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Risk of false decision on conformity of a multicomponent material when test results of the components' content are correlated

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Abstract: The probability of a false decision on conformity of a multicomponent material due to measurement uncertainty is discussed when test results are correlated. Specification limits of the components' content of such a material generate a multivariate specification interval/domain. When true values of components' content and corresponding test results are modelled by multivariate distributions (e.g. by multivariate normal distributions), a total global risk of a false decision on the material conformity can be evaluated based on calculation of integrals of their joint probability density function. A total specific risk can be evaluated as the joint posterior cumulative function of true values of a specific batch or lot lying outside the multivariate specification domain, when the vector of test results, obtained for the lot, is inside this domain. It was shown, using a case study of four components under control in a drug, that the correlation influence on the risk value is not easily predictable. To assess this influence, the evaluated total risk values were compared with those calculated for independent test results and also with those assuming much stronger correlation than that observed. While the observed statistically significant correlation did not lead to a visible difference in the total risk values in comparison to the independent test results, the stronger correlation among the variables caused either the total risk decreasing or its increasing, depending on the actual values of the test results.

Opposed Reviewers:

Cover letter

Professor Jean-Michel Kauffmann,

Talanta, Editor

21 May, 2017

Dear Prof. Kauffmann,

Please find attached the manuscript by Ilya Kuselman, Francesca R. Pennecchi, Ricardo J.N.B. da Silva and D. Brynn Hibbert, titled "Risk of false decision on conformity of a multicomponent material when test results of the components' content are correlated", which we would like to publish in Talanta in continuation of our position paper (Talanta 164 (2017) 189-195).

Novelty Statement: A statistical procedure is developed for evaluation of a total risk (due to measurement uncertainty) of a false decision on conformity of a multi-component material when test results of the components' content are correlated. Correlation among test results complicates conformity assessment. In a case study of correlated test results for four components under control in a drug, it is shown that strong correlation may lead either to decreasing or increasing of the total risk, depending on the actual test results.

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Best regards,



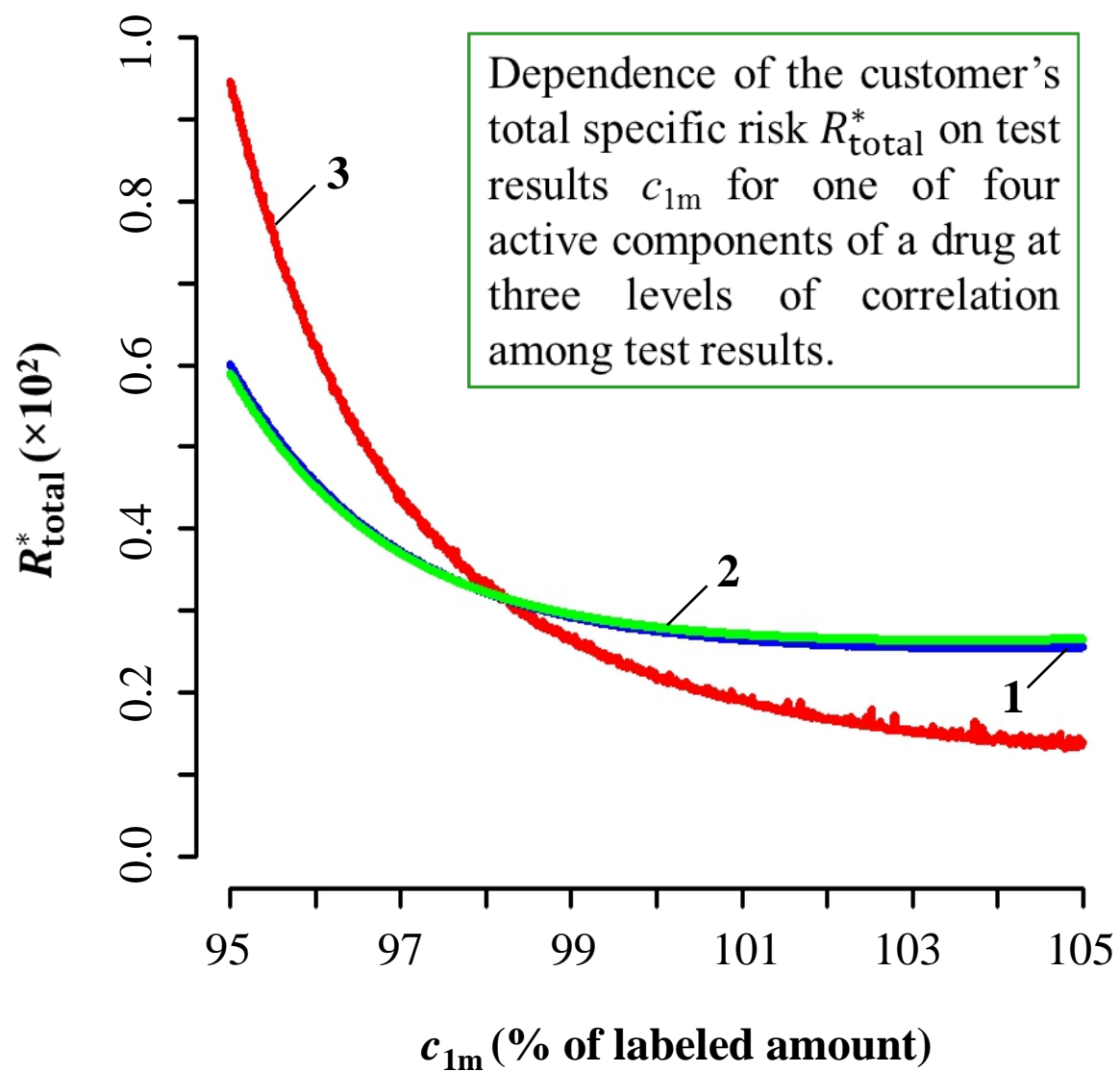
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Novelty Statement

A statistical procedure is developed for evaluation of a total risk (due to measurement uncertainty) of a false decision on conformity of a multi-component material when test results of the components' content are correlated. Correlation among test results complicates conformity assessment. In a case study of correlated test results for four components under control in a drug, it is shown that strong correlation may lead either to decreasing or increasing of the total risk, depending on the actual test results.

HIGHLIGHTS

- Correlation among test results of a multicomponent material complicates its conformity assessment.
- A statistical procedure for evaluation of a total risk of false decision on the drug conformity is developed.
- A case of correlated test results for four components under control in a drug is studied.
- Strong correlation may lead either to decreasing or increasing of the total risk, depending on the actual test results.



**Risk of false decision on conformity of a multicomponent material
when test results of the components’ content are correlated**

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Abstract The probability of a false decision on conformity of a multicomponent material due to measurement uncertainty is discussed when test results are correlated. Specification limits of the components' content of such a material generate a multivariate specification interval/domain. When true values of components' content and corresponding test results are modelled by multivariate distributions (e.g. by multivariate normal distributions), a total global risk of a false decision on the material conformity can be evaluated based on calculation of integrals of their joint probability density function. A total specific risk can be evaluated as the joint posterior cumulative function of true values of a specific batch or lot lying outside the multivariate specification domain, when the vector of test results, obtained for the lot, is inside this domain. It was shown, using a case study of four components under control in a drug, that the correlation influence on the risk value is not easily predictable. To assess this influence, the evaluated total risk values were compared with those calculated for independent test results and also with those assuming much stronger correlation than that observed. While the observed statistically significant correlation did not lead to a visible difference in the total risk values in comparison to the independent test results, the stronger correlation among the variables caused either the total risk decreasing or its increasing, depending on the actual values of the test results.

Keywords:

Conformity assessment

Multicomponent material

Measurement uncertainty

Risk of false decision

Correlated test results

Case study

1. Introduction

Risk of false decision on conformity of a multicomponent material due to measurement uncertainty was recently discussed in the position paper of the IUPAC task group [1]. There are several kinds of such risk. The probability of accepting a batch or lot of the material, when it should have been rejected, is named ‘consumer’s risk’, whereas the probability of falsely rejecting the lot is the ‘producer’s risk’. For a specified lot, they are referred to as the ‘specific consumer’s risk’ and the ‘specific producer’s risk’, R_{ci}^* , for i -th particular component of the material under control, $i = 1, 2, \dots, n$, respectively. The risks of incorrect conformity assessment of a lot randomly drawn from a statistical population of such lots are the ‘global consumer’s risk’ and the ‘global producer’s risk’, R_{ci} , for i -th particular component, since they characterize the material production globally [2]. Even if conformity assessment for each i -th component of a material is successful (i.e. the particular specific R_{ci}^* or global R_{ci} risks are small enough), the total probability of a false decision concerning the material as a whole (the total specific R_{total}^* or global R_{total} risks) might still be significant. A scheme summarizing the terminology used here is shown in Fig. 1.

