductivities and source parameters. The conductivity field is represented with only five parameters using a Karhunen-Loève expansion.
93	Ayvaz (2016)	Identification of a distributed source of arbitrary shape. The conductivity is heterogeneous but known.
94	Bashi-Azghadi et al. (2016)	Application to the Tehran aquifer in the Tehran refinery region.
95	Borah and Bhattacharjya (2016)	The paper includes a comparison of genetic algorithms and artificial neural networks.
96	Hansen and Vesselinov (2016)	Unsupervised machine optimization to evaluate the most likely location and time of point contamination .
97	Koch and Nowak (2016)	Conditional realizations of conductivity are generated and used to build probabilistic estimates of DNAPL presence.
98	Xu and Gómez-Hernández (2016)	First application of the ensemble Kalman filter for the identification of the space-time coordinates of a contaminant source.
99	Yeh et al. (2016)	Application of simulated annealing to fit some analytical functions to observed concentrations to reconstruct the release function of a contaminant of known location.
100	Zanini and Woodbury (2016)	Application of the method developed by Woodbury and Ferguson (2006) for heat flow inversion to contaminant release function identification.
101	Zhang et al. (2016a)	Application of surrogate models to Markov chain Monte Carlo implemented in a two-stage manner to improve the accuracy of the surrogate model.
102	Zhang et al. (2016b)	Backward tracking with a fractional advection-dispersion model applied to the MADE-2 tracer tests.
103	Zhao et al. (2016)	A kriging surrogate model is used to solve a simulation-optimization problem with known source locations in a conductivity-zoned aquifer.

	Reference	Highlights
104	Gu et al. (2017)	Many realizations of conductivity are generated and plumes are computed from potential sources. These plumes are weighted to approximate the observed values. From these weights the most likely source location and strength are determined.
105	Hamdi (2017)	Self-organized maps are used to build the surrogate models. In one of the applications, conductivity is only known at a few locations and it is interpolated by inverse distance weighting over the rest of aquifer.
106	Long et al. (2017)	A standard application of the geostatistical approach including a thorough sensitivity analysis to different kinds of errors.
107	Onyari and Taigbenu (2017)	Use of the Green element method.
108	Rajeev Gandhi et al. (2017)	Application to the identification of the source of a virus in a three-dimensional unconfined aquifer.
109	Zhang et al. (2017)	Application at the MADE-2 site of backward probabilities computed using a fractional advection dispersion equation.
110	Chen et al. (2018)	Application of the ensemble Kalman filter to identify a source but also the position and length of a plank that was inserted in a laboratory sandbox.
111	Esfahani and Datta (2018)	Adaptive simulated annealing for the identification of source concentrations in a contaminated mine site in Queensland, Australia.
112	Guneshwor et al. (2018)	Application to an industrial site in Gujarat, India. Model is homogeneous and known.
113	Hou and Lu (2018)	A comparison of support vector regression, kernel extreme learning machine and kriging for multiphase flow .
114	Huang et al. (2018)	Very simplistic model to test a new optimization algorithm: the shuffled complex evolution algorithm.
115	Jiang et al. (2018)	A concentration field library is constructed and used as a surrogate during the identification. Conductivities are heterogeneous but known.
116	Stanev et al. (2018)	Application of blind source separation to identify the number of sources. The authors also identify key parameters such as advective velocity and dispersivity, although they are homogeneous.
117	Vesselinov et al. (2018)	Non-negative matrix factorization is applied to synthetic and real data to identify the original source from a series of observations that include different geochemical constituents. Unsupervised machine learning is used. Application at the regional aquifer beneath Los Alamos National Laboratory.
118	Xu and Gómez-Hernández (2018)	First attempt to identify jointly contaminant source and conductivity field without simplifications.
119	Amirabdollahian et al. (2019)	The authors apply the adaptive simulated annealing to the Eastlakes Experimental Site at the Botany Sands aquifer, South Wales, Australia.
120	Ayub et al. (2019)	After presenting a groundwater model of the Duplin county research site in North Carolina, the authors build a synthetic exercise based on this model to demonstrate their application of Markov chain Monte Carlo for the sampling of the posterior distribution of source contaminant concentrations.
121	Cao et al. (2019)	First attempt to bring model uncertainty into play. Although the alternative models analyzed only differ on the geometry of the zonation of the conductivity spatial distribution.

	Reference	Highlights
122	Jiao et al. (2019)	A heterogeneous aquifer of known conductivities based on the Texas High Plain is used to test a new inverse method based on local approximation solutions of the transport equation.
123	Li et al. (2019)	Improved Kalman filter coupled with 0-1 mixed-integer nonlinear programming and simulated annealing.
124	Mo et al. (2019)	Joint identification of a heterogeneous conductivity field and the contaminant source parameters. Unfortunately, the authors use a Gaussian covariance function to characterize the spatial heterogeneity of the log-conductivities, which is completely unrealistic but helps in the inversion process.
125	Vesselinov et al. (2019)	Continuation of paper by Vesselinov et al. (2018) to further analyze the use of blind source separation coupled with non-negative matrix factorization applied at the Los Alamos Laboratories chromium-contaminated site.
126	Xia et al. (2019a)	Another simulation-optimization approach using genetic algorithms.
127	Xia et al. (2019b)	The self-organized map-based surrogate model can solve the identification problem without using a simulation-optimization approach.
128	Xing et al. (2019)	Ensemble of three surrogate models in which each model is weighted according to an adaptive Metropolis-Markov chain Monte Carlo.
129	Yan et al. (2019)	Bayesian approach with a very efficient kriging surrogate model.
130	Zhang et al. (2019)	Bayesian approach coupled with Markov chain Monte Carlo using an improved Metropolis-Hastings algorithm.
131	Chaubey and Srivastava (2020)	Artificial neural networks in one dimension.
132	Colombo et al. (2020)	Interesting application of backward tracking to identify potential PCE sources in Milan, Italy.
133	Essouayed et al. (2020)	Gaussian-Levenberg-Marquardt algorithm using pilot points to identify a heterogeneous conductivity field, homogeneous dispersivity and the source location.
134	Han et al. (2020)	Genetic algorithm applied to a laboratory experiment and then to a gas station in Beijing .
135	Jamshidi et al. (2020)	Simulation-optimization approach in a groundwater-river integrated system.
136	Kang et al. (2020)	Joint inversion of hydraulic heads and self-potential measurements to improve conductivity estimation, followed by the inversion of tracer mean travel times to identify the source.
137	Li et al. (2020)	Use of several surrogate models with extreme learning machine.
138	Lu et al. (2020)	Heuristic search to determine the coordinates of the source and the strength of the release together with the discrete values of a zoned conductivity, and homogeneous porosity and dispersivities.
139	Wang et al. (2020)	Extremely similar to the previous one.
140	Wang and Lu (2020)	Extremely similar to the two previous ones.
141	Zhang et al. (2020)	Very ingenious combination of the ensemble smoother and deep learning for the joint identification of source parameters and non-Gaussian heterogeneous conductivity distributions.
142	Zhao et al. (2020b)	Identification of the contaminant source by the interpretation of concentration time series after an artificially enhanced catchment is generated. Application to a low natural flow velocity in the city of Cangzhou, China.
143	Zhao et al. (2020a)	Application in the valley of the Wawolnica river to identify the source of lindane.
144	Ayaz (2021)	Artificial neural network application.

	Reference	Highlights
145	Ayaz et al. (2021)	Genetic algorithm application.
146	Chakraborty and Prakash (2021)	Evolutionary search algorithm application.
147	Dodangeh et al. (2021)	Contaminant source identification in a coastal aquifer using the ensemble Kalman filter and artificial neural networks.
148	He et al. (2021)	Fitting an analytical solution to observed concentration by least-squares. Application to a gas station site in Beijing .
149	Hou et al. (2021)	Comparison of several heuristic algorithms.
150	Jiang et al. (2021)	Simultaneous identification of hydraulic conductivity using pilot points and source strengths for two known contaminant sources.
151	Liu et al. (2021)	Application of the ensemble smoother to identify source and conductivities. Conductivity fields are built using multipoint geostatistics conditioned at some pilot points that are subject to identification by the ensemble smoother
152	Todaro et al. (2021)	Ensemble smoother applied to a calibrated model of a laboratory experiment
153	Wang et al. (2021a)	Multiphase flow case with joint identification of source strengths and aquifer parameters, although the later are homogeneous within the aquifer. A surrogate model based on an adaptive chaotic particle swarm optimization and extreme learning machine is used.
154	Wang and Zhang (2021)	A case of contamination source detection in a lake where the state equation is the diffusion equation.
155	Wang et al. (2021b)	Combination of heuristic approaches to solve the joint identification of the source strengths plus zone conductivity values
156	Yuan and Liang (2021)	One-dimensional exercise.
157	Zhou and Tartakovsky (2021)	The source is instantaneous and described by two Gaussian pulses, the parameters to identify are those that define the Gaussian bells. The posterior distribution is sampled using Markov chain Monte Carlo using a fast surrogate model based on deep convolutional networks. Conductivity is treated as heterogeneous but known.

