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Geostatistical Analyses of Soil Electrical Conductivity in a Vegetable Greenhouse Field with Different Data Sets

[1]Yong Jiang, [1,3]Wei Hao, [1,2]Yuge Zhang and [1]Wenju Liang
[1]Institute of Applied Ecology, Chinese Academy of Science, Shenyang 110016, China
[2]College of Biological and Environmental Engineering, Shenyang University, Shenyang 110044, China
[3]Graduate School of the Chinese Academy of Sciences, Beijing 100039, China

Abstract: The study was conducted at Damintun town, Shenyang city, Liaoning Province of China, in order to analyze the spatial variability of soil Electrical Conductivity (EC) under greenhouse vegetable plantation and to compare the differences of the spatial variability using different data sets. A micro area of 8×5.7 m with 0.4×0.3 m regular rectangle grids subdivision was chosen and totally 420 points of soil EC was *in-situ* measured using a W.E.T.- sensor. The total data was named as data sets A and was divided into 3 groups that named as data sets B, C and D. The results showed that the mean, minimum, maximum, percentiles 25, median and percentiles 75 values were a little different among the four data sets. The histograms for soil EC showed that the data fitted normal distribution for each data sets. Soil EC was spatially dependent and modeled quite well with different data sets. The anisotropic semivariograms showed that the structural component of sample variance for data sets B and D was highly spatial dependence with the ratio of $C/(C_0+C)$ >75%, while data sets A and C exhibited middle spatial dependence. The isotropic semivariograms showed that all the data sets having middle values of nugget effects and 50% of the $C/(C_0+C)$, indicated that the greenhouse vegetable plantation have led to sample dissimilarity in the small sampling distance within a small area. The maps obtained with kriging were quite similar with different data sets. Although, the smoothing effect existed with all the four data sets, kriging remains the best local estimator when the data is reduced. The smoothing effect of kriging can be supplemented with classical statistics. It is concluded that geostatistics combined with classical statistics is an ideal way to examine the spatial variability of soil properties in a micro- field scale. Because the soil EC was high in this study, it is suggested that measures be taken to avoid the accumulation of soil salt in greenhouses by applying fertilizers rationally according to soil fertility, vegetable varieties and fertilizer properties in the study region.

Key words: Soil electrical conductivity, geostatistics, spatial variability, vegetable greenhouse

INTRODUCTION

Soil physical, chemical and biological properties are all likely to change markedly across small distances, within a few hectares of farmland, within a suburban house lot and even within a single soil individual (Cambardella *et al.*, 1994; Chien *et al.*, 1997; Jiang *et al.*, 2005a; Liang *et al.*, 2003; Paz-González *et al.*, 2000). Spatial variability in soils occurs naturally from pedogenetic factors, while much variability can also occur as a result of land use and management (Jiang *et al.*, 2005b, 2005c; Paz-González *et al.*, 2000). The small-scale variability may be difficult to measure and not apparent to the casual observe, but it has practical uses in managing soil fertility for a given field (Brady and Weil, 2002; Jiang *et al.*, 2006; Van Meirvenne, 2003).

Salt-affected soils adversely affect plants because of the total concentration of salts (salinity) in the soil solution and because of concentrations of special ions, especially sodium. Salinity is measured primarily as the Total Dissolved Solids (TDS) or Electrical Conductivity (EC). Pure water is a poor conductor of electricity, but conductivity increase as more and more salt is dissolved in the water, thus, the EC of the soil solution gives us an indirect measurement of salt contents. The EC can be measured both on samples of soil or on the bulk soil *in situ* (Brady and Weil, 2002). Advance in instrumentation now allows rapid, continuous field measurement of bulk soil conductivity, which, in turn, is directly related to soil salinity. Enough EC data can be transformed into a map that showing the spatial variation of soil salinity of a field or across a parcel of land.