Fig. 1

A model of the total risk for the case of independent quantities has been formulated on the basis of the law of total probability [3]. Using this model, the total risk can be evaluated as a combination of the particular risks of conformity assessment of the material components. For a more complicated task, i.e. for an increased number of components of the material under control, the total risk increases. Examples for three and four components ($n = 3$ and 4, respectively) are given below in the Appendix. General expressions for evaluating the total global consumer’s risk

for any number n of the material components are also provided [1]. The counterpart models for the total producer's risk are easily obtainable as well.

However, the problem is that the assumption of independence of true values of each component content c_i from other(s) and independence of corresponding measurement/test results c_{im} is not always acceptable. Correlation of true values may be caused by stoichiometry of native compounds, or by technological conditions in production of materials, etc. In their turn, test results may be correlated because of correlation of true values, and/or due to systematic effects in the measurement/test process, common for two or more analytes.

The task of evaluating the total risks for correlated quantities is detailed in the present paper, based on a case study of test results of NyQuil tablets. This cold/flu medication contains four active components: 1) acetaminophen (APAP) as a pain reliever and fever reducer; 2) dextromethorphan hydrobromide (DEX) as a cough suppressant; 3) doxylamine succinate (DOX) as an antihistamine and hypnotic; and 4) phenylephrine hydrochloride (PE) as a nasal decongestant [4]. However, there are publications which have claimed that the last component (PE) is no more effective than placebo [5]. Therefore, the case study is performed for both scenarios: when particular risks of conformity assessment of four and three only (without PE) components contribute to the total risks. To assess influence of the correlation of the test results on the evaluated total risk values, they are compared with those calculated for independent test results by formulas (A.1) – (A.4) shown in the Appendix, and also with the values obtained supposing much stronger correlation than that observed.

2. Experimental

2.1. Specification and acceptance limits

The assay test lower and upper specification limits, lsl_i and usl_i , for the product release for each active component $i = 1, 2, 3, 4$ are 95.0 - 105.0 % of the labeled amount l_i , respectively. The labeled amounts are the following: $l_1 = 325$ mg for APAP, $l_2 = 10$ mg for DEX, $l_3 = 6.25$ mg for DOX, and $l_4 = 5$ mg for PE, per tablet (775 mg on average). The acceptance limits of test results coincide with the specification limits in this study.

2.2. Test method

2.2.1. Sample preparation

A sample of the tablets is weighted, dissolved in solution of phosphoric acid and acetonitrile in water on a magnetic stirrer plate, and then centrifuged. An aliquot is transferred into an autosampler vial for determination of the low-dose active components – DEX, DOX and PE. Another diluted aliquot is used for determination of the high-dose active component – APAP.

2.2.2. Standard solution preparation

The stock standard solution containing the four active components, in concentrations higher than those in the sample solutions, is prepared from the USP reference standards [6], produced also by Merck [7].

The working standard solution is prepared from the stock standard solution by dilution to bring the analyte concentrations to the values as in the sample solutions. Two independent working standards solutions are prepared according to the USP <621> chromatography

requirements [8]: one for quantitation of the analyte content, and the second one for the system suitability control.

2.2.3. Separation, quantification and calculation

Separation and quantification of the analytes are performed using HPLC System with diode-array ultra violet detector (DAD-UV) or multichannel detector and column (C18) heater. Blank solution used is phosphoric acid and acetonitrile in water in concentrations as in a sample solution. After injection of the blank solution, the first working standard solution is injected five times, followed by injection of the second working standard solution for determination of system suitability by USP <621>. Then the sample solutions are injected. At least one additional injection of first working standard solution is performed after every 6 sample injections and at the end of the sample sequence.

All replicates of the first working standard solution (at least 6) are averaged and used for calculation of a test result c_{im} :

$$c_{im} = \frac{A_{is}}{A_{iws}} \frac{(\gamma_i f) V_s D_s}{n_t l_i} \times 100 \%, \quad (1)$$

where A_{is} is the i -th component/analyte peak area of the sample solution; A_{iws} - the averaged i -th analyte peak area of the first working standard solution; γ_i - the i -th analyte mass concentration in the first working standard solution (the analyte mass, mg, per volume, mL, taking into account its dilution factor); $f = 1$ is the concentration factor, not changing the test result value, but indicating a comparison of the first and the second working standards, used below in section 2.3 for the measurement uncertainty evaluation according to the Eurachem/CITAC Guide [9]; V_s and

D_s are the sample volume, mL, and its dilution factor, respectively; n_t is the number of tablets in the sample (the sample mass divided by the tablet average mass). A test result c_{im} is expressed in % of labeled amount l_i .

2.3. Measurement uncertainty

The test method requirement is that the relative standard deviation, RSD, of the analyte peak area for all injections/replicates of the first working standard solution (6 or more) will be 2.5 % or less. The same $RSD \leq 2.5 \%$ should hold also for a single analyte peak area of a sample solution. The relative standard deviation of the averaged peak area is $RSD_{avg} \leq 2.5 \%/ \sqrt{6} = 1.0 \%$. Therefore, the relative standard measurement uncertainty, u_r , of the ratio of the analyte peak area of the sample solution and the averaged peak area of the first working standard solution, A_{is}/A_{iws} , is $u_r \leq \sqrt{(2.5 \%)^2 + (1.0 \%)^2} = 2.7 \%$.

By another requirement of the test method, the relative difference between the averaged normalized (to the analyte concentrations) peak areas obtained for the two working standard solutions must be 2.0 % or less. This condition is a limitation on the error which may affect preparation of the first working standard solution, shown in formula (1) as factor f . Its contribution to the measurement uncertainty, evaluated as the standard deviation of a rectangular distribution [9], is $u_{ws} \leq 2.0 \%/ (2\sqrt{3}) = 0.6 \%$ for any component.

Contributions from other uncertainty sources, such as purity of USP reference standards, weights, volumes and dilutions, are negligible here in comparison to u_r and u_{ws} . Therefore, the relative combined standard uncertainty of a test result c_{im} for each active component is $u_{rel} \leq \sqrt{u_r^2 + u_{ws}^2} = \sqrt{(2.7 \%)^2 + (0.6 \%)^2} = 2.8 \%$. Such measurement uncertainty is typical for

HPLC [10-12]. However, note that in this study 2.8 % is the target relative measurement uncertainty [13], whereas the actual measurement uncertainty may be lower.

3. Results and discussion

3.1. Global distributions of the components' content values

A total of $N = 105$ lots of the medication produced and released at the same factory during a year were tested in the same laboratory belonging to the factory. Histograms of the test results c_{im} are shown in Fig. 2 for: a) APAP, $i = 1$; b) DEX, $i = 2$; c) DOX, $i = 3$; and d) PE, $i = 4$. Mean, m_i , and standard deviation, s_i , values of the test results are presented in Table 1.

Note that the s_i values are smaller than the target measurement uncertainty $u_i = (u_{rel}/100 \%) c_{im} = 0.028 c_{im}$, % of labeled amount, in spite of the fact that the lot-to-lot variation of test results is formed by variation of the production/technological factors and the measurement uncertainty. The reason is that each released lot has passed not only assay determination, but also tests of uniformity of dosage units by USP <905>, dissolution by USP <711> [8] and some others. Any out-of-specification and/or out-of-trend test result investigation pointing out a production problem prevents the lot release. As a result, s_i values are minimized in this way and the lot-to-lot (empirical) distributions of test results are truncated by the specification limits.

Goodness-of-fit of the empirical and theoretical normal distributions with unknown parameters was tested by the Kolmogorov-Smirnov criterion [14]. Empirical criterion values, i.e. values of the maximal absolute difference, D_i , between empirical and theoretical cumulative

distribution functions, calculated using R software [15] are shown in Table 1. The critical values for $N = 105$ test results were approximated as $D_{\text{crit}} = 0.895/(\sqrt{N} - 0.01 + 0.85/\sqrt{N}) = 0.087$ for confidence level $P = 0.95$ and as $D_{\text{crit}} = 1.035/(\sqrt{N} - 0.01 + 0.85/\sqrt{N}) = 0.101$ for $P = 0.99$ [16]. When an empirical criterion value is greater than the critical one, then the null hypothesis about goodness-of-fit of the empirical and theoretical distributions at the chosen level of confidence P should be rejected. One can see from Table 1 that the empirical value of the criterion is equal for DEX to the critical value D_{crit} for $P = 0.95$, but exceeded it for other components. However, there is no empirical value exceeding D_{crit} for $P = 0.99$. Therefore, the null hypothesis is not rejected at that confidence level.