Table 2: Paper characteristics

	Reference	D[1]	Source	$f(t)$	Solution approach	State eq.[2]	CS[3]	Source parameters	O.[4]	H.[5]
1	Gorelick (1981)				All items same as next one					
2	Gorelick et al. (1983)	2	Multiple	N	Linear programming and multiple regression. State equation produces linear constraints at the points and times where solute concentrations are measured	Response function	S	Source strengths and locations out of a predetermined set of potential ones	N	N
3	Hwang and Koerner (1983)	2	Point	N	System sensitivity theory with feedback	Transport equation	S	Location and strength	N	N
4	Datta et al. (1989)	2	Point	N	Expert system based on a statistical patter recognition	Response function	S	Source strength and location	N	N
5	Bagtzoglou et al. (1991)	2	Multiple	N	Backward solution of transport equation	Random walk solution of transport equation	S	Most likely location	N	Y
6	Ala and Domenico (1992)	2	Areal	N	Inverse analytical regression-like technique	Transport equation	F	Source extent and location, strength, starting time	Y	N
7	Bagtzoglou et al. (1992)	2	Point	N	Backward solution of transport equation	Random walk	S	Most likely location	N	Y
8	Wagner (1992)	2	Point	N	Non-linear maximum likelihood estimation	Flow and transport solved with SUTRA	S	Mass flux at two potential locations and during two stress periods	Y	Z
9	Skaggs and Kabala (1994)	1	Point	Y	Optimization with Tikhonov regularization	Response function	S	Time-dependent release history	N	N
10	Wilson and Liu (1994)	1	Point	N	backward-in-time location and time probabilities	Response function	S	Most likely location	N	N
11	Macdonald (1995)	1	Pulse	N	Non-linear least-square fitting of a convolution integral	Diffusion equation	S	Location and strength	N	N
12	Skaggs and Kabala (1995)	1	Point	Y	Method of quasi-reversibility to solve the advection diffusion equation backward in time	Backward solution of transport equation	S	Release function	N	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
13	Aral and Guan (1996)	2	Multiple	Y	Genetic algorithm	Response function	S	Locations and stress periods out of a collection of candidates, plus strengths	N	N
14	Sonnenborg et al. (1996)	2	Areal	N	Non-linear least-squares optimization	Flow and transport equations	F	Solute concentration at the source	Y	Z
15	Woodbury and Ulrych (1996)	1	Point	Y	Minimum relative entropy estimation	Convolution integral	S	Release function	N	N
16	Mahar and Datta (1997)	2	Multiple	N	Weighted least-squares optimization	Flow and transport equations	S	Source locations out of a potential set plus source strengths	N	N
17	Snodgrass and Kitanidis (1997)	1	Point	Y	Geostatistical approach	Response function	S	Release function	N	N
18	Sidauruk et al. (1998)	2	Point	N	Method of correlation coefficient optimization	Analytical solutions of transport equations	S	Strength and location	Y	N
19	Skaggs and Kabala (1998)	1	Point	Y	Monte-Carlo analysis of the optimization with Tikhonov regularization	Transport equation	S	Release function	N	N
20	Woodbury et al. (1998)	3	Areal	Y	Minimum relative entropy inversion	Analytical solutions of transport equations	S	Release function	N	N
21	Birchwood (1999)	1	Point	Y	Fourier-based inverse method	Transport equation	S	Location and release function	N	N
22	Liu and Ball (1999)	1	Interface	Y	Least-squares minimization with Tikhonov regularization	Diffusion equation with linear sorption	F	Release function	N	Z
23	Neupauer and Wilson (1999)	1	Pulse	N	Adjoint method to solve backward-in-time location and travel probabilities	Adjoint of the advection-dispersion equation	S	Likely locations	N	N
24	Seibert and Stohl (1999)	2	Point	Y	Backward tracking coupled with regularized non-linear optimization	Lagrangian particle dispersion model	F	Release function	N	N
25	Alapati and Kabala (2000)	1	Point	Y	Non-linear least-squares without regularization	Convolution integral	S	Gradual release function	N	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
26	Mahar and Datta (2000)	2	Multiple	Y	Non-linear weighted least-squares optimization with the flow and transport equations acting as binding equality constraints	Finite difference solution of flow and transport	S	Magnitude and duration of release plus location out of a number of candidates	N	N
27	Morrison (2000)	-	-	-	Review paper of forensic techniques for age dating and source identification	-	-	-	-	-
28	Neupauer et al. (2000)	1	Point	Y	A comparison between Tikhonov regularization and minimum relative entropy	Transport equation	S	Release function	N	N
29	Sciortino et al. (2000)	3	Volumetric	N	Weighted least-squares optimization	Analytical solutions of transport equations	L	Contaminant pool location and size	N	N
30	Aral et al. (2001)	2	Point	Y	Non-linear optimization using a progressive genetic algorithm. Source location and release histories are defined as explicit unknown variables	Transport equation	S	Release function and source locations	N	N
31	Atmadja and Bagtzoglou (2001a)	1	Point	Y	Marching-Jury Backward Beam Equation method for the solution of the advection-dispersion equation with heterogeneous (by zones) transport parameters	Transport equation solved backward in time	S	Release function	N	N
32	Atmadja and Bagtzoglou (2001b)	-	-	-	This was a very good review paper at the time	-	-	-	-	
33	Duffy and Brandes (2001)	2	Areal	N	Principal component analysis applied to a set of data on organic and inorganic chemicals at a given time. The results help to reduce the dimensionality of the problem and the identification of the sources	No state equation	F	Potential sources	Y	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
34	Mahar and Datta (2001)	2	Multiple	Y	Non-linear programming solved with the projected augmented Lagrangian algorithm	Flow and transport equations	S	Source strengths and locations out of a predetermined set of potential ones	Y	N
35	Michalak and Kitanidis (2002)	3	Areal	Y	Bayesian/geostatistical approach enforcing non-negativity of results	Transport equation	F	Release function	N	N
36	Sohn et al. (2002a)	3	Room	N	Bayesian approach	Air flow and pollutant transport in buildings represented as a collection of well-mixed zones	F	Room source	N	N
37	Sohn et al. (2002b)	3	Room	N	Bayesian approach	Same as above	S	Room source	N	N
38	Akçelik et al. (2003)	2	Multiple	Y	Constrained least-squares method with regularization	Transport equation	S	Release function	N	N
39	Bagtzoglou and Atmadja (2003)	1	Point	Y	Marching-jury backward beam equation versus quasi-reversibility	Transport equation	S	Release function	N	Y
40	Butera and Tanda (2003)	2	Multiple	Y	Geostatistical approach extended in two dimensions	Convolution integral	S	Release function	N	N
41	Michalak and Kitanidis (2003)	1	Interface	Y	Bayesian approach based on the geostatistical approach	Diffusion equation	F	Release function	N	Z
42	Michalak and Kitanidis (2004b)	2	Areal	N	Geostatistical approach with the adjoint method	Transport equation	S	Historical contaminant distribution	N	Y
43	Michalak and Kitanidis (2004a)	1	Interface	Y	Geostatistical approach	Diffusion equation	F	Release function	N	Z
44	Singh and Datta (2004)	2	Multiple	Y	Artificial neural network	USGS Konikow code	S	Release function	Y	N
45	Singh et al. (2004)	-	-	-	Same approach as previous one	-	-	-	-	-
46	Bagtzoglou and Atmadja (2005)	-	-	-	Best review paper until then	-	-	-	-	-
47	Boano et al. (2005)	1	Multiple	Y	Geostatistical approach applied to contamination source identification in rivers	Transient storage equation	S	Release function	N	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
48	Mahinthakumar and Sayeed (2005)	3	Areal	N	Simulation-optimization approach using a hybrid genetic algorithm with local search	Flow and transport equations	S	Coordinates of the corners of the rectangular source and its concentration	N	N
49	Mahinthakumar and Sayeed (2006)	3	Volumetric	Y	Several hybrid genetic algorithms with local search strategies compared	Transport equation	S	Coordinates of the corners of the parallelepiped source and its concentration	N	N
50	Neupauer and Lin (2006)	2	Point	N	Backward probabilities using the adjoint state method	Adjoint equations conditioned to concentration data	S	Source location	N	Y
51	Newman et al. (2006)	3	Volumetric	N	Combination of simulated annealing and minimum relative entropy	Flux plane model	L	Magnitude and distribution of mass influx from the DNAPL source zones	N	N
52	Singh and Datta (2006)	-	-	-	Same as Singh and Datta (2004) and Singh et al. (2004) but different cases	-	-	-	-	-
53	Sun et al. (2006a)	2	Point	Y	Constrained robust least-squares optimization	MODFLOW and MT3DMS and convolution approach	S	Release function	N	N
54	Sun et al. (2006b)	2	Multiple	Y	Constrained robust least-squares optimization to identify release history and branch and bound for location	Flow and transport equations	S	Release function and source locations	N	N
55	Wang and Zabaras (2006)	2	Point	N	Posterior mean estimate using a Gibbs sampler	Flow and transport equations	S	Location of instantaneous release	N	Y
56	Liu and Zhai (2007)	-	-	-	Although in the field of air pollution, the paper includes an extensive review of groundwater literature	-	-	-	-	-

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
57	Milnes and Perrochet (2007)	2	Point	N	Backtracking using flow reversal with FEFLOW	FEFLOW	S	Location and time	N	Y
58	Sun (2007)	2	Point	Y	Robust geostatistical approach	Transport equation	S	Release function	N	YN
59	Yeh et al. (2007)	2	Multiple	Y	Combination of simulated annealing and tabu search	MODFLOW and MOC	S	Source location, strength and release period	N	YN
60	Sun (2008)	-	-	-	CONSID, a program that implements nonnegative least squares, constrained robust least squares and robust geostatistical inversion	MODFLOW	-	-	-	-
61	Datta et al. (2009)	2	Multiple	Y	Nonlinear optimization with MINOS	SUTRA	S	Source strengths and locations out of a predetermined set of potential ones	Y	Z
62	Dokou and Pinder (2009)	3	Multiple	N	Optimal search strategy including a Monte Carlo flow and transport model and a predetermined set of potential sources	Flow and transport equations	S	Location out of set of potential ones	N	YN
63	Jin et al. (2009)	3	Prism	N	Parallel hybrid optimization with the real genetic algorithm and local search approaches	Transport equation	F	Seven unknowns: the corners of the prism plus the concentration at the source	N	Y
64	Liu and Zhai (2009)	2	Point	N	The adjoint probability method by Neupauer and Wilson (1999) applied to the detection of an air pollution in a building	Contaminant transport equation	S	Room source	N	N
65	Mirghani et al. (2009)	3	Cuboid	N	Simulation-optimization approach coupling numerical modeling and an evolutionary search algorithm.	Transport equation	S	Coordinates of the corners of the parallelepiped source and its concentration	N	Y

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
66	Ayvaz (2010)	2	Multiple	Y	Simulation-optimization using heuristic harmony search	Transport equation	S	Locations and release histories for a total of 12 parameters	N	Z
67	Cheng and Jia (2010)	2	Point	N	Backward location probability density function	Backward probability density function model in an open water body	S	Source location	N	N
68	Datta et al. (2011)	2	Multiple	Y	Classical optimization-simulation approach	SUTRA	S	Source strengths and locations out of a predetermined set of potential ones	N	Z
69	Hosseini et al. (2011)	2	Areal	N	Sequential self-calibration coupled with distance functions to determine the size and shape of DNAPL source.	Flow and transport equation	S	Shape of the DNAPL pool	Y	YN
70	Jha and Datta (2011)	2	Multiple	N	Simulated annealing for a global heuristic search optimization	MODFLOW and MT3DMS	S	Strength, location and timing	N	N
71	Li and zhong Mao (2011)	2	Areal	Y	Least-squares radial basis collocation method based on the global space-time multiquadric	GST-MQ collocation method	S	Release function	N	N
72	Telci and Aral (2011)	1	Multiple	N	Classification routine to associate observations with candidate source locations. Applied in a river network.	Storm water management model, SWMM	F	Source locations and timings	N	N
73	Chadalavada et al. (2012)	3	Multiple	Y	Simulation-optimization approach	MODFLOW and MT3DMS	F	Locations out of three potential ones, plus strengths	N	N
74	Zeng et al. (2012)	2	Point	Y	Bayesian method based on adaptive sparse grid interpolation	Surrogate model	S	Locations out of potential candidates, plus release function	N	N
75	Aghasi et al. (2013)	3	Volumetric	N	Joint inversion of geophysical data and concentration data to delimit a DNAPL pool	Multiphase flow and electrical resistance tomography	S	DNAPL pool and intensity	N	Y

