| Taxonomy Category | Strategy | Reference | Title | From |
|---|---|---|---|---|
| *Pre* | RF with SI | Behrens et al. (2018) | *Spatial modelling with Euclidean distance fields and machine learning* | Q |
| | | Dhara et al. (2018) | *Machine learning based methods for estimation and stochastic simulation* | Q |
| | | Hengl et al. (2018) | *Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables* | S |
| | | Møller et al. (2020) | *Oblique geographic coordinates as covariates for digital soil mapping* | S |
| | | Sekulić et al. (2020) | *Random forest spatial interpolation* | S |
| | | Còrdoba & Balzarini (2021) | *A random forest-based algorithm for data-intensive spatial interpolation in crop yield mapping* | S |
| | | Hu et al. (2022) | *Incorporating spatial autocorrelation into house sale price prediction using random forest model* | Q |
| | | Santiago-Rosario et al. (2022) | *Contrasts among cationic phytochemical landscapes in the southern United States* | Q |
| | | Talebi et al. (2022) | *A truly spatial random forests algorithm for geoscience data analysis and modelling* | Q |
| | RF with FFS | Meyer et al. (2019) | *Importance of spatial predictor variable selection in machine learning applications* | S |
| *Post* | RF-RK | Guo et al. (2015) | *Digital mapping of soil organic matter for rubber plantation at regional scale: an application of random forest plus residuals kriging approach* | S |
| | | Hengl et al. (2015) | *Mapping soil properties of Africa at 250 m resolution: random forests significantly improve current predictions* | S |
| | | Fayad et al. (2016) | *Regional scale rain-forest height mapping using regression-kriging of spaceborne and airborne LiDAR data: application on French Guiana* | S |
| | | Ahmed et al. (2017) | *Assessing soil carbon vulnerability in the Western USA by geospatial modeling of pyrogenic and particulate carbon stocks* | S |
| | | Garcìa-Tomillo et al. (2017) | *Estimating soil organic matter using interpolation methods with a electromagnetic induction sensor and topographic parameters: a case study in a humid region* | Q |
| | | Vaysse & Lagacherie (2017) | *Using quantile regression forest to estimate uncertainty of digital soil mapping products* | S |
| | | dos Reis et al. (2018) | *Spatial prediction of basal area and volume in Eucalyptus stands using Landsat TM data: an assessment of prediction methods* | Q |
| | | Liu et al. (2018) | *Improve ground-level PM2.5 concentration mapping using a random forests-based geostatistical approach* | Q |
| | | Fox et al. (2020) | *Comparing spatial regression to random forests for large environmental data sets* | S |
| | | Còrdoba et al. (2021) | *A spatially based quantile regression forest model for mapping rural land values* | Q |
| | | Paccioretti et al. (2021) | *Statistical models of yield in on-farm precision experimentation* | Q |
| | | Makungwe et al. (2021) | *Performance of linear mixed models and random forests for spatial prediction of soil Ph* | Q |
| | | Mammadov et al. (2021) | *Estimation and mapping of surface soil properties in the Caucasus Mountains, Azerbaijan using high-resolution remote sensing data* | Q |
| | | Szatmàri et al. (2021) | *Estimating soil organic carbon stock change at multiple scales using machine learning and multivariate geostatistics* | Q |
| | | da Silva-Sangoi et al. (2022) | *Soil organic matter and clay predictions by laboratory spectroscopy: data spatial correlation* | Q |
| | | Smith et al. (2022) | *Spatial variability and uncertainty of soil nitrogen across the conterminous United States at different depths* | Q |
| | RF-sGs | Koch et al. (2019) | *Modeling depth of the redox interface at high resolution at national scale using random forest and residual Gaussian simulation* | Q |
| *In-Post* | RF-GLS-RK | Saha et al. (2021) | *Random forests for spatially dependent data* | Q |
| *Pre-Post* | RF-RK with SI | Li et al. (2011) | *Can we improve the spatial predictions of seabed sediments? A case study of spatial interpolation* | S |
| | | Kurina et al. (2019) | *Spatial predictive modelling essential to assess the environmental impacts of herbicides* | Q |
| | RF-RK with SB | Viscarra Rossel et al. (2014) | *Mapping gamma radiation and its uncertainty from weathering products in a Tasmanian landscape with a proximal sensor and random forest kriging* | S |
| | | Szatmàri & Pàsztor (2019) | *Comparison of various uncertainty modelling approaches based on geostatistics and machine learning algorithms* | S |

**Table 1** List of the 32 documents identified through the PRISMA methodology and categorised by the proposed taxonomy (see Figure 5).
Adopted strategy: RF with SI: Random Forest with Spatial Information; RF with FFS: Random Forest with Forward Feature Selection; RF-RK: Random Forest Residual Kriging; RF-sGs: Random Forest sequential Gaussian simulation; RF-RK with SI: Random Forest Residual Kriging with Spatial Information; RF-RK with SB: Random Forest Residual Kriging with Spatial Bootstrap; RF-GLS-RK: Random Forest based on GLS Residual Kriging.
From: Q: query; S: backward snowballing.

study would be desirable. However, this is beyond the purpose of this review and could be considered as future research.

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