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Location, Location, Location: Applying Spatial Statistics to the Relationship Landscape

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Abstract

The desire to understand relationships is a passion shared by professionals in research, clinical, and educational settings. Questionnaires are frequently used in each of these settings for a multitude of purposes-- such as screening, assessment, program evaluation, or establishing therapeutic effectiveness. However, clinical issues arise when a couple's answers on questionnaires do not match clinical judgment or lack clinical utility, while statistical problems arise when data from both partners are put into analyses. This paper introduces the use of geospatial statistics to analyze couple data plotted on a two-dimensional "relational map." Relationship maps can increase assessment sensitivity, track treatment progress, and remove statistical issues typically associated with couple data. This article briefly introduces core assumptions of spatial models, illustrates the use of spatial models in creating a relational landscape of divorce, offers suggestions for the use of relational maps in a clinical setting, and explores future research ideas.

Keywords

dyadic/couple data; adjustment; satisfaction; national survey of families and households

The gap between research and application is a widely discussed issue in couple and family therapy (e.g., Oka & Whiting, 2013; Pinsof & Wynne, 2000). Ironically, professionals involved in research and applied settings are both confronted with the problem of quantitatively assessing relationship quality in a meaningful way. In research, statistically using questionnaire data from each partner in the same relationship violates critical statistical assumptions. Solutions to couple data heretofore have been to reduce the unique perception of each partner into a couples' average or total score prior to statistical analysis. It is important to note that statistical procedures that utilize scores from both partners separately without violating statistical assumptions are now available (see Gonzalez & Griffin, 2002; Kenny, Kashy, & Cook, 2006; Ledermann & Kenny, 2011). These statistical approaches enable greater insight into overall couple dynamics and require large samples to increase the statistical power and improve generalizability of the findings.

Similar to zooming out on a satellite image in order to see the entire United States, large scale studies tend to reveal a broad relationship landscape. However, the cost of an overall picture comes at the expense of specificity, such that details of specific homes or neighborhoods are lost. The trade-off between generalizability and specificity has been reflected in the utility of relationship questionnaires. Specifically, Weiss (2005) argued that relational satisfaction questionnaires were found effective as screening instruments to determine relational distress vs. non-distress, but were of little utility beyond that. In the landscape metaphor, these questionnaires would be able to predict if you lived in the north or south of the U.S.

The clinical refrain frequently heard at conferences and workshops justifiably remains couple specific. Akin to zooming in on a satellite image to see a specific home, professionals seek an in-depth understanding of the couple in front of them. A nuanced understanding of the couple is essential in order to develop a treatment plan or identify appropriate programs. However, as nuance is lost in the big picture, zooming in too far potentially eliminates the ability to place the couple in the overall research landscape. Ideally, clinicians and researchers need to zoom in *and* out on the relational landscape, thereby facilitating understanding of a specific couple in the context of the greater relational landscape.

The geographical metaphors given in this article have been used to set a conceptual and intuitive stage to introduce an analytic bridge for the researcher-practitioner gap. The bridge in question comes via applying geographically-based statistical procedures to couples data. The nature of geospatial statistics, or spatial analysis, relies on objects or things located in physical space-- such as homes, trees, or 911 calls-- and looks for patterns across the landscape. Just as different parts of the country have unique characteristics, couples that are similar to one another may also be aggregated in a similar way over the relationship landscape (e.g., Rauer & Volling, 2013). This article introduces the use of spatial statistics in couples work through a clinical vignette, a conceptual introduction to spatial statistics, exploring the relational map of divorce risk, and offering recommendations for office based use and future research.

Clinical Vignette

Two hypothetical couples, the Smiths and Jones, are seeking enrollment in an empirically supported enrichment program. Based on the outcome research for the program, distressed couples are not appropriate for the course and should be referred to therapy. The program developers determined that couples falling below the cutoff score on the Revised Dyadic Adjustment Scale (RDAS; Busby, Christensen, Crane, & Larson, 1995) should be considered distressed. In this case, the cutoff was defined by a couple's average score being below 48, or a couple's total score being below 96. The Smiths' questionnaire results had an average score above the cutoff (RDAS=49). However, a moderate discrepancy between the couple's scores existed such that Mr. Smith is happy in his relationship (RDAS= 53) while Mrs. Smith reports being dissatisfied (RDAS=45). The practitioner is concerned about including the Smiths in the program based on their experience with the happy husband/ distressed wife configuration. Additionally, they perceive that the Smiths are more distressed than the questionnaires would indicate and a therapy referral is warranted.

