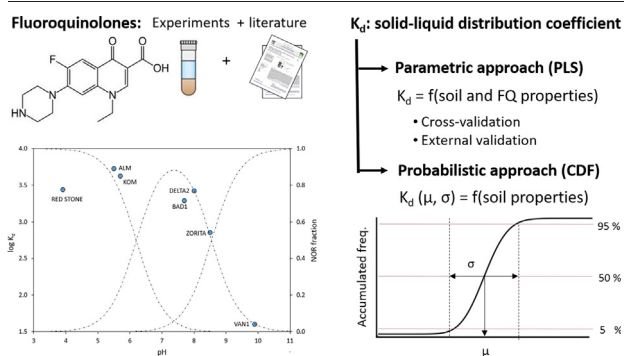


Deriving parametric and probabilistic  $K_d$  values for fluoroquinolones in soilsJoel Fabregat-Palau<sup>a,c</sup>, Zhiqiang Yu<sup>c</sup>, Xiangying Zeng<sup>c</sup>, Miquel Vidal<sup>a</sup>, Anna Rigol<sup>a,b,\*</sup><sup>a</sup> Department of Chemical Engineering and Analytical Chemistry, Universitat de Barcelona (UB), Martí i Franquès 1-11, 08028 Barcelona, Spain<sup>b</sup> Institut de Recerca de l'Aigua (IdRA), Universitat de Barcelona (UB), Martí i Franquès 1-11, 08028 Barcelona, Spain<sup>c</sup> State Key Laboratory of Organic Geochemistry, Guangzhou Institute of Geochemistry, Chinese Academy of Sciences, Wuzhan, Guangdong 510640, People's Republic of China

## HIGHLIGHTS

- Sorption isotherms of NOR in soils were linear at the concentration range tested.
- pH was the main soil factor affecting sorption, which was maximized at pH 5–7.
- Sorption of NOR, CIP, ENR and OFL in soils was statistically comparable.
- The PLS-based model was insufficient to accurately predict  $K_d$  (FQ).
- Best-estimate  $K_d$  values were derived according to soil properties.

## GRAPHICAL ABSTRACT



## ARTICLE INFO

Editor: Jay Gan

**Keywords:**  
 Fluoroquinolones  
 Soils  
 Sorption  
 $K_d$   
 Modelling

## ABSTRACT

The evaluation of the sorption affinity of fluoroquinolone antibiotics (FQs) in soils, by means of the derivation of solid-liquid distribution coefficients ( $K_d$ ), is a valuable information for assessing their environmental mobility. Aiming to develop  $K_d$  (FQ) prediction tools in soils, in the first stage of this study we constructed a  $K_d$  (FQ) sorption dataset using current literature data. Furthermore, additional sorption and desorption data for norfloxacin were obtained in seven different soils of contrasting properties. Sorption isotherms of norfloxacin were linear under the experimental conditions tested and desorption percentages increased for scenarios in which low sorption was noted. Sorption tests in the same soils were then extended to ciprofloxacin, enrofloxacin and ofloxacin and pooled in the dataset, revealing comparable  $K_d$  (FQ) values among the FQ tested after analyzing the overall dataset consisting in 312 entries of  $K_d$  (FQ). A partial least square (PLS) regression model was then developed to predict values of  $K_d$  (FQ) based on specific relevant soil properties (i.e., pH, cation exchange capacity and organic carbon and texture information), and, for the first time, FQ properties (fraction of cationic FQ species) affecting sorption. Additionally, probabilistic,  $K_d$  (FQ) best estimates in soils were derived through cumulative distribution functions (CDFs) for the overall and for partial datasets created by grouping  $K_d$  (FQ) values according to key soil properties affecting FQ sorption (i.e., pH, organic carbon content and texture information). This latter approach permitted to derive more representative  $K_d$  (FQ) best estimates for the soils to be assessed, and with a lower related variability than that derived from the overall dataset. Best estimates  $K_d$  (FQ) values were  $> 1000 \text{ L kg}^{-1}$  for most acidic to neutral soils, suggesting strong sorption, although lower sorption and thus higher environmental mobility may be expected in scenarios with soils with alkaline pH, low OC and high sand contents.

**Synopsis:** This study aims to derive parametric and probabilistic  $K_d$  values for fluoroquinolone antibiotics in soils on the basis of a few relevant soil physicochemical properties.

\* Corresponding author at: Department of Chemical Engineering and Analytical Chemistry, Universitat de Barcelona (UB), Martí i Franquès 1-11, 08028 Barcelona, Spain.  
 E-mail address: [annarigol@ub.edu](mailto:annarigol@ub.edu) (A. Rigol).

## 1. Introduction

FQs have long been prescribed for treating human and animal diseases caused by Gram-positive and Gram-negative pathogens (Andersson and MacGowan, 2003; Van et al., 2020). Due to their widespread use, partial elimination in the organism, and low photo and biodegradation (Girardi et al., 2011; Lin et al., 2018), high levels of FQs have been reported in environmental compartments. Specifically, FQs have been detected at mg kg<sup>-1</sup> levels in animal manure such as chicken droppings, poultry and piggery (Riaz et al., 2018), and the application of manure as a soil amendment is considered an important FQ input pathway in the environment (Picó and Andreu, 2007). Thus, FQs have been detected in soils at levels of up to a few hundred µg kg<sup>-1</sup> (Riaz et al., 2018); these levels may lead to bacterial resistance against these drugs (Van et al., 2020), and thus disrupt the balance of the original ecosystems.

The environmental fate of FQs is mainly controlled by their sorption to soil particles (Chen et al., 2015). Norfloxacin (NOR), ciprofloxacin (CIP) and enrofloxacin (ENR) sorption increases in acidic soils with clay content (Leal et al., 2013), and sorption of ENR in pure clay minerals is mainly controlled by cation exchange interactions at acidic to neutral pH (Wan et al., 2013). The addition of humic acid to soils also increases CIP and ENR sorption at acidic to neutral pH (Teixidó et al., 2014), involving cation exchange, electrostatic and hydrogen-bonding interactions (Martínez-Mejía et al., 2017). Besides, the presence of metal oxides may increase ofloxacin (OFL) sorption at neutral to basic pH through surface complexation mechanisms (Paul et al., 2014), while soluble metals may decrease NOR sorption due to competition for exchangeable sites (Kong et al., 2014).

Due to the multiple mechanisms that may govern FQ sorption, the development of models to predict FQ solid-liquid distribution coefficients (K<sub>d</sub>) based on the soils physicochemical properties as descriptors of these chemical interactions is challenging. In addition, some of the currently available commercial FQs differ slightly in their chemical structure (Van Doorslaer et al., 2014), and it is not yet clear whether their soil sorption can be considered analogous. A few empirical equations aiming to predict K<sub>d</sub> for FQs in soils have been reported. For instance, a set of five equations have been proposed at different pH aiming to predict CIP sorption by multiple linear regressions (MLR) (Vasudevan et al., 2009). However, these equations were developed after forcing CIP sorption in 30 soils at different pH, thus modifying the surface charge of the original soil particles, and they may not be totally representative of real environmental scenarios. In addition, a parametric model aiming to predict NOR sorption was proposed after a partial least square (PLS) regression (Gong et al., 2012). However, the model was not tested against external validation data, and so its predictive effectiveness for other scenarios not contemplated in its construction is unclear. Alternatively, to consider probabilistic tools allowing the derivation of K<sub>d</sub> best estimates with their associated variability through cumulative distribution functions (CDFs) is also of interest (USEPA, 2014). CDFs describe the population and variability of a given property, like K<sub>d</sub> (FQ), and their related accumulated frequency through a continuous function. CDFs have been successfully used to describe K<sub>d</sub> variability and to derive K<sub>d</sub> best estimates of several pollutants after refining datasets according to the key soil properties governing interaction, instead of suggesting an overall K<sub>d</sub> value regardless of soil properties (Ramírez-Guinart et al., 2020a, 2020b, 2020c).

