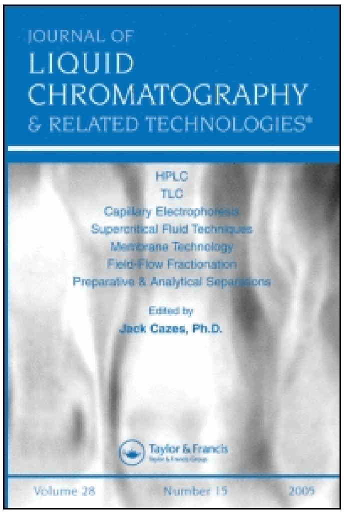

Journal of Liquid Chromatography & Related Technologies
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713597273

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To cite this Article Zagyi, M. and Cserháti, T.(2007) 'Quantitative Structure-Retention Relationship Study on the Binding of Organic Solvents to the Corn Protein, Zein', Journal of Liquid Chromatography & Related Technologies, 30: 3, 351 — 362

To link to this Article: DOI: 10.1080/10826070601084795

URL: http://dx.doi.org/10.1080/10826070601084795

Journal of Liquid Chromatography & Related Technologies®, 30: 351–362, 2007

ISSN 1082-6076 print/1520-572X online
DOI: 10.1080/10826070601084795

Quantitative Structure-Retention Relationship Study on the Binding of Organic Solvents to the Corn Protein, Zein

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Abstract: The strength and the character of the binding of 12 organic solvents to the corn protein zein were determined by high performance liquid chromatography. The relationship between the physicochemical parameters and binding characteristics of solvents was elucidated by canonical correlation analyses (CCA). As the number of physicochemical parameters was higher than that of our observations, three empirical methods have been employed for the preselection of variables exerting a marked impact on the binding characteristics. Calculations established that the binding of solvents to the protein is of mixed characters involving hydrophobic and electrostatic interactive forces. Sterical correspondence between the interacting molecules and molecular substructures also influence the binding of solvents to zein. The use of different preselection methods resulted in similar but not identical relationships.

Keywords: Organic solvents, Zein, Canonical correlation analysis, Preselection

INTRODUCTION

Because of the growing complexity and sophistication of high speed analytical instruments the number of raw data and the dimensionality of data matrices increased considerably. The evaluation of large data matrices became difficult even impossible with traditional linear correlation analyses. Various multivariate mathematical statistical methods have been developed and

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successfully employed to overcome this difficulty.[1] Canonical correlation analysis (CCA), a multivariate mathematical statistical method, is suitable for the assessment of the quantitative relationships between two sets of variables.[2] One set of variables contains generally measured values (biological activity, toxicity, adsorption, or other physicochemical parameters, etc.), while the other set is composed of calculated molecular descriptors.[3] CCA has many times been applied in up-to-date data handling procedures. Thus, it has been recently used in food technology for predicting the quality of wheat,[4] for assessing the performance of natural resource systems[5] for water research,[6] weather forecast,[7] educational observations,[8] environmental protection studies,[9] microbiology,[10] and decision making.[11] CA has also found application in the evaluation of chromatographic retention data both in thin-layer[12] and high performance liquid chromatography (HPLC).[13,14]

The calculation of a large number of structural and physicochemical parameters became feasible with the development and commercialization of software specialized in the computation of molecular parameters, such as Dragon 2.1 2002 (R. Todeschini, V. Consonni, M. Pavan, Milano Chemometrics and QSAR Research Group, Italy), Codessa (A. Katritzky, M. Karelson, University of Florida, USA and University of Tartu, Estonia), Adapt (P. C. Jurs, Jurs Research Group, The Pennsylvania State University, PA, USA), 3 DNET 2.0 1999 (I. Kövesdi, Egis Pharmaceuticals Ltd., Budapest, Hungary), etc. These molecular parameters have found extensive application in many quantitative structure activity relationship (QSAR) studies. Thus, they were used to study drug transfer,[15] to predict intestinal permeability[16] and solubility,[17] to classify stationary phases in gas chromatography,[18,19] to facilitate the rational design of new pharmaceuticals,[20] etc.

As can be concluded from the discussion above, the computation of a large set of molecular parameters is less time consuming and more economical than the performance of concrete experiments, therefore, matrices containing more variables than observations can easily occur. The inclusion of as many as possible molecular parameters in QSAR calculations is motivated by the fact that higher number of variables increases the probability of the occurrence of significant relationships between descriptors and measured biological data. However, it is obvious that CCA cannot be carried out on such type of matrices.