3.2. Correlation

Linear correlation among the test results for different components was estimated by the Pearson's correlation coefficients r_{ij} , $i \neq j = 1, 2, 3, 4$, reported in Table 2. The two-sided critical values of the coefficient r_{crit} for $N - 2 = 103$ degrees of freedom are 0.195 for the level of confidence $P = 0.95$, and 0.254 for $P = 0.99$ [17, 18]. Therefore, only the test results for APAP are independent of the others, since $r_{1j} < r_{\text{crit}}$ for each j and for both the confidence levels. The test results for the low-dose active components – DEX, DOX and PE – are correlated significantly. There is no indication for systematic errors which could cause correlation in the chemical analysis/testing. Random chemical analytical factors contributing to measurement uncertainty are able only to decrease the correlation as any noise. Probably the root cause is in the technological conditions. However, the reason of the observed correlation is not important in framework of this study, since correlation should be taken into account irrespective of its origin.

3.3. Prior and likelihood functions

Since ‘producer’ in this study is the factory (pharmaceutical company), the probability density functions, pdfs, of theoretical normal distributions with means $\mu_i = m_i$ and standard deviations $\sigma_i = s_i$, shown in Fig. 2, are used as pdfs approximating the global distributions of the true components’ content values c_i in the lots, i.e. as prior pdfs.

‘Consumer’ here is fuzzy: they are people who may catch cold or get sick with the flu. Their interests are defended by regulatory authorities supported by official medicines control laboratories controlling the quality of marketed medicinal products [19, 20]. The following evaluation of the consumer’s risks is performed for a case when tablets from a lot, released already by the producer for a market, are tested by such a control laboratory (external for the producer). The laboratory uses the same test method for assay as discussed above. Therefore, pdfs of normal distributions with measurement result c_{im} as mean and standard deviation $u_i = 0.028 c_{im}$, % of labeled amount, are used as the likelihood functions.

3.4. Treatment of the correlated data

Principal component analysis (PCA) is the oldest widely-used technique of multivariate analysis. The idea of PCA is to reduce the dimensionality of a data set in which there are a number of interrelated variables, retaining as much as possible the variation of the initial data [21]. PCA was applied, for example, in the EURAMET guide for a bivariate study of skin cream friction and adhesion [22]. However, for a larger number of variables PCA is sensitive to the

scaling of the data, and there is no consensus which scale is the best to obtain optimal results. Another problem is that converting the original correlated variables c_i and c_{im} into fewer orthogonal/uncorrelated ‘principal components’ complicates the drug conformity assessment, since the ‘principal components’ and their specification limits can not be expressed in % of labeled amount.

In the current study, the true content values of the four components are jointly described by a multivariate prior normal pdf, and the likelihood function of their test results is also modelled by a multivariate normal distribution. Therefore, the joint posterior function is a multivariate normal pdf, as well [23].

The prior covariance matrix is the following:

$$S_c = \begin{pmatrix} 1.8769 & 0.1495 & 0.1798 & 0.2958 \\ 0.1495 & 1.0404 & 0.3331 & 0.5027 \\ 0.1798 & 0.3331 & 1.1025 & 0.6905 \\ 0.2958 & 0.5027 & 0.6905 & 1.4884 \end{pmatrix},$$

where the diagonal elements are variances $\sigma_i^2 = s_i^2$ (Table 1), while others - covariances $cov_{ij} = r_{ij} \cdot \sigma_i \cdot \sigma_j$, $i \neq j$ (r_{ij} as in Table 2).

If the “noise” of the random chemical analytical factors contributing to measurement uncertainty in a control laboratory is negligible, the correlation among the test results is the same as shown in Table 2. Then, the likelihood covariance matrix for test results c_{im} equal to the prior means $\mu_i = m_i$ (Table 1), for example, is:

$$S_{cm} = \begin{pmatrix} 7.7120 & 0.8129 & 0.9655 & 1.3617 \\ 0.8129 & 7.4835 & 2.3662 & 3.0617 \\ 0.9655 & 2.3662 & 7.7353 & 4.1530 \\ 1.3617 & 3.0617 & 4.1530 & 7.6747 \end{pmatrix},$$

where the diagonal elements are variances $u_i^2 = (0.028 c_{im})^2$; and the covariances are $cov_{ij} = r_{ij} \cdot u_i \cdot u_j$, $i \neq j$.

For comparison with the case of uncorrelated data, the covariance matrices were transformed into corresponding diagonal ones, setting correlation coefficient values equal to zero. Another chosen point for comparison was the case of much stronger correlation than that observed, assuming correlation coefficients $r_{ij} = 0.7$. Thus, three points on the correlation scale ($r_{ij} = 0$, r_{ij} as in Table 2, and $r_{ij} = 0.7$) are addressed.

The joint posterior function was calculated as a multivariate normal pdf having the following parameters [23]:

$$S_{\text{post}} = (S_c^{-1} + n_{\text{rep}} S_{\text{cm}}^{-1})^{-1} \text{ and } \mathbf{c}_{\text{post}} = S_{\text{post}}(S_c^{-1} \mathbf{c} + n_{\text{rep}} S_{\text{cm}}^{-1} \overline{\mathbf{c}_m})^{-1}, \quad (2)$$

where S_{post} and \mathbf{c}_{post} are the posterior covariance matrix and the vector of the posterior means, respectively; \mathbf{c} is the vector of the prior mean values $[\mu_1, \mu_2, \mu_3, \mu_4]$; $\overline{\mathbf{c}_m}$ is the vector of the arithmetic means of replicate measurement/test results; and n_{rep} is the number of such replicates (in this study, for a single test result $n_{\text{rep}} = 1$, $\overline{\mathbf{c}_m} = \mathbf{c}_m = [c_{1m}, c_{2m}, c_{3m}, c_{4m}]$).

The use of such a posterior pdf was validated, in the case of independent quantities, by evaluation of the risks of false decisions with formulas (A.1) – (A.4). For an additional validation, calculation of the parameters of the posterior multivariate normal distribution was performed also by Markov Chain Monte Carlo (MCMC) simulations of the posterior distribution, using Metropolis-Hasting algorithm [23] and Cholesky decomposition of the

covariance matrix in MS Excel ambient [24]. Both the developed R code and Excel spreadsheet program can be sent upon request to the corresponding author.

3.5. Global risks

According to the framework developed in ref. [1], the total global consumer's risk R_{total} is the probability of the following event:

$$C \cap B = (C \cap B_1) \cup (C \cap B_2) \cup (C \cap B_3) \cup (C \cap B_4), \quad (3)$$

where $C = C_1 \cap C_2 \cap C_3 \cap C_4$ is the event occurring when all the test results c_{im} are in their acceptance intervals simultaneously, and $B = B_1 \cup B_2 \cup B_3 \cup B_4$ is the event occurring when at least one of the true values of the components' content c_i is outside its specification interval.

Therefore, R_{total} can be considered as the following:

$$\begin{aligned} R_{\text{total}} = P(C \cap B) = & P(C \cap B_1) + P(C \cap B_2) + P(C \cap B_3) + P(C \cap B_4) - \\ & P(C \cap B_1 \cap B_2) - P(C \cap B_1 \cap B_3) - P(C \cap B_1 \cap B_4) - P(C \cap B_2 \cap B_3) - P(C \cap B_2 \cap B_4) - \\ & P(C \cap B_3 \cap B_4) + P(C \cap B_1 \cap B_2 \cap B_3) + P(C \cap B_1 \cap B_2 \cap B_4) + P(C \cap B_1 \cap B_3 \cap B_4) + \\ & P(C \cap B_2 \cap B_3 \cap B_4) - P(C \cap B_1 \cap B_2 \cap B_3 \cap B_4). \end{aligned} \quad (4)$$

Each probability term in the expression (4) was calculated as a multiple integral of the product of the multivariate prior normal pdf (modelling events $B_i \cap B_j$, etc.) and the multivariate normal likelihood (modelling conditional event $C|[c_1, c_2, c_3, c_4]$), i.e. as the integral of the joint

distribution of true values and test results. Concerning the relevant integration limits, note that the test results spread in their multivariate acceptance interval (coinciding in this study with the specification interval/domain $lsl_i - usl_i$), whereas true values are outside the specification domain if probability of events B_i needed to be calculated. Otherwise, they spread on the whole range of real numbers leading to marginalization of the joint distribution with respect to those quantities.