Corresponding Author: Dr. Yong Jiang, Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110016, China

Greenhouse plantation is a major way of vegetable production during winter in North China. Many problems have already appeared in soils of vegetable greenhouses under heavy application of fertilizers and other chemicals like pesticides and hormones, e.g., the frequent occurrence of soil borne diseases, soluble salt accumulation, degradation of soil quality and decrease in soil productivity (Jiang *et al.*, 2003; Jiao and Li, 2003; Li *et al.*, 2004; Liu *et al.*, 2005; Zhang *et al.*, 2006). Soil salt accumulation has been regarded as a key factor that limits vegetable production in greenhouses in North China, thus the survey of salinity in greenhouse soils is the basis on which sustainable measures can be taken (Li *et al.*, 2004; Zhang *et al.*, 2006).

The objectives of this study were to analyze the spatial variability of soil electrical conductivity in a vegetable greenhouse field with different data sets and to map and compare the distribution of soil EC using different data sets.

MATERIALS AND METHODS

This study was conducted at Damintun town (41°50' N, 122°55' E), Shenyang city, Liaoning Province of China in October 2005. It is located in a continental temperate monsoon zone, with a dry-cold winter and a warm-wet summer. The annual temperature ranges 7.0-8.0°C, annual precipitation ranges 650-700 mm and annual non-frost period ranges 150-170 days. A vegetable greenhouse with 11 years of plantation was selected as the study site. The greenhouse was about 0.1 ha and the previous vegetable planted was tomato. The greenhouse soil was amended with 4000 kg synthetic fertilizer ha^{-1} and 80 t chicken manure ha^{-1} each year. The soil at the study site is meadow soil. A micro area of 8×5.7 m with 0.4×0.3 m regular rectangle grids subdivision was chosen and totally 420 points of soil Electrical Conductivity (EC) was *in-situ* measured using a W.E.T.-sensor. The W.E.T.-sensor is a frequency domain dielectric sensor that measures permittivity, conductivity and temperature, which can be used for monitoring soil water content and EC in horticulture. Figure 1 shows the spatial location of the total sampling points and the corresponding soil EC values.

To compare the spatial variability of soil EC with different data sets, we used the 420 in-site measured EC values as data sets A and divided the total data into three groups and named as data sets B, C and D according to the data number, i.e., data sets B consists in number 1, 4, 7 and so on, data sets consists in number 2, 5, 8 and so on and data sets C consists in number 3, 6, 9 and so on.

Classical statistical parameters, i.e., mean, standard deviation, coefficient of variation, median, minimum, maximum and data normality, were calculated using SPSS 11.0 software. Isotropic and anisotropic semivariances of data were calculated using GS+ geostatistical software (Gamma Design Software, 2000). Semivariance γ(h) is defined in the following equation:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i + h) \right]^2 \qquad (1)$$

where N(h) is the number of sample pairs at each distance interval h and $z(x_i)$ and z(xi+h) are the values of variable at any two places separated by distance h. The semivariogram is the plot of the semivariance against the distance. Its shape indicates whether the variable is spatially dependent. Experimental semivariograms were fitted by theoretical models that have well-known parameters nugget C_0, sill C_0+C and range of spatial dependence a.

The contour maps of soil EC obtained with different data sets were constructed using GS+ software.

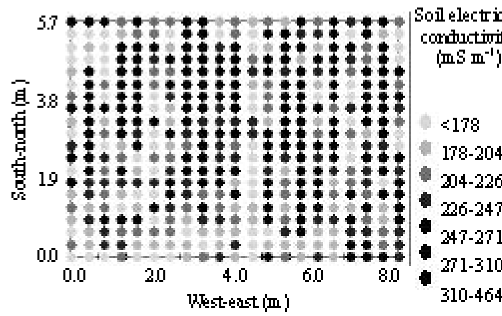

Fig. 1: Spatial location of the total sampling points and the corresponding soil electrical conductivity value

RESULTS AND DISCUSSION

Summary statistics: The summary statistics of soil EC for the four data sets were listed in Table 1. The mean, minimum, maximum, percentiles 25, median and percentiles 75 values were a little different among the four data sets. Compared with data sets A, data sets B had higher while data sets D had lower mean value, data sets C had higher while data sets D had lower coefficient of variation.

Although, the soil EC data were obtained within an area of only 45.6 m^2, the highest value was about twice as much as the lowest value for each data sets. The median values were a little lower than the mean values in each data sets (Table 1), indicating that the test variable was affected by some extreme higher values at the studied scale (Jiang *et al.*, 2005a).