In this study, we aimed to develop tools for the prediction of K<sub>d</sub> (FQ) values in soils. To this end, a literature-based K<sub>d</sub> (FQ) compilation was created. Sorption experiments of four FQs (NOR, CIP, ENR and OFL) in seven soils with contrasting physicochemical properties were additionally carried out. As these latter K<sub>d</sub> (FQ) values were obtained under the same experimental conditions, variability of the data was lower than in literature data and the key soil properties responsible for FQ sorption were confirmed. Our experimental data were then pooled into the dataset, and sorption analogy among FQs in soils was assessed. Then, a PLS prediction model was constructed, and its prediction ability tested against available literature data. Complementary to the PLS model, we derived probabilistic K<sub>d</sub> (FQ) best estimates through CDFs for the overall and partial datasets created

by grouping K<sub>d</sub> (FQ) data according to the most relevant soil properties affecting sorption.

## 2. Materials and methods

### 2.1. Reagents and materials

The antibiotics NOR, CIP, ENR and OFL, all with ≥ 95 % purity, were purchased from Sigma-Aldrich (Germany). Their main FQ physicochemical properties are summarized in Table S1. Milli-Q double deionized water (18.2 MΩ cm<sup>-1</sup>) was obtained from a water purification system (USF PureLaB Plus, Spain). A 1000 mg L<sup>-1</sup> FQ stock solution was prepared in acidified (pH 4) Milli-Q water. HPLC grade methanol, formic acid (>95 %) and NaOH (>95 %) were purchased from Panreac (Spain). The soil samples used in this study were selected to cover a wide range of physicochemical properties, especially pH, cationic exchange capacity (CEC), and organic carbon (OC) and clay contents. The main soil properties are summarized in Table 1, and exchangeable and water-soluble cation contents for Na, K, Ca and Mg are provided in Table S2. Additional soil characterization information can be found in the supporting data (Section S1) and elsewhere (Gil-García et al., 2008; Ramírez-Guinart et al., 2017). The pH of the samples ranged from 3.9 to 9.9, whereas the OC varied from 0.3 % to 41 %. The CEC of the soils ranged from 22 to 185 cmol<sub>c</sub> kg<sup>-1</sup>, and clay content ranged from 0.2 % to 28 %. The sum of water-soluble and exchangeable cations ranged from 0.90 to 9.5 meq L<sup>-1</sup> and from 5.9 to 116 cmol<sub>c</sub> kg<sup>-1</sup>, respectively. DOC contents in the supernatants ranged from 4 to 187 mg C L<sup>-1</sup> and correlated with soil OC (*p* < 0.05).

### 2.2. Batch experiments

Batch experiments were applied to construct sorption isotherms for NOR and to determine K<sub>d</sub> at a single initial concentration for CIP, ENR and OFL (OECD, 2000). Briefly, 25 mL of Milli-Q water were added in 50 mL polypropylene centrifuge tubes containing 1 g of soil. Tubes were shaken in an end-over-end shaker at 30 rpm and room temperature (22–25 °C) for 16 h to reach a pre-equilibrium state. Next, a certain amount of NOR solution was added to achieve a concentration range of 10–80 mg L<sup>-1</sup> (1–8 mg L<sup>-1</sup> for the VAN soil), whereas for CIP, ENR and OFL a concentration of 50 mg L<sup>-1</sup> (5 mg L<sup>-1</sup> for the VAN soil) was used, after ensuring that the selected concentrations fell within the NOR sorption linear range. After the spike, the tubes were shaken again wrapped with aluminum foil. After 48 h, a shaking time identified in previous kinetic studies as sufficiently long to achieve the equilibrium stage (Pan et al., 2012; Peruchi et al., 2015), tubes were centrifuged at 7800 g for 15 min (AJ2-HS, Beckman Coulter, USA), and then the supernatants were filtered through a 0.45 µm filter and analyzed as described in Section 2.3. Desorption experiments were run similarly with the solid residues obtained for the NOR sorption isotherms, after drying the residues at 40 ± 1 °C. It was also anticipated that desorption equilibrium would be reached after 48 h in the light of previous kinetic studies in pure soil components (Martínez-Mejía et al., 2017; Wu et al., 2012). The pH of the resulting sorption and desorption supernatants did not significantly differ (± 0.2) from the soil pH reported in Table 1. Both sorption and desorption experiments were run in triplicate, and quality control samples were run in parallel in each batch. These controls included blank samples, to ensure that no background FQs were present in the soils, and control samples were run without any soil to account for possible losses through the experimental stages. Blank samples revealed that no FQs were in the soils prior to analysis, and control samples revealed null FQ losses during the experimental setup, with recovery rates higher than 95 % for all four FQs and in agreement with previous observations (Leal et al., 2013; Peruchi et al., 2015).

### 2.3. HPLC determination

The HPLC separation conditions were adapted from elsewhere (Teixidó et al., 2014). An Agilent 1200 chromatograph was used for the FQ

**Table 1**  
Physicochemical properties of the soils.

Soil	pH	CEC ( $\text{cmol}_e \text{ kg}^{-1}$ )	OC (%)	Sand (%)	Clay (%)	$\text{Fe}_{\text{amorph}}$ ( $\text{mg kg}^{-1}$ )	$\text{Al}_{\text{amorph}}$ ( $\text{mg kg}^{-1}$ )	$\text{CaCO}_3$ (%)	DOC ( $\text{mg L}^{-1}$ )	$\Sigma$ Ex cations ( $\text{cmol}_e \text{ kg}^{-1}$ )	$\Sigma$ WS cations ( $\text{meq L}^{-1}$ )
RED STONE	3.9	68	9.3	46	6	4420	584	1.3	180	17	0.90
ALM	5.5	23	1.6	54	10	1010	404	2.0	15	5.9	1.6
KOM	5.7	185	41	20	0.2	19,670	481	0.5	187	116	4.5
BAD1	7.7	22	0.9	50	19	580	493	2.0	11	8.3	3.5
DELTA2	8.0	87	7.7	12	28	2970	230	51	39	66	9.5
ZORITA	8.5	27	1.0	41	20	56	118	40	7	11	4.3
VANI	9.9	25	0.3	86	6	238	138	5	4	15	4.1

$\Sigma$  Ex cations: sum of exchangeable Na, K, Ca and Mg concentrations.