The objectives of the study were the elucidation of the relationship between the measured binding characteristics of organic solvents to the corn protein zein and their calculated physicochemical parameters by CCA, and the development of a new approach for the preselection of variables for CCA (method of the sum of coefficients of determination, SCD). In order to compare the efficacy of the SCD method, the preselection procedure was also performed with two other well established techniques, such as partial last squares (PLS)[21,22] and pair correlation methods (PCM).[23–26] CCA was carried out with all the three sets of variables preselected by SCD, PLS, and PCM.

EXPERIMENTAL

Three binding parameters (strength of binding = log k_w, width of the distribution of the binding strength of adsorption centers = N, deviation of the distribution of the binding strength of adsorption centers from the Gaussian one = AF) of 12 organic solvents on the surface of the corn protein zein has been measured by HPLC as previously described.[27,28] The smaller (left side) matrix was composed from these data (3 variables × 12 observations). The larger (right side) matrix consisted of the following calculated molecular parameters: π = Hansch-Fujita's substituent constants characterizing hydrophobicity; H-Ac and H-Do = indicator variables for proton acceptor and proton donor properties, respectively; M-RE = molar refractivity; F and R = Swain and Luton's electronic parameters characterizing the inductive and resonance effects; S-Me and S-Pa = Hammett's constants characterizing the electron-withdrawing power of the substituents at meta and para position; Es = Taft's constant characterizing the steric effects of substituents; $B_1$and B_4 = Sterimol width parameters determined by distance of substituents at their maximum point perpendicular to attachment; E_{TOTAL} = total energy of the molecule; E_{HOMO} = energy of the highest occupied molecular orbital; E_{LUMO} = energy of the lowest unoccupied molecular orbital; V = molar volume of the molecule; μ = dipole moment; X = topological index. Variables 1–11, in the right side matrix, were calculated according to the additivity rule from the fragmental constants. Variables 12–16, in the right side matrix, were calculated with the software Gaussian 98 (Gaussian, Inc., Pittsburgh PA, 1998), the method of calculation can be found in the software in detail. Topological indices (χ), variable 17, were calculated by:

$$(\chi) = \Sigma(\delta_i \cdot \delta_j)^{1/2} \tag{1}$$

where $\delta_i = z_i - H_i$ and z_i and H_i are the number of valence electrons and hydrogen atoms, respectively.[29] The elements of the left and right matrices are compiled in Table 1.

Reduction in the number of variables was essential to obtain appropriate data matrix eligible for CCA. In the SCD method, linear correlations were calculated between the three binding parameters in the left and the 17 variables in right side matrices (calculations were only performed between the elements of the right and left side matrices), then, the three coefficients of determination related to binding parameters were summarized for each variable in the right side matrix. Physicochemical parameters having a summarized coefficient of determination over 0.750 were selected and used for CCA (altogether seven parameters).

In the PLS method, squares of the scaled PLS regression coefficients between the three binding parameters in the left and the 17 variables in right side matrices were calculated (calculations were not performed among

Table 1. Binding characteristics and physicochemical parameters of organic solvents (elements of left and right side matrices). For symbols see Experimental

No of solute	log k_w	N	AF	π	H-Ac	H-Do	M-RE	F	R	S-Me
I	0,37	83,6	0,42	0,01	1	0	16,83	0,28	0,07	0,31
II	0,70	33,4	0,29	0,30	1	0	20,34	0,01	0,02	0,18
III	0,15	114,5	0,44	−0,57	1	0	11,14	0,21	−0,18	0,16
IV	0,46	17,0	0,28	−0,26	2	0	23,56	0,27	−0,49	0,30
V	0,14	41,8	0,55	0,27	2	1	19,19	0,47	−1,21	0,15
VI	0,49	15,1	0,33	0,73	2	1	24,59	0,46	−1,18	0,15
VII	0,97	17,9	0,38	1,26	2	1	29,25	0,45	−1,16	0,15
VIII	0,85	19,6	0,22	0,47	1	0	21,48	0,27	0,10	0,31
IX	−0,25	125,1	0,47	−0,32	2	2	14,97	0,53	−1,38	0,17
X	−0,07	82,5	0,72	0,21	2	2	19,63	0,52	−1,36	0,17
XI	−0,25	113,1	0,60	−0,46	3	3	21,45	0,81	−2,00	0,29
XII	0,43	22,9	0,33	0,88	1	1	17,81	0,23	−0,72	0,05

