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Metal Print-FLR: An Exposure-Aware Fuzzy Regression Framework for Tissue Trace-Metal Burden among Vineyard Workers

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Abstract: *Trace-metal concentrations measured in hair, nail, blood, or urine may reflect occupational and environmental exposure, but their interpretation is complicated by analytical error, heterogeneous exposure histories, external contamination, and imprecise self-reported work practices. This study proposes Metal Print-FLR, a hybrid fuzzy regression framework that models the center and epistemic spread of a composite Tissue Metal Burden Score (TMBS) among grape-farming workers. Exposure intensity, years in vineyard work, personal protective equipment (PPE) adherence, age, and smoking are encoded as predictors; tissue arsenic, cadmium, lead, nickel, and chromium contribute to the response score. Model centers are estimated by least squares, whereas coefficient spreads are obtained through a possibility-constrained linear program at a predefined level h. A reproducible synthetic cohort of 72 workers illustrates the workflow. The center model explained 89.3% of TMBS variation (adjusted R2 = 0.884; RMSE = 4.23). Higher exposure intensity and longer work duration increased the predicted center, while stronger PPE adherence reduced it. At h = 0.50, the fuzzy envelope achieved 100% in-sample inclusion by construction and 93.1% mean six-fold validation inclusion, with a validation RMSE of 4.72. The framework makes uncertainty visible and supports ranking, surveillance prioritization, and sensitivity analysis without claiming probabilistic confidence intervals. A field-validation protocol is specified for conversion of this methodological demonstration into an ethically approved occupational biomonitoring study.*

Keywords: fuzzy linear regression; trace metals; vineyard workers; occupational exposure; biomonitoring; hair and nail; PPE; possibility theory

I. INTRODUCTION

Grape production involves repeated contact with pesticide formulations, treated foliage, contaminated equipment, soil dust, fertilizers, and irrigation water. Vineyard work may therefore create mixed chemical exposures rather than a single-agent problem. Biomonitoring can connect external work conditions to internal dose, but an observed concentration is not a perfectly precise truth: sampling time, digestion recovery, instrument performance, matrix effects, hydration, smoking, diet, and individual toxico kinetics all affect the result [1-6]. Hair and nails are attractive for long-term, non-invasive screening, and recent farmer studies have used them to compare trace-element profiles [1,2]. Their convenience does not remove major interpretive limitations. External deposition can be difficult to distinguish from endogenous incorporation, washing protocols are not fully harmonized, and population reference ranges may be incomplete [7,8]. Blood and urine remain preferable for several metal-specific questions, such as recent lead exposure or speciated urinary arsenic. A defensible statistical framework should therefore carry analytical and classification uncertainty forward instead of discarding it. Classical regression represents unexplained variation through a stochastic error term and usually requires assumptions about its distribution. Fuzzy regression addresses a different question: how wide must a possibility distribution be to include imprecise observations at a chosen compatibility level? Tanaka, Uejima, and Asai introduced

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linear-programming-based fuzzy regression; later work extended possibilistic and least-squares formulations [9-15]. The approach is suitable when uncertainty includes ambiguity in exposure ratings and measurement tolerances that cannot be interpreted solely as random sampling error.

Research Gap and Novel Contribution: Most occupational biomonitoring analyses either regress one metal at a time or convert uncertain questionnaire and laboratory values into single crisp numbers. This can overstate precision and obscures whether an apparently elevated prediction is robust to plausible measurement and recall error. The proposed framework contributes:
(i) a multi-metal tissue burden score;
(ii) triangular fuzzy encoding of exposure and laboratory uncertainty;
(iii) a hybrid center-and-spread estimator that preserves interpretable regression centers;
(iv) possibility-level sensitivity analysis; and
(v) a field protocol that separates methodological demonstration from human-subject conclusions.