$\Sigma$  WS cations: sum of water-soluble Na, K, Ca and Mg concentrations.

determination in both sorption and desorption supernatants, using an isocratic 75:25 0.01 M oxalic acid:methanol mobile phase and a ZORBAX SB-C<sub>18</sub> (5  $\mu\text{m}$ , 4.6  $\times$  250 mm) separation column. Flow rate and injection volume were set at 1  $\text{mL min}^{-1}$  and 10  $\mu\text{L}$  respectively. NOR, CIP, ENR and OFL detection was carried out using a fluorescence detector set at excitation/emission wavelengths of 280/447, 284/449, 284/467 and 298/499 nm respectively. Limits of quantification (LOQ), determined as a signal-to-noise ratio of 10:1, were 0.01  $\text{mg L}^{-1}$  for all FQs. In order to avoid biased results during the HPLC determination due to possible matrix effects (Peruchi et al., 2015), matrix-matched calibration curves were prepared during both sorption and desorption experiments for each soil and FQ pair. Seven-point calibration curves were prepared for each case, and Pearson coefficients rose to 0.99. The quantification precision of 10 consecutive injections of a 0.2  $\text{mg L}^{-1}$  NOR aqueous standard was 3.8 % RSD, whereas the quantification precision of 10 injections of 0.2  $\text{mg L}^{-1}$  NOR aqueous standards on 10 different days was 6.1 % RSD. Similar results were obtained for CIP, ENR and OFL.

#### 2.4. Creation of a sorption dataset

A critically-reviewed dataset was created including batch sorption  $K_d$  data of FQs in soils, subsoils and sediments, all environmental matrices considered as analogues, in addition to ancillary information on physicochemical properties such as pH, OC and mineral contents. The dataset also included information on the experimental conditions in which the batch experiments were carried out. The sorption data obtained in this study for NOR, CIP, ENR and OFL were also included in the dataset. Other geochemical materials (i.e., humic acids and pure oxide and phyllosilicate minerals) were not considered. As levofloxacin (LEV) and OFL are two isomeric FQs, sorption of OFL and LEV was assumed to be analogous and was pooled into OFL data. As only a few sorption data were found for other FQs such as danofloxacin (i.e. Leal et al., 2013; Rath et al., 2019) the final dataset included only entries for NOR, CIP, ENR, OFL.

The dataset had a total of 312 entries, and the list of references used to build up the dataset can be found in Table S3. OC was reported in all entries, and material pH was reported in 295. pH, OC and textural mineral (sand/silt/clay) data were simultaneously available in only 251 entries, which originated from samples that were representative for a wide range of soil texture types according to the United States Department of Agriculture (USDA) classification (see Fig. S1).

#### 2.5. Data treatment and statistical analysis

The sorbed concentration on the solid phase ( $C_s$ ,  $\text{mg kg}^{-1}$ ) was calculated as the difference between the initial spiked concentration ( $C_{\text{in}}$ ,  $\text{mg L}^{-1}$ ) and the FQ concentration determined in solution ( $C_{\text{eq}}$ ,  $\text{mg L}^{-1}$ ), according to Eq. (1):

$$C_s = \frac{(C_{\text{in}} - C_{\text{eq}}) \cdot V}{m} \quad (1)$$

where  $V$  (L) is the total volume of contact solution and  $m$  (kg) refers to the dry mass of soil added.

The solid-liquid distribution coefficient,  $K_d$  ( $\text{L kg}^{-1}$ ), was calculated as follows:

$$K_d = \frac{C_s}{C_{\text{eq}}} \quad (2)$$

Similarly, the concentration remaining in the solid phase after running the desorption experiments ( $C_{s,\text{des}}$ ,  $\text{mg kg}^{-1}$ ) was calculated according to Eq. (3):

$$C_{s,\text{des}} = C_{\text{in,des}} - \frac{C_{\text{eq,des}} \cdot V}{m} \quad (3)$$

where  $C_{\text{eq,des}}$  ( $\text{mg L}^{-1}$ ) is the FQ concentration in the solid and aqueous phases after desorption experiments, whereas  $C_{\text{in,des}}$  ( $\text{mg kg}^{-1}$ ) is the sorbed concentration in the solid phase before running the desorption experiments. Thus,  $C_{\text{in,des}}$  is  $C_s$  corrected by the amount of FQ present in the residual volume of solution ( $V_{\text{res}}$ ,  $\text{L}^{-1}$ ) removed after drying the residues of the sorption experiments:

$$C_{\text{in,des}} = C_s + \frac{C_{\text{eq}} \cdot V_{\text{res}}}{m} \quad (4)$$

Desorption yield was calculated as:

$$\%D = \frac{C_{\text{eq,des}} \cdot V}{C_{\text{in,des}} \cdot m} \cdot 100 \quad (5)$$

The experimental data obtained after the isotherm experiments were fitted to a linear equation (Eq. (2)). The sorption data for NOR, CIP, ENR and OFL for our own experiments were compared by a two-way ANOVA with replicates at  $\alpha = 0.05$ , whereas the sorption data derived from the literature dataset were examined by classifying  $\log K_d$  values in box and whisker plots, setting a threshold of three times the interquartile range to identify whether a given value was an outlier, and the Fisher Least Significant Differences (FLSD) test was run at  $\alpha = 0.05$  (Statgraphics Technologies, USA) for statistical comparison of FQ populations.

#### 2.6. Development of a PLS prediction model

Partial least squares (PLS) is a multivariate regression method that builds a model for predictive purposes in a low-dimensional space formed by Latent Variables (LVs). PLS can also be used to determine which variables are more important for correlating with the Y property, here  $K_d$  (FQ), by checking certain indexes such as the Variable Importance in Projection (VIP). In addition, the influence plot allows the identification of samples with extreme properties for the model (those with a high Hotelling  $T^2$  value) or samples with a high error between observed and predicted  $K_d$  (those with a high Q residual value). The PLS regression was run using Matlab (PLS Toolbox703, Matlab® R2009a (MathWorks 181 Inc., USA)),

and all data were  $\log_{10}$  transformed (with the exception of pH) and autoscaled prior to running the PLS analysis.

Aiming to construct the model only with those soil and FQ physicochemical properties significantly affecting sorption (identified by the VIP scores of each property), we considered only those entries of the overall dataset in which reported  $K_d$  values were informed with all pH, soil texture, CEC, OC and Fe contents. Other properties that may also affect sorption (i.e., DOC content, total amount and nature of exchangeable cations or soluble cations present at equilibrium) could not be considered due to the lack of quantitative information on these properties in the dataset. For building up the PLS model we also considered the fraction of each FQ species at a given pH. This was calculated as described elsewhere (Septian et al., 2018). To further refine the calibration dataset, after confirming the sorption analogy of the tested FQs, only the  $K_d$  value of a one single representative FQ was kept when  $K_d$  (FQ) of various FQs were reported. Only in a few cases,  $K_d$  values for different FQs obtained in the same soil were accepted in the calibration matrix for those soils with extreme values for soil properties (e.g., pH and OC) in order to improve the calibration set. The resulting calibration set comprised only 80 soils and 92 entries, although still representative for a wide range of scenarios (Table S4).

The samples selected for the calibration set had pH and OC values ranging from 3.2 to 9.9 and from 0.04 to 41 % respectively. Besides, sand, silt and clay percentages, all of them referring to the bulk soil, ranged 1.0–92, 1.8–72 and 0.04–60 respectively. Soil CEC ranged 0.98–218  $\text{cmol}_c \text{kg}^{-1}$ , whereas Fe contents ranged 0.01–364  $\text{g kg}^{-1}$ . The histograms of the selected properties revealed a good distribution of their values within the calibration set (Fig. S2). The quality of the model was analyzed through both cross-validation (using the venetian blind method with 10 data splits) and external validation. The external validation dataset included data from the overall dataset not considered in the calibration set and with available information on the physicochemical variables used in the PLS model (Table S5). The external validation set comprised 59 soils, with a total of 89  $K_d$  (FQ) entries. The samples in this external validation set had pH, OC, sand and CEC values ranging 4.1–8.7, 0.21–11 %, 6.5–92 % and 1.9–190  $\text{cmol}_c \text{kg}^{-1}$  respectively, and fell within the variable ranges contemplated in the calibration set (Fig. S2). Quantitative parameters for estimating prediction quality were calculated as described in Section S4.