No of solute	S-Pa	S	B_1	B_4	E_{TOTAL}	E_{HOMO}	E_{LUMO}	V	μ	X
I	0,33	−3,84	3,42	4,97	−192	−0,24	−0,010	69,2	2,71	1,20
II	0,03	−1,63	1,02	3,00	−231	−022	0,107	46,2	2,02	2,08
III	0,01	−2,38	2,02	4,62	−132	−033	0,045	42,5	3,61	0,72
IV	−0,24	−2,04	2,37	5,47	−304	−0,18	0,000	66,5	0,00	2,16
V	−0,78	−2,59	3,72	6,83	−268	−0,24	0,081	72,4	0,28	1,51
VI	−0,76	−2,66	3,72	7,76	−307	−0,24	0,094	92,6	2,95	2,10
VII	−0,74	−2,95	3,72	8,20	−346	−0,24	0,082	81,4	0,46	2,60
VIII	0,35	−3,91	3,42	5,90	−231	−0,24	−0,009	57,6	2,58	1,76
IX	−0,89	−2,41	3,72	6,33	−229	−0,25	0,076	46,2	0,00	1,13
X	−0,87	−2,70	3,72	6,77	−268	−0,23	0,074	58,2	3,26	1,56
XI	−1,24	−3,25	4,57	8,20	−229	−0,25	0,076	46,2	0,00	1,71
XII	−0,50	−2,15	2,87	5,37	−193	−0,24	0,097	62,3	1,62	1,52

I = Acetone; II = Tetrahydrofuran; III = Acetonitrile; IV = 1,4-Dioxane; V = 2-Methoxyethanol; VI = 2-Ethoxyethanol; VII = 2-Propoxyethanol; VIII = Methyl-ethyl-ketone; IX = Ethyleneglycol; X = Propyleneglycol; XI = Glycerine; XII = 1-Propanol.

the elements of the same matrix), and the sum of square of PLS regression coefficients was used as selection criterion.

In the PCM method, ranking of variables was carried out one by one for the binding parameters log k_w, N, and AF, comparing the variables pair wise. Always, the largest value among the three was considered and the probability weighted differences were calculated. Variables with the largest probability weighted differences were selected.

In order to elucidate the similarities and dissimilarities between the three parameter sets, linear relationships were calculated between the elements.

CCA calculations were performed three times, including the seven variables complying with the requirements in SCD, and including the largest seven variables calculated with PLS and PCM (Table 2). The selection of seven variables in PLS and PCM was motivated by the fact, that to facilitate the comparison the number of variables has to be the same as for SCD, which selected seven variables.

Calculation of coefficients of determination, PLS and CCA was performed by Statistica 6.0 software (Stasoft Inc., Tulsa, OK, USA), PCM was carried out using an MS Excel VBA code. Linear regressions were calculated by the Drugidea software (Compudrug, Budapest, Hungary).

Table 2. Preselection criteria calculated by the three methods. For explanation of symbols see Experimental

Descriptor	SCD	PLS	PCM
π	1.174	0.900	10.995
H-Ac	0.593	4.893	6.948
H-Do	1.212	9.588	9.883
M-RE	0.837	3.064	10.978
F	0.984	0.211	4.997
R	0.867	2.788	9.906
S-Me	0.030	1.810	−6.985
S-Pa	0.750	2.473	9.906
Es	0.029	9.533	−0.998
B_1	0.446	9.933	3.996
B_4	0.203	15.395	−1.996
E_{TOTAL}	0.445	2.346	9.966
E_{HOMO}	0.393	1.812	9.965
E_{LUMO}	0.106	0.415	−5.994
V	0.679	1.906	9.883
μ	0.033	1.916	−6.000
X	1.078	5.775	10.971

I = sum of the coefficients of determination (SCD); II = sum of square of scaled regression coefficients (PLS); III = probability weighted differences (PCM).

RESULTS AND DISCUSSION

The data in Table 1 show marked deviations in both the left and right side matrices. This result suggests that the affinity of solvents to zein are considerably different and their physicochemical parameters included in the calculation are also diverse.