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
76	Amirabdollahian and Datta (2013)	-	-	-	Review paper on source identification, network monitoring design, joint use of them, and identification of distributed sources	-	-	-	-	-
77	Butera et al. (2013)	2	Point	Y	Geostatistical approach	Convolution integral	S	Release function and source location	N	Y
78	Jha and Datta (2013)	3	Multiple	Y	Simulation-optimization	MT3DMS	S	Strengths at two known locations	N	N
79	Wang and Jin (2013)	3	Point	N	Bayesian approach coupled with Markov chain Monte Carlo using the Metropolis-Hastings algorithm	Flow and transport equations	S	Location coordinates and strength	N	Y
80	Amirabdollahian and Datta (2014)	2	Multiple	Y	Adaptive simulated annealing and fuzzy logic	MODFLOW and MT3DMS	S	Intensities at three locations	N	Y
81	Gzyl et al. (2014)	2	Areal	Y	Geostatistical approach	MODFLOW and MT3D	F	Release function	N	N
82	Jha and Datta (2014)	2	Point	Y	Simulation-optimization approach using a dynamic time warping distance	Flow and transport equations	S	Release function	N	N
83	Jin et al. (2014)	3	Cuboid	N	Network design for groundwater contaminant source identification	Flow and transport equations	S	Location and concentration	N	Y
84	Srivastava and Singh (2014)	2	Point	Y	Artificial neural network	MODFLOW-GWT	S	Location (out of two potential sources), strength and duration	N	N
85	Yeh et al. (2014)	3	Point	Y	Simulated annealing plus tabu search plus ordinal optimization plus roulette wheel.	MF2K-GWT	S	Location and release function	N	Z
86	Cupola et al. (2015)	2	Point	Y	A comparison between the simultaneous release function and location identification method by Butera et al. (2013) and the backward probability model using the adjoint method	Convolution integral	L	Location and release function	N	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
87	Gurarslan and Karahan (2015)	2	Multiple	Y	Differential evolution optimization	MODFLOW and MT3DMS	S	Source strengths and locations out of a predetermined set of potential ones	N	N
88	Jha and Datta (2015)	3	Areal	Y	Adaptive simulated annealing	MODFLOW and MT3DMS	F	Location, starting time and duration	N	Z
89	Ngamsritrakul et al. (2015)	2	Point	N	Non-linear optimization as proposed by Aral et al. (2001)	MODFLOW and MT3DMS	S	Location	N	N
90	Prakash and Datta (2015)	3	Areal	Y	Simulated annealing coupled with optimal monitoring network design	GMS	F	Location and starting time	N	Z
91	Srivastava and Singh (2015)	2	Point	Y	Artificial neural network	MOC	S	Source location	Y	N
92	Zhang et al. (2015)	2	Point	Y	Full Bayesian approach for optimal sampling well location and source parameter identification using Markov chain Monte Carlo	Flow and transport equations	S	Location, starting time, ending time and strength	Y	YN
93	Ayvaz (2016)	2	Areal	N	Simulation-optimization using a hybrid optimization where a binary genetic algorithm and a generalized gradient method are used	MODFLOW and MT3DMS	S	Shape of areal source and input concentration	N	Z
94	Bashi-Azghadi et al. (2016)	2	Multiple	N	Regret-based optimization model to minimize the number of monitoring wells. Bayesian network trained to identify pollutant source	MODFLOW and MT3DMS	F	Location	N	N
95	Borah and Bhattacharjya (2016)	2	Multiple	Y	Simulation-optimization approach using a new genetic algorithm	GMS	S	Strengths	N	N
96	Hansen and Vesselinov (2016)	2	Point	N	Monte-Carlo analysis to run multiple forward models to generate simulated data which are later used to identify the source by an inverse procedure using a simplified model	Transport equation	S	Location and time	N	Y

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
97	Koch and Nowak (2016)	3	Volumetric	N	Inverse Bayesian methodology for the joint inversion of source geometry and aquifer parameters	Galerkin finite element code	S	Probability of DNAPL presence	Y	YN
98	Xu and Gómez-Hernández (2016)	2	Point	Y	Ensemble Kalman filter used for the identification of a contaminant source	Transport equation	S	Coordinates of source, starting and ending time, and strength	N	Y
99	Yeh et al. (2016)	3	Volumetric	Y	Function fitting by simulated annealing	Analytical solutions of transport equations	S	Release function plus some geometric parameters of source	N	N
100	Zanini and Woodbury (2016)	2	Point	Y	Empirical Bayesian method combined with Akaike's Bayesian Information Criterion	Convolution integral	S	Release function	N	N
101	Zhang et al. (2016a)	2	Point	Y	Bayesian formulation for experimental design	Surrogate model integrated with Markov chain Monte Carlo	S	Source locations and strengths	Y	YN
102	Zhang et al. (2016b)	1	Point	N	Backward tracking using a fractional advection dispersion model	Fractional advection dispersion model	F	Source location	N	N
103	Zhao et al. (2016)	2	Multiple	Y	Simulation-optimization approach using a surrogate model	Kriging surrogate model	S	Strengths per stress period	N	Z
104	Gu et al. (2017)	2	Multiple	N	Monte Carlo approach	Transport equation	S	Number, location and strength of sources	N	Y
105	Hazrati Y. (2017)	3	Multiple	N	Surrogate models based on self-organized maps	MODFLOW and MT3DMS	S	Strengths at two known locations	N	Y
106	Long et al. (2017)	1	Point	Y	Geostatistical approach	Convolution integral	S	Release function	N	N
107	Onyari and Taigbenu (2017)	2	Point	Y	Green element method to solve inverse contaminant transport problems	Green element method	S	Release function	N	N
108	Rajeev Gandhi et al. (2017)	3	Multiple	Y	Simulated annealing coupled with analytical solutions	MODFLOW and MT3DMS	S	Wastewater release at potential locations	N	N

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
109	Zhang et al. (2017)	1	Point	N	Backward probabilities computed assuming a fractional advection-dispersion equation	Fractional advection-dispersion model	F	Location	N	N
110	Chen et al. (2018)	2	Point	N	Ensemble Kalman filter used for the identification of a contaminant source and the geometry of the system	MODFLOW and MT3DMS	L	Location, starting time, ending time and strength, and geometry of system	N	N
111	Esfahani and Datta (2018)	3	Multiple	N	Fractal singularity-based multi-objective monitoring networks	Genetic programming-based surrogate model for reactive transport	F	Source concentrations at known locations	N	Z
112	Guneshwor et al. (2018)	2	Multiple	Y	Simulation-optimization approach using particle swarm optimization	Mesh-free simulator using radial point collocation method	F	Source strengths at potential locations	N	N
113	Hou and Lu (2018)	2	Multiple	N	Comparative study of surrogate models	UTCHEM	S	Potential sources	N	N
114	Huang et al. (2018)	2	Multiple	N	Simulation-optimization using a shuffled complex evolution algorithm	MODFLOW and MT3DMS	S	Sources out of a potential set plus strengths	N	N
115	Jiang et al. (2018)	2	Multiple	N	Network design using Kalman filter to improve source identification	MODFLOW and MT3DMS	S	Five potential sources of unknown strengths	N	Y
116	Stanev et al. (2018)	2	Multiple	Y	Machine learning combined with Green's function inverse method	Green's function	S	Number, location and strength of sources accounting for different components	Y	N
117	Vesselinov et al. (2018)	2	Point	N	Blind source separation coupled with non-negative matrix factorization	Linear mixing of unknown signals	F	Origin of mixed waters observed	N	N
118	Xu and Gómez-Hernández (2018)	2	Point	Y	Simultaneous estimation of conductivity spatial distribution and source parameters using the ensemble Kalman filter	MODFLOW and MT3DMS	S	Location, strength	Y	YN

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
119	Amirabdollahian et al. (2019)	3	Multiple	N	Simulation-optimization approach using adaptive simulated annealing	MODFLOW and MT3DMS	F	Candidate locations out a set of potential sources	N	N
120	Ayub et al. (2019)	2	Multiple	N	Bayesian approach coupled with Markov chain Monte Carlo	Flow and transport equations	S	Locations out of potential candidates, plus release function	N	Y
121	Cao et al. (2019)	3	Multiple	Y	Bayesian model selection	MODFLOW and MT3DMS	S	Source strengths and locations out of a predetermined set of potential ones	N	Z
122	Jiao et al. (2019)	2	Point	Y	Local approximation solution of concentrations	MT3DMS	S	Release function and source locations	N	Y
123	Li et al. (2019)	2	Multiple	N	Simulation-optimization model with a surrogate model and Kalman filtering combined with a mixed-integer nonlinear programming	Kriging surrogate model	S	Location and release function	N	Y
124	Mo et al. (2019)	2	Point	Y	Joint identification using deep autoregressive neural networks	Surrogate model	S	Location and strengths	Y	YN
125	Vesselinov et al. (2019)	3	Multiple	Y	Unsupervised machine learning based on nonnegative tensor factorization of the original geochemical componentes	Unsupervised machine learning	F	Source locations	N	N
126	Xia et al. (2019a)	2	Multiple	Y	Simulation-optimization approach using a genetic algorithm tuned using Taguchi experimental design	MODFLOW and MT3DMS	S	Source strengths for given stress periods	N	Z
127	Xia et al. (2019b)	2	Multiple	Y	Optimal self-organized map-based surrogate model	Surrogate model	S	Strengths per stress period	N	Y
128	Xing et al. (2019)	2	Multiple	Y	Simulation-optimization solved with a genetic algorithm	Ensemble of surrogate models	S	Strengths per stress period	N	Z
129	Yan et al. (2019)	2	Multiple	Y	Bayesian approach coupled with Markov chain Monte Carlo using the Metropolis-Hastings algorithm	Kriging surrogate model	S	Strengths per stress period	N	Z