Aim and Objectives: To develop and demonstrate an exposure-aware fuzzy regression model for estimating tissue trace-metal burden among grape-farming workers.
Construct a normalized composite score from arsenic (As), cadmium (Cd), lead (Pb), nickel (Ni), and chromium (Cr).
Represent exposure intensity and tissue measurements as triangular fuzzy numbers with transparent spreads.
Estimate center effects and minimum compatible spreads at selected possibility levels.
Compare center fit, fuzzy inclusion, cross-validated performance, and sensitivity to h.
Specify safeguards and a validation protocol for a future real-worker study.

II. METHODOLOGY

This is a methodological simulation study. No person was recruited, no biological specimen was collected, and no health conclusion about grape-farming workers is made. A seed-controlled synthetic cohort (n = 72) was generated to resemble plausible variability in age, years of work, annual spray days, PPE adherence, mixing/loading duties, smoking, heat load, and tissue-metal measurements. The reproducible algorithm is given below:

- Collect and quality-check worker, task, PPE, and matrix-specific metal data.
- Normalize metal concentrations and compute the prespecified TMBS.
- Assign each observed exposure and TMBS a documented triangular spread.
- Standardize continuous predictor centers using training-sample parameters.
- Estimate center coefficients by least squares (or a prespecified robust alternative).
- Choose h and solve the non-negative linear program for coefficient spreads.
- Generate predicted centers, spreads, h-cuts, and worker-level compatibility flags.
- Use nested or repeated cross-validation; refit preprocessing and both model stages inside every fold.
- Repeat over prespecified h values, spread rules, metal weights, and alternative matrices.
- Report centers and spreads separately; do not label possibility intervals as confidence intervals.

2.1 Proposed field sampling protocol

Component	Recommended specification
Population	Adult grape-farming workers with ≥ completed season; comparison group from the same region where feasible.
Design	Repeated measures: pre-spray season, peak application, and post-harvest.

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Component	Recommended specification
Questionnaire	Task diary, product/formulation, mixing/loading, spray days, re-entry work, PPE use, smoking, diet, water source, residence.
Matrices	Metal-specific primary matrices (blood/urine) plus standardized hair and nail collection for longer-window exploratory analysis.
Laboratory	ICP-MS or validated equivalent; blanks, duplicates, certified reference material, recovery, LOD/LOQ, batch randomization.
Ethics	Consent, confidentiality, withdrawal, occupational-health referral, and prespecified communication thresholds.

2.2 Trace-metal response construction

Let C_{im} denote the concentration of metal m for worker i, and let R_m be a prespecified reference or study median used only for normalization. A log-ratio index limits domination by a single right-skewed metal. Weights w_m are non-negative and sum to one. For demonstration, $w = (0.25, 0.20, 0.25, 0.15, 0.15)$ for As, Cd, Pb, Ni, and Cr.

$$TMBS\_i = 50 + 15 * \sum_m [\, w_m \, log(C_{im} / R_m) \,]$$

In the simulation, the score was bounded to 0-100 for interpretability. In a real study, R_m and weights must be fixed before outcome analysis, and sensitivity to alternative toxicological or data-driven weights should be reported.

2.3 Fuzzy representation

A symmetric triangular fuzzy number is written $A = (a, s)$, where a is the center and $s \geq 0$ is the support half-width. Its membership function is:

$$\mu_A(z) = max\{0, 1 - |z - a| / s\}; \quad A_h = [a - (1-h)s, a + (1-h)s].$$

Exposure intensity is assigned a spread using task-frequency uncertainty and inverse PPE consistency. The TMBS spread combines laboratory imprecision, sampling variability, and uncertainty propagated from the component metals. These spreads are measurement-uncertainty inputs, not standard errors and not 95% confidence intervals.