The various preselection criteria computed by SCD, PLS, and PCM techniques are compiled in Table 2. The data demonstrate that the preselection criteria show considerable variations, both according to the character of the descriptor and the method of computation, suggesting that the use of different preselection methods may result in different sets of criteria.

Significant linear relationships were found between the criteria computed with SCD and PCM ($r = 0.8178$; $n = 17$), while the results of PLS did not correlate with those of the two other methods, demonstrating the similarity of SCD and PCM techniques and the dissimilarity of PLS.

The parameters of the three CCA calculations are compiled in Tables 3–5. CCAs proved, unambiguously, the existence of significant relationships between the binding characteristics and physicochemical parameters of organic solvents. CCAs selected, in each instance, two significant relationships between the two sets of variables (see eigenvalues). The occurrence of significant relationships indicates that the preselected

Table 3. Canonical weights of variables in the first and second roots and the ratios of variance extracted (results of canonical correlation analysis performed on the parameters preselected by SCD). For symbols see Experimental. (Eigenvalues: root 1 = 0.996; root 2 = 0.980; root 3 = 0.208)

Variable	Root 1	Root 2
Canonical weights		
log k_w	−0.50	−0.65
N	−0.71	0.84
AF	0.98	−0.79
π	−2.75	1.10
H-Do	7.05	−3.55
M-RE	18.90	−11.40
F	10.53	−3.61
R	76.35	−35.48
S-Pa	−59.02	27.45
X	−16.31	9.36
Variance extracted		
Left side matrix	0.47	0.45
Right side matrix	0.30	0.29

Table 4. Canonical weights of variables in the first and second roots and the ratios of variance extracted (results of canonical correlation analysis performed on the parameters preselected by PLS). For symbols see Experimental. (Eigenvalues: root 1 = 0.992; root 2 = 0.958; root 3 = 0.624)

Variable	Root 1	Root 2
Canonical weights		
log k_w	0.94	0.35
N	−0.87	−0.09
AF	−0.54	−0.82
H-Ac	−0.32	−0.53
H-Do	−0.52	−0.57
M-RE	0.70	−0.24
Es	−0.07	0.05
B_1	−0.22	−0.49
B_2	−0.01	−0.53
X	0.73	−0.11
Variance extracted		
Left side matrix	0.64	0.26
Right side matrix	0.21	0.17

physicochemical parameters exert a considerable impact on the affinity of this set of organic solvents to zein.

The canonical weights of the binding characteristics are comparable in the significant roots suggesting their basic similarity. Interestingly, in each case various molecular parameters such as hydrophobicity, sterical, and electronic parameters equally influenced the various aspects of the binding of solvents to zein. This result can be tentatively explained by the assumption that the solvent molecules can bind by hydrophobic forces to the apolar side chains of amino acids and can interact electrostatically with the polar substructures (probably peptide bonds) on the surface of zein. Furthermore, the results illustrate that the availability of the interactive sites also depends on the sterical correspondence of solvent molecules and the characteristics of the zein surface. We are well aware of the fact that the inclusion of isomers in the investigation may corroborate our conclusion concerning the role of sterical correspondence in the affinity of solvents to zein. However, our investigation was concentrated on the study of the behavior of solvents employed on an industrial scale, and not on the study of the affinity of isomers to the model protein. The ratio of variance explained is similarly high in roots 1 and 2 in each CCA. It means that the relative importance of both roots is commensurable, and the elucidation of the biochemical and biophysical bases of this solvent-protein interaction of the data in roots 1 and 2 have similar importance.

Table 5. Canonical weights of variables in the first and second roots and the ratios of variance extracted (results of canonical correlation analysis performed on the parameters preselected by PCM). For symbols see Experimental. (Eigenvalues: root 1 = 0.998; root 2 = 0.594; root 3 = 0.337)

Variable	Root 1	Root 2
Canonical weights		
log k_w	−0.96	−0.27
N	0.90	−0.16
AF	0.63	0.64
π	−0.80	0.34
M-RE	−0.68	0.46
R	−0.43	−0.81
S-Pa	−0.39	−0.83
E_{TOTAL}	0.49	−0.64
V	−0.58	0.48
X	−0.72	0.33
Variance extracted		
Left side matrix	0.71	0.17
Right side matrix	0.36	0.34

The ratio of variance explained by the three preselected sets of parameters is slightly different. The highest ratio of variance explained was achieved by the use of the PCM method followed by SCD and PLS. This finding indicates that each technique is suitable for the preselection of variables for CCA, however, the best results can be achieved by applying the PCM method.