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
130	Zhang et al. (2019)	2	Point	N	Bayesian approach coupled with Markov chain Monte Carlo using an improved Metropolis-Hastings algorithm	Analytical solution	S	Strength, location and timing	N	N
131	Chaubey and Srivastava (2020)	1	Point	N	Artificial neural network	Analytical solution	S	Location and strength	N	N
132	Colombo et al. (2020)	3	Point	Y	Null-space Monte Carlo backward particle tracking	MODFLOW and MODPATH	F	Source location	N	Y
133	Essouayed et al. (2020)	2	Point	N	Standard non-linear optimization including pilot points	MODFLOW and MT3DMS	S	Source location	Y	YN
134	Han et al. (2020)	1	Point	N	Genetic algorithm	Analytical solution	F	Strength, location and timing	N	N
135	Jamshidi et al. (2020)	2	Multiple	Y	Standard gradient descent approach using Newton-Raphson	Convolution integral	S	Release function and source location	N	Z
136	Kang et al. (2020)	3	Volumetric	N	Principal component geostatistical approach using temporal moments of concentration instead of individual concentrations	COMSOL Multiphysics	S	Initial DNAPL saturation	Y	YN
137	Li et al. (2020)	2	Multiple	Y	Simulation-optimization using hybrid particle swarm optimization and extreme learning machine	Several surrogate models	S	Location out of set of potential ones	N	Z
138	Lu et al. (2020)	3	Point	Y	Parallel heuristic search based on a Bayesian approach	Surrogate model combining Gaussian process, kernel extreme learning machine and support vector machine	S	Coordinates of source, strength	Y	Z
139	Wang et al. (2020)	-	-	-	Extremely similar to the previous one	-	-	-	-	
140	Wang and Lu (2020)	-	-	-	Extremely similar to the two previous ones	-	-	-	-	-
141	Zhang et al. (2020)	2	Point	Y	Ensemble smoother modified with deep learning	MODFLOW and MT3DMS	S	Coordinates of source, strength	Y	YN

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
142	Zhao et al. (2020b)	2	Multiple	N	Artificially enhanced catchment	Interpretation of concentration time series	F	Location	N	N
143	Zhao et al. (2020a)	2	Multiple	N	Simulation-optimization using four different heuristic approaches	Surrogate model using kernel-based extreme machine learning	F	Strengths per stress period	N	Z
144	Ayaz (2021)	3	Point	Y	Artificial neural network	Transport equation	S	Release function	N	N
145	Ayaz et al. (2021)	2	Line	N	Constrained non-linear optimization with genetic algorithm	Transport equation	S	Source location, strength and release period	N	N
146	Chakraborty and Prakash (2021)	3	Multiple	Y	Simulation-optimization coupling numerical modeling and evolutionary search algorithm	Flow and transport equation	S	Source locations and strengths	N	N
147	Dodangeh et al. (2021)	3	Point	Y	Ensemble Kalman filter	Surrogate model	S	Source coordinates and initial concentration	N	N
148	He et al. (2021)	1	Point	N	Least squares	Analytical solution	F	Source location and strength	N	N
149	Hou et al. (2021)	3	Point	N	Homotopy-based hyper-heuristic approach	Multiphase surrogate model	S	Source location and strength	Y	N
150	Jiang et al. (2021)	2	Multiple	Y	Construction of a large table of inputs and outputs	Surrogate model based on self-organized maps	S	Source strengths for given stress periods	Y	YN
151	Liu et al. (2021)	2	Point	N	Ensemble smoother	MODFLOW and MT3DMS	S	Location and strength	Y	YN
152	Todaro et al. (2021)	2	Point	Y	Ensemble smoother	MODFLOW and MT3DMS	L	Location and release function	N	Y
153	Wang et al. (2021a)	3	Point	Y	Iterative updating heuristic search strategy	Surrogate multiphase flow	S	Strengths per stress period	Y	N
154	Wang and Zhang (2021)	2	Point	Y	Standard gradient descent	Diffusion equation	S	Location and strength	N	N
155	Wang et al. (2021b)	2	Point	Y	Differential evolution and tabu search optimization	Ensemble of surrogate models	S	Strengths per stress period	Y	Z

	Reference	D	Source	$f(t)$	Solution approach	State eq.	CS	Source parameters	O.	H.
156	Yuan and Liang (2021)	1	Point	Y	Simulation-optimization approach using genetic algorithms	Transport equation	S	Release function	N	N
157	Zhou and Tartakovsky (2021)	2	Areal	N	Bayesian approach coupled with Markov chain Monte Carlo	Surrogate model using a deep convolutional neural network	S	Location and Gaussian spread of initial concentrations	N	Y

[1] Dimensionality, 1: One-dimensional, 2: Two-dimensional, 3: Three-dimensional

[2] Acronyms used in the table: SUTRA, the flow and transport model by Voss (1984); MODFLOW, the modular groundwater flow code by McDonald and Harbaugh (1984); MT3DMS, the mass transport code by Zheng and Wang (1999); GMS, the Groundwater Modeling System by Aquaveo; MOC, the transport model developed by Konikow and Bredehoeft (1978); MF2K-GWT, implementation of MOC in MODFLOW, see, for instance, Konikow and Hornberger (2006); UTCHEM, the University of Texas multiphase simulator code; MODPATH, the particle tracking code by Pollock (1994); COMSOL Multiphysics, a general purpose simulation software by COMSOL; EPANET, flow and transport in water distribution networks by Rossman et al. (2000)

[3] Case Study, S: Synthetic, L: Laboratory, F: Field

[4] Other non-source parameters also identified

[5] Aquifer heterogeneity, N: Homogeneous, Z: Zonation, Y: Heterogeneous and unknown, YN: Heterogeneous but known

References

Aanonsen S, Nævdal G, Oliver D, Reynolds A, Vallès B (2009) The ensemble kalman filter in reservoir engineering–a review. SPE Journal 14(3):393–412

Aghasi A, Mendoza-Sanchez I, Miller EL, Ramsburg CA, Abriola LM (2013) A geometric approach to joint inversion with applications to contaminant source zone characterization. Inverse Problems 29(11):115014, DOI 10.1088/0266-5611/29/11/115014, URL https://iopscience.iop.org/article/10.1088/0266-5611/29/11/115014

Akçelik V, Biros G, Ghattas O, Long KR, Van Bloemen Waanders B (2003) A variational finite element method for source inversion for convective-diffusive transport. Finite Elements in Analysis and Design 39(8):683–705, DOI 10.1016/S0168-874X(03)00054-4

Ala NK, Domenico PA (1992) Inverse Analytical Techniques Applied to Coincident Contaminant Distributions at Otis Air Force Base, Massachusetts. Groundwater 30(2):212–218, DOI 10.1111/j.1745-6584.1992.tb01793.x

Alapati S, Kabala ZJ (2000) Recovering the release history of a groundwater contaminant using a non-linear least-squares method. Hydrological Processes 14(6):1003–1016, DOI 10.1002/(SICI)1099-1085(20000430)14:6⟨1003::AID-HYP981⟩3.0.CO;2-W

Amirabdollahian M, Datta B (2013) Identification of Contaminant Source Characteristics and Monitoring Network Design in Groundwater Aquifers: An Overview. Journal of Environmental Protection DOI 10.4236/jep.2013.45a004

Amirabdollahian M, Datta B (2014) Identification of pollutant source characteristics under uncertainty in contaminated water resources systems using adaptive simulated anealing and fuzzy logic. International Journal of GEOMATE 6(1):757–762, DOI 10.21660/2014.11.3258

Amirabdollahian M, Datta B, Beck PH (2019) Application of a link simulation optimization model utilizing quantification of hydrogeologic uncertainty to characterize unknown groundwater contaminant sources. Modeling Earth Systems and Environment 5(1):119–131, DOI 10.1007/s40808-018-0522-1, URL http://link.springer.com/10.1007/s40808-018-0522-1

Aral MM, Guan J (1996) Genetic Algorithms in Search of Groundwater Pollution Sources. In: Advances in Groundwater Pollution Control and Remediation, Springer Netherlands, Dordrecht, pp 347–369, DOI 10.1007/978-94-009-0205-3_17, URL http://link.springer.com/10.1007/978-94-009-0205-3_17

Aral MM, Guan J, Maslia ML (2001) Identification of Contaminant Source Location and Release History in Aquifers. Journal of Hydrologic Engineering 6(3):225–234, DOI 10.1061/(asce)1084-0699(2001)6:3(225)

Atmadja J, Bagtzoglou AC (2001a) Pollution source identification in heterogeneous porous media. Water Resources Research 37(8):2113–2125, DOI 10.1029/2001WR000223

Atmadja J, Bagtzoglou AC (2001b) State of the art report on mathematical methods for groundwater pollution source identification. Environmental Forensics 2(3):205–214, DOI 10.1006/enfo.2001.0055

Ayaz M (2021) Estimation of release history of groundwater pollution source using ANN model. Modeling Earth Systems and Environment DOI 10.1007/s40808-021-01142-3, URL https://doi.org/10.1007/s40808-021-01142-3http://link.springer.com/10.1007/s40808-021-01142-3

Ayaz M, Ansari SA, Singh OK (2021) Detection of pollutant source in groundwater using hybrid optimization model. International Journal of Energy and Water Resources DOI 10.1007/s42108-021-00118-4, URL http://link.springer.com/10.1007/s42108-021-00118-4

Ayub R, Messier KP, Serre ML, Mahinthakumar K (2019) Non-point source evaluation of groundwater nitrate contamination from agriculture under geologic uncertainty. Stochastic Environmental Research and Risk Assessment pp 1–18, DOI 10.1007/s00477-019-01669-z, URL http://link.springer.com/10.1007/s00477-019-01669-z

Ayvaz MT (2010) A linked simulation-optimization model for solving the unknown groundwater pollution source identification problems. Journal of Contaminant Hydrology DOI 10.1016/j.jconhyd.2010.06.004

Ayvaz MT (2016) A hybrid simulation-optimization approach for solving the areal groundwater pollution source identification problems. Journal of Hydrology 538:161–176, DOI 10.1016/j.jhydrol.2016.04.008, URL https://www.sciencedirect.com/science/article/pii/S0022169416301895

Bagtzoglou AC, Atmadja J (2003) Marching-jury backward beam equation and quasi-reversibility methods for hydrologic inversion: Application to contaminant plume spatial distribution recovery. Water Resources Research 39(2)

Bagtzoglou AC, Atmadja J (2005) Mathematical Methods for Hydrologic Inversion: The Case of Pollution Source Identification. Water Pollution 5:65–96, DOI 10.1007/b11442, URL http://www.springerlink.com/index/10.1007/b11442http://link.springer.com/10.1007/b11442

Bagtzoglou AC, Tompson AFB, Dougherty DE (1991) Probabilistic Simulation for Reliable Solute Source Identification in Heterogeneous Porous Media. In: Water Resources Engineering Risk Assessment, Springer Berlin Heidelberg, Berlin, Heidelberg, pp 189–201, DOI 10.1007/978-3-642-76971-9_12, URL http://link.springer.com/10.1007/978-3-642-76971-9_12

Bagtzoglou AC, Dougherty DE, Tompson AFB (1992) Application of particle methods to reliable identification of groundwater pollution sources. Water Resources Management 6(1):15–23, DOI 10.1007/BF00872184

Bashi-Azghadi SN, Kerachian R, Bazargan-Lari MR, Nikoo MR (2016) Pollution Source Identification in Groundwater Systems: Application of Regret Theory and Bayesian Networks. Iranian Journal of Science and Technology, Transactions of Civil Engineering 40(3):241–249, DOI 10.1007/s40996-016-0022-3, URL http://link.springer.com/10.1007/s40996-016-0022-3

