STRUCTURE-TOXICITY STUDY OF SOME PYRETHROIDAL ESTER INSECTICIDES

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INTRODUCTION

- Pyrethroids constitute one of the most widely used classes of insecticides worldwide, having the following characteristics [1]: quick knock-down effect against insects, efficacy against insects with organophosphorus and/or carbamate-resistant strains, easy decomposition in the environment and low mammalian toxicity
- Although the specific mechanism of activity is uncertain, pyrethroids act primarily on the nervous system [2], on a variety of putative biochemical and physiological target sites, four of which merit consideration as sites of toxic action: voltagesensitive sodium, calcium and chloride channels, and peripheral-type benzodiazepine receptors [3].

[1]. Y. Katsuda, *Pestic. Sci.*, 1999, 55, 775-782.

[2]. A. Anadón, M.R. Martínez-Larranãaga, M.A. Martínez, Vet. J., 2009, 182, 7–20.

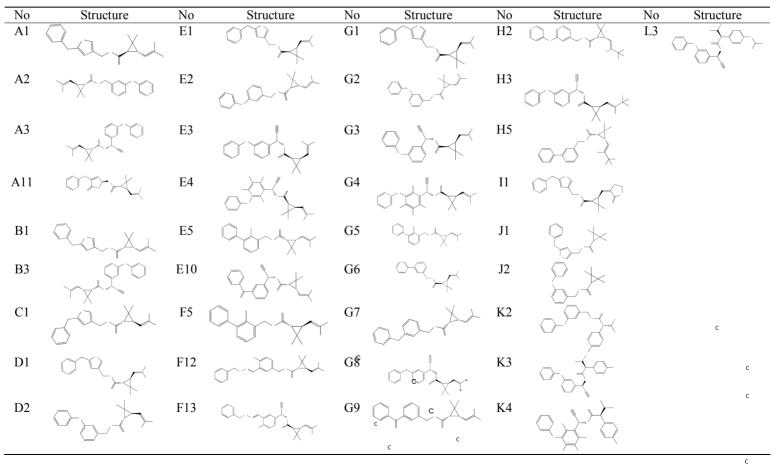
[3]. D. M. Soderlund, J. M Clark, L. P. Sheets, L. S. Mullin, V. J. Piccirillo, D. Sargent, J. T. Stevens, M. L. Weiner, *Toxicology*, 2002, *171(1)*, 3–59

AIM:

- Toxicity of 37 pyrethroidal esters (Table 1), expressed by the logarithm of LD₅₀ values, measured against a susceptible strain of housefly (*Musca domestica*) was studied by multiple linear regression (MLR).
- Stereoisomers selected according to the literature [4] were modeled by conformational analysis performed by molecular mechanics calculations. Structural descriptors of the title compounds calculated for these isomers were correlated to the logarithm of LD₅₀ values.

[4]. A. W. Farnham, B. P. S. Khambay, *Pestic. Sci.* 1995, *44*, 269-275.

Table 1. Pyrethroidal ester structure



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Definition of target property and molecular structures

- Experimental LD₅₀ values of 37 pyrethroidal ester derivatives have been previously [4] measured against a susceptible strain of housefly (*Musca domestica*). Their logarithm was considered as dependent variable.
- Starting structures were first built by the Marwin Sketch [5] software and then conformational analysis was performed by the OMEGA [6] program.

[5]. Marwin Sketch 6.0, 2013, ChemAxon, http://www.chemaxon.com

[6]. OMEGA (version 2.4.6), OpenEye Science Software, Santa Fe, USA, 2010), http://www.eyesopen.com, 2010

- Compound descriptors were calculated by several programs: Dragon (Dragon Professional 5.5/2007, Talete S.R.L., Milano, Italy), Instant JChem (Instant JChem v. 6.0, Chemaxon Ltd., Budapest, Hungary) and EPI Suite™ (US EPA. [2012]. Estimation Programs Interface Suite™ for Microsoft® Windows, v. 4.11. United States Environmental Protection Agency, Washington, DC, USA.)
- Multiple linear regression (MLR) analysis [7] has been applied after variable selection carried out by the genetic algorithm included in the QSARINS v. 1.2 program [8].

[7]. S. Wold, W.J. Dunn III, J. Chem..Inf. Comput. Sci. 1983, 23, 6-13.

[8]. N. Chirico, E. Papa, S. Kovarich, S. Cassani, P. Gramatica, QSARINS, software for QSAR MLR model development and validation. 2012, QSAR Res. Unit in Environ. Chem. and Ecotox., DiSTA, University of Insubria, Varese, Italy. http://www.qsar.it.

Model validation

- The leave-one-out cross-validation procedure was employed for internal validation, the over fitting of data and model applicability was controlled by comparing the root-mean-square errors (RMSE) of training and validation sets and the predictive power of the model by the concordance correlation coefficient (CCC) [9].
- Y-scrambling was used to check the model robustness and predictive power.
- The Multi-Criteria Decision Making (MCDM) [16] was employed to summarize the performances of a certain number of criteria simultaneously

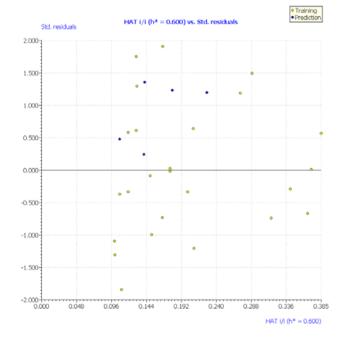
[9]. N. Chirico, P. Gramatica, *J. Chem. Inf. Model.* 2011, *51*, 2320-2335. [10]. H.R. Keller, D.L. Massart, J.P. Brans, *Chemom. Int.Lab. Syst.* 1991, *11*, 175-189.