The second couple, the Jones, present a happy wife/dissatisfied husband configuration in that Mrs. Jones' questionnaire indicates that she is happy with the relationship (RDAS=53) while Mr. Jones' score indicates relational distress (RDAS=45). The Jones' average score is identical to the Smiths', RDAS=49, and is also above the cutoff for the program. The practitioner's experience with couples who have a happy wife/dissatisfied husband configuration and direct observation of the Jones leads them to conclude that the Jones would be good candidates for the enrichment program.

The professional is now facing a dilemma; do they refer the Smiths to therapy and retain the Jones based on their professional experience and judgment after meeting with the couples? Do they retain both the Smiths and Jones because each couple's average RDAS score was above the program's cutoff score? At the end of the day, the program developers/researchers may be frustrated if the practitioner "didn't follow the protocol" while the practitioner might be frustrated because the researchers "do not understand the nature of working with 'real' couples."

While this vignette is simplified, it illustrates the tension that results from the difference in perspective, i.e., zooming in or out of the satellite image. Large scale program evaluations, effectiveness research, and efficacy studies have helped give a big picture of what works. These studies have typically analyzed partner scores independently (i.e., husbands only, wives only), or averaged/totaled scores from both partners. However, these research strategies wash out differences between couples by focusing on one partner/gender, or have eliminated differences between partners by averaging partner scores. An average score for a couple is forcing a couple to literally meet in the middle, giving them each the same overall perception of the relationship mathematically speaking. Averaging scores creates minimal issues when partners genuinely have similar perspectives. However, an average score will give an increasingly distorted view of couples as the discrepancy between partners' perceptions (i.e., scores) increases. Additionally, using average scores remove gender dynamics in the analysis. The Jones and Smiths in the example above have identical average scores, suggesting that these couples are identical. It is clear however that these two couples live in very different relational homes, and maybe in different relational neighborhoods.

Large-scale research with couples utilizing a geospatial lens can create a relationship landscape complete with an RPS—Relational Positioning System. The different areas, or relational neighborhoods on the map may have unique characteristics, just as physical neighborhoods are sometimes differentiated by unique characteristics. Practitioners with a copy of a relational map would be able to plot the address of a specific couple they are working with on the overall landscape, deriving clues to potential characteristics their couple may share with other couples. For example, couples in one relational neighborhood may be more prone to divorce, respond better to a particular therapeutic model, or have better health outcomes, etc.

An example relational map based on data from a nationally representative sample can be found in Figure 1. Figure 1 is a relational map of divorce risk with the Smiths and Jones data plotted over it. It is important to note that while the Smith and Jones couples are hypothetical, the relational map in Figure 1 represent results from actual data. Using the map

in Figure 1, we found that the Smith's relational address is within the higher divorce risk oval while the Jones' relational address is in the typical, or expected divorce risk for this map. We intuitively know which neighborhoods in our physical world are “bad,” “good,” “rich,” or “poor.” For better or worse, we make many associations about people when we know their physical address. So too, when the analysis and creation of the relational map is complete, professionals can quickly find where couples “live” and know about the characteristics of that area.

Conceptual Introduction to Spatial Analysis

In order to introduce assumptions behind a geospatial analytic approach, a hypothetical geospatial researcher is asked to describe what they see in Figure 2. The researcher stated:

Figure 2 is a point-pattern. The x and y-axis of the grid represent distance units such as feet, meters, or miles running north to south (y-axis) and west to east (x-axis). Each point represents the physical location of an object or event. Objects tend to be tangible things, like an anthill, tree, or house. An individual point on the map may also be where an event like 911 calls, earthquake epicenters, or the addresses of cancer patients are located.

When we use statistics with point patterns of physical objects, we make the assumption that any grouping of objects in space is nothing more than just random chance. In the case of event based point patterns, we assume that the dispersion of occurrences, i.e., events, are also random with every location having an equal chance of having the event and then test against that assumption. Before we assert that there is a statistically significant aggregation of points in our map, we want to ensure that our observed aggregations would only randomly appear less than five percent of the time. If we found significant groupings of cancer patients, we may then explore other attributes of the location/area of aggregation finding things such as a chemical plant or a polluted stream.