Birchwood R (1999) Identifying the location and release characteristics of a groundwater pollution source using spectral analysis. In: 19th Annual American Geophysical Union Hydrology Days Conference, pp 37–50

Boano F, Revelli R, Ridolfi L (2005) Source identification in river pollution problems: A geostatistical approach. Water Resources Research DOI 10.1029/2004WR003754

Borah T, Bhattacharjya RK (2016) Development of an Improved Pollution Source Identification Model Using Numerical and ANN Based Simulation-Optimization Model. Water Resources Management 30(14):5163–5176, DOI 10.1007/s11269-016-1476-6, URL http://link.springer.com/10.1007/s11269-016-1476-6

Butera I, Tanda MG (2003) A geostatistical approach to recover the release history of groundwater pollutants. Water Resources Research 39(12), DOI 10.1029/2003WR002314, URL http://doi.wiley.com/10.1029/2003WR002314

Butera I, Tanda MG, Zanini A (2013) Simultaneous identification of the pollutant release history and the source location in groundwater by means of a geostatistical approach. Stochastic Environmental Research and Risk Assessment 27(5):1269–1280, DOI 10.1007/s00477-012-0662-1

Cao T, Zeng X, Wu J, Wang D, Sun Y, Zhu X, Lin J, Long Y (2019) Groundwater contaminant source identification via Bayesian model selection and uncertainty quantification. Hydrogeology Journal 27(8):2907–2918, DOI 10.1007/s10040-019-02055-3, URL http://link.springer.com/10.1007/s10040-019-02055-3

Capilla JE, Rodrigo J, Gómez-Hernández JJ (1999) Simulation of non-gaussian transmissivity fields honoring piezometric data and integrating soft and secondary information. Math Geosc 31(7):907–927

Carrera J (1984) Estimation of aquifer parameters under transient and steady-state conditions. PhD thesis, Univ. of Arizona, Dep. of Hydrology and Water Resources

Carrera J, Neuman SP (1986) Estimation of aquifer parameters under transient and steady state conditions, 1, Maximum likelihood method incorporating prior information. Water Resources Research 22(2):199–210

Chadalavada S, Datta B, Naidu R (2012) Optimal Identification of Groundwater Pollution Sources Using Feedback Monitoring Information: A Case Study. Environmental Forensics 13(2):140–153, DOI 10.1080/15275922.2012.676147, URL http://www.tandfonline.com/doi/abs/10.1080/15275922.2012.676147

Chakraborty A, Prakash O (2021) CHARACTERIZATION OF GROUNDWATER POLLUTION SOURCES BY KRIGING BASED LINKED SIMULATION

OPTIMIZATION. International Journal of GEOMATE 20(81):79–85, DOI 10.21660/2021.81.6209, URL https://www.geomatejournal.com/sites/default/files/articles/79-85-6209-Anirban-May-2021-81.pdf

Chaubey J, Srivastava R (2020) Simultaneous identification of groundwater pollution source location and release concentration using Artificial Neural Network. Environmental Forensics 0(0):1–8, DOI 10.1080/15275922.2020.1850566, URL https://doi.org/10.1080/15275922.2020.1850566

Chen Y, Zhang D (2006) Data assimilation for transient flow in geologic formations via ensemble kalman filter. Advances in Water Resources 29(8):1107–1122

Chen Z, Gómez-Hernández JJ, Xu T, Zanini A (2018) Joint identification of contaminant source and aquifer geometry in a sandbox experiment with the restart ensemble Kalman filter. Journal of Hydrology 564:1074–1084, DOI 10.1016/j.jhydrol.2018.07.073, URL https://linkinghub.elsevier.com/retrieve/pii/S0022169418305870

Cheng WP, Jia Y (2010) Identification of contaminant point source in surface waters based on backward location probability density function method. Advances in Water Resources 33(4):397–410, DOI 10.1016/j.advwatres.2010.01.004, URL http://dx.doi.org/10.1016/j.advwatres.2010.01.004

Colombo L, Alberti L, Mazzon P, Antelmi M (2020) Null-Space Monte Carlo Particle Backtracking to Identify Groundwater Tetrachloroethylene Sources. Front Environ Sci 8:142, DOI 10.3389/fenvs.2020.00142, URL www.frontiersin.org

Cupola F, Tanda MG, Zanini A (2015) Laboratory sandbox validation of pollutant source location methods. Stochastic Environmental Research and Risk Assessment 29(1):169–182, DOI 10.1007/s00477-014-0869-4

Dagan G (1982) Stochastic modeling of groundwater flow by unconditional and conditional probabilities: 2. the solute transport. Water Resources Research 18(4):835–848

Datta B, Beegle J, Kavvas M, Orlob G (1989) Development of an expert system embedding pattern recognition techniques for pollution source identification. Tech. rep., University of California-Davis

Datta B, Chakrabarty D, Dhar A (2009) Simultaneous identification of unknown groundwater pollution sources and estimation of aquifer parameters. Journal of Hydrology 376(1-2):48–57, DOI 10.1016/j.jhydrol.2009.07.014

Datta B, Chakrabarty D, Dhar A (2011) Identification of unknown groundwater pollution sources using classical optimization with linked simulation. Journal of Hydro-Environment Research 5(1):25–36, DOI 10.1016/j.jher.2010.08.004, URL http://dx.doi.org/10.1016/j.jher.2010.08.004

Dodangeh A, Rajabi MM, Fahs M (2021) Simultaneous identification of contaminant source location, initial contaminant concentration, horizontal and vertical hydraulic conductivity in a three-dimensional coastal aquifer via ensemble Kalman filter. In: EGU General Assembly 2021, online, 19–30 Apr 2021, p 10890, DOI 10.5194/egusphere-egu21-10890

Dokou Z, Pinder GF (2009) Optimal search strategy for the definition of a DNAPL source. Journal of Hydrology 376(3-4):542–556, DOI 10.1016/j.jhydrol.2009.07.062, URL http://dx.doi.org/10.1016/j.jhydrol.2009.07.062

Duffy CJ, Brandes D (2001) Dimension reduction and source identification for multispecies groundwater contamination. Journal of Contaminant Hydrology DOI 10.1016/S0169-7722(00)00169-8

Esfahani HK, Datta B (2018) Fractal Singularity–Based Multiobjective Monitoring Networks for Reactive Species Contaminant Source Characterization. Journal of Water Resources Planning and Management 144(6):04018021, DOI 10.1061/(ASCE)WR.1943-5452.0000880, URL http://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0000880

Essouayed E, Verardo E, Pryet A, Chassagne R, Atteia O (2020) An iterative strategy for contaminant source localisation using GLMA optimization and Data Worth on two synthetic 2D Aquifers. Journal of Contaminant Hydrology 228:103554, DOI 10.1016/j.jconhyd.2019.103554, URL https://linkinghub.elsevier.com/retrieve/pii/S0169772219301251

Evensen G (2003) The ensemble kalman filter: Theoretical formulation and practical implementation. Ocean dynamics 53(4):343–367

Gómez-Hernández J, Wen XH (1994) Probabilistic assessment of travel times in groundwater modeling. Stochastic Hydrology and Hydraulics 8(1):19–55

Gorelick SM (1981) Numerical Management Models of Groundwater Pollution. Ph.d., Stanford University

Gorelick SM, Evans B, Remson I (1983) Identifying sources of groundwater pollution: An optimization approach. Water Resources Research 19(3):779–790, DOI 10.1029/WR019i003p00779, URL http://doi.wiley.com/10.1029/WR019i003p00779

Gu W, Lu W, Zhao Y, Ouyang Q, Xiao C (2017) Identification of groundwater pollution sources based on a modified plume comparison method. Water Science and Technology: Water Supply 17(1):188–197, DOI 10.2166/ws.2016.122

Guneshwor L, Eldho TI, Vinod Kumar A (2018) Identification of Groundwater Contamination Sources Using Meshfree RPCM Simulation and Particle Swarm Optimization. Water Resources Management 32(4):1517–1538, DOI 10.1007/s11269-017-1885-1, URL http://link.springer.com/10.1007/s11269-017-1885-1

Gurarslan G, Karahan H (2015) Solving inverse problems of groundwater-pollution-source identification using a differential evolution algorithm. Hydrogeology Journal 23(6):1109–1119, DOI 10.1007/s10040-015-1256-z, URL http://link.springer.com/10.1007/s10040-015-1256-z

Gzyl G, Zanini A, Fraczek R, Kura K (2014) Contaminant source and release history identification in groundwater: A multi-step approach. Journal of Contaminant Hydrology 157:59–72, DOI 10.1016/j.jconhyd.2013.11.006

Haario H, Laine M, Mira A, Saksman E (2006) Dram: efficient adaptive mcmc. Statistics and computing 16(4):339–354

Hamdi A (2017) Detection and identification of multiple unknown time-dependent point sources occurring in 1D evolution transport equations. Inverse Problems in Science and Engineering 25(4):532–554, DOI 10.1080/17415977.2016.1172224, URL https://www.tandfonline.com/doi/full/10.1080/17415977.2016.1172224

Han K, Zuo R, Ni P, Xue Z, Xu D, Wang J, Zhang D (2020) Application of a genetic algorithm to groundwater pollution source identification. Journal of Hydrology p 125343, DOI 10.1016/J.JHYDROL.2020.125343, URL https://www.sciencedirect.com/science/article/pii/S0022169420308039#b0105

Hansen SK, Vesselinov VV (2016) Contaminant point source localization error estimates as functions of data quantity and model quality. Journal of Contaminant Hydrology 193:74–85, DOI 10.1016/j.jconhyd.2016.09.003, URL https://linkinghub.elsevier.com/retrieve/pii/S0169772216301875

Hazrati Y S (2017) Self-organigizing map based surrogate models for contaminant source identification under parameter uncertainty. International Journal of GEOMATE 13(36), DOI 10.21660/2017.36.2750, URL http://www.geomatejournal.com/sites/default/files/articles/11-18-2750-Shahrbanoo-Aug-2017-36-a1.pdf

He Z, Zuo R, Zhang D, Ni P, Han K, Xue Z, Wang J, Xu D (2021) A least squares method for identification of unknown groundwater pollution source. Hydrology Research pp 1–11, DOI 10.2166/nh.2021.088

Hosseini AH, Deutsch CV, Mendoza CA, Biggar KW (2011) Inverse modeling for characterization of uncertainty in transport parameters under uncertainty of source geometry in heterogeneous aquifers. Journal of Hydrology 405(3-4):402–416, DOI 10.1016/j.jhydrol.2011.05.039, URL http://dx.doi.org/10.1016/j.jhydrol.2011.05.039

Hou Z, Lu W (2018) Comparative study of surrogate models for groundwater contamination source identification at DNAPL-contaminated sites. Hydrogeology Journal 26(3):923–932, DOI 10.1007/s10040-017-1690-1, URL http://link.springer.com/10.1007/s10040-017-1690-1