2.4 Center model

Continuous predictors were standardized to mean 0 and standard deviation 1; binary smoking retained its $0/1$ coding. The design vector was $x_i = (1$, exposure intensity, years of vineyard work, PPE adherence, age, smoking$)$.

$$m_i = a_0 + a_1E_i + a_2Y_i + a_3P_i + a_4A_i + a_5S_i.$$

Center coefficients a_j were estimated by ordinary least squares to retain familiar partial-effect interpretation. This hybrid choice also prevents the spread optimization from shifting center effects solely to reduce envelope width.

2.5 Possibility-constrained spread model

Each coefficient is represented as $A_j = (a_j, c_j), c_j \geq 0$. For crisp standardized inputs, the predicted spread is $s_i = \sum_j c_j |x_{ij}|$. At possibility level h, the predicted h-cut must contain the observed TMBS h-cut. Given observed center y_i and measurement spread e_i, containment is equivalent to:

$$\sum_j c_j |x_{ij}| \geq \frac{|y_i - m_i|}{(1-h)} + e_i, \quad i = 1, \dots, n.$$

The coefficient spreads are obtained by minimizing total sample-weighted ambiguity:

$\min_c \sum_i \sum_j c_j |x_{ij}|$, subject to the containment constraints and $c_j \geq 0$.

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The optimization is a linear program. The selected primary level was h = 0.50; h = 0.25 and 0.75 were examined for sensitivity. Larger h requires a wider support distribution to preserve inclusion at a narrower h-cut.

2.6 Evaluation

Center performance was summarized by R2, adjusted R2, RMSE, coefficient standard errors, t statistics, and two-sided p values. Fuzzy performance was summarized by observed-fuzzy-set inclusion and mean h-cut width. Six-fold cross-validation refitted both center and spread components in each training fold. Inclusion is a compatibility measure, not frequentist coverage probability.

III. DATA DESCRIPTION

In this section Table 1 shows twelve records selected at evenly spaced row positions out of 72 synthetic cohort and Table 2 shows descriptive statistics for the synthetic cohort (n = 72).

ID	Age	Years	Spray days	PPE	Exposure	TMBS	Spread
GW-001	23	3	16	0.58	0.09	19.65	3.65
GW-007	61	33	83	0.36	9.15	66.97	5.63
GW-013	47	5	55	0.50	3.22	34.55	4.31
GW-020	42	5	55	0.75	2.14	19.02	3.36
GW-026	62	13	76	0.93	5.26	43.48	4.33
GW-033	32	16	38	0.38	4.05	46.60	5.14
GW-039	60	8	22	0.81	0.80	30.32	3.66
GW-046	29	13	16	0.54	0.14	27.79	3.38
GW-052	42	10	25	0.45	2.40	34.29	4.22
GW-059	61	5	85	0.73	6.16	47.92	4.54
GW-065	50	20	37	0.28	5.07	57.28	5.66
GW-072	59	9	29	0.37	2.60	37.30	4.63

Table 1. Twelve records selected at evenly spaced row positions.

Variable	Unit	Mean	SD	Min	Median	Max
Age	years	44.01	12.45	22.00	43.00	62.00
Years	years	14.18	10.30	1.00	11.50	35.00
Spray Days	days/year	59.82	29.94	16.00	60.50	107.00
PPE	proportion 0-1	0.55	0.22	0.12	0.53	0.98
Exposure	index 0-10	4.48	2.73	0.00	4.07	10.00
As	mg/kg	1.15	0.45	0.57	1.06	2.44

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Variable	Unit	Mean	SD	Min	Median	Max
Cd	mg/kg	0.29	0.09	0.15	0.28	0.56
Pb	mg/kg	3.60	1.30	1.65	3.44	8.61
Ni	mg/kg	1.52	0.48	0.88	1.47	3.04
Cr	mg/kg	1.23	0.35	0.61	1.21	2.51
Burden	TMBS points	42.53	13.00	19.02	41.31	68.63

Table 2. Descriptive statistics for the synthetic cohort (n = 72). Metal units are illustrative and do not constitute reference values.