The integration was performed in R ambient by application of the ‘adaptIntegrate’ function from the R package ‘cubature’ [25]. The numerical tolerance was set equal to 0.01, rather than the default value 0.00001, due to time issues in the calculation. The theoretical minus and plus infinity integration limits were substituted with more feasible values in the numerical evaluation of the integral, 70 % and 130 % of labeled amount, respectively, outside which any probability of a true components’ content c_i and/or a test result value c_{im} for a released for a market medication is practically zero.

For diagonal matrices S_c and S_{cm} , defined above in section 3.4 for uncorrelated variables, $R_{total} = 0.19 \times 10^{-2}$. This value is equal to that calculated by formula (A.2). The observed correlation did not influence visibly the total risk: it is again $R_{total} = 0.19 \times 10^{-2}$, whereas for the correlation coefficients $r_{ij} = 0.7$ the calculated value is $R_{total} = 0.10 \times 10^{-2}$.

Practically the same risk values were obtained at all the levels of correlation when PE content was not taken into account, as well as by formula (A.1). That is apparently due to the minor contribution of the particular PE risk to the total probability.

3.6. Specific risks

The total specific risk R_{total}^* was evaluated, using the ‘pmvnorm’ function from the R package ‘mvtnorm’ [26], as the joint posterior cumulative function of true values c_i of a specific lot lying outside the multivariate specification domain, when the vector of test results c_{im} , obtained for the lot, is inside this domain.

The dependences of the total specific risk $R_{\text{total}}^* (\times 10^2)$ on test results c_{im} in the specification interval, 95-105 % of labeled amount, when test results for other active components c_{jm} , $j \neq i$, are equal to their prior pdf means $\mu_j = m_j$ (Table 1) are shown in Fig. 3. The plots are for: a) APAP, c_{1m} ; b) DEX, c_{2m} ; c) DOX, c_{3m} ; and d) PE, c_{4m} . Line 1 is for the observed correlation among test results (Table 2); line 2 – for the case when there is no correlation (correlation coefficients $r_{ij} = 0$); line 3 – for a case when the correlation is much stronger than that observed ($r_{ij} = 0.7$). The “noise” in line 3 is due to the numerical errors in ‘pmvnorm’ function computing joint probability values for the strong correlation case. Fig. 3 shows that the correlation influence on the risk values is not easily predictable, especially when the correlation coefficients are different as in this study (Table 2). There is no significant difference between the risk values, if the test results are independent or correlated as observed (lines 2 and 3, respectively). However, when the correlation among the test results is stronger (lines 3), it may lead either to a decreasing of the total risk or to its increasing, depending on the actual values of the test results.

One may expect that the risk values are increasing symmetrically when c_{im} are moving away from the midpoint of the specification interval (100 % of labeled amount) towards the specification limits (95 and 105 % of labeled amount), whereas that is not observed in Fig. 3. The reason is that all the prior means μ_i are shifted to the left side of the specification interval and the likelihood covariance matrix varies for different c_{im} values.

Note that results of calculations by formula (2) using the multivariate normal distributions for uncorrelated test results of content of three and four components (diagonal covariance matrices) coincide with those obtained by formulas (A.3) and (A.4), respectively. If PE is not taken into account, whereas independent c_{1m} , c_{2m} and c_{3m} values are equal to their prior pdf means μ_i (Table 1), the total risk is $R_{\text{total}}^* = 0.27 \times 10^{-2}$. Considering any possible c_{4m} values for PE in the specification interval for the same conditions on the other components (independent test results and $c_{im} = \mu_i$, $i = 1, 2, 3$), it was found that the minimal value of the total risk for all the four components is also, after rounding, $R_{\text{total}}^* = 0.27 \times 10^{-2}$. That is because of the minor contribution of the particular PE specific risk to R_{total}^* , as for the total global risk above. However, in general, R_{total}^* for the four components is greater than for three only components under control, i.e. increases with the number of the components under control, the fact observed in ref. [1] for denatured alcohols as well.

4. Conclusions

Correlation among test results of a multicomponent material complicates its conformity assessment. When true values of components' content and corresponding test results are modelled by multivariate distributions, for example normal pdfs (prior and likelihood, respectively), a total global risk of a false decision on the material conformity can be evaluated based on calculation of integrals of their joint pdf.

A total specific consumer's risk is evaluated as the joint posterior cumulative function of true values of a specific batch or lot lying outside the multivariate specification domain, when the

vector of test results, obtained for the lot, is inside this domain. The counterpart models for the total producer's risk are obtainable analogously.

It was shown, using a case study of four components under control in a drug, that the correlation influence on the total risk values is not easily predictable. In particular, when the correlation among the test results is strong, it may lead either to decreasing or increasing of the total risk, depending on the actual values of the test results.

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Appendix. Total risk calculation for three and four components under control, when test results are uncorrelated.

For three components $i = 1, 2, 3$, assuming independent true values of each component's content c_i and independent corresponding measurement/test results c_{im} , the total global consumer's risk is:

$$R_{\text{total}} = P(C_2)P(C_3)R_{c1} + P(C_1)P(C_3)R_{c2} + P(C_1)P(C_2)R_{c3} - P(C_3)R_{c1}R_{c2} - P(C_2)R_{c1}R_{c3} - P(C_1)R_{c2}R_{c3} + R_{c1}R_{c2}R_{c3}, \quad (\text{A.1})$$

where $P(C_i)$ is the probability that the test result c_{im} for component i is in its acceptance interval; R_{ci} is the particular global consumer's risk for the i -th component, i.e. the probability of false

conformance when the corresponding test result falls within its acceptance limits, whereas the true value is outside the tolerance/specification limits. For example, for particular risks $R_{ci} = 0.05$ and probabilities $P(C_i) = 0.90$ for all i , formula (A.1) gives $R_{\text{total}} = 0.12$.

For four components $i = 1, 2, 3, 4$, under the same assumption of the independence of the true values c_i and the test results c_{im} , the total global consumer's risk is:

$$\begin{aligned}
 R_{\text{total}} = & P(C_2)P(C_3)P(C_4)R_{c1} + P(C_1)P(C_3)P(C_4)R_{c2} + P(C_1)P(C_2)P(C_4)R_{c3} + \\
 & P(C_1)P(C_2)P(C_3)R_{c4} - P(C_3)P(C_4)R_{c1}R_{c2} - P(C_2)P(C_4)R_{c1}R_{c3} - \\
 & P(C_2)P(C_3)R_{c1}R_{c4} - P(C_1)P(C_4)R_{c2}R_{c3} - P(C_1)P(C_3)R_{c2}R_{c4} - \\
 & P(C_1)P(C_2)R_{c3}R_{c4} + P(C_4)R_{c1}R_{c2}R_{c3} + P(C_3)R_{c1}R_{c2}R_{c4} + P(C_2)R_{c1}R_{c3}R_{c4} + \\
 & P(C_1)R_{c2}R_{c3}R_{c4} - R_{c1}R_{c2}R_{c3}R_{c4}. \tag{A.2}
 \end{aligned}$$

For particular risks $R_{ci} = 0.05$ and probabilities $P(C_i) = 0.90$ for all i , one can obtain by formula (A.2) $R_{\text{total}} = 0.13$.

Total specific consumer's risk for a given lot with three components $i = 1, 2, 3$ under control is:

$$\begin{aligned}
 R_{\text{total}}^* = & R_{c1}^* + R_{c2}^* + R_{c3}^* - R_{c1}^*R_{c2}^* - R_{c1}^*R_{c3}^* - R_{c2}^*R_{c3}^* + R_{c1}^*R_{c2}^*R_{c3}^*, \\
 \tag{A.3}
 \end{aligned}$$

where R_{ci}^* is the particular specific consumer's risks for the i -th component. For example, when the particular specific risks are $R_{ci}^* = 0.05$, the total risk by formula (A.3) is $R_{\text{total}}^* = 0.14$.