Hou Z, Lao W, Wang Y, Lu W (2021) Homotopy-based hyper-heuristic searching approach for reciprocal feedback inversion of groundwater contamination source and aquifer parameters. Applied Soft Computing 104:107191, DOI 10.1016/j.asoc.2021.107191, URL https://doi.org/10.1016/j.econlet.2020.109008https://linkinghub.elsevier.com/retrieve/pii/S1568494621001149

Huang L, Wang L, Zhang Y, Xing L, Hao Q, Xiao Y, Yang L, Zhu H (2018) Identification of groundwater pollution sources by a SCE-UA algorithm-based simulation/optimization model. Water (Switzerland) 10(2):193, DOI 10.3390/w10020193, URL http://www.mdpi.com/2073-4441/10/2/193

Hwang JC, Koerner RM (1983) Groundwater Pollution Source Identification From Limited Monitoring Data. Part 1 - Theory and Feasibility. Journal of Hazardous Materials 8:105–119

Jamshidi A, Samani JMV, Samani HMV, Zanini A, Tanda MG, Mazaheri M (2020) Solving Inverse Problems of Unknown Contaminant Source in Groundwater-River Integrated Systems Using a Surrogate Transport Model Based Optimization. Water 12(9):2415, DOI 10.3390/w12092415, URL https://www.mdpi.com/2073-4441/12/9/2415

Jha M, Datta B (2013) Three-Dimensional Groundwater Contamination Source Identification Using Adaptive Simulated Annealing. Journal of Hydrologic Engineering 18(3):307–317, DOI 10.1061/(ASCE)HE.1943-5584.0000624, URL http://ascelibrary.org/doi/10.1061/%28ASCE%29HE.1943-5584.0000624

Jha M, Datta B (2015) Application of Unknown Groundwater Pollution Source Release History Estimation Methodology to Distributed Sources Incorporating Surface-Groundwater Interactions. Environmental Forensics 16(2):143–162, DOI 10.1080/15275922.2015.1023385, URL http://www.tandfonline.com/doi/full/10.1080/15275922.2015.1023385

Jha MK, Datta B (2011) Simulated annealing based simulation-optimization approach for identification of unknown contaminant sources in groundwater aquifers. Desalination and Water Treatment 32(1-3):79–85, DOI 10.5004/dwt.2011.2681, URL http://www.tandfonline.com/doi/abs/10.5004/dwt.2011.2681

Jha MK, Datta B (2014) Linked Simulation-Optimization based Dedicated Monitoring Network Design for Unknown Pollutant Source Identification using Dynamic Time Warping Distance. Water Resources Management 28(12):4161–4182, DOI 10.1007/s11269-014-0737-5, URL http://link.springer.com/10.1007/s11269-014-0737-5

Jiang S, Fan J, Xia X, Li X, Zhang R (2018) An effective Kalman filter-based method for groundwater pollution source identification and plume morphology characterization. Water (Switzerland) 10(8):1063, DOI 10.3390/w10081063, URL http://www.mdpi.com/2073-4441/10/8/1063

Jiang S, Liu J, Xia X, Wang Z, Cheng L, Li X (2021) Simultaneous identification of contaminant sources and hydraulic conductivity field by combining geostatistics method with self-organizing maps algorithm. Journal of Contaminant Hydrology 241:103815, DOI 10.1016/j.jconhyd.2021.103815, URL https://linkinghub.elsevier.com/retrieve/pii/S0169772221000541

Jiao J, Zhang Y, Wang L (2019) A new inverse method for contaminant source identification under unknown solute transport boundary conditions. Journal of Hydrology 577:123911, DOI 10.1016/j.jhydrol.2019.123911, URL https://linkinghub.elsevier.com/retrieve/pii/S0022169419306316

Jin X, Mahinthakumar GK, Zechman EM, Ranjithan RS (2009) A genetic algorithm-based procedure for 3D source identification at the Borden emplacement site. Journal of Hydroinformatics 11(1):51–64, DOI 10.2166/hydro.2009.002, URL https://linkinghub.elsevier.com/retrieve/pii/S0022169409004053https://iwaponline.com/jh/article/11/1/51/30998/A-genetic-algorithmbased-procedure-for-3D-source

Jin X, Ranjithan RS, Mahinthakumar GK (2014) A Monitoring Network Design Procedure for Three-Dimensional (3D) Groundwater Contaminant Source Identification. Environmental Forensics 15(1):78–96, DOI 10.1080/15275922.2013.873095, URL http://www.tandfonline.com/doi/abs/10.1080/15275922.2013.873095

Kang X, Kokkinaki A, Kitanidis P, Shi X, Revil A, Lee J, Soueid Ahmed A, Wu J (2020) Improved characterization of DNAPL source zones via sequential hydrogeophysical inversion of hydraulic-head, self-potential and partitioning-tracer data. Water Resources Research pp 1–26, DOI 10.1029/2020WR027627

Koch J, Nowak W (2016) Identification of contaminant source architectures-A statistical inversion that emulates multiphase physics in a computationally practicable manner. Water Resources Research 52(2):1009–1025, DOI 10.1002/2015WR017894, URL http://doi.wiley.com/10.1002/2015WR017894

Konikow LF, Bredehoeft JD (1978) Computer model of two-dimensional solute transport and dispersion in ground water, vol 7. US Government Printing Office Washington, DC

Konikow LF, Hornberger GZ (2006) Use of the multi-node well (mnw) package when simulating solute transport with the modflow ground-water transport process. Tech. rep., US Geological Survey

Li J, Lu W, Wang H, Fan Y (2019) Identification of groundwater contamination sources using a statistical algorithm based on an improved Kalman filter and simulation optimization. Hydrogeology Journal 27(8), DOI 10.1007/s10040-019-02030-y

Li J, Lu W, Wang H, Fan Y, Chang Z (2020) Groundwater contamination source identification based on a hybrid particle swarm optimization-extreme learning machine. Journal of Hydrology 584(February):124657, DOI 10.1016/j.jhydrol.2020.124657, URL https://doi.org/10.1016/j.jhydrol.2020.124657

Li L, Zhou H, Franssen H, Gómez-Hernández J (2011a) Groundwater flow inverse modeling in non-multigaussian media: performance assessment of the normal-score ensemble kalman filter. Hydrol Earth Syst Sci Discuss 8(4):6749–6788

Li L, Zhou H, Gómez-Hernández JJ (2011b) A comparative study of three-dimensional hydraulic conductivity upscaling at the macro-dispersion experiment (made) site, columbus air force base, mississippi (usa). Journal of Hydrology 404(3-4):278–293

Li L, Zhou H, Gómez-Hernández J, Hendricks Franssen H (2012) Jointly mapping hydraulic conductivity and porosity by assimilating concentration data via ensemble kalman filter. Journal of Hydrology

Li Z, zhong Mao X (2011) Global multiquadric collocation method for groundwater contaminant source identification. Environmental Modelling and Software DOI 10.1016/j.envsoft.2011.07.010

Liu C, Ball WP (1999) Application of inverse methods to contaminant source identification from aquitard diffusion profiles at Dover AFB, Delaware. Water Resources Research 35(7):1975–1985, DOI 10.1029/1999WR900092

Liu Jb, Jiang Sm, Zhou Nq, Cai Y, Cheng L, Wang Zy (2021) Groundwater contaminant source identification based on. Journal of Groundwater Science and Engineering 9(1):73–82, DOI 10.19637/j.cnki.2305-7068.2021.01.007

Liu X, Zhai Z (2007) Inverse modeling methods for indoor airborne pollutant tracking: Literature review and fundamentals. Indoor Air 17(6):419–438, DOI 10.1111/j.1600-0668.2007.00497.x

Liu X, Zhai Z (2009) Prompt tracking of indoor airborne contaminant source location with probability-based inverse multi-zone modeling. Building and Environment 44(6):1135–1143, DOI 10.1016/j.buildenv.2008.08.004, URL http://dx.doi.org/10.1016/j.buildenv.2008.08.004

Long YQ, Cui TT, Li W, Yang ZP, Gai YW (2017) Sensitivity analysis of geostatistical approach to recover pollution source release history in groundwater Sensitivity analysis of geostatistical approach to recover pollu-tion source release history in groundwater. IOP Conf Ser: Earth Environ Sci 81:12105, DOI 10.1088/1755-1315/81/1/012105, URL https://iopscience.iop.org/article/10.1088/1755-1315/81/1/012105/pdf

Lu W, Wang H, Li J (2020) Parallel heuristic search strategy based on a Bayesian approach for simultaneous recognition of contaminant sources and aquifer parameters at DNAPL-contaminated sites. Environmental Science and Pollution Research

Macdonald JR (1995) Solution of an "impossible" diffusion-inversion problem. Computers in Physics 9(5):546, DOI 10.1063/1.168551, URL http://scitation.aip.org/content/aip/journal/cip/9/5/10.1063/1.168551

Mahar PS, Datta B (1997) Optimal Monitoring Network and Ground-Water–Pollution Source Identification. Journal of Water Resources Planning and Management 123(4):199–207, DOI 10.1061/(ASCE)0733-9496(1997)123:4(199), URL http://ascelibrary.org/doi/10.1061/%28ASCE%290733-9496%281997%29123%3A4%28199%29

Mahar PS, Datta B (2000) Identification of pollution sources in transient groundwatersystems. Water Resources Management 14(3):209–227, DOI 10.1023/A:1026527901213

Mahar PS, Datta B (2001) Optimal Identification of Ground-Water Pollution Sources and Parameter Estimation. Journal of Water Resources Planning and Management 127(1):20–29, DOI 10.1061/(asce)0733-9496(2001)127:1(20)

Mahinthakumar GK, Sayeed M (2005) Hybrid Genetic Algorithm-Local Search Methods for Solving Groundwater Source Identification Inverse Problems. Journal of Water Resources Planning and Management 131(1):45–57, DOI 10.1061/(asce)0733-9496(2005)