CONCLUSIONS

It can be concluded from the results, that the methods outlined above represent a useful approximation for the reduction of the number of variables for CCA and for their preselection, in the case of data matrices containing more variables than observations. Each method tested was suitable for the preselection of physicochemical parameters influencing, significantly, the affinity of solvent to zein. However, the variance applied by application of PCM was slightly higher than those of the two other preselection methods. Various preselection methods, such as SCD (method of the sum of coefficients of variation), PLS (partial last squares), and PCM (pair correlation method) can be successfully applied for the reduction of the dimensionality of data matrices, otherwise unsuitable for canonical correlation analysis. The applicability of this combined procedure has been demonstrated in the calculation of the relationship between the physicochemical parameters of organic solvents and the character of their binding to the corn protein zein. Similar to other mulivariate mathematical statistical methods, this technique can be employed in the future for the evaluation of other complicated data matrices to simplify the application of multivariate mathematical statistical methods. Thus, the method can be employed to increase of the efficacy of the rational design of new bioactive compounds, such as pharmaceuticals and pesticides,[30] for the selection of molecular parameters for the prediction of the behavior of organic compounds,[31] and for the elucidation of the mechanism of water pollution by pesticides.[32]

REFERENCES

1. Vandeginste, B.G.M.D.; Massart, L.; Buydens, L.M.C.; De Jong, S.P.; Lewi, P.J.; Smeyers-Verbeke, J. *Handbook of Chemometrics and Qualimetrics: Part B. Data Handling in Science and Technology*; Elsevier: Amsterdam, 1998, 20B.
2. Hotelling, H. Relationships between two sets of variates. Biometrika **1936**, *28*, 321–327.
3. Livingstone, D.J.; Martyn, M.G.; Huuskonen, J.J.; Salt, D.W. Simultaneous prediction of aqueous solubility and octanol/water partition coefficient based on descriptors derived from molecular structure. J. Comp-Aid. Mol. Des. **2001**, *15*, 741–752.
4. Butt, M.S.; Faqir, F.M.; Van Zuilichem, D.J.; Shaheen, M. Development of predictive models for end-use quality of spring wheats through canonical analysis. Int. J. Food Sci. Technol. **2001**, *36*, 433–440.
5. Campbell, B.; Sayer, J.A.; Forst, P.; Vermeulen, S.; Perez, M.R.; Cunningham, A.; Prabhu, R. Assessing the performance of natural resource systems. Conserv. Ecol. **2002**, *5*, 309–336.
6. Cavadias, G.S.; Ouarda, T.B.M.J.; Bobee, B.; Girard, C. A canonical correlation approach to the determination of homogeneous regions for regional flood estimation of ungauged basins. Hydr. Sci. J.-J. Sci. Hydr. **2001**, *46*, 499–512.
7. Landman, W.A.; Tennant, W.J. Statistical downscaling of monthly forecast. Int. J. Climatol. **2000**, *20*, 1521–1532.
8. Onwuegbuzie, A.J. Statistics anxiety and role of self-perceptions. J. Educat. Res. **2000**, *93*, 323–330.
9. Kasap, R. An analysis of temperature data by using scalar component models. Environmetrics **1999**, *10*, 625–631.
10. Hitzl, W.; Henrich, M.; Kessel, M.; Insam, H. Application of multiariate analysis of variance and related techniques in soil studies with substrate utilization tests. J. Microbiol. Meth. **1997**, *30*, 81–89.
11. Friedman, L.; Sinuany-Stern, Z. Scaling units via the canonical correlation analysis in the DEA context. Eur. J. Oper. Res. **1997**, *100*, 629–637.
12. Cserháti, T.; Forgács, E. Use of canonical correlation analysis for the evaluation of chromatographic retention data. Chemom. Intell. Lab. Syst. **1995**, *28*, 305–313.