When four components $i = 1, 2, 3, 4$ are under control, the total specific customer's risk is:

$$R_{\text{total}}^* = R_{c1}^* + R_{c2}^* + R_{c3}^* + R_{c4}^* - R_{c1}^*R_{c2}^* - R_{c1}^*R_{c3}^* - R_{c1}^*R_{c4}^* - R_{c2}^*R_{c3}^* - R_{c2}^*R_{c4}^* - R_{c3}^*R_{c4}^* + R_{c1}^*R_{c2}^*R_{c3}^* + R_{c1}^*R_{c2}^*R_{c4}^* + R_{c1}^*R_{c3}^*R_{c4}^* + R_{c2}^*R_{c3}^*R_{c4}^* - R_{c1}^*R_{c2}^*R_{c3}^*R_{c4}^*. \quad (\text{A.4})$$

For example, when the particular risks are again $R_{ci}^* = 0.05$, formula (A.4) gives $R_{\text{total}}^* = 0.19$ [1].

Note that these examples are for equal contributions of particular risks (R_{ci} and $P(C_i)$, as well as R_{ci}^* values), for simplicity. When the contributions are not equal, the increase of the total risk with the number of components under control may be not assured for any test results, e.g. if one or more of the risk contributions are negligible.

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Figure captions

Fig. 1. Relationship among kinds of risk of false decision on conformity of a multicomponent material. Specific risk refers to given lot, whereas global risk – to population of lots. Particular risk (specific R_{ci}^* or global R_{ci}) refers to i -th component of the material under control, $i = 1, 2, \dots, n$; and total risk (specific R_{total}^* or global R_{total}) - to the material as a whole. These four kinds of risks are relevant as for the material producer as for its consumer: they are producer’s risks and/or consumer’ risks.

Fig. 2. Global distributions of the components' content values. Histograms of the test results c_{im} , and corresponding theoretical normal pdfs for true c_i values, both in % of labeled amounts, for: a) APAP, $i = 1$; b) DEX, $i = 2$; c) DOX, $i = 3$; and d) PE, $i = 4$.

Fig. 3. Total specific risk in the specification interval. Dependence of the consumer's total specific risk R_{total}^* ($\times 10^2$) on test results c_{im} in the specification interval, 95-105 % of labeled amount, when test results for other active components c_{jm} , $j \neq i$, are equal to their prior pdf mean (Table 1). The plots are for: a) APAP, c_{1m} ; b) DEX, c_{2m} ; c) DOX, c_{3m} ; and d) PE, c_{4m} . Line 1 is for the observed correlation among the test results (Table 2); line 2 – for the case when there is no correlation (correlation coefficients $r_{ij} = 0$); line 3 – for a case when the correlation is much stronger than that observed ($r_{ij} = 0.7$).

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Table 1. Parameters of the global distributions

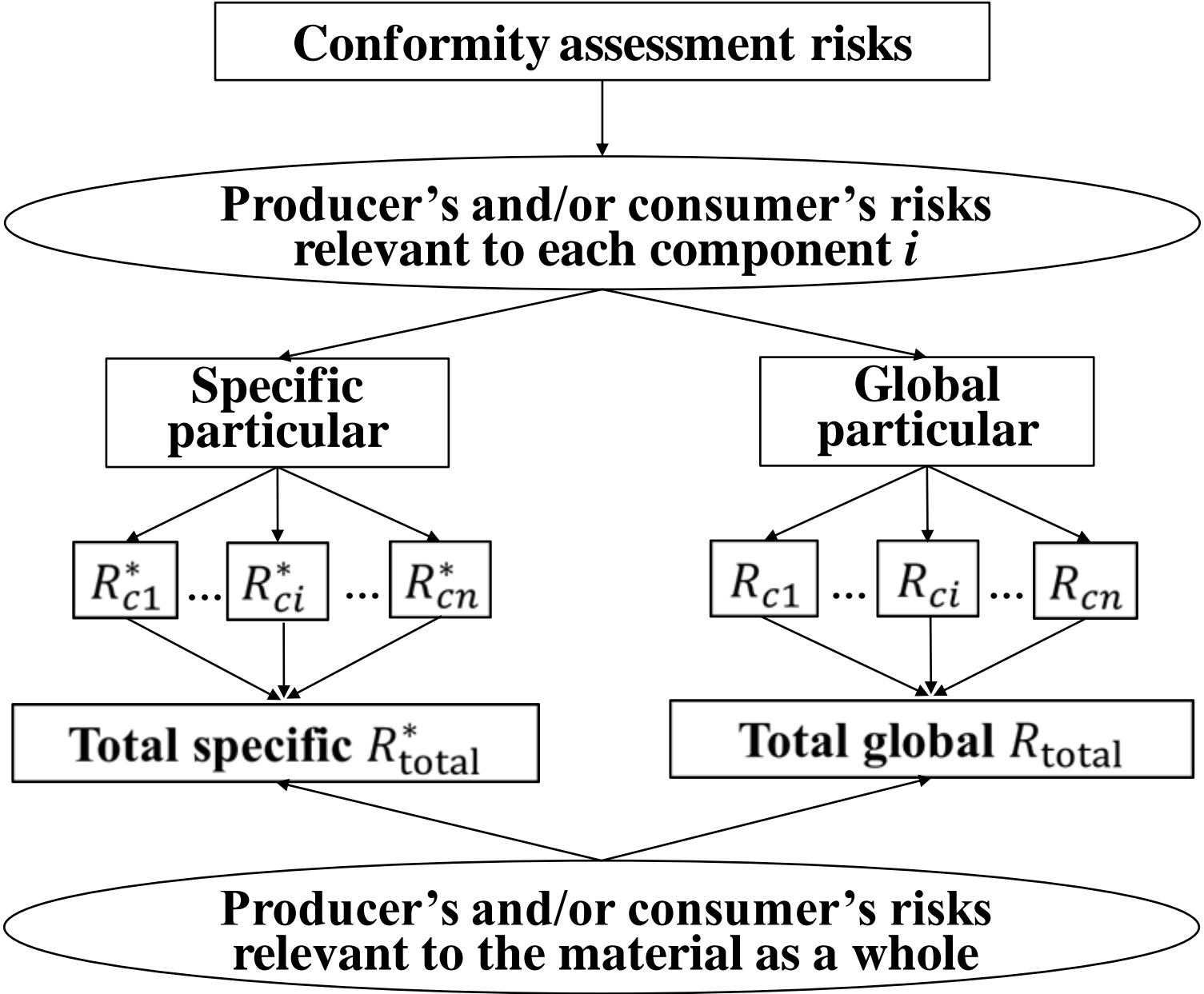
Component	Index	Parameter		
	i	$m_i, \%$	$s_i, \%$	D_i
APAP	1	99.18	1.37	0.099
DEX	2	97.70	1.02	0.087
DOX	3	99.33	1.05	0.088
PE	4	98.94	1.22	0.101

Note: m_i is the mean, and s_i - the standard deviation, both in % of labeled amount; D_i - the maximal absolute difference between empirical and theoretical cumulative distribution functions.