Table 1: Summary statistics of soil electrical conductivity with different sampling data sets

	Data sets A	Data sets B	Data sets C	Data sets D
Sampling number	420.0	140.0	140.0	140.0
Mean (mS m^{-1})	241.7	246.3	243.4	235.4
Standard deviation	61.50	62.40	63.30	58.60
Coefficient variation (%)	25.45	25.36	26.00	24.91
Minimum (mS m^{-1})	129.0	135.0	129.0	140.0
Maximum (mS m^{-1})	464.0	464.0	445.0	430.0
Percentiles 25 (mS m^{-1})	198.0	201.0	200.0	190.0
Median (mS m^{-1})	235.0	236.0	238.0	225.0
Percentiles 75 (mS m^{-1})	277.0	279.0	280.0	268.0
Skewness	0.650	0.770	0.390	0.820
Kurtosis	0.400	0.970	-0.150	0.520

Although, the differences of the ordinary statistical data were not too great, the Skewness and Kurtosis were different from each other. The Kurtosis for data sets B was 0.97, but it was -0.15 for data sets C (Table 1), indicating that the neighboring data was quite different from each other within the small field scale.

As shown in Fig. 2 from data set A, about 15% of the total samples had soil EC value lower than 180 mS m^{-1}, about 70% of the total samples had soil EC value from 180 mS m^{-1} to 300 mS m^{-1} and only about 6% of the total samples had soil EC value greater than 350 mS m^{-1}. The histograms for soil EC showed that the data fitted normal distribution for each data sets.

Variograms: The directional variograms were computed in four principle directions of east-west (0°), southeast-northwest (45°), south-north (90°) and northwest-southeast (135°) with a tolerance of 22.5°. The model-fitted parameters were listed in Table 2. The best-fitted model for data sets A, C and D was exponential, while that for data sets B was linear. The F-test showed that all the best-fitted semivarigram models were significant at the 0.01 or 0.05 level. The anisotropic semivariograms indicated that the spatial structures of data sets A, B, C and D were geometrically nested with an anisotropic ratio of 1.10, 3.55, 1.04 and 1.56, respectively. The anisotropic semivariograms for all the four data sets in the 0° exhibited the strongest anisotropies, as indicated by their maximal differences between the major and minor axis range parameters (A_1 and A_2) in their models (Fig. 3 and Table 2). The anisotropic semivariograms showed that the structural component of sample variance for data sets B and D was highly spatial dependence with the ratio of $C/(C_0+C)$ >75%, while data sets A and C exhibited middle spatial dependence (Cambardella *et al.*, 1994).

Figure 4 showed the scaled experimental semivariances and the adjusted semivariogram models for soil EC with different data sets and the corresponding model-fitted parameters were listed in Table 3. Soil EC was spatially dependent and modeled quite well with different