IV. RESULTS AND DISCUSSION

In this section we see the results of the data that we have considered:

4.1 Center-model performance

Predictor	Center coef.	SE	t	p
Intercept	41.982	0.594	70.70	<0.001
Exposure intensity	8.853	0.646	13.70	<0.001
Years in vineyard work	3.962	0.745	5.32	<0.001
PPE adherence	-1.472	0.528	-2.79	0.007
Age	0.877	0.659	1.33	0.188
Smoking	2.442	1.284	1.90	0.062

Table 3. Center regression. Continuous predictors are standardized; smoking is 0/1. R2 = 0.893; adjusted R2 = 0.884; RMSE = 4.23.

The center model explained 89.3% of the synthetic TMBS variance. Statistically detectable partial effects at alpha = 0.05 were: Exposure intensity, Years in vineyard work, PPE adherence. The exposure coefficient is the largest positive standardized continuous-predictor effect, while PPE adherence has a negative coefficient, consistent with its protective encoding.

4.2 Fuzzy coefficients and envelope

Coefficient	Triangular pair (center, spread)	Support interval
Intercept	(41.982, 21.050)	[20.932, 63.032]
Exposure intensity	(8.853, 0.618)	[8.235, 9.471]
Years in vineyard work	(3.962, 1.846)	[2.116, 5.808]
PPE adherence	(-1.472, 0.883)	[-2.355, -0.588]
Age	(0.877, 0.000)	[0.877, 0.877]

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Coefficient	Triangular pair (center, spread)	Support interval
Smoking	(2.442, 0.000)	[2.442, 2.442]

Table 4. Estimated fuzzy coefficients at h = 0.50. A zero or small spread does not mean the predictor is certain; the linear program allocates minimum aggregate ambiguity across correlated absolute-design columns.

The fitted h = 0.50 envelope included 100% of observed fuzzy outcomes in the estimation sample, as imposed by the optimization. The mean h-cut width was 23.90 TMBS points. In six-fold validation, mean RMSE was 4.72, mean inclusion was 93.1%, and mean interval width was 24.00. The difference between estimation and validation inclusion demonstrates why in-sample containment alone is not evidence of generalization.

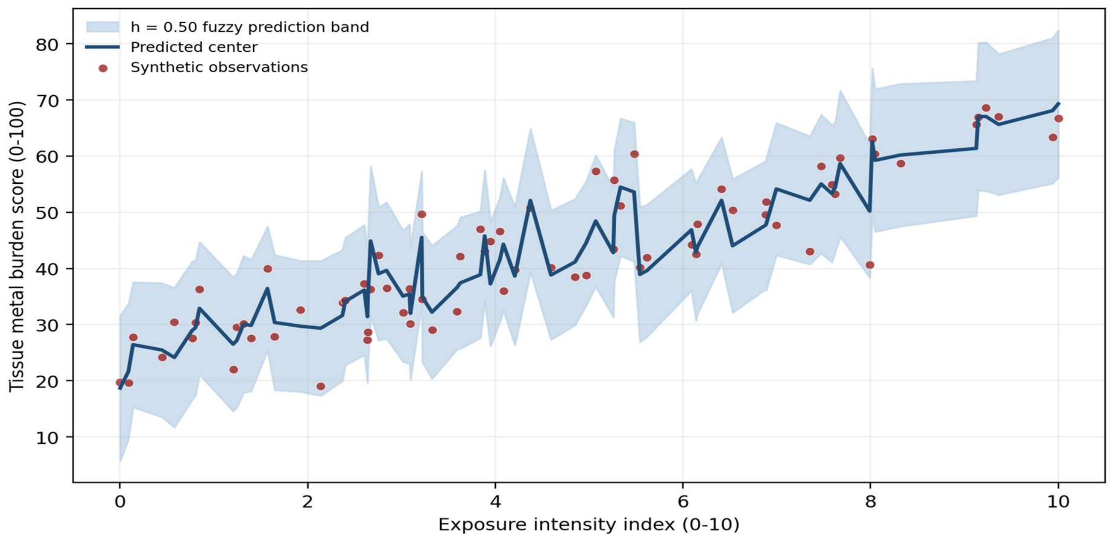

Figure 1. TMBS observations, predicted centers, and the h = 0.50 fuzzy prediction envelope.