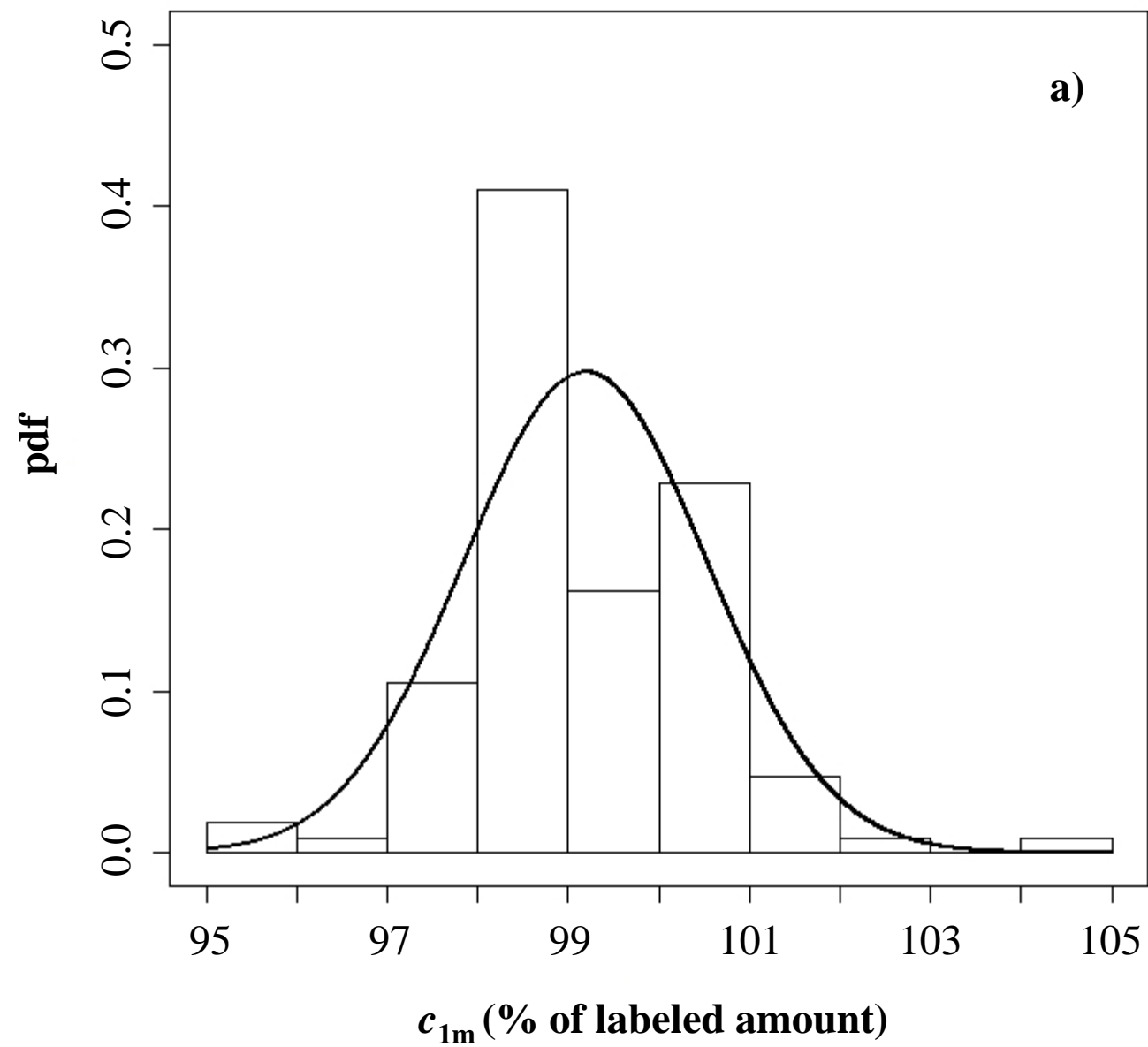
Table 2. Pearson’s correlation coefficients of test results r_{ij}

Component	Index	APAP	DEX	DOX	PE
	$i \backslash j$	1	2	3	4
APAP	1	1	0.107	0.125	0.177
DEX	2		1	0.311	0.404
DOX	3			1	0.539
PE	4				1