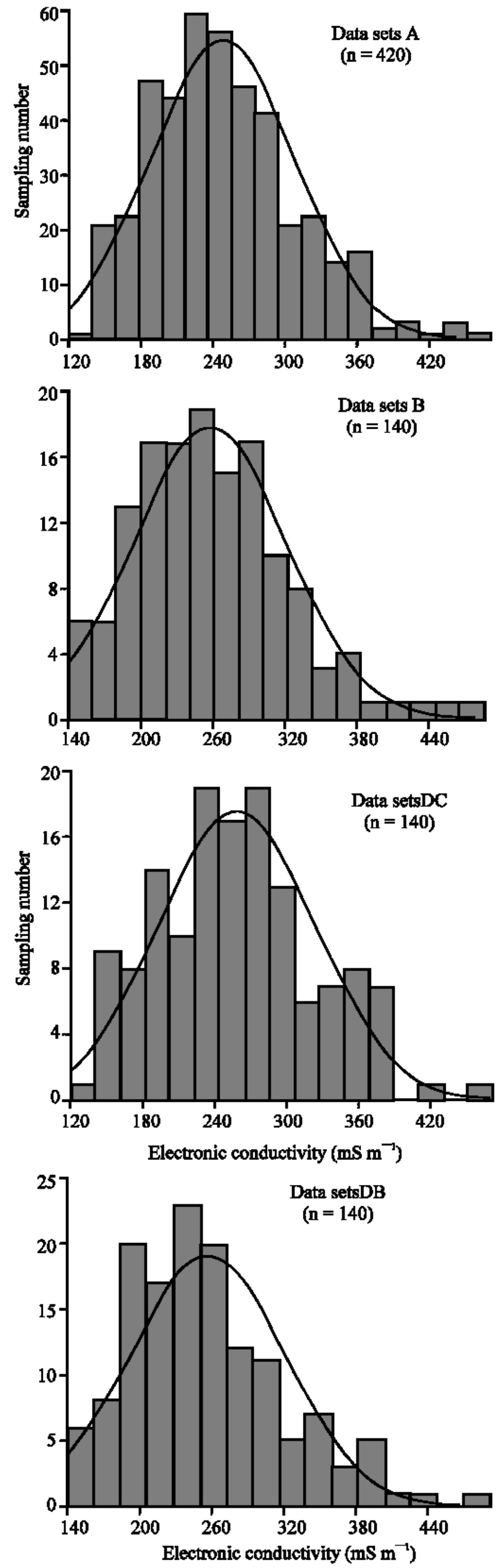

Fig. 2: Histograms for soil electrical conductivity with different data sets

Table 2: Parameters of the best-fitted semivariogram model for anisotropic variograms

Item	Model	Nugget C_0	Sill C_0+C	Effective range A_1 (m)	Effective range A_2 (m)	C/(C_0+C) (%)	Model R^2	RSS	F-test
Data sets A (n = 420)	Exponential	3491	8499	75.4	68.8	58.9	0.217	5.99×10^6	4.57*
Data sets B (n = 140)	Linear	3218	12953	68.5	19.3	75.2	0.485	1.56×10^7	13.71**
Data sets C (n = 140)	Exponential	3670	9010	72.7	70.2	59.3	0.361	7.15×10^6	8.22**
Data sets D (n = 140)	Exponential	2831	11757	19.8	12.72	75.9	0.596	6.17×10^7	21.47**

*,** F test significant at the 0.05 and 0.01 levels, respectively

Table 3: Parameters of the best-fitted semivariogram model for isotropic variograms

Item	Model	Nugget C_0	Sill C_0+C	C/(C_0+C) (%)	Range A(m)	Model R^2	RSS	F-test
Data sets A (n = 420)	Exponential	3260	6521	50.0	20.99	0.413	3.33×10^5	11.61**
Data sets B (n = 140)	Exponential	3390	6781	50.0	20.99	0.564	2.08×10^5	18.83**
Data sets C (n = 140)	Exponential	3430	6861	50.0	20.99	0.514	2.81×10^5	15.39**
Data sets D (n = 140)	Spherical	3420	6841	50.0	13.93	0.576	4.32×10^5	19.77**

** F test significant at the 0.01 level

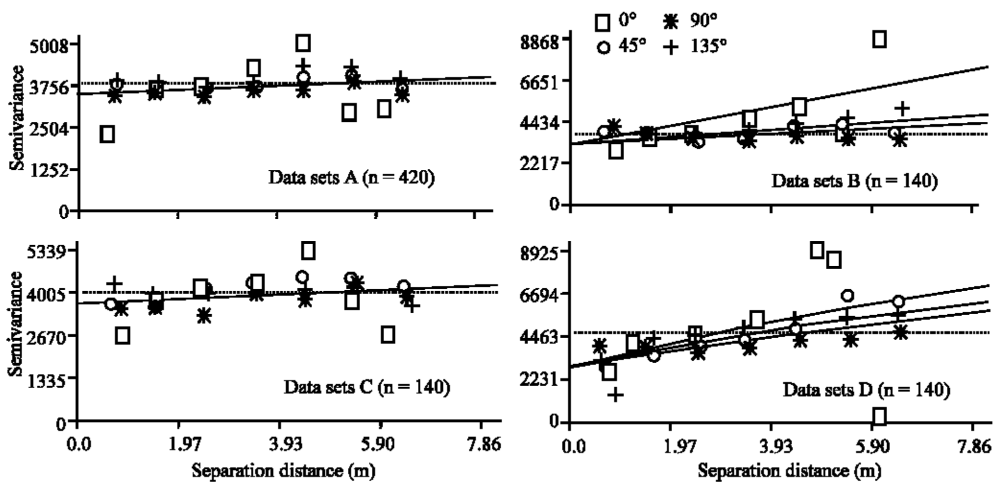

Fig. 3: Anisotropic semivariograms for soil electrical conductivity with different data sets