Table 2. MLR statistical results for the training , cross-validated and test sets

Model	Equation	\mathbb{R}^2	Q^2	R_{adj}^2	SEE	RMSEtr	RMSEex	K _{XX}	ΔΚ	CCCtr	CCCex	MCDM	R^2_{LMO}	Q^2_{LMO}	$R^2 Y_{scr}$	Q ² Y _{scr}
												all				
1	$log LD_{50} = -0.35(\pm 0.22) - 0.99(\pm 0.47) EEig02d - 0.55(\pm 0.31) BEHm3 + 0.62(\pm 0.32) BELm8 - 1.92(\pm 0.76) KOAWIN log Kaw$	0.857	0.789	0.828	0.252	0.225	0.231	0.209	0.151	0.923	0.812	0.794	0.860	0.860	0.17	-0.32
2	$log LD_{50} = -0.54(\pm 0.24) - 0.97(\pm 0.44) EE ig 04d + 0.44(\pm 0.30) nCp - 2.06(\pm 0.82) KOA WIN log Kaw$	0.759	0.668	0.724	0.319	0.292	0.222	0.377	0.101	0.863	0.808	0.742	0.761	0.761	0.13	-0.25
3	$log LD_{50} = -0.41(\pm 0.25) - 0.79(\pm 0.37) EE ig 02d - 0.74(\pm 0.30) MW + 0.52(\pm 0.27) BELm8 - 1.83(\pm 0.72) KOAWIN log Kaw$	0.834	0.756	0.800	0.271	0.243	0.258	0.261	0.148	0.909	0.769	0.754	0.840	0.840	0.17	-0.33

* R^2 – correlation coefficient, Q^2 – leave-one-out 'crossvalidated r2', R^2_{adj} - adjusted R², SEE – standard error of estimates, RMSE - root mean squared error, MAE - mean absolute error, CCC - concordance correlation coefficient, for the training (tr), and test (ex) sets; MCDM all -Multi-Criteria Decision Making calculated for fitting cross-validation and external validation; R^2_{LMO} and Q^2_{LMO} – leave many-out correlation coefficient and cross-validation coefficients; R^2Y_{scr} and Q^2Y_{scr} -Y scramble correlation and cross-validation coefficients; EEig02d-Eigenvalue 02 from edge adj. matrix weighted by dipole moments; BEHm3-highest eigenvalue n. 3 of Burden matrix / weighted by atomic masses; BELm8-lowest eigenvalue n. 8 of Burden matrix / weighted by atomic masses; KOAWIN Log Kaw–air-water partition coefficients; nCpnumber of terminal primary C(sp3); MW-molecular weight

- The dataset was divided in training and a randomly selected (25% of the total number of compounds) test set.
 Compounds: C1, D1, G1, H3 and L3 were included in the test set.
- Seven outliers (compounds A1, B1, B3, F12, F13, G2 and H5) were found and removed from the final MLR models.
- The MLR models are completely satisfactory in the fitting, but have modest predictive power.
- Model 1 (considered best) is stable and internally predictive, not obtained by chance.



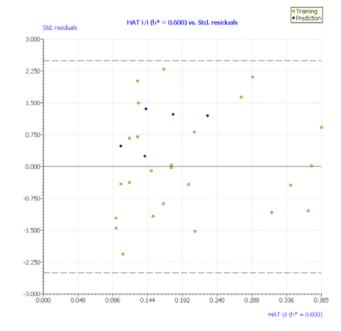
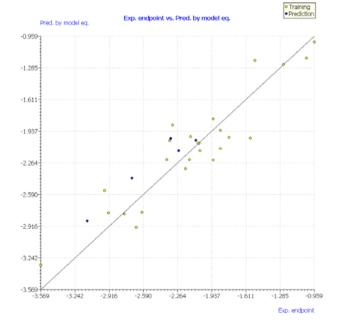


Figure 1. Williams plot – predicted by fitting for model 1

Figure 2. Williams plot – predicted by leave-one-out (LOO) for model 1



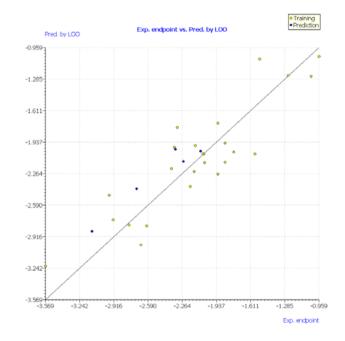


Figure 3. Experimental versus logLD₅₀ values predicted by fitting for model 1 Figure 4. Experimental versus logLD₅₀ values predicted by LOO for model

CONCLUSIONS

- The obtained MLR models are satisfactory in the fitting, but have modest predictive power.
- The presence number of terminal primary C(sp3) group is favorable for low toxicity.
- High values of air-water partition coefficients and of molecular weight can be associated with high toxicity of the title compounds.

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