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Editorial: Application of remote sensing and non-invasive hydrogeophysics to integrated hydrological models

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Editorial on the Research Topic
Application of remote sensing and non-invasive hydrogeophysics to integrated hydrological models

Traditionally, standalone groundwater models have required highly uncertain recharge and groundwater evapotranspiration inputs as driving forces. Such models, together with land surface and unsaturated zone standalone models, are gradually being replaced by integrated hydrological models (IHMs), which dynamically couple surface and groundwater fluxes across the unsaturated zone. Remote sensing (RS) and hydrogeophysics (HG) can provide a wealth of data for IHMs.

As the top boundary of IHMs is at the land surface, satellite RS can contribute to defining: (i) driving force components (precipitation, interception, potential evapotranspiration); (ii) model boundaries and terrain slopes, constraining surface runoff through digital elevation model (DEM); (iii) parametrization of spatial infiltration through soil type and texture; (iv) stages of surface water bodies applied either as boundary condition or as observations to constrain state variables in model calibration and data assimilation; (v) actual evapotranspiration and soil moisture applied as observations to constrain state variables in model calibration and data assimilation; and (vi) changes in terrestrial water storage (TWS) from GRACE satellite data (Humphrey et al., 2023), applied to validate mesoscale models or to constrain their calibration and data assimilation.

Satellite RS data have many advantages such as: (i) readily-available, internet-provided RS products, which do not require specialized RS knowledge; (ii) spatio-temporal formats easily adaptable to IHMs; and (iii) they are archived so their time-series are particularly suitable for transient IHMs. The main disadvantages of RS products are: (i) their uncertainty, which however, is continuously reduced through better sensors, systematically increasing spatial and temporal resolutions and through bias-correction applying ground measurements, e.g. Gebremedhin et al. (2021) and Gebremedhin et al. (2022); (ii) still limited spatial resolution; currently, only some selected satellite missions (e.g., IKONOS, WorldView) can provide very high-resolution data (in order of 1 m or better), but most of these are commercial; (iii) limited depth-penetration, restricted to very shallow subsurface of a few centimeters only; the exception is the GRACE mission, which provides a depth-integrated gravity signal from large depth, to assess the change of TWS, but with a nominal resolution of $3^\circ \times 3^\circ$, so it is suitable for large-mesoscale models only.

Very high spatial resolution and large depth penetration data can be obtained from different HG data acquisition platforms: (i) airborne HG, i.e. piloted aircraft; (ii) drone-borne HG, i.e. remotely controlled drones; and (iii) surface HG surveys. Airborne and drone-borne HG can obtain data from similar sensors as used in satellite RS, but also by applying certain hydrogeophysical techniques such as electromagnetic and ground penetrating radar. However, all the non-invasive HG methods (Rubin and Hubbard, 2005) are still available only from the surface HG surveys. As HG is capable of identifying subsurface heterogeneities, considering the required input for IHM, HG is particularly suitable for: (i) acquisition of surface and shallow subsurface imaging with the same types of sensors as onboard of satellites, but providing higher resolution and instantaneously; (ii) hydro-stratification (all HG methods); (iii) identification of fractures and faults (all electrical methods and seismic reflection); (iv) assessment of salinity distribution (all electrical methods but mainly the electromagnetic method); and (v) hydraulic system parameterization (only magnetic resonance sounding method). The main disadvantages of airborne and drone-borne HG are: (i) high cost of campaigns; (ii) low spatial efficiency due to relatively small footprint (but high resolution); (iii) low temporal efficiency due to the lack of time series archives (as in satellite RS); and (iv) requirement of specialized knowledge and cumbersome data processing. The main disadvantage of surface HG surveys is the lowest spatial efficiency (but the highest resolution) among the presented methods.

In this Research Topic, four different studies are presented by Cooley et al., Gelsinari et al., Francés and Lubczynski, and Van Riet et al..