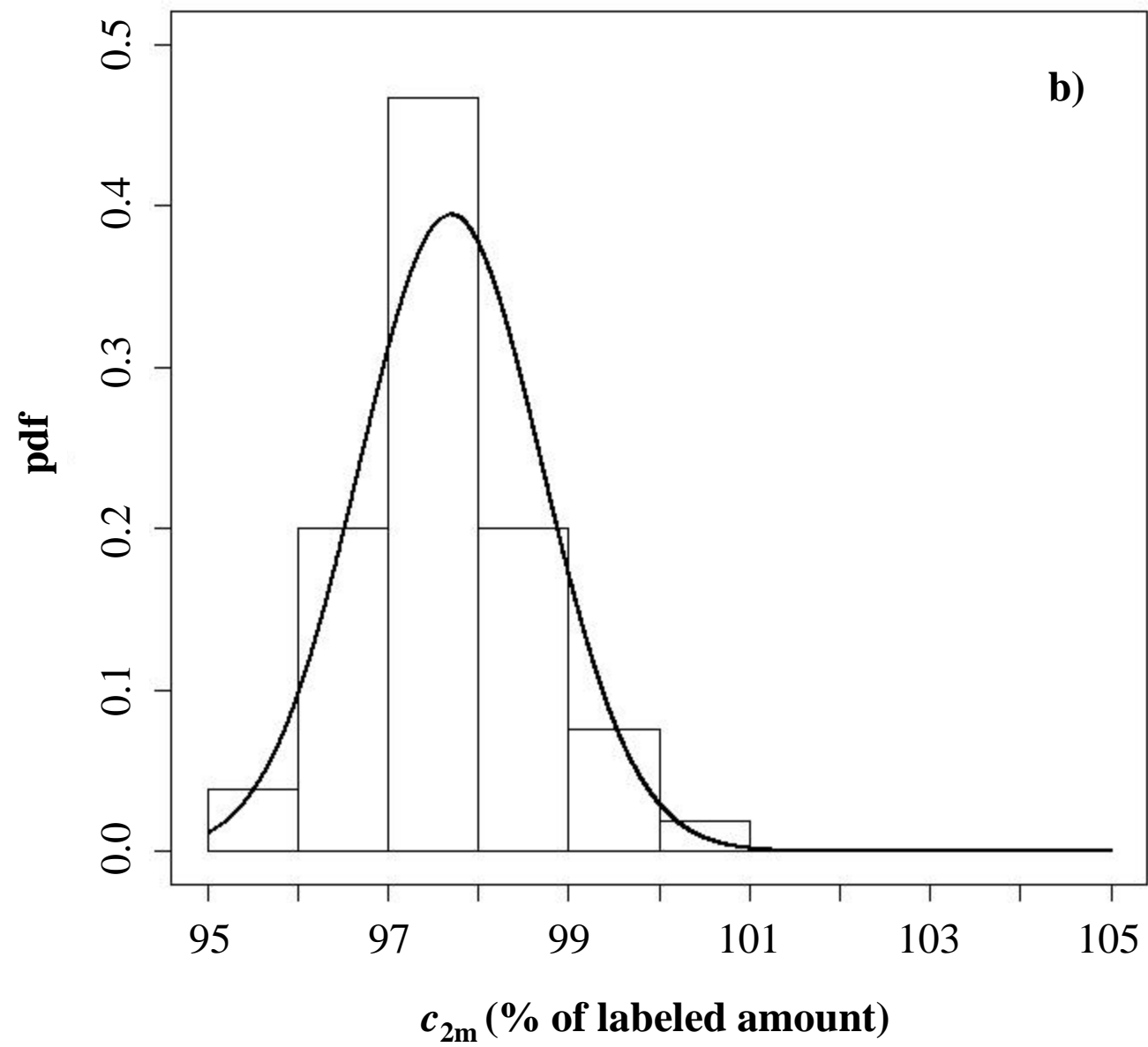
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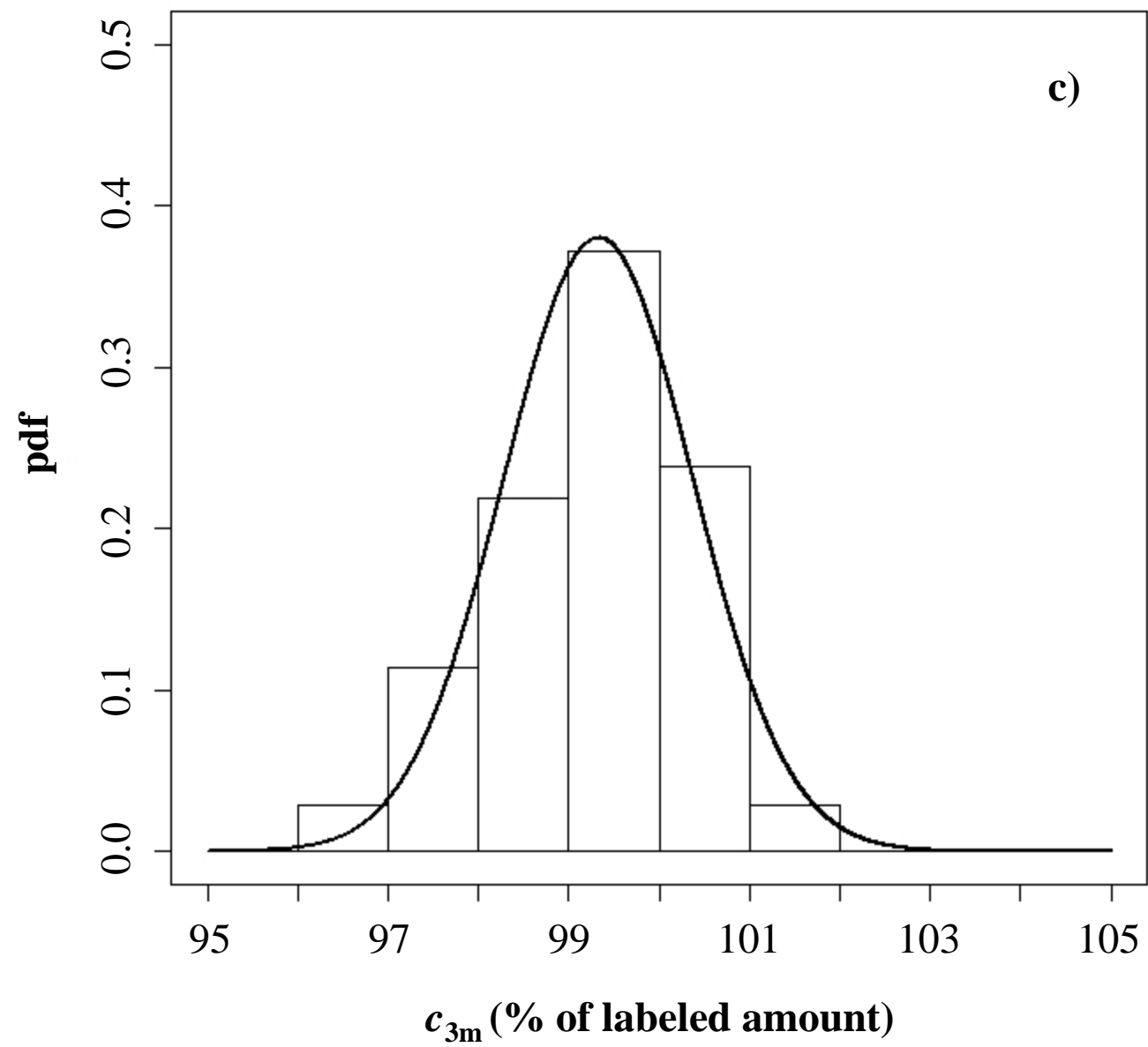
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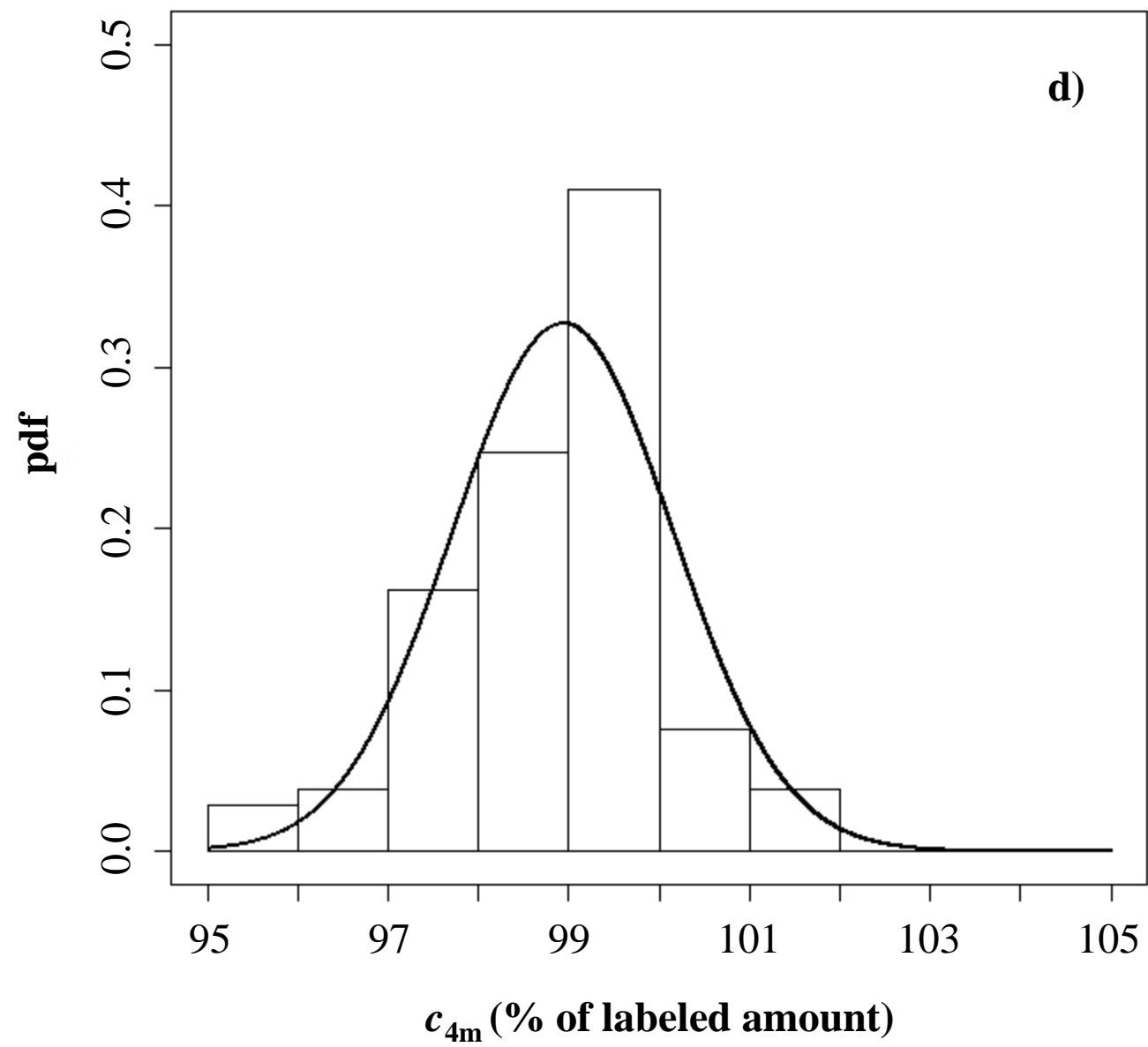
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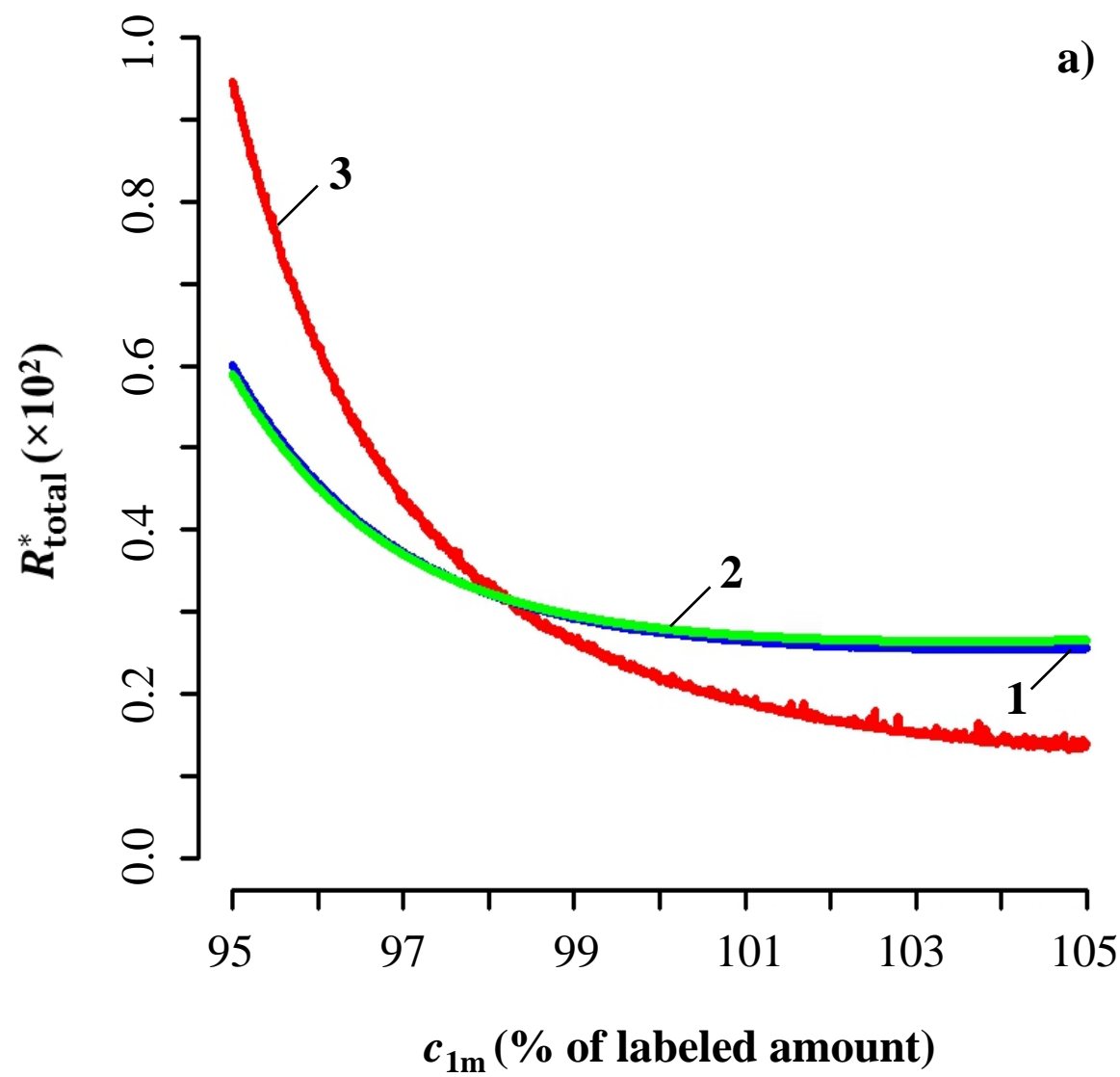