Similar to a projective test, the geospatial researcher's description illustrates key, interrelated assumptions behind spatial data. 1) The focus of spatial research is on the location of the points in space, what happens at the points, or the spacing between the points themselves. 2) The x and y-axes of spatial plots are distance units used to identify the relative location of the points on the plot. Each of these assumptions will be contrasted with traditional social science approaches in order to highlight the advantages of spatial modeling. Readers are encouraged to read Bailey and Gatrell (1995), Cressie (1993), and Diggle (2013) for more detailed treatment of spatial statistics.

Locations in space

In traditional social science research, Figure 2 would likely be described as a scatterplot. Scatterplots are frequently the starting point to analyze the relationship between two variables. If the y-axis represents the male partners' scores and the x-axis is the females' relational adjustment scores, the dispersion of points are used to determine the strength of the correlation between partners. A positive correlation is the extent that partner scores are similar to each other and would appear as a cloud of points elongated along a 45 degree line.

A negative correlation would appear as a cloud of points elongated along a -45 degree line and occurs when each partner's score is diametrically opposed to the other. Correlations between partner scores are not likely to be found if points on the scatterplot are distributed in a spherical shape (i.e., no apparent connection, and equal variation between husband and wife scores), stretched horizontally (i.e., wide variation in wife scores and little variation in husband scores), or vertically (wide variation in husbands' scores and little variation in wives' scores). Correlation is to be controlled for, avoided, or taken out of the equation in traditional statistical approaches. Only couple data that indicates random agreement or disagreement between the partners could meet traditional statistical assumptions. Ironically, it is precisely the extent to which and how couples agree or disagree that is critical knowledge in practice settings.

Spatial models seek to understand and describe the clouds of points/events and find significant aggregations and locations of any aggregations of points/events on the map. Thus, in a spatial model, the shape and distribution of points over the map does not reflect the relationship between the axis variables. Applying a traditional correlation analysis on a spatial map would be akin to trying to determine the relationship of north/south with east/west based on the location of homes in a city—it doesn't make any logical sense.

On the other hand, spatial models are able to test if characteristics of points are more similar to their neighbors and more dissimilar to homes that are farther away. For example, these approaches can test if there is an association for home prices, crime rates, or greater incidences of healthcare use across a city. Similarly, if points were “relational homes” with addresses determined by the intersection of Husband Adjustment (north/south) and Wife Adjustment (east/west), a researcher could determine the location of relational neighborhoods where divorce rates were higher or lower, find neighborhoods of couples where a specific type of therapy is effective vs. ineffective, or which relational homes have better child outcomes. In summary, spatial statistics test if *events* on a map are related to each other while traditional statistical methods test if the axis *variables* are related.

Distance units

The use of axis units on spatial plots provides a critical distinction between spatial models and traditional approaches for couple data. The numbering system used on the axes of traditional statistical plots, such as scatterplots, can vary in range of scores, measurement type, and inferred meaning-- for example, a 69 point marital adjustment scale on the x-axis and a 15 point depression scale on the y-axis. Typically, a line is drawn through the points which minimizes the average distance between all the points on the plot and the line. The numerical value of the line, be it a correlation or regression coefficient(s), denotes the relationship between the variables (axes).

The axes of a spatial plot are not variables in and of themselves, as they are in traditional family science statistics. Axis units are used to measure distance such as inches, feet, meters, miles, latitude, or longitude. Spatial researchers are interested in *where* the points and events are located on the map in relation to each other and require at least two points of reference to mark the location. Therefore, distance units become coordinates for point description and

are used to calculate distance between points, not variables for analysis in and of themselves.

If relational adjustment scores from each partner are used as distance units in a spatial approach, those scores become coordinates to locate the relational home address on a larger relational map. Furthermore, using husband and wife scores in a coordinate system does not violate any statistical assumptions of spatial analytic approaches. Each partner's perspective on their relationship, as quantified by a questionnaire score and used to locate a point in space, are foundational for spatial analysis rather than a statistical problem to be controlled. Therefore, a husband and wife score are both *required* to locate a “relational home address.”