4.3 Worked calculation

Term	Model value	Center coef.	Contribution
Intercept	1.000	41.982	41.982
Exposure intensity	-0.159	8.853	-1.407
Years in vineyard work	0.178	3.962	0.705
PPE adherence	-0.784	-1.472	1.154
Age	-0.972	0.877	-0.852
Smoking	0.000	2.442	0.000

Table 5. Worked center prediction for GW-033. Predicted center = 41.58; observed synthetic TMBS = 46.60.

Predicted fuzzy TMBS for GW-033 at h=0.50: [30.50, 52.67], center 41.58.

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4.4 Possibility-level sensitivity

h	Mean h-cut width	Sum coefficient spreads	In-sample inclusion
0.25	26.12	17.43	100%
0.50	23.90	24.40	100%
0.75	22.09	46.56	100%

Table 6. Sensitivity of ambiguity and inclusion to the selected possibility level.

All fitted models satisfy their own in-sample containment constraints. As h increases, the support spreads expand because the h-cut contracts toward the center. Reporting h alongside the fitted spread is therefore essential; a spread has no standalone interpretation without its membership function and calibration rule.

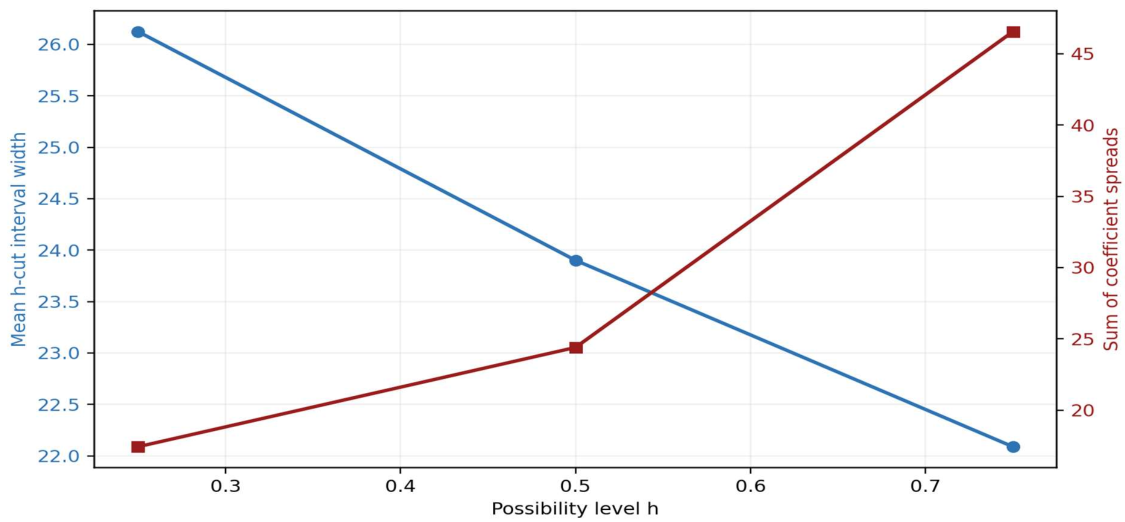

Figure 2. Effect of possibility level on h-cut width and coefficient ambiguity.

4.5 Discussion

The worked example shows how fuzzy regression can express two layers that are routinely collapsed in occupational biomonitoring: a center relationship and an uncertainty envelope. The positive exposure-intensity and work-duration centers are structurally consistent with a simulation in which repeated spraying, mixing, soil contact, and cumulative work increase metal burden. PPE adherence shifts the center downward. More important methodologically, the fuzzy spreads prevent a single predicted TMBS from appearing more exact than the questionnaire and analytical process can support.