131:1(45)
Mahinthakumar GK, Sayeed M (2006) Reconstructing Groundwater Source Release Histories Using Hybrid Optimization Approaches. Environmental Forensics 7(1):45–54, DOI 10.1080/15275920500506774, URL http://www.tandfonline.com/doi/abs/10.1080/15275920500506774
McDonald MG, Harbaugh AW (1984) A modular three-dimensional finite-difference groundwater flow model. Open-file report 83-875, U.S. Geological Survey
Michalak AM, Kitanidis PK (2002) Application of Bayesian inference methods to inverse modelling for contaminants source identification at Gloucester Landfill, Canada. In: Computational methods in water resources - Proceedings of the XIVth International Conference on Computational Methods in Water Resources (CMWR XIV) - Volume 2, Elsevier, pp 1259–1266
Michalak AM, Kitanidis PK (2003) A method for enforcing parameter nonnegativity in Bayesian inverse problems with an application to contaminant source identification. Water Resources Research 39(2):1–14, DOI 10.1029/2002WR001480
Michalak AM, Kitanidis PK (2004a) Application of geostatistical inverse modeling to contaminant source identification at Dover AFB, Delaware. Journal of Hydraulic Research 42(EXTRA ISSUE):9–18, DOI 10.1080/00221680409500042
Michalak AM, Kitanidis PK (2004b) Estimation of historical groundwater contaminant distribution using the adjoint state method applied to geostatistical inverse modeling. Water Resources Research 40(8), DOI 10.1029/2004WR003214
Milnes E, Perrochet P (2007) Simultaneous identification of a single pollution point-source location and contamination time under known flow field conditions. Advances in Water Resources 30(12):2439–2446, DOI 10.1016/j.advwatres.2007.05.013
Mirghani BY, Mahinthakumar KG, Tryby ME, Ranjithan RS, Zechman EM (2009) A parallel evolutionary strategy based simulation-optimization approach for solving groundwater source identification problems. Advances in Water Resources 32(9):1373–1385, DOI 10.1016/j.advwatres.2009.06.001, URL http://dx.doi.org/10.1016/j.advwatres.2009.06.001
Mo S, Zabaras N, Shi X, Wu J (2019) Deep Autoregressive Neural Networks for High-Dimensional Inverse Problems in Groundwater Contaminant Source Identification. Water Resources Research DOI 10.1029/2018WR024638, 1812.09444
Morrison RD (2000) Application of Forensic Techniques for Age Dating and Source Identification in Environmental Litigation. Environmental Forensics 1(3):131–153, DOI 10.1006/enfo.2000.0015, URL http://www.tandfonline.com/doi/abs/10.1006/enfo.2000.0015
Neupauer RM, Lin R (2006) Identifying sources of a conservative groundwater contaminant using backward probabilities conditioned on measured concentrations. Water Resources Research 42(3):1–13, DOI 10.1029/2005WR004115
Neupauer RM, Wilson JL (1999) Adjoint method for obtaining backward-in-time location and travel time probabilities of a conservative groundwater contaminant. Water Resources Research 35(11):3389–3398, DOI 10.1029/1999WR900190
Neupauer RM, Borchers B, Wilson JL (2000) Comparison of inverse methods for reconstructing the release history of a groundwater contamination source. Water Resources Research 36(9):2469–2475, DOI 10.1029/2000WR900176
Newman MA, Hatfield K, Hayworth J, Rao PSC, Stauffer T (2006) Inverse Characterization of NAPL Source Zones. Environmental Science & Technology 40(19):6044–6050, DOI 10.1021/es060437s, URL https://pubs.acs.org/doi/10.1021/es060437s
Ngamsritrakul T, Ruangrassamee P, Putthividhya A (2015) Backward Probabilistic Model for Contaminant Source Identification in Thailand. In: World Environmental and Water Resources Congress 2015, American Society of Civil Engineers, Reston, VA, pp 475–485, DOI 10.1061/9780784479162.043, URL http://ascelibrary.org/doi/10.1061/9780784479162.043
Onyari E, Taigbenu A (2017) Inverse Green element evaluation of source strength and concentration in groundwater contaminant transport. Journal of Hydroinformatics 19(1):81–96, DOI 10.2166/hydro.2016.028, URL https://iwaponline.com/jh/article/19/1/81/3526/Inverse-Green-element-evaluation-of-source

Pollock DW (1994) User's Guide for MODPATH/MODPATH-PLOT, Version 3: A Particle Tracking Post-processing Package for MODFLOW, the US: Geological Survey Finite-difference Ground-water Flow Model

Prakash O, Datta B (2015) Optimal characterization of pollutant sources in contaminated aquifers by integrating sequential-monitoring-network design and source identification: methodology and an application in Australia. Hydrogeology Journal 23(6):1089–1107, DOI 10.1007/s10040-015-1292-8, URL http://link.springer.com/10.1007/s10040-015-1292-8

Rajeev Gandhi BG, Bhattacharjya RK, Satish MG (2017) Simulation–Optimization-Based Virus Source Identification Model for 3D Unconfined Aquifer Considering Source Locations and Number as Variable. Journal of Hazardous, Toxic, and Radioactive Waste 21(2):04016019, DOI 10.1061/(ASCE)HZ.2153-5515.0000334, URL http://ascelibrary.org/doi/10.1061/%28ASCE%29HZ.2153-5515.0000334

Rossman LA, et al. (2000) Epanet 2 users manual, us environmental protection agency. Water Supply and Water Resources Division, National Risk Management Research Laboratory, Cincinnati, OH 45268

Sciortino A, Harmon TC, Yeh WW (2000) Inverse modeling for locating dense nonaqueous pools in groundwater under steady flow conditions. Water Resources Research 36(7):1723–1735, DOI 10.1029/2000WR900047

Seibert P, Stohl A (1999) Inverse modelling of the ETEX-1 release with a Lagrangian particle model. In: Third GLOREAM Workshop

Sidauruk P, Cheng AH, Ouazar D (1998) Ground water contaminant source and transport parameter identification by correlation coefficient optimization. DOI 10.1111/j.1745-6584.1998.tb01085.x

Singh RM, Datta B (2004) Groundwater pollution source identification and simultaneous parameter estimation using pattern matching by artificial neural network. Environmental Forensics 5(3):143–153, DOI 10.1080/15275920490495873

Singh RM, Datta B (2006) Identification of Groundwater Pollution Sources Using GA-based Linked Simulation Optimization Model. Journal of Hydrologic Engineering 11(2):101–109, DOI 10.1061/(ASCE)1084-0699(2006)11:2(101), URL http://ascelibrary.org/doi/10.1061/%28ASCE%291084-0699%282006%2911%3A2%28101%29

Singh RM, Datta B, Jain A (2004) Identification of Unknown Groundwater Pollution Sources Using Artificial Neural Networks. Journal of Water Resources Planning and Management 130(6):506–514, DOI 10.1061/(ASCE)0733-9496(2004)130:6(506), URL http://ascelibrary.org/doi/10.1061/%28ASCE%290733-9496%282004%29130%3A6%28506%29

Skaggs TH, Kabala ZJ (1994) Recovering the release history of a groundwater contaminant. Water Resources Research 30(1):71–79, DOI 10.1029/93WR02656, URL http://doi.wiley.com/10.1029/93WR02656

Skaggs TH, Kabala ZJ (1995) Recovering the History of a Groundwater Contaminant Plume: Method of Quasi-Reversibility. Water Resources Research 31(11):2669–2673, DOI 10.1029/95WR02383, URL http://doi.wiley.com/10.1029/95WR02383

Skaggs TH, Kabala ZJ (1998) Limitations in recovering the history of a groundwater contaminant plume. Journal of Contaminant Hydrology 33(3-4):347–359, DOI 10.1016/S0169-7722(98)00078-3

Snodgrass MF, Kitanidis PK (1997) A geostatistical approach to contaminant source identification. Water Resources Research 33(4):537–546, DOI 10.1029/96WR03753

Sohn M, Reynolds P, Gadgil A, Sextro R (2002a) Rapidly locating sources and predicting contaminant dispersion in buildings. In: Proceedings ofthe Indoor Air 2002 Conference, vol 2002, pp 211–216, URL http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Rapidly+locating+sources+and+predicting+contaminant+dispersion+in+buildings#0

Sohn MD, Reynolds P, Singh N, Gadgil AJ (2002b) Rapidly locating and characterizing pollutant releases in buildings. Journal of the Air and Waste Management Association 52(12):1422–1432, DOI 10.1080/10473289.2002.10470869

Sonnenborg TO, Engesgaard P, Rosbjerg D (1996) Contaminant transport at a waste residue deposit. 1. Inverse flow and nonreactive transport modeling. Water Resources Research 32(4):925–938, DOI 10.1029/95WR03823

Srivastava D, Singh RM (2014) Breakthrough Curves Characterization and Identification of an Unknown Pollution Source in Groundwater System Using an Artificial Neural Network (ANN). Environmental Forensics 15(2):175–189, DOI 10.1080/15275922.2014.890142, URL http://www.tandfonline.com/doi/abs/10.1080/15275922.2014.890142

Srivastava D, Singh RM (2015) Groundwater System Modeling for Simultaneous Identification of Pollution Sources and Parameters with Uncertainty Characterization. Water Resources Management 29(13):4607–4627, DOI 10.1007/s11269-015-1078-8, URL http://link.springer.com/10.1007/s11269-015-1078-8

Stanev VG, Iliev FL, Hansen S, Vesselinov VV, Alexandrov BS (2018) Identification of release sources in advection–diffusion system by machine learning combined with Green's function inverse method. Applied Mathematical Modelling 60:64–76, DOI 10.1016/J.APM.2018.03.006, URL https://www.sciencedirect.com/science/article/pii/S0307904X18301227

Sun AY (2007) A robust geostatistical approach to contaminant source identification. Water Resources Research 43(2):1–12, DOI 10.1029/2006WR005106

Sun AY (2008) CONSID: A toolbox for contaminant source identification. Ground Water DOI 10.1111/j.1745-6584.2008.00434.x

Sun AY, Painter SL, Wittmeyer GW (2006a) A constrained robust least squares approach for contaminant release history identification. Water Resources Research 42(4):1–13, DOI 10.1029/2005WR004312

Sun AY, Painter SL, Wittmeyer GW (2006b) A robust approach for iterative contaminant source location and release history recovery. Journal of Contaminant Hydrology 88(3-4):181–196, DOI 10.1016/j.jconhyd.2006.06.006

Tarantola A (2005) Inverse problem theory and methods for model parameter estimation. SIAM

Telci IT, Aral MM (2011) Contaminant Source Location Identification in River Networks Using Water Quality Monitoring Systems for Exposure Analysis. Water Quality, Exposure and Health 2(3-4):205–218, DOI 10.1007/s12403-011-0039-6

Todaro V, D'Oria M, Tanda MG, Gómez-Hernández JJ (2021) Ensemble smoother with multiple data assimilation to simultaneously estimate the source location and the release history of a contaminant spill in an aquifer. Journal of Hydrology 598:126215, DOI 10.1016/j.jhydrol.2021.126215, URL https://linkinghub.elsevier.com/retrieve/pii/S0022169421002626

Vesselinov VV, Alexandrov BS, O'Malley D (2018) Contaminant source identification using semi-supervised machine learning. Journal of Contaminant Hydrology 212:134–142, DOI 10.1016/J.JCONHYD.2017.11.002, URL https://www.sciencedirect.com/science/article/pii/S0169772217301201

Vesselinov VV, Alexandrov BS, O'Malley D (2019) Nonnegative tensor factorization for contaminant source identification. Journal of Contaminant Hydrology 220:66–97, DOI 10.1016/j.jconhyd.2018.11.010, URL https://linkinghub.elsevier.com/retrieve/pii/S0169772218300809