## 2.7. Construction of cumulative distribution functions (CDFs)

Since  $K_d$  is a ratio between concentrations (see Eq. 2),  $K_d$  data are expected to follow a  $\log_{10}$  normal distribution (Sheppard, 2011). Therefore, the statistical parameters describing a symmetrical log  $K_d$  distribution are the location parameter ( $\mu$ ), considered as the most probable log  $K_d$  value corresponding to the 50th percentile (which permits derivation of the best estimate of a  $K_d$  population), and the scale parameter ( $\sigma$ ), which gives an estimation of the variability of log  $K_d$  values.

The log  $K_d$  data within each dataset were sorted by increasing value and an empirical frequency ( $f_{\text{exp},i}$ ) equal to  $1/N$  (where  $N$  is the total number of entries) was assigned to each entry. Experimental cumulative frequency distribution was constructed by assigning to each sorted log  $K_d$  value its corresponding cumulative frequency ( $F_{\text{exp},i}$ ), i.e. the sum of the preceding frequencies ( $F(K_{d,j}) = \sum_{i=0}^j f(K_{d,i})$ ). The Kolmogorov-Smirnov test was applied to ensure the lognormal distribution of each resulting CDF, and then these were fitted to the theoretical normal CDF equation (Eq. (6)) using the *cftool* toolbox of Matlab (Matlab® R2009a (MathWorks Inc., USA)):

$$P(\log K_{d,i} \leq \log K_{d,j}) = \sum_{\log K_{d,i} \leq \log K_{d,j}} p(\log K_{d,i}) \quad (6)$$

$$= \frac{1}{2} + \frac{1}{2} \operatorname{erf}\left(\frac{\log(K_{d,i}) - \mu}{\sigma \sqrt{2}}\right); K_{d,i} > 0$$

where  $P$  is the cumulative probability,  $\operatorname{erf}$  is the error function, and subscripts  $i$  and  $j$  represent two different  $K_d$  values in the ranked grouping (Ramírez-

Guinart et al., 2020a). The fitting function permitted to calculate  $K_d$  best estimate (BE), which is the antilog of  $\mu$ , and related variability, expressed as a geometric standard deviation (GSD), as the antilog of  $\sigma$ .

In addition to obtain descriptors of the overall dataset, a few soil physicochemical properties affecting FQ sorption were also tested to refine the overall dataset to obtain  $K_d$  (FQ) best estimates with a higher representativeness for the soils to be assessed and lower related variability. To do this, the overall  $K_d$  dataset was split into partial datasets by grouping soils according to their pH, and also by the combination of pH with OC and sand contents, as further described in Section 3.4. The soil groups were set up on the basis of expert judgement and to ensure a sufficient number of entries to derive CDFs with a good fitting (Ramírez-Guinart et al., 2020a). Fisher Least Significant Differences (FLSD) tests were run at  $\alpha = 0.05$  (Statgraphics Technologies, USA) to statistically compare the populations resulting from the soil grouping and to check whether the derived  $K_d$  (FQ) best estimates were significantly different.

## 3. Results and discussion

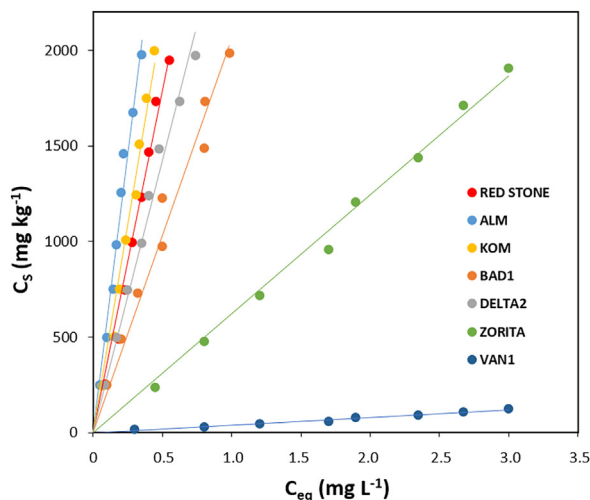
### 3.1. Sorption and desorption pattern of NOR in soils

Fig. 1 shows the NOR sorption isotherms in the seven soils and summarizes the results of the fitting of the isotherms to the linear model. Although previous studies performing sorption of NOR on soils found non-linear isotherms (Kong et al., 2014; Peruchi et al., 2015), the isotherms in the present study had a linear trend, as revealed by their high Pearson coefficients. The linearity of the isotherms obtained could be attributed to both the lower initial concentration range ( $\leq 80 \text{ mg L}^{-1}$ ) tested and to the higher soil-to-solution ratio ( $40 \text{ g L}^{-1}$ ) than those used in previous work, leading to a higher number of available sorption sites able to interact with NOR. Therefore, the linearity of the isotherms allowed the derivation of  $K_d$  values from the slope of the respective sorption isotherm.

The derived  $K_d$  values varied within the 44–5600  $\text{L kg}^{-1}$  range, and in general they indicated a strong sorption and therefore a low expected mobility of FQs in soils, with the exception of the ZORITA and (especially) VAN1 soils. The sequence of  $K_d$  (NOR) variation between soils agreed with the changes in the soil properties that are expected to govern NOR sorption. ALM presented the highest  $K_d$ , followed by KOM, despite their contrasting mineral and organic contents. However, the two soils had a pH around 5.5, at which FQ sorption is favored at both clay minerals and humic substances sites (Martínez-Mejía et al., 2017; Wan et al., 2013). RED STONE presented a slightly lower  $K_d$  value than KOM probably due to its lower pH (3.9), which does not favor sorption of NOR cationic species due both to a decrease in the negative charges in the soil surface particles and to the competition of protons for exchangeable sites (Wan et al., 2013). BAD1 presented a lower  $K_d$  value than ALM, despite containing a higher clay content, probably due to its lower OC and its slightly basic pH, which strongly affects the sorption in mineral phases due to the negative repulsions of the zwitterion NOR form and the negative charges present in mineral particles (Wan et al., 2013). DELTA2, although slightly more alkaline than BAD1, presented a higher  $K_d$  value. Although the presence of mono- and divalent cations in solution may compete for exchangeable sorption sites with the zwitterion NOR species (Kong et al., 2014), its higher  $K_d$  could be attributed both to its higher Fe content, which may favor NOR sorption by complexation mechanisms with Fe-minerals at this specific neutral pH conditions (Paul et al., 2014), and to its higher OC content. The much lower  $K_d$  value found in ZORITA than in DELTA2 could therefore be attributed to higher pH, lower OC and higher sand contents, which all negatively affect sorption of FQs (Vasudevan et al., 2009). Finally, the  $K_d$  value found for VAN1 was the lowest among the soils analyzed. Although no sorption data obtained in soils at pH 10 could be found in the literature, this extremely low sorption could be attributed to its alkaline pH, low OC and high sand content.