The approach complements rather than replaces conventional statistics. Probability models quantify sampling or stochastic uncertainty under a distributional model. Possibility models quantify compatibility under graded sets and analyst-defined spreads. A strong applied study should report both where appropriate: classical or Bayesian uncertainty for population inference, and fuzzy sensitivity for measurement ambiguity, linguistic exposure categories, or uncertain thresholds.

Matrix selection remains central. Hair and nails can be useful for non-invasive, longer-window screening, and studies among farmers have reported measurable trace elements in these matrices [1,2]. However, ATSDR has emphasized external contamination, uncertain background ranges, and the difficulty of separating internal from external metal sources

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[7,8]. Consequently, the proposed field design pairs hair/nail sampling with metal-specific primary matrices and rigorous laboratory quality control. The model cannot repair a biologically inappropriate specimen.

Recent vineyard biomonitoring has demonstrated that short occupational exposures can be measured when sampling is timed to the work task [3], and systematic reviews emphasize repeated sampling, sensitive analytical methods, and improved exposure characterization [4,5]. Metal Print-FLR extends these principles to trace-metal mixtures and makes uncertainty parameters auditable.

4.6 Occupational-Health Interpretation

Model pattern	Prudent interpretation
High center, narrow spread	Consistently elevated model estimate; prioritize confirmatory testing and exposure-control review.
High center, wide spread	Potentially elevated but uncertain; improve sampling, task records, and matrix-specific confirmation.
Low center, wide spread	Do not conclude low risk; uncertainty is too large for reassurance.
Low center, narrow spread	Relatively stable low estimate within the model; continue routine prevention and surveillance.

Table 7. Decision interpretation. None of these categories is a medical diagnosis or exposure limit.

The model should trigger process improvements rather than individual blame. Preferred controls follow the hierarchy of controls: substitution where feasible, closed transfer and mixing systems, drift and re-entry management, hygiene facilities, training, fit-for-purpose PPE, and medical surveillance designed with occupational-health professionals.

4.7 Limitations

The dataset is synthetic; numerical effects, p values, and rankings have no empirical or clinical meaning.

A composite score can hide metal-specific toxicology, kinetics, and action thresholds.

Symmetric triangular fuzzy numbers may be inadequate for skewed or asymmetric analytical uncertainty.

The hybrid center estimator treats fuzzy predictor centers as fixed; a full fuzzy-input model could propagate predictor spreads into the center fit.

Linear additivity may miss interactions among metals, heat, dehydration, task, and PPE.

In-sample fuzzy inclusion is guaranteed by construction and must not be advertised as validation.

Hair and nail values may include external contamination and require standardized cleaning, collection, and confirmatory matrices.

V. CONCLUSION

Metal Print-FLR provides a transparent way to relate vineyard work characteristics to a multi-metal tissue burden while retaining uncertainty from exposure classification and laboratory measurement. In the synthetic demonstration, exposure intensity, work duration, PPE adherence, and smoking contributed to an interpretable center model, while a linear program estimated the minimum fuzzy spreads required for h-level compatibility. The method is most useful as an uncertainty-aware complement to conventional occupational epidemiology. Its scientific value depends on ethical field sampling, matrix-appropriate biomonitoring, laboratory quality assurance, prespecified fuzzy spreads, and external validation.

Declarations:

Ethics approval: Not applicable to the synthetic methodological demonstration. Required before any real-worker recruitment or specimen collection.

Funding: No external funding is declared for this demonstration.

Competing interests: Authors do not have any competing interests.

Clinical disclaimer: The TMBS and fuzzy intervals are research constructs, not diagnostic tests or occupational exposure limits.

Data availability: The illustrative data are deterministically generated within the analysis workflow, no real participant data are used.

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