13. Cserháti, T.; Forgács, E.; Bordás, B. Comparison of the retention behaviour of phenol derivatives on porous graphitized and octadecylsilica columns. Chromatographia **1993**, *36*, 19–26.
14. Jakab, A.; Héberger, K.; Forgács, E. Comparative analysis of different plant oils by high-performance liquid chromatography-atmospheric pressure chemical ionization mass spectrometry. J. Chromatogr. A **2002**, *976*, 255–263.
15. Agatonovic-Kustrin, A.; Tucker, I.G.; Zecevic, M.; Zivanovic, L.J. Prediction of drug transfer into human milk from theoretically derived descriptors. Anal. Chim. Acta **2000**, *418*, 181–195.
16. Egan, W.J.; Lauri, G. Prediction of intestinal permeability. Adv. Drug Deliv. Rev. **2002**, *54*, 273–289.
17. Lipinski, C.A.; Lombardo, F.; Dominy, B.W.; Feeney, P.J. Experimental and computational approaches to estimate solubility and permeability in drug discovery and development settings. Adv. Drug Deliv. Rev. **2001**, *46*, 3–26.
18. Abraham, M.H.; Poole, C.H.; Poole, S.K. Classification of stationary phases and other materials by gas chromatography. J. Chromatogr. A **1999**, *842*, 79–114.
19. Héberger, K. Evaluation of polarity indicators and stationary phases by principal component analysis in gas-liquid chromatography. Chemom. Intell. Lab. Syst. **1999**, *47*, 41–49.
20. Estrada, E.; Uriarte, E. Recent advances on the role of topological indices in drug discovery research. Curr. Med. Chem. **2001**, *8*, 1573–1588.
21. Wold, S. PLS for multivariate linear modeling. In *Chemometric Methods in Molecular Design*; van de Waterbeemd, H., Ed.; VCH: Weinheim, 1995; 195–218.
22. Héberger, K.; Görgényi, M.; Sjöström, M. Partial least squares modeling of retention data of oxo compounds in gas chromatography. Chromatographia **2000**, *51*, 595–600.
23. Héberger, K.; Rajkó, R. Discrimination of statistically equivalent variables in quantitative structure-activity relationships. In *QSAR in Environmental Sciences*; Chen, F., Schüürmann, G., Eds.; SETAC Special Publication Series, SETAC Press, 1997, VII; 425–433.
24. Rajkó, R.; Héberger, K. Conditional Fisher's exact test as a selection criterion for pair-correlation method. Type I and type II errors. Chemom. Intell. Lab. Sys. **2001**, *57*, 1–14.
25. Héberger, K.; Rajkó, R. Variable selection using pair-correlation method. Environmental applications. SAR QSAR Env. Res. **2002**, *13*, 541–554.
26. Héberger, K.; Rajkó, R. Generalization of pair-correlation method (PCM) for nonparametric variable selection. J. Chemom. **2002**, *16*, 436–443.
27. Forgács, E.; Kósa, A.; Csiktusnádi Kiss, G.; Cserháti, T.; Kaliszan, R.; Haber, P.; Nasal, A. Use of a modified nonlinear mapping method in quantitative structure retention relationship study. J. Liq. Chromatogr. & Rel. Technol. **1998**, *21*, 2523–2534.
28. Cserháti, T.; Forgács, E.; Kósa, A.; Csiktusnádi Kiss, G.; Kaliszan, R.; Haber, P.; Nasal, A.; Örsi, F. Binding of environmental pollutants to the wheat protein gliadin studied by high-performance liquid chromatography. J. Chromatogr. Sci. **1999**, *37*, 159–164.
29. Rücker, G.; Rücker, C. On topological indices, boiling points, and cycloalkanes. J. Chem. Inf. Comp. Sci. **1999**, *39*, 788–802.
30. Frecer, V.; Kabelac, M.; De Nardi, P.; Pricl, S.; Miertus, S. Structure-based design of inhibitors of NS3 serine protease of hepatities C virus. J. Mol. Graphics Modell. **2004**, *22*, 209–220.

31. Hilal, S.H.; Karickhoff, S.W.; Carreira, L.A. Prediction of the vapor pressure boiling point, heat of vaporization and diffusion coefficient of organic compounds. Quant. Struct-Act. Relat. Comb. Sci. **2003**, *22*, 565–574.
32. Worall, F.; Thomsen, M. Quantum vs topological descriptors in the development of molecular models of groundwater pollution by pesticides. Chemosphere **2004**, *54*, 585–596.

Received September 14, 2006
Accepted October 30, 2006
Manuscript 6943