Since NOR sorption is affected by multiple soil properties, our sorption  $K_d$  data for NOR were correlated with soil properties. A preliminary overview of our data revealed that  $K_d$  (NOR) values were not linearly correlated to any single property of the soils at  $\alpha = 0.05$ , with the exception of





Soil	$K_d$ (L kg <sup>-1</sup> )	$r^2$	% Desorption
RED STONE	3940 ± 400	0.989	0.37 ± 0.10
ALM	5600 ± 560	0.988	0.36 ± 0.16
KOM	4810 ± 530	0.988	0.25 ± 0.11
BAD	2080 ± 200	0.989	1.07 ± 0.08
DELTA2	2920 ± 290	0.988	0.50 ± 0.10
ZORITA	640 ± 37	0.996	1.45 ± 0.09
VAN1	44 ± 4	0.989	20 ± 2.4

Fig. 1. Sorption isotherms and desorption yields obtained for NOR in the seven soils. Solid lines indicate the linear fitting.

pH ( $r^2 = 0.72, p = 0.02$ ). However, this correlation has to be taken with caution, as it is not representative for the complex pH-dependence of FQ sorption in soils. In this regard, Fig. 2 displays the  $K_d$  (NOR) values for all tested soils along with soil pH, superimposed over the NOR speciation diagram over pH, to illustrate the key role of pH and NOR speciation in  $K_d$  (NOR) variability. At low pH, the soil surface will be slightly protonated or neutral and the interaction with the cationic NOR specie will be unfavored. At intermediate pH, the surface of the soil will be deprotonated and will favor the sorption of cationic and zwitterion NOR species. As soil pH increases, the soil surface is increasingly deprotonated and anionic NOR species become predominant, its sorption being unfavored, likely due to the increase in electrostatic repulsions between the carboxylate group of the anionic NOR specie and the negatively charged soil surface.

Desorption percentages of NOR in soils are also shown in Fig. 1. They were extremely low (generally <1 %), with the exception of VAN1 (20 %). In fact, the sequence of desorption yields roughly agreed with the inverse of the sequence of  $K_d$  (FQ) in the soils tested. These results, combined with the previous sorption data, strongly suggest a low leaching potential of FQs in slightly acidic soils, but a higher mobility is expected, and therefore a higher environmental risk, for basic sandy soils with low OC content, in agreement with previous leaching data obtained in the laboratory (Pan and Chu, 2017; Domínguez et al., 2014).

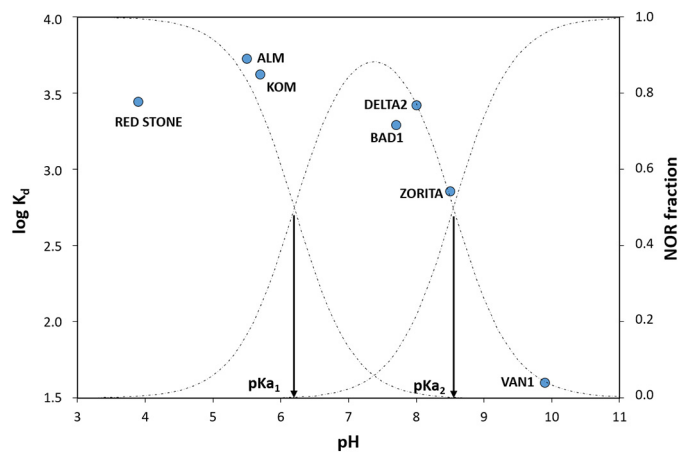


Fig. 2. Dependence of  $K_d$  (NOR) values with soil pH superimposed with NOR speciation diagram. Dashed lines indicate the respective NOR fraction of each NOR species at each pH.

### 3.2. Assessing the sorption analogy between NOR, CIP, ENR and OFL

In order to test sorption analogy between FQs in the tested soils,  $K_d$  values for CIP, ENR and OFL were derived using the same batch methodology. Since  $K_d$  (NOR) was constant along the range of concentrations tested, the  $K_d$  values for CIP, ENR and OFL could be obtained at a single initial concentration within the range tested for NOR. Fig. 3A displays the  $K_d$  values derived for the four FQs. Smaller differences were observed between FQs for a given soil than between soils for a given FQ, suggesting a lesser role of the FQ structure for the tested FQs in soil sorption. A two-way ANOVA analysis confirmed that  $K_d$  (FQ) was significantly affected by the soil factor but not by the FQ factor.

In order to extend these comparisons to a larger scale, the sorption data for NOR, CIP, ENR and OFL gathered in the literature dataset were analyzed by box and whisker plots (Fig. 3B). FLSD results showed that sorption of these four FQs was statistically comparable, with median  $K_d$  (L kg<sup>-1</sup>) values of 2500, 2300, 1900 and 2100 for NOR, CIP, ENR and OFL respectively, suggesting that sorption differences that could be attributed to target FQs have a much lower contribution to  $K_d$  (FQ) variability than that caused by soil physicochemical properties.

### 3.3. Development of a multivariate PLS-based $K_d$ (FQ) prediction model

PLS regression was used to construct a multivariate  $K_d$  (FQ) prediction model. Considering the data in the calibration dataset ( $n = 92$ ; see Table S4), the PLS explained 75 % of the  $K_d$  (FQ) data variance using five LVs. The influence plot revealed that most samples in the calibration set were within the Q vs T<sup>2</sup> influencing zone, except for a few extreme soils (Fig. S3A). The VIP projection of the original variables (Fig. S3B) confirmed that pH, CEC, OC and sand contents were good descriptors (VIP score > 1) of  $K_d$  (FQ), while silt, clay and Fe contents had VIP scores <1. Whereas pH, OC and CEC are common relevant variables explaining electrostatic interactions, the sand fraction of the soil can be considered as representative of texture. Although clay minerals that are present mainly in the clay and to a lesser extent in the silt soil textural fractions, may have a positive relationship with  $K_d$ , the sand soil textural fraction, which is expected to be free of clay minerals, shows an inverse but unequivocal relationship with  $K_d$  as evidenced by the VIP analyses, then being an excellent variable to be considered in prediction equations. Among the FQ species, only the cationic species (FQ(+)) contributed significantly (VIP score > 1) to  $K_d$  (FQ).

After, a new and simplified model was created considering only the relevant properties with VIP score > 1. The new PLS model, with 61 % of the

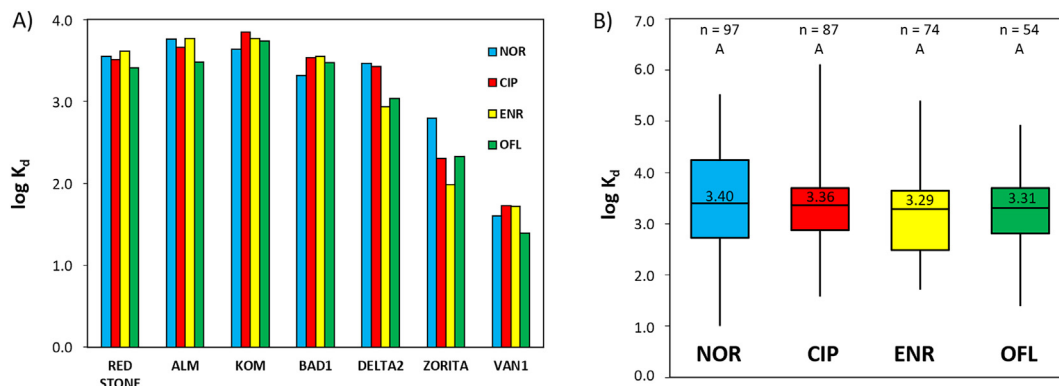


Fig. 3. Comparison of  $K_d$  values obtained for NOR, CIP, ENR and OFL in the set of seven soils (A); Box and whisker plots of  $K_d$  values for NOR, CIP, ENR and OFL derived from the overall dataset (B).