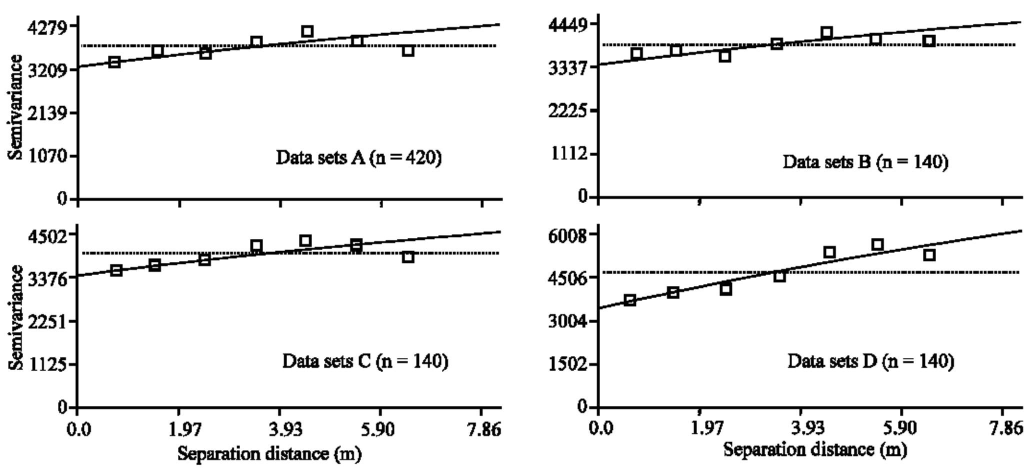

Fig. 4: Isotropic semivariograms for soil electrical conductivity with different data sets

data sets. The best-fitted model for data sets A, B and C was exponential, while that for data sets D was spherical. The F-test showed that all the best-fitted semivarigram models were significant at the 0.01 level. The nugget and

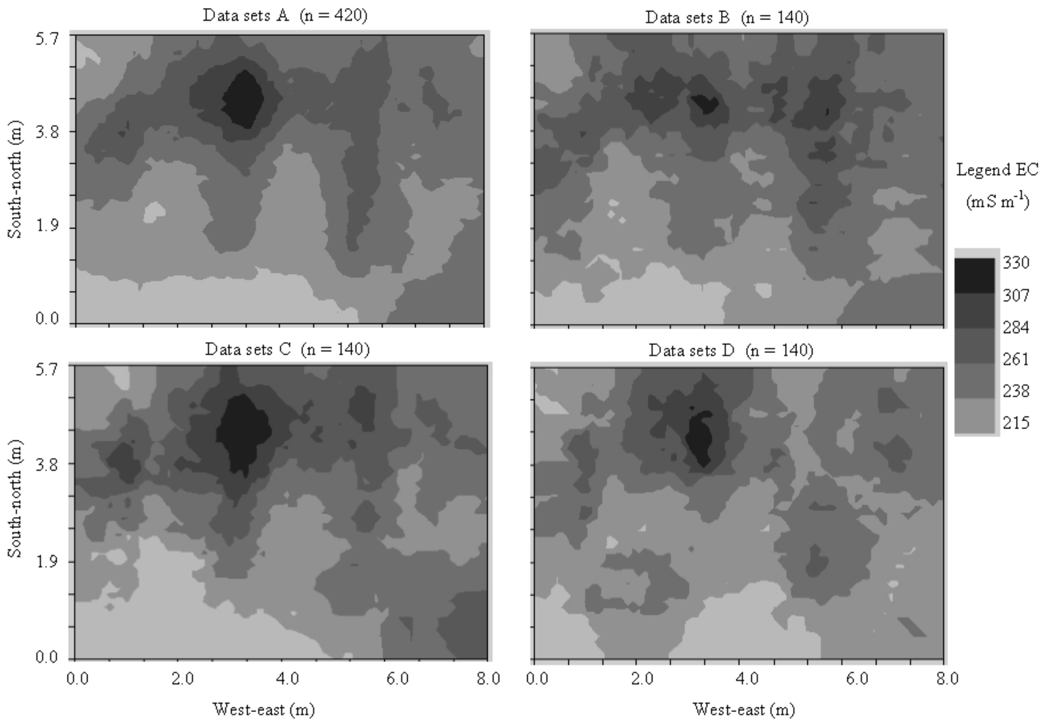

Fig. 5: Maps obtained with block kriging showing the spatial distribution of soil electrical conductivity with different data sets