Knowing how to orient on a relational map and identify relational home addresses is crucial to professionals using maps with couples in practice settings and foundational for researchers to implement formal hypothesis testing. Any point on a relationship map explicitly contains the following information: 1) The husband's relational adjustment score, 2) the wife's relational adjustment score, and 3) the location of their relational home on the entire map. Areas of the relational maps as used in this article have the following characteristics based on the relational adjustment coordinates: The upper right portion of the map has both partners feeling satisfied in their relationship with the lower left having both partners feeling dissatisfied in their marriage. Upper left and lower right portions of the map suggest relational neighborhoods characterized by spousal differences with low wife satisfaction-high husband satisfaction in the upper left portion and high wife-low husband satisfaction in the lower right.

Once relational home addresses are identified, professionals and researchers can start analyzing if different areas of the landscape have greater or lesser incidents of various events or experiences. The analytic approach is akin to exploring the distribution of crime rates across a city, state, or country. In the present article, the relational landscape of divorce is offered in order to elucidate the research-practice bridging capability of relational maps.

Divorce Risk over the Relational Landscape

As previously stated, a common finding in the relationship assessment literature has suggested that marital adjustment scales are not of much use beyond a screening tool (e.g., Fincham & Beach, 2010; Gottman & Ryan, 2005; Weiss, 2005). Interestingly, profound questions regarding the use of questionnaires as a screening tool remain. What score should the professional use when there is a need to screen? The husband's score? The wife's score? The couple's average score? The most distressed partner's score?

To approach the study of divorce from a spatial analytic perspective, each partner's score is used to create the coordinate for the relationship address. In the example below, there are 3,969 potential addresses in the relational landscape. The null hypothesis in spatial statistics would hold that the chance of divorce is the same across the relational landscape. In other words, the relational adjustment *address* is not associated, or is randomly associated, with divorce. Statistically significant results would indicate the presence of relational neighborhoods with unusually high rates of divorce (e.g., “hot spots”) or statistically

significant low rates (e.g., “cold spots”). All of the results can be visually displayed, intuitively interpreted, and readily used in practice.

Method

The data for the relational map come from Waves 2 and 3 of the National Survey of Families and Households (NSFH; Sweet & Bumpass, 1996; Sweet & Bumpass, 2002). Demographic data reported herein come from Wave 1 data (Sweet, Bumpass, & Call, 1988).

Sample

Wave 2 data originally had 4,836 couples identified in the data where 84.4% of the respondents were white, 8.9% African American, 4.1% were Hispanic, and other ethnicities made up the remaining 2.6%. Average age for the sample was approximately 46.55 ($SD = 23.546$). There were 1,960 couples that were married during Wave 2 (collected between 1992 and 1994) and also had relational status data available during Wave 3 (collected between 2001-2002), and this data was used in the present example.

Measures

The coordinate system for the relational map comes from a 12 item relationship adjustment questionnaire identified in Wave 2 of the NSFH. Scale items were identified using a combination of parallel analysis and exploratory factor analysis on items whose face validity was similar to established relational adjustment measures (contact the corresponding author for additional details in identifying the scale items). The NSFH relationship adjustment scale had strong reliability for husbands ($\alpha = .837$) and wives ($\alpha = .848$). There was a theoretical 63 point range of scores (12-75) with higher scores representing good adjustment. When plotted on a 2-dimensional plane, 3,969 possible relational addresses were generated ($63 \times 63 = 3969$). Average adjustment scores for wives were 59.957 ($SD = 9.270$) and 60.107 ($SD = 8.710$) for husbands.

Each relational address was plotted based on husband and wife adjustment score during Wave 2 of the NSFH data collection. The “event” placed on each relational address was determined by participants identifying themselves as “still together” or “separated/divorced” approximately 8 to 10 years later (Wave 3). The map was subdivided into observational units, similar to census tracts or counties on a map.

Figure 3 shows the subdivided map with darker squares indicating the units with at least two couples present. Each relational address was plotted based on husband and wife adjustment score during Wave 2 of the NSFH data collection. The “event” placed on each relational address was determined by participants identifying themselves as “still together” or “separated/divorced” approximately 8 to 10 years later (Wave 3). There were 1,589 couples still married at Wave 3, while 371 couples had divorced. When attempting to analyze any event, such as divorce, at one of these relational addresses, the odds of randomly finding high divorce counts in a “city” would be higher because there are more relationships represented in that area. If a traditional point pattern analysis were to be performed, it may be concluded that moderately to highly adjusted relationships have greater rates of divorce present. This would be an erroneous assumption as the overall density of “homes” (aka,

relational addresses) is greater in that area of the plot (Kulldorff & Nagarwalla, 1995). To account for differences in the number of homes in a given area, a spatial scan statistic was used in the present analysis (Naus, 1965, Kulldorff & Nagarwalla, 1995).