$K_d$  (FQ) data variance explained by only using three LVs, was much simpler than when using all the variables and resulted in the following equation:

$$\log K_d = -0.06 \text{ pH} - 0.17 \log \text{ OC} - 0.48 \log \text{ sand} + 0.79 \log \text{ CEC} + 0.34 \log \text{ FQ}(+) + 3.54 \quad (7)$$

Cross-validation revealed that the prediction ability of the model was acceptable, obtaining RMSE and RPD values of 0.51 and 1.62 respectively, although a slope and y-intercept between the experimental and predicted  $\log_{10}$ -transformed  $K_d$  values significantly differed to one and zero respectively (Fig. S3C).

The use of the simplified model allowed to have a larger dataset for external validation purposes, as the required number of informed variables was decreased (especially Fe content). The predictive ability of the model was lower when the external validation set was tested, describing only 32 % of the  $K_d$  (FQ) data variance, and obtaining RMSE and RPD values of 0.57 and 1.13 respectively and a slope and y-intercept between the experimental and predicted  $\log_{10}$ -transformed  $K_d$  values significantly different to one and zero respectively (Fig. S3D). The low predictive quality of the PLS-based model could be attributed to its inability to explain the complex sorption trend with pH observed in Section 3.1. Hence, due to the low predictive quality of the PLS-based prediction model,  $K_d$  (FQ) best estimates with informed variability were derived by a probabilistic approach.

### 3.4. Deriving $K_d$ (FQ) best estimates in soils

CDFs were constructed to derive  $K_d$  (FQ) best estimates for the overall dataset and for partial datasets originated by soil groups defined according to the values of specific soil properties relevant to FQ sorption and sufficiently informed in the dataset: pH, and the combination of pH and OC and sand contents. Further groupings according to other soil properties (i.e., DOC content, soluble cations) were not possible due to the lack of characterization data in the literature, which would have led to partial datasets with a very low number of entries.

Regarding pH grouping criteria, the soil groups were defined according to FQ  $pK_a$  values in order to represent the effect of each FQ species on sorption. The first group comprised soils with  $\text{pH} < 5.5$ , whereas the second and third groups were formed by soils with  $\text{pH}$  ranging 5.5–7.5 and  $\text{pH} \geq 7.5$ , respectively. The median pH values of the entries in each group were 4.7, 6.6 and 7.8 respectively, thus confirming that these partial datasets could be considered descriptors of the presence of cationic, zwitterion and, to a less extent, anionic FQ species.

Every pH soil group was further segregated regarding OC and sand contents. The pH + OC groups were created for soils with an OC content  $< 2\%$  (representative for mineral soils) and  $\text{OC} \geq 2\%$ . A third pH group for soils with a higher OC content (for instance,  $\text{OC} > 10\%$ ) was not possible due to the lack of entries for such organic soils. The pH + Sand groups were

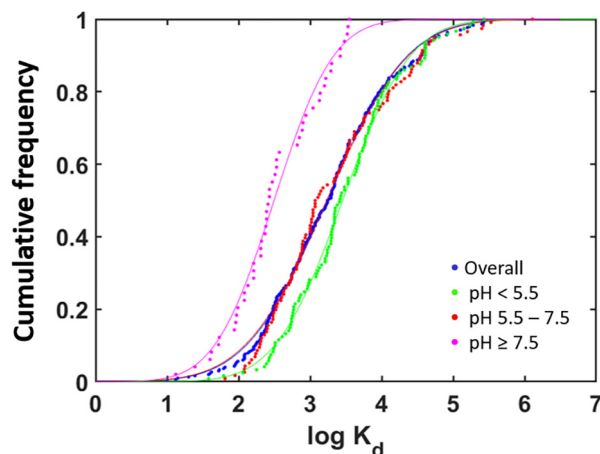
created for soils having  $< 50\%$  and  $\geq 50\%$  sand content. Hierarchical combinations of pH + Sand + OC factors were also tested.

Fig. 4 displays the CDFs derived for the overall dataset and for pH partial datasets. This approach permitted the derivation of  $K_d$  (FQ) best estimates of 1700 and 3400  $\text{L kg}^{-1}$  for the acidic and neutral soil datasets respectively, whereas for basic soils the  $K_d$  (FQ) best estimate was nearly one order of magnitude lower (320  $\text{L kg}^{-1}$ ; see Table 2). These values agree with the pH trend observed in Section 3.1, in which sorption was maximized at pH 5–7. Moreover, the FLSD test revealed that pH grouping led to the quantification of statistically different  $K_d$  (FQ) best estimates, confirming that pH was an important parameter affecting sorption and that  $K_d$  (FQ) best estimates may change within one order of magnitude solely based on changes in soil pH, besides generally decreasing the data variability with respect to that of the overall dataset.

To reduce data variability and derive  $K_d$  (FQ) best estimates more representative for the soils to be assessed, double groupings were tested according to pH + OC and pH + Sand criteria. These groupings led to datasets that were significantly different according to FLSD tests for soils with  $\text{pH} < 5.5$  (see Figs. S3 and S4) and  $\text{pH} 5.5\text{--}7.5$  (see Figs. S6 and S7). For soils with  $\text{pH} \geq 7.5$ , the application of both the pH + OC and pH + Sand criteria did not result in significantly different datasets (Figs. S8 and S9), suggesting a minor additional effect of the organic matter and textural characteristics in  $K_d$  (FQ) for soils with basic pH. The  $K_d$  (FQ) best estimates obtained from the application of the pH + OC criterion (see Table 2) agreed with the pH-dependent sorption of FQs in soil organic matter components (Martínez-Mejía et al., 2017) and confirmed the positive effect of OC on FQ sorption in acidic and neutral soils (Teixidó et al., 2014). In addition, application of the pH + OC criterion allowed the derivation of  $K_d$  (FQ) best estimates with a generally lower variability than the overall data. Similarly, the refinement by the pH + Sand criterion revealed a negative effect of the sand content on  $K_d$  (FQ) best estimates for acidic and neutral soils, which confirm the higher FQ leaching observed in sandy soils than in loamy and clay soils (Pan and Chu, 2017). Data variability was also generally reduced in each refinement with respect to that of the overall dataset.

Triple groupings according to the pH + Sand + OC criterion were also examined (see Figs. S10 – S14). Although the simultaneous application of the three soil properties was affected by deriving partial datasets with a low number of entries, this approach permitted to quantify significantly different  $K_d$  (FQ) best estimates in a few cases and to achieve a further general decrease in  $K_d$  (FQ) variability.

In brief, the application of CDFs to the overall  $K_d$  (FQ) dataset allowed the derivation of more representative  $K_d$  values for the specific environmental scenario to be assessed. Specifically, the  $K_d$  (FQ) best estimates ranged from 320 to 7500  $\text{L kg}^{-1}$  depending on easily-derivable soil physicochemical properties (pH, OC and sand contents), indicating that the most suitable  $K_d$  (FQ) best estimates for use as input data for risk assessment might vary within more than one order of magnitude according to properties of the target soils.