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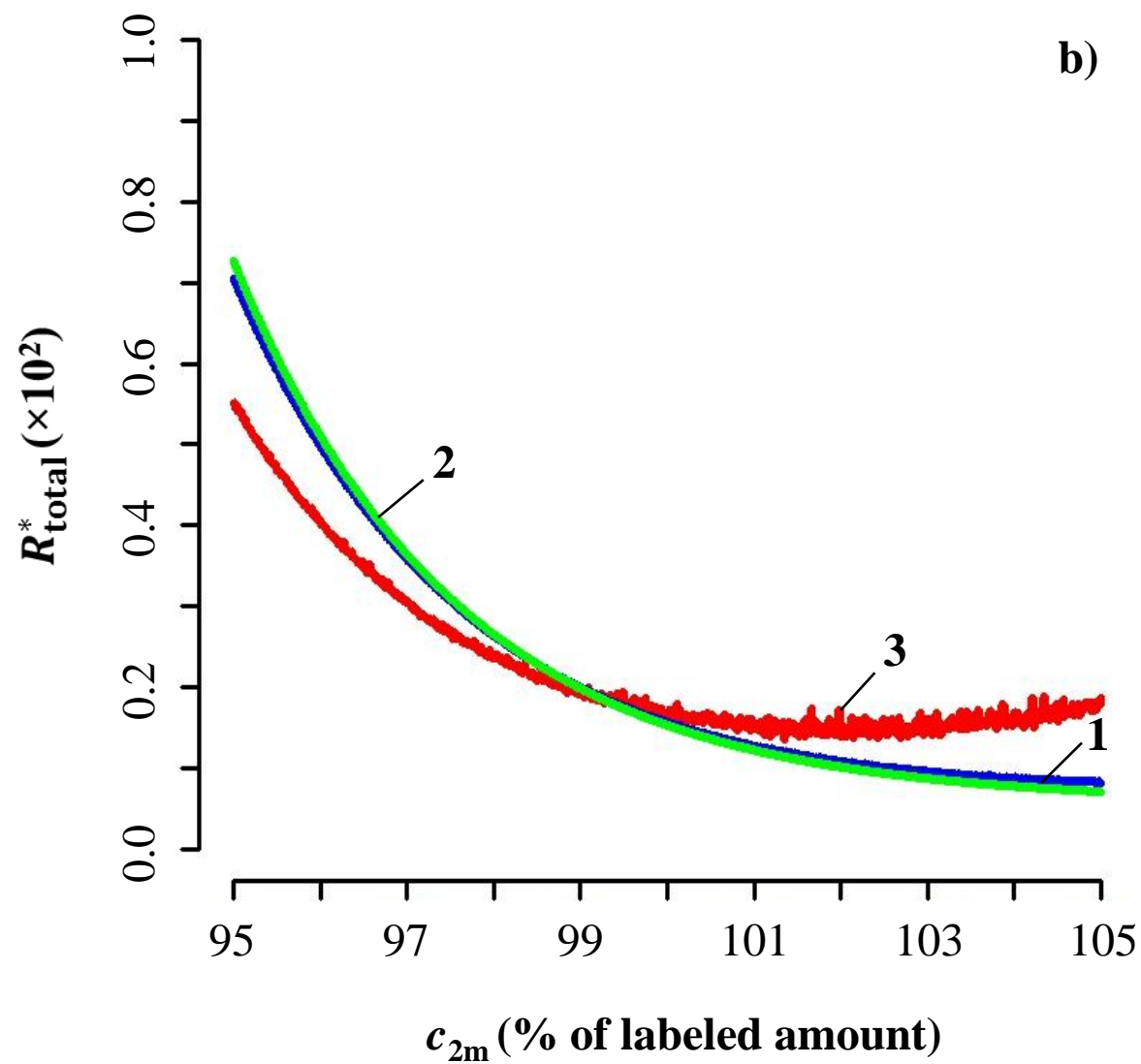
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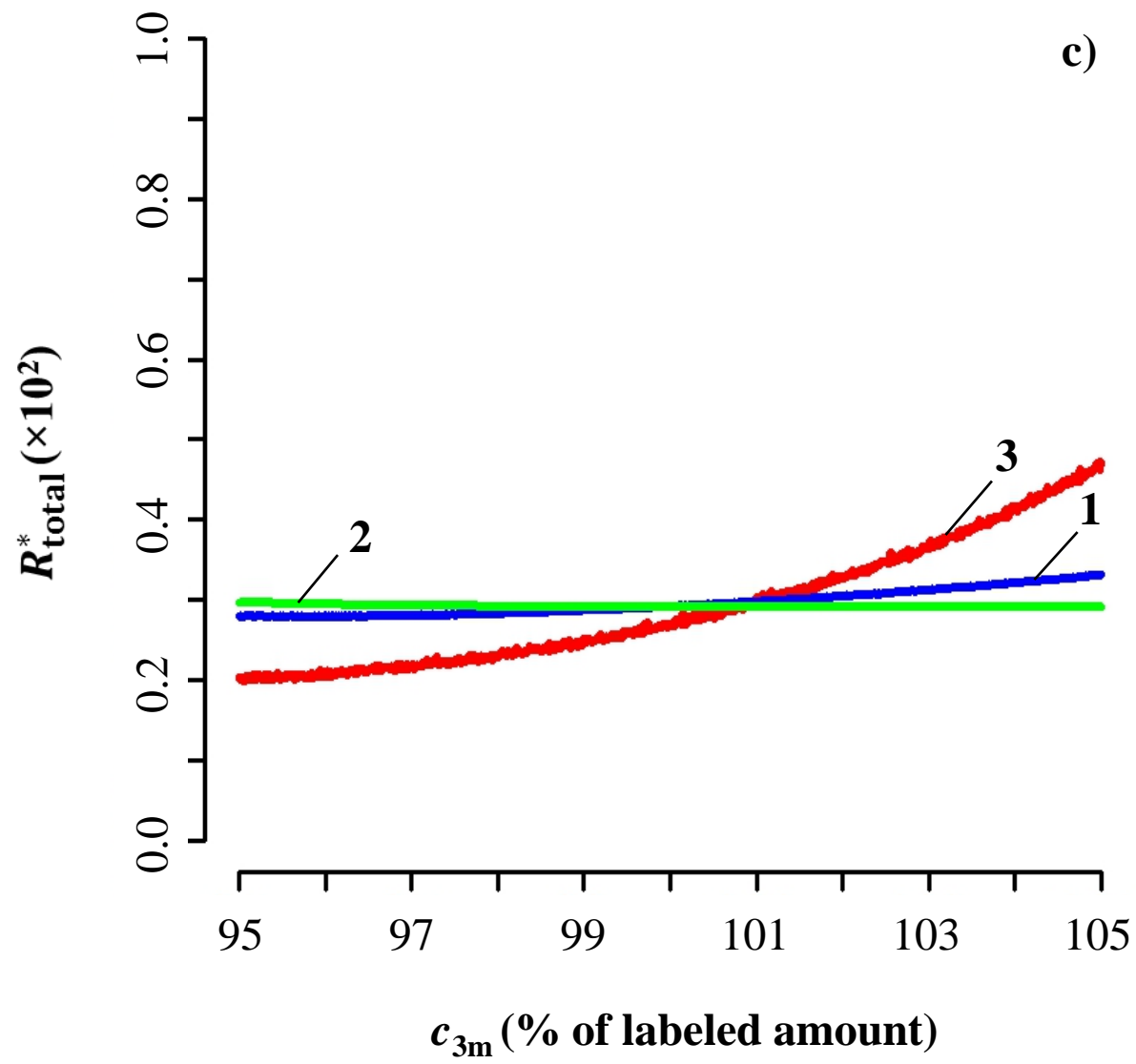
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