the $C/(C_0+C)$ for all the 4 data sets were quite similar. The range of spatial dependence was 20.99 m for data sets A, B and C, while that for data sets D was 13.93 m.

The nugget effect could be viewed as an indicator of continuity at close distances, as a semivariogram was basically a plot of sample dissimilarity between sample distances (Paz-González *et al.*, 2000). All the data sets having middle values of nugget effects and 50% of the $C/(C_0+C)$, indicated that the greenhouse vegetable plantation have led to sample dissimilarity in the small sampling distance within a small area.

Spatial distribution of soil EC via kriging: Figure 5 showed the contour maps of soil EC obtained with kriging with different data sets, respectively. On the whole, the contour maps were quite similar with each other, but differences existed in some local areas. The maps obtained with kriging showed that the smoothing effect existed with all the four data sets. Kriging aims at local accuracy through minimization of a covariance-based error variance, it provides a unique estimation map with a characteristic uneven smoothing effect that increases further away from the data locations: the kriging estimator is locally accurate but does not reflect the texture (spatial variability) of the sample data as modeled by the covariance (Journel *et al.*, 2000). The smoothing effect in this study is clear in this study. Firstly, as comparing Fig. 1 with Fig. 5, some points with soil EC greater than 310 mS m^{-1} in Fig. 1 were neglected in Fig. 5. Secondly, there were about 10% of the samples having soil EC greater than 330 mS m^{-1} as shown in Fig. 2 with data sets A, but it could not be identified how much area having soil EC greater than that value in Fig. 5. However, when the sampling points reduced to one-third of the total number, as from data sets A to data sets B, C and D, the maps were similar as shown in Fig. 5, but two-third of the total data were missing in data sets B, C and D using classical statistical method. It appears that global accuracy (semivariogram reproduction) cannot be obtained without sacrificing local accuracy. Kriging, notwithstanding its smoothing effect, remains the best local estimator when it comes to selection at an unsampled point considered one at a time (Journel *et al.*, 2000).

Figure 5 showed that soil EC was very high in the study area. Zhang *et al.* (2006) had examined the changes in soil EC and soil salt ions, i.e., Ca^{2+}, Mg^{2+}, K^+, Na^+, HCO_3^-; Cl^-, SO_4^{2-} and NO_3^- in vegetable greenhouses in the same region as in this study and found that Soil EC was 1.91, 2.39 and 3.15 times as much in 1, 4 and 10 year greenhousesas as in the adjacent upland soil at the depth of 30 cm. The mean soluble salt concentration in 1, 4 and 10 year greenhouses at the depth of 30 cm was 2.09, 2.31 and 3.69 times as much as in the adjacent upland soil, respectively and it was 77 and 60% higher in 10 year greenhouse than in 1 and 4 year greenhouses, respectively. Soil EC value was significantly correlated with soluble salt concentration and the main contributor to the salt ions were NO_3^- and K^+. The EC value in this study was similar to that in the 10 year greenhouse in their study (Zhang *et al.*, 2006). Since, organic fertilizers are often preferred rather than chemical fertilizers to prolong the time of soil salinization in greenhouses. It is suggested that measures be taken to avoid the accumulation of soil salt in greenhouses by applying fertilizers rationally according to soil fertility, vegetable varieties and fertilizer properties in the study region.

CONCLUSION

The classical statistical data of soil EC was similar but little difference existed with different data sets. Soil EC was spatially dependent and modeled quite well with different data sets. The maps obtained with kriging were quite similar with different data sets. Although, the smoothing effect existed with all the four data sets, kriging remains the best local estimator when the data is reduced. Geostatistics combined with classical statistics is considered as an ideal way to examine the spatial variability of soil properties in a micro- field scale.

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