Results

There were 371 couples of the 1,960 couples in the dataset that were divorced by Wave 3 resulting in an overall divorce rate of 18.928% for the couples included in the analysis. Utilizing SaTScanTM software, a Spatial Scan Statistic was performed for case/control studies (i.e., Bernoulli analysis). This analysis compares the observed rates of divorce within a generated ellipse against the expected rate of divorce for the entire population (i.e., 18.928% in this case). Monte Carlo simulations provided the probability that the observed divorce rate within the ellipse was due to chance. Different sizes, shapes, and angles of ellipses were tested at each unit center. Other parameters of note in the analysis were (a) searching for any aggregations with unusually high or low values; (b) for greater scanning flexibility, elliptical windows were used with medium compactness penalty (Kulldorff, Huang, Pickle, & Duczmal, 2006); and (c) scan windows set at default to select up to 50% of the population (Kulldorff & Nagarwalla, 1995). Figures were generated using R (R-Core Team, 2013) and several packages for spatial analysis within R (e.g., Baddeley & Turner, 2005).

Relational Landscape of Divorce Risk

Returning to Figure 1, the relational map of relative divorce risk illustrates the statistically significant areas of high and low rates of divorce found in the analysis. Geospatial researchers refer to these types of aggregations as “hot spots” for unusually high rate aggregations and “cold spots” for unusually low-rate aggregations. Couples within the ellipse in the upper-right quadrant were found to be in a cold spot of divorce. Based on the expected divorce rate of 18.7%, 179 of the 945 couples within the ellipse should have divorced by Wave 3 and yet only 142 couples had divorced. The relative risk of divorce for this aggregation was 6.7% ($p = .023$). The relational address of the center of this relational neighborhood was located where the wife score was 56.67 and the husband score was 63.33.

A divorce hot spot was found in the light gray area of the map (see Figure 1). There were a total of 47 couples in this area and based on the overall rate of divorce for the sample, there should have only been 9 divorces over the 8-10 year period between data collection waves. However, the divorce/separation rate within this aggregation was found to be 46.8% (22 out of the 47, $p = .011$). The center of this ellipse had a more distressed wife than husband with the corresponding wife and husband adjustment scores as 23.33 and 36.67 respectively.

Additional views of the divorce landscape can be seen in Figure 4. The size of the circle on the left figure is directly related to risk, i.e., the smaller the circle, the smaller the risk. Each circle is centered on the middle of each unit that had couples data. The figure on the right is a Gaussian smoothed projection of relative risk, the higher the terrain, the greater the risk of divorce. The lower-left portions of the left figure and bottom corner of the right figure are areas where both partners report low adjustment.

Discussion

The differences between spatial and traditional family science quantitative approaches to couple scores also have profound implications for research and practice. A spatial approach can make large scale research readily useful in the clinical setting through the use of relational maps. As future research generates relational maps similar to Figure 1, clinicians could have a copy of the map readily available in their office. When clients arrive at the office, the clinician would have each person fill out the same relational assessment questionnaire as was used to create the relational map. The professional would plot a couple's address on the printout to ascertain divorce risk as illustrated by the Smith and Jones couples in the present example.

In this case, the Smiths had a relational address of Wife =30, Husband=50 and relationally live in the divorce hot spot (See Figure 1). The Jones have a relational address of Wife=50, Husband =30 and “live” in a relational neighborhood where their divorce risk is about the same as the overall sample, roughly 18%. The professional's instinct of suggesting that the Smith's may need therapy while the Jones may benefit from an enrichment program would now 1) have empirical support behind their decision and 2) require the clinician to administer the questionnaire and plot the point on a pre-generated map (i.e., Figure 1).

Beyond the ability to directly plot an individual couple on the overall relational landscape, statistically significant aggregations revealed by spatial analysis may show insignificant or non-meaningful results in traditional approaches. Using the same data from the present study, three t-tests comparing divorced vs. married couples were performed to compare the spatial approach to a traditional approach. The results using an average couple score was significant ($t = -2.122$, $df = 478.789$, $p = .034$), as was the wives' score ($t = -2.340$, $df = 484.018$, $p = .020$), but the husbands' score was not significantly different between the divorced and married groups ($t = -1.500$, $df = 498.035$, $p = .135$). While some of the t-tests were significant, there were no meaningful differences between the married and divorced groups (e.g., divorced wife mean = 58.784, married wife mean = 60.231). Furthermore, utilizing results like those from t-tests, regression, and even path models into a practice setting in meaningful ways is also difficult.