Soil groups	N	BE ( $K_d$ , $L\ kg^{-1}$ )	GSD	$r^2$	FLSD <sup>1</sup>
Overall	312	1,679	7.6	0.998	
pH < 5.5	117	1,690	7.9	0.998	A
pH 5.5 – 7.5	127	3,390	5.8	0.995	B
pH ≥ 7.5	51	324	4.5	0.989	C

N = number of observations; BE: best estimate  $K_d$ ; GSD: geometric standard deviation; <sup>1</sup>Different letters in the datasets indicate statistically significant differences between  $K_d$  (FQ) best estimates according to the Fisher's Least Significant Differences test.

Fig. 4. CDFs of  $\log K_d$  (FQ) distributions for soil groups according to the pH criterion.

#### 4. Conclusions

Sorption  $K_d$  values of NOR in soils followed a non-linear pattern along changes in pH, reaching a peak at pH 5–7, in which the cationic and zwitterion FQ species were predominant, confirming that pH was the main soil parameter affecting FQ sorption, both by modifying soil surface charges and affecting FQ speciation. The construction of a literature-assembled sorption  $K_d$  (FQ) dataset, including  $K_d$  data from NOR, CIP, ENR and OFL, confirmed that their sorption was statistically comparable. The development of a PLS-based prediction model based on relevant soil and FQ properties affecting sorption (pH, fraction of

cationic FQ, CEC, OC and sand contents) led to a poor prediction of the  $K_d$  (FQ) when externally tested with literature data. Therefore, CDFs were constructed to derive  $K_d$  (FQ) best estimates with a known associated variability as input data for environmental risk assessment according to the specific characteristics of the scenario to be assessed, specifically pH, OC and sand content. Refining the sorption  $K_d$  dataset according to soil properties permitted derivation of more representative  $K_d$  (FQ), often with a lower related variability than that derived from the overall dataset. These  $K_d$  values were above  $1000\ L\ kg^{-1}$  under most environmental conditions, suggesting a strong sorption to soil particles and therefore a low predicted mobility, although higher environmental

Table 2

$K_d$  best estimate (BE,  $L\ kg^{-1}$ ), geometrical standard deviation (GSD), 5th and 95th percentiles ( $L\ kg^{-1}$ ) and maximum and minimum values ( $L\ kg^{-1}$ ) for each partial dataset defined according to relevant soil properties affecting FQ sorption in soils.

Group 1	Group 2	Group 3	N	BE ( $K_d$ )	GSD	5th	95th	Min	Max
Overall			312	1679	7.6	93	56,234	10	1,288,250
pH < 5.5			117	1690	7.9	141	125,892	65	1,288,250
pH < 5.5	Sand <50		64	4581	8.6	347	251,189	245	1,288,250
pH < 5.5	Sand ≥50		50	478	4.1	120	12,022	65	26,303
pH < 5.5	OC < 2		67	1028	4.2	123	33,884	65	54,954
pH < 5.5	OC ≥ 2		50	3837	14	170	263,027	120	1,288,250
pH < 5.5	Sand <50	OC < 2	27	2148	5.8	525	36,307	302	54,954
pH < 5.5	Sand <50	OC ≥ 2	37	7516	9.4	331	45,708	245	1,288,250
pH < 5.5	Sand ≥50	OC < 2	37	621	3.7	89	5888	65	9120
pH < 5.5	Sand ≥50	OC ≥ 2	13	240	2.0	141	12,589	120	26,303
pH 5.5–7.5			127	3390	5.8	269	83,176	38	269,153
pH 5.5–7.5	Sand <50		61	3846	2.9	654	22,579	282	169,284
pH 5.5–7.5	Sand ≥50		26	750	3.2	115	5370	38	5888
pH 5.5–7.5	OC < 2		71	2028	6.4	354	40,738	38	190,546
pH 5.5–7.5	OC ≥ 2		56	3828	4.3	324	83,176	229	269,153
pH 5.5–7.5	Sand <50	OC < 2	31	2636	3.1	363	18,197	282	40,738
pH 5.5–7.5	Sand <50	OC ≥ 2	30	6561	3.6	1738	63,096	832	169,824
pH 5.5–7.5	Sand ≥50	OC < 2	17	619	3.7	115	5370	38	5888
pH 5.5–7.5	Sand ≥50	OC ≥ 2	9	914	2.2	254	1445	229	1995
pH ≥ 7.5			51	324	4.5	40	3311	13	3548

N = number of observations.

mobility might be expected in scenarios with alkaline pH, low OC and high sand contents as their associated  $K_d$  (FQ) values could be one order of magnitude lower.

### CRedit authorship contribution statement

Joel Fabregat-Palau: conceptualization, methodology, investigation, formal analysis, data curation, writing – original draft;

Zhiqiang Yu: conceptualization, methodology, investigation, supervision, formal analysis, review and editing;

Xiangying Zeng: conceptualization, methodology, investigation, supervision, formal analysis, review and editing;

Miquel Vidal: conceptualization, methodology, investigation, supervision, formal analysis, review and editing;

Anna Rigol: conceptualization, methodology, investigation, supervision, formal analysis, review and editing.

### Data availability

Data will be made available on request.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgements

This work was supported by the Ministerio de Ciencia e Innovación of Spain (PID2020-114551RB-I00). Joel Fabregat-Palau acknowledges funding from the European Union Europe Aid 'SEW-REAP' project [ECRIP ICI + /2014/348–010].

### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.160266>.

### References

- Andersson, M.I., MacGowan, A.P., 2003. Development of the quinolones. *J. Antimicrob. Chemother.* 51 (90001), 1–11. <https://doi.org/10.1093/jac/dkg212>.
- Chen, G., Li, M., Liu, X., 2015. Fluoroquinolone antibacterial agent contaminants in soil/groundwater: a literature review of sources, fate, and occurrence. *Water Air Soil Pollut.* 226 (12). <https://doi.org/10.1007/s11270-015-2438-y>.
- Domínguez, C., Flores, C., Caixach, J., Mita, L., Piña, B., Comas, J., Bayona, J.M., 2014. Evaluation of antibiotic mobility in soil associated with swine-slurry soil amendment under cropping conditions. *Environ. Sci. Pollut. Res.* 21 (21), 12336–12344. <https://doi.org/10.1007/s11356-014-3174-3>.
- Gil-García, C.J., Rigol, A., Rauret, G., Vidal, M., 2008. Radionuclide sorption-desorption pattern in soils from Spain. *Appl. Radiat. Isot.* 66 (2), 126–138. <https://doi.org/10.1016/j.apradiso.2007.07.032>.
- Girardi, C., Greve, J., Lamshöft, M., Fetzter, I., Miltner, A., Schäffer, A., Kästner, M., 2011. Biodegradation of ciprofloxacin in water and soil and its effects on the microbial communities. *J. Hazard. Mater.* 198, 22–30. <https://doi.org/10.1016/j.jhazmat.2011.10.004>.
- Gong, W., Liu, X., He, H., Wang, L., Dai, G., 2012. Quantitatively modeling soil-water distribution coefficients of three antibiotics using soil physicochemical properties. *Chemosphere* 89 (7), 825–831. <https://doi.org/10.1016/j.chemosphere.2012.04.064>.
- Kong, X., Feng, S., Zhang, X., Li, Y., 2014. Effects of bile salts and divalent cations on the adsorption of norfloxacin by agricultural soils. *J. Environ. Sci.* 26 (4), 846–854. [https://doi.org/10.1016/S1001-0742\(13\)60480-5](https://doi.org/10.1016/S1001-0742(13)60480-5).