Voss CI (1984) Sutra (saturated-unsaturated transport). a finite-element simulation model for saturated-unsaturated, fluid-density-dependent ground-water flow with energy transport or chemically-reactive single-species solute transport. Tech. rep., Geological Survey Reston Va Water Resources Div

Wagner BJ (1992) Simultaneous parameter estimation and contaminant source characterization for coupled groundwater flow and contaminant transport modelling. Journal of Hydrology 135(1-4):275–303, DOI 10.1016/0022-1694(92)90092-A

Wang H, Jin X (2013) Characterization of groundwater contaminant source using Bayesian method. Stochastic Environmental Research and Risk Assessment 27(4):867–876, DOI 10.1007/s00477-012-0622-9

Wang H, Lu W (2020) Recognizing groundwater DNAPL contaminant source and aquifer parameters using parallel heuristic search strategy based on Bayesian approach. Stochastic Environmental Research and Risk Assessment DOI 10.1007/s00477-020-01909-7, URL http://link.springer.com/10.1007/s00477-020-01909-7

Wang H, Lu W, Chang Z, Li J (2020) Heuristic search strategy based on probabilistic and geostatistical simulation approach for simultaneous identification of groundwater contaminant source and simulation model parameters. Stochastic Environmen-

tal Research and Risk Assessment 1, DOI 10.1007/s00477-020-01804-1, URL https://doi.org/10.1007/s00477-020-01804-1
Wang H, Lu W, Chang Z (2021a) An iterative updating heuristic search strategy for groundwater contamination source identification based on an ACPSO–ELM surrogate system. Stochastic Environmental Research and Risk Assessment 2, DOI 10.1007/s00477-021-01994-2, URL https://doi.org/10.1007/s00477-021-01994-2http://link.springer.com/10.1007/s00477-021-01994-2
Wang H, Lu W, Chang Z (2021b) Simultaneous identification of groundwater contamination source and aquifer parameters with a new weighted–average wavelet variable–threshold denoising method. Environmental Science and Pollution Research DOI 10.1007/s11356-021-12959-x, URL http://link.springer.com/10.1007/s11356-021-12959-x
Wang J, Zabaras N (2006) A Markov random field model of contamination source identification in porous media flow. International Journal of Heat and Mass Transfer 49(5-6):939–950, DOI 10.1016/j.ijheatmasstransfer.2005.09.016
Wang X, Zhang D (2021) Inverse identification of multiple contaminant sources and pollution states using future spatial-temporal information. Journal of Cleaner Production 289:125790, DOI 10.1016/j.jclepro.2021.125790, URL https://doi.org/10.1016/j.jclepro.2021.125790https://linkinghub.elsevier.com/retrieve/pii/S095965262100010X
Wasilkowski GW, Wozniakowski H (1995) Explicit cost bounds of algorithms for multivariate tensor product problems. Journal of Complexity 11(1):1–56
Wilson JL, Liu J (1994) Backward tracking to find the source of pollution. Water Manage Risk Remediation 1:181–199
Woodbury A, Sudicky E, Ulrych TJ, Ludwig R (1998) Three-dimensional plume source reconstruction using minimum relative entropy inversion. Journal of Contaminant Hydrology 32(1-2):131–158, DOI 10.1016/S0169-7722(97)00088-0
Woodbury AD, Ferguson G (2006) Ground surface paleotemperature reconstruction using information measures and empirical bayes. Geophysical research letters 33(6)
Woodbury AD, Ulrych TJ (1996) Minimum Relative Entropy Inversion: Theory and Application to Recovering the Release History of a Groundwater Contaminant. Water Resources Research 32(9):2671–2681, DOI 10.1029/95WR03818, URL http://doi.wiley.com/10.1029/95WR03818
Xia X, Jiang S, Zhou N, Li X, Wang L (2019a) Genetic algorithm hyper-parameter optimization using taguchi design for groundwater pollution source identification. Water Science and Technology: Water Supply 19(1), DOI 10.2166/ws.2018.059
Xia X, Zhou N, Wang L, Li X, Jiang S (2019b) Identification of transient contaminant sources in aquifers through a surrogate model based on a modified self-organizing-maps algorithm. Hydrogeology Journal 27(7):2535–2550, DOI 10.1007/s10040-019-02003-1
Xing Z, Qu R, Zhao Y, Fu Q, Ji Y, Lu W (2019) Identifying the release history of a groundwater contaminant source based on an ensemble surrogate model. Journal of Hydrology 572, DOI 10.1016/j.jhydrol.2019.03.020
Xu T, Gómez-Hernández JJ (2016) Joint identification of contaminant source location, initial release time, and initial solute concentration in an aquifer via ensemble Kalman filtering. Water Resources Research 52(8):6587–6595, DOI 10.1002/2016WR019111, URL http://doi.wiley.com/10.1002/2016WR019111
Xu T, Gómez-Hernández JJ (2018) Simultaneous identification of a contaminant source and hydraulic conductivity via the restart normal-score ensemble Kalman filter. Advances in Water Resources 112:106–123, DOI 10.1016/j.advwatres.2017.12.011, URL https://linkinghub.elsevier.com/retrieve/pii/S030917081730756X
Xu T, Gómez-Hernández JJ, Zhou H, Li L (2013a) The power of transient piezometric head data in inverse modeling: An application of the localized normal-score EnKF with covariance inflation in a heterogenous bimodal hydraulic conductivity field. Advances in Water Resources 54:100–118, DOI 10.1016/j.advwatres.2013.01.006, URL http://dx.doi.org/10.1016/j.advwatres.2013.01.006
Xu T, Jaime Gómez-Hernández J, Li L, Zhou H (2013b) Parallelized ensemble kalman filter for hydraulic conductivity characterization. Computers & Geosciences 52:42–49
Yan X, Dong W, An Y, Lu W (2019) A Bayesian-based integrated approach for identifying groundwater contamination sources. Journal of Hydrology 579, DOI 10.1016/j.jhydrol.

2019.124160
Yeh HD, Chang TH, Lin YC (2007) Groundwater contaminant source identification by a hybrid heuristic approach. Water Resources Research 43(9):1–16, DOI 10.1029/2005WR004731
Yeh HD, Lin CC, Yang BJ (2014) Applying hybrid heuristic approach to identify contaminant source information in transient groundwater flow systems. Mathematical Problems in Engineering 2014:1–14, DOI 10.1155/2014/369369
Yeh HD, Lin CC, Chen CF (2016) Reconstructing the release history of a groundwater contaminant based on AT123D. Journal of Hydro-Environment Research 13:89–102, DOI 10.1016/j.jher.2015.06.001, URL https://linkinghub.elsevier.com/retrieve/pii/S1570644315000441
Yuan Y, Liang D (2021) Optimization of Identifying Point Pollution Sources for the Convection-Diffusion-Reaction Equations. Advances in Applied Mathematics and Mechanics 13(1):1–17, DOI 10.4208/aamm.OA-2019-0121
Zanini A, Woodbury AD (2016) Contaminant source reconstruction by empirical Bayes and Akaike's Bayesian Information Criterion. Journal of Contaminant Hydrology 185-186:74–86, DOI 10.1016/j.jconhyd.2016.01.006, URL https://www.sciencedirect.com/science/article/pii/S0169772216300067
Zeng L, Shi L, Zhang D, Wu L (2012) A sparse grid based Bayesian method for contaminant source identification. Advances in Water Resources 37:1–9, DOI 10.1016/j.advwatres.2011.09.011, URL http://dx.doi.org/10.1016/j.advwatres.2011.09.011
Zhang J, Zeng L, Chen C, Chen D, Wu L (2015) Efficient Bayesian experimental design for contaminant source identification. Water Resources Research 51(1):576–598, DOI 10.1002/2014WR015740, URL http://doi.wiley.com/10.1002/2014WR015740
Zhang J, Li W, Zeng L, Wu L (2016a) An adaptive Gaussian process-based method for efficient Bayesian experimental design in groundwater contaminant source identification problems. Water Resources Research 52(8):5971–5984, DOI 10.1002/2016WR018598, URL https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2016WR018598
Zhang J, Zheng Q, Wu L, Zeng L (2020) Using Deep Learning to Improve Ensemble Smoother: Applications to Subsurface Characterization. Water Resources Research 56(12):1–15, DOI 10.1029/2020WR027399, 2002.09100
Zhang S, Liu H, Qiang J, Gao H, Galar D, Lin J (2019) Optimization of Well Position and Sampling Frequency for Groundwater Monitoring and Inverse Identification of Contamination Source Conditions Using Bayes' Theorem. Computer Modeling in Engineering & Sciences 119(2):373–394, DOI 10.32604/cmes.2019.03825, URL http://www.techscience.com/CMES/v119n2/29791
Zhang Y, Meerschaert MM, Neupauer RM (2016b) Backward fractional advection dispersion model for contaminant source prediction. Water Resources Research 52(4):2462–2473, DOI 10.1002/2015WR018515, URL http://doi.wiley.com/10.1002/2015WR018515
Zhang Y, Sun H, Lu B, Garrard R, Neupauer RM (2017) Identify source location and release time for pollutants undergoing super-diffusion and decay: Parameter analysis and model evaluation. Advances in Water Resources 107:517–524, DOI 10.1016/j.advwatres.2017.05.017, URL https://linkinghub.elsevier.com/retrieve/pii/S0309170817301628
Zhao H, Zhang J, Chen H, Wang L, Yang Z (2020a) Localization of Groundwater Contaminant Sources Using Artificially Enhanced Catchment. Water 12(7):1949, DOI 10.3390/w12071949, URL https://www.mdpi.com/2073-4441/12/7/1949
Zhao Y, Lu W, Xiao C (2016) A Kriging surrogate model coupled in simulation-optimization approach for identifying release history of groundwater sources. Journal of Contaminant Hydrology 185-186:51–60, DOI 10.1016/j.jconhyd.2016.01.004, URL https://www.sciencedirect.com/science/article/pii/S0169772216300043
Zhao Y, Qu R, Xing Z, Lu W (2020b) Identifying groundwater contaminant sources based on a KELM surrogate model together with four heuristic optimization algorithms. Advances in Water Resources 138:103540, DOI 10.1016/j.advwatres.2020.103540, URL https://linkinghub.elsevier.com/retrieve/pii/S0309170819309698
Zheng C, Wang PP (1999) MT3DMS: A Modular Three-Dimensional Multispecies Transport Model
Zhou H, Gómez-Hernández JJ, Li L (2014) Inverse methods in hydrogeology: evolution and recent trends. Advances in Water Resources 63:22–37

Zhou Z, Tartakovsky DM (2021) Markov chain monte carlo with neural network surrogates: Application to contaminant source identification. Stochastic Environmental Research and Risk Assessment 35(3):639–651