Francés and Lubczynski propose a novel, two-way coupled, distributed, MARMITES-MODFLOW (MM-MF) code, which couples the land surface, soil and saturated zone, providing an original, quantitative partitioning and sourcing of evapotranspiration (ET). The MARMITES partitioning of ET, i.e., its separation into rainfall interception loss (E_I, estimated by a Gash model), evaporation from subsurface (E) and transpiration (T), was designed to integrate satellite remote sensing data easily. The MM-MF sourcing of E and T involves the separation of each of the two processes into soil zone (E_{soil} and T_{soil}) and groundwater (Eg and Tg) components. The E sourcing follows Shah et al. (2007), but for T sourcing, a novel phenomenological function was proposed based on soil moisture availability and transpiration demand. The estimation of the sources of T differs from other functions available in the literature and from the one used in MODFLOW. It is driven by climatic conditions and only indirectly by the depth to the water table. The MM-MF IHM was tested for the La Mata catchment (4.8 km^2 Spain). The IHM was set up using a conceptual model after Francés et al. (2014), designed using RS and HG combined with field data acquisition. The calibrated numerical model provided catchment water dynamics and a detailed water balance, including numerical partitioning and sourcing of ET into E_I, E_{soil}, T_{soil}, E_g, and T_g and their comparison with experimental data. With its unique capability of partitioning and sourcing of ET, the MM-MF is particularly suitable for mapping groundwater-dependent ecosystems and analyzing the impacts of climate and land cover changes on groundwater resources.

Gelsinari et al. show that ET can provide an additional constraint on IHM calibration beyond the typically used water table fluctuation point data. They used the UnSat (unsaturated zone and SATellite) conceptual water balance model coupled to MODFLOW 2005 (through the net recharge) to investigate how dependent the ET is on groundwater levels. They calibrated four simple, five-cell models at four silvicultural sites in the Otway and Murray basins in Australia, differing by depth to water table (WT). The remotely-sensed ET estimates were obtained from the CMRSET dataset (Guerschman et al., 2009) based on interpolated climate data and MODIS-Terra surface reflectance, applied to rescale Priestley-Taylor potential ET into actual ET. The sites were modeled under three different data configurations: (1) only WT calibrated; (2) WT and ET calibrated; and (3) ET assimilated through Ensemble Kalman Filter. Large error reduction in ET was obtained in configuration 2, while further improvement with configuration 3 was achieved when the WT was $<$6.5 m. Overall, configuration 3, improved ET and the ensemble predictions of the WT, while slightly worsening the RMSE and values of WT predictions compared to configuration 1.

Cooley et al. used a U-net deep learning model (Saraiva et al., 2020), which applies machine-learning based on artificial neural networks (Schmidhuber, 2014), to locate center pivot irrigation systems (CPIS) throughout the Ogallala Aquifer. They applied Google Earth Engine over cloud-free Landsat 5 and Landsat 7 images. The advantage of the U-net is that it labels each pixel so the model is able to predict CPIS locations reliably. However, the initial results of the simulation were poor so the model was trained on the labels and satellite imagery over Nebraska (part of Ogallala Aquifer) using Google Colab Pro. After validation tests, the CPIS over the Ogallala Aquifer was used to estimate groundwater pumping in Kansas, based on a detailed study by Pfeiffer and Lin (2012). The results were compared with an IHM (1×1 km) of Condon and Maxwell (2019) and indicated a dramatic, almost 3-times difference between the two estimates. Following Cooley et al., the reason was that the Condon and Maxwell (2019) IHM used global (11 km) estimates of pumping after Wada et al. (2010) and aquifer depletion after Konikow (2015), which is thought to have introduced uncertainty in the IHM. The study Cooley et al. postulated that the presented deep learning approach can be used as input for hydrologic and economic models for planning agricultural processes and does not require supercomputers.

Van Riet et al. studied a site in Belgium with four production boreholes and a number of piezometers penetrating a fractured chalk aquifer. Monitored hydraulic heads showed a possible influence of fracture zones upon the distribution of drawdowns. Six electrical resistivity (ERT) profiles with different lengths and in different directions were set up to image fractures. The objective was to predict the average drawdown resulting from pumping the four boreholes. For that purpose, a steady-state, 9-layer groundwater model (not IHM) was set up with varying yearly stress periods, from 2001 before pumping started, to 2017. Different scenarios of the positioning of fracture zones were tested within the area investigated by ERT and outside. The study showed that including fractures detected by ERT improved model calibration and understanding of aquifer hydrogeological behavior.

The use of RS and HG methods in IHMs opens up avenues for novel and conjunctive applications in water-related studies. Earth observation from space provides a range of products that are highly beneficial to constraining uncertainty in IHM input, are freely available online and accessible to non-experts of RS. HG offers complementary techniques that provide subsurface data at higher resolutions and supplies valuable information on system boundaries, hydro-stratification and key parameters. Studies integrating both RS and HG data-acquisition platforms in IHMs are still rare in the literature, but are very promising for making IHMs better and more reliable.

Author contributions

MWL drafted and revised the manuscript. ML and OB revised the manuscript. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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