- Leal, R.M.P., Alleoni, L.R.F., Tornisiello, V.L., Regitano, J.B., 2013. Sorption of fluoroquinolones and sulfonamides in 13 Brazilian soils. *Chemosphere* 92 (8), 979–985. <https://doi.org/10.1016/j.chemosphere.2013.03.018>.
- Lin, Y.-C., Hsiao, K.-W., Lin, A.Y.-C., 2018. Photolytic degradation of ciprofloxacin in solid and aqueous environments: kinetics, phototransformation pathways, and byproducts. *Environ. Sci. Pollut. Res.* 25, 2303–2312. <https://doi.org/10.1007/s11356-017-0666-y>.
- Martínez-Mejía, M.J., Sato, I., Rath, S., 2017. Sorption mechanism of enrofloxacin on humic acids extracted from Brazilian soils. *Environ. Sci. Pollut. Res.* 24, 15995–16006. <https://doi.org/10.1007/s11356-017-9210-3>.
- OECD, 2000. OECD 106 Adsorption - Desorption Using a Batch Equilibrium Method. OECD Guideline for the Testing of Chemicals. <https://doi.org/10.1787/9789264069602-en>.
- Pan, M., Chu, L.M., 2017. Leaching behavior of veterinary antibiotics in animal manure-applied soils. *Sci. Total Environ.* 579, 466–473. <https://doi.org/10.1016/j.scitotenv.2016.11.072>.
- Pan, B., Wang, P., Wu, M., Li, J., Zhang, D., Xiao, D., 2012. Sorption kinetics of ofloxacin in soils and mineral particles. *Environ. Pollut.* 171, 185–190. <https://doi.org/10.1016/j.envpol.2012.07.037>.
- Paul, T., Liu, J., Machesky, M.L., Strathmann, T.J., 2014. Adsorption of zwitterionic fluoroquinolone antibacterials to goethite: a charge distribution-multisite complexation model. *J. Colloid Interface Sci.* 428, 63–72. <https://doi.org/10.1016/j.jcis.2014.04.034>.
- Peruchi, L.M., Fostier, A.H., Rath, S., 2015. Sorption of norfloxacin in soils: analytical manure, kinetics and Freundlich isotherms. *Chemosphere* 119, 310–317. <https://doi.org/10.1016/j.chemosphere.2014.06.008>.
- Picó, Y., Andreu, V., 2007. Fluoroquinolones in soil-risks and challenges. *Anal. Bioanal. Chem.* 387 (4), 1287–1299. <https://doi.org/10.1007/s00216-006-0843-1>.
- Ramírez-Guinart, O., Salaberria, A., Vidal, M., Rigol, A., 2017. Assessing soil properties governing radiocesium sorption in soils: can trivalent lanthanides and actinides be considered as analogues? *Geoderma* 290, 33–39. <https://doi.org/10.1016/j.geoderma.2016.12.010>.
- Ramírez-Guinart, O., Kaplan, D., Rigol, A., Vidal, M., 2020a. Deriving probabilistic soil distribution coefficients ( $K_d$ ). Part 1: general approach to decreasing and describing variability and example using uranium  $K_d$  values. *J. Environ. Radioact.* 222, 106362. <https://doi.org/10.1016/j.jenvrad.2020.106362>.
- Ramírez-Guinart, O., Kaplan, D., Rigol, A., Vidal, M., 2020b. Deriving probabilistic soil distribution coefficients ( $K_d$ ). Part 2: reducing caesium  $K_d$  uncertainty by accounting for experimental approach and soil properties. *J. Environ. Radioact.* 223–224. <https://doi.org/10.1016/j.jenvrad.2020.106407>.
- Ramírez-Guinart, O., Kaplan, D., Rigol, A., Vidal, M., 2020c. Deriving probabilistic soil distribution coefficients ( $K_d$ ). Part 3: reducing variability of americium  $K_d$  best estimates using soil properties and chemical and geological material analogues. *J. Environ. Radioact.* 223–224, 106378. <https://doi.org/10.1016/j.jenvrad.2020.106378>.
- Rath, S., Fostier, A.H., Pereira, L.A., Dioniso, A.C., de Oliveira Ferreira, F., Doretto, K.M., Maniero Peruchi, L., Viera, A., de Oliveira Neto, O.F., Dal Bosco, S.M., Martínez-Mejía, M.J., 2019. Sorption behaviors of antimicrobial and antiparasitic veterinary drugs on subtropical soils. *Chemosphere* 214, 111–122. <https://doi.org/10.1016/j.chemosphere.2018.09.083>.
- Riaz, L., Mahmood, T., Khalid, A., Rashid, A., Ahmed Siddique, M.B., Kamal, A., Coyne, M.S., 2018. Fluoroquinolones (FQs) in the environment: a review on their abundance, sorption and toxicity in soil. *Chemosphere* 191, 704–720. <https://doi.org/10.1016/j.chemosphere.2017.10.092>.
- Septian, A., Oh, S., Shin, W.S., 2018. Sorption of antibiotics onto montmorillonite and kaolinite: competition modelling. *Environ. Technol.* 1–14. <https://doi.org/10.1080/09593330.2018.1459870>.
- Sheppard, S.C., 2011. Robust prediction of  $K_d$  from soil properties for environmental assessment. *Hum. Ecol. Risk Assess.* 17 (1), 263–279. <https://doi.org/10.1080/10807039.2011.538641>.
- Teixidó, M., Medeiros, J., Beltrán, J., Prat, M.D., Granados, M., 2014. Sorption of enrofloxacin and ciprofloxacin in agricultural soils: effect of organic matter. *Adsorpt. Sci. Technol.* 32 (2–3), 153–163. <https://doi.org/10.1260/0263-6174.32.2.3.153>.
- USEPA, 2014. Risk Assessment Forum White Paper: Probabilistic Risk Assessment Methods and Case Studies. U. S. Environmental Protection Agency, EPA/100/R-14/004.
- Van Doorslaer, X., Dewulf, J., Van Langenhove, H., Demeester, K., 2014. Fluoroquinolone antibiotics: An emerging class of environmental micropollutants. *Sci. Total Environ.* 500–501, 250–269. <https://doi.org/10.1016/j.scitotenv.2014.08.075>.
- Van, T.T.H., Yidana, Z., Smooker, P.M., Coloe, P.J., 2020. Antibiotic use in food animals worldwide, with a focus on Africa: pluses and minuses. *J. Global Antimicrob. Resist.* 20, 170–177. <https://doi.org/10.1016/j.jgar.2019.07.031>.
- Vasudevan, D., Bruland, G.L., Torrance, B.S., Upchurch, V.G., Mackay, A.A., 2009. pH-dependent ciprofloxacin sorption to soils: interaction mechanisms and soil factors influencing sorption. *Geoderma* 151, 68–76. <https://doi.org/10.1016/j.geoderma.2009.03.007>.
- Wan, M., Li, Z., Hong, H., Wu, Q., 2013. Enrofloxacin uptake and retention on different types of clays. *J. Asian Earth Sci.* 77, 287–294. <https://doi.org/10.1016/j.jseaes.2013.02.032>.
- Wu, Q., Li, Z., Hong, H., Li, R., Jiang, W., 2012. Desorption of ciprofloxacin from clay mineral surfaces. *Water Res.* 47 (1), 259–268. <https://doi.org/10.1016/j.watres.2012.10.010>.