Clinical Application

Given the scarcity of relational maps in research, the most immediate application of the relationship landscape in a clinical setting would be within the patient-focused research paradigm (Howard et al., 1996). Patient-focused research has clinicians regularly assessing and plotting the progress of their client relative to a normative trajectory of client change. Inroads on patient focused research specifically for couples work have been initiated by Pinsof et al. (2009) while Anker, Duncan, and Sparks (2009) have also used their individually focused measures in a couples therapy setting as well.

While the change trajectory research for comparison purposes has yet to be completed for a relationship landscape, clinicians could administer a relationship questionnaire, such as the RDAS, to couples every other session and create their own relationship map that includes the couple's path in therapy (Wood & Crawford, 2012). The map could be placed in the

clinical file and used to track pre-post change, or therapy progress in general. Following Wood and Crawford (2012), when plotting scores on a regular basis, the angle of the line(s) connecting the points are informative. To wit, the couple's path on a relational map informs the clinician of each partner's progress, and the overall couple's progress in therapy simultaneously.

The more vertical the trajectory moving toward the top of the map, the more men would be benefiting in therapy relative to their partner. It is important to note that flat lines on a relationship map still represent change. If the trajectory of change is moving horizontally to the right of the map, the greater the benefit of the approach is to the wife relative to her partner. If the trajectory of change falls along a 45 degree angle toward the upper right corner, male and female are equally benefiting. Deterioration would be movement down toward the bottom of the map (male) and/or toward the left side (female). No change in therapy, or slow change, would be indicated by very short lines between the dots or dots very close together.

Directions for Future Research

In order for couple and family therapists and family life educators to fully utilize a patient focused research paradigm, broad scale research is required to create the normative paths for comparison purposes. Normative curves on a spatial map may appear as roads or paths across the relational landscape. For example, if Wilde and Doherty's (2013) relationship education program for fragile families used a spatial approach as part of their research, they would plot each couple's relational address at regular intervals throughout their program. By analyzing the paths of change over the couple landscape, paths of deterioration and growth may be identified.

It would be interesting to explore if couples that benefited from the program started their path from the same relational neighborhood as couples that may not have benefited. The possibility of addressing different starting points of couples prior to intervention has not been available to researchers to the degree that spatial models offer. To the extent that previous efficacy or effectiveness research has used relational scales such as the Dyadic Adjustment Scale (Spanier, 1976) with both partners, a great number of existing efficacy and effectiveness studies could reinterpret their results through a spatial lens without the need of additional data collection.

Research exploring relationships in general, especially relational stability, such as Kelmer, Rhoades, Stanley, and Markman's (2013) study on long-distance relationships are also fertile ground for spatial approaches. To analyze Kelmer, et al., (2013) through a spatial lens, the relational address could be established by using the relational quality scores for each partner in the relationship. It is important to note that spatial approaches *require* dyadic level data which Kelmer and colleagues did not utilize. The physical distance between partners at the beginning of the study and relational status at follow-up would be connected to each relational address for analysis. The resulting map would potentially show relational neighborhoods where relational stability was better or worse as well as illustrating the influence of distance on relational stability.

Conclusion

In principle, there is not a gap between research and practice. Researchers and practitioners are unified in that each are working to understand couples and to find ways to strengthen relationships. Relational maps are readily interpreted and give practitioners and researchers more sensitive methods when working with couples. In other words, relational maps can provide a common language between large scale research and the couple in the practitioner's office. Sharing a common language of couples will provide the opportunity to unify the laboratory and office in practice in addition to principle.

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Figure 1. Marital adjustment landscape and areas of higher divorce risk. High scores represent better relational adjustment.

Figure 2.

Point pattern of relational addresses with quadrants. Each circle represents a relational address based on the couple's score on a 12 item marital adjustment questionnaire from Wave 2 of the NSFH (n=1960).

Figure 3.
Distribution of marriage and divorce over the relationship landscape.

Figure 4.
Alternative perspectives of the relative divorce risk over the relational landscape.