

Emerging school structures and collective dynamics in spawning herring: A simulation study

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ABSTRACT

Schooling fish are known to display various collective behaviours depending on ecological context and life history situation. In Norwegian spring spawning herring (NSS-herring) (Clupea harengus) different trade-offs during the seasons of feeding, overwintering, migration and spawning are likely to influence school morphology and behaviour. In the field, hydro acoustics are able to record collective patterns, but hardly the mechanisms of how individual decisions and interactions lead to the observed formations. Individual based models (IBMs) on the other hand, are promising simulation tools for investigating how low-level individual behaviour influences large-scale behaviour. We have used this approach with a rule based school model in order to gain understanding of how certain school patterns can emerge during the spawning of NSS-herring. Response to predation and motivation towards spawning are added to the response to nearby fish. Simply by varying population size and synchronisation of spawning motivation we find different system responses in terms of school morphology and dynamics. With high motivational synchronisation, the system is mainly represented by one integrated school, whereas low degree of synchronisation presents a system with frequent split-offs of small schools. An intermediate degree of synchronisation leads to a more complex situation with schools or layers in a dynamic vertical contact and formation of vertical 'hourglasses' or cylindrical shaped schools. This suggests that the degree of motivational synchronisation between individuals in a school will determine whether or to what degree a school splits into different components or remains integrated. We also find that with increasing population size there are new system behaviours emerging, not present with lower population size. Larger populations lead to horizontal extension of the pre-spawning components resulting in a double layer system where vertical bridges connecting the two layers are established. The cylindrical bridges are truly emergent properties of the system, formed and maintained by ovulating and spent herring moving across these structures. Similar school formations with vertical connections have been observed acoustically in spawning herring schools.

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1. Introduction

Aggregate and group behaviour are found in different social animals including mammals, birds, insects and fish (Parrish

and Edelstein-Keshet, 1999). From modern system biology, large societies of animal aggregations containing thousands or millions of individuals are understood as leaderless decentralised systems. The organised group level behaviour

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emerging in these societies is understood as self organising from the local interactions between individuals (Camazine et al., 2001; Couzin and Krause, 2003). Schooling in fish is a good example of self-organised group behaviour, where collective behaviour emerges as a result of numerous fish simultaneously responding to the movement of neighbouring fish and the local environment (Parrish et al., 2002).

In the large marine ecosystems of the world more than 4000 species of pelagic fish school, and several solitary species swarm as juveniles (Shaw, 1978). For a better understanding of the dynamics of schooling fish we need to build knowledge, which can link the individual interactions and decisions within a school to the collective behaviour seen in large schools of fish. Obligatory schooling fish like herring live their lives in a constant context of social interaction. This implies that even if the fish are driven by internal motivations (e.g. hunger, fear or drive to reproduce) and respond to environmental factors like predation, food, temperature and light, the local decision will always to some degree be influenced by the actions of the nearby individuals within the school. The kind and degree of interaction taking place may therefore have a major influence on the emerging school patterns. This mechanism of how individual interactions leads to school patterns is poorly known, as field observations are mainly able to monitor resulting patterns, not the mechanism itself. Keeping in mind that such individual interactions are of a nonlinear nature, we are facing a complex system, which is not trivial to understand from observations alone. Several fields of research including social science, biochemistry, communication networks, system ecology and economics are dealing with similar problems of understanding emergent system properties from the interactions between distributed agents or entities/nodes (Auyang, 1998). A common approach to deal with such complex systems is the application of IBMs or agent-based models (ABMs) (Grimm, 1999). The strength of this model approach lies in the ability to explore the link between individual behaviour and emerging system behaviour. Several studies have applied IBMs able to simulate fish schools from individual behavioural rules (Aoki, 1982, 1984; Huth and Wissel, 1992, 1994; Reuter and Breckling, 1994; Romey, 1996; Vabø and Nøttestad, 1997; Inada, 2001; Couzin et al., 2002; Inada and Kawachi, 2002; Parrish et al., 2002; Couzin et al., 2005; Hemelrijk and Kunz, 2005; Viscido et al., 2005). The early models of schooling fish were typically focused on the model's ability to produce realistic schooling behaviour by comparing properties like cohesion, nearest neighbour distance and polarisation with lab experiments (Huth and Wissel, 1994). Some models have focused on the collective responses of fish schools (Couzin et al., 2002, 2005; Inada and Kawachi, 2002). Few studies, however, have applied such models to investigate collective behaviour in an ecological context, where schooling behaviour is influenced by the external environment and internal motivational state of the fish. A review of different models of schooling fish is presented in Parrish et al. (2002).

We present here a model framework of schooling fish applied on the ecological context of spawning herring. Our model is not a predictive model but rather of an exploratory or heuristic type, aiming at the elucidation of possible essential mechanisms through manipulations of the model parameters. The model is based upon the classical type of fine scale rulebased school models (Reynolds, 1987; Huth and Wissel, 1992; Viscido et al., 2005). Our rational for doing so is the assumption that the direct interactions between fish, taking place on a fine temporal and spatial scale, are essential in a model aiming at understanding the collective behaviour emerging in spawning herring. We add motivation as a parameter independent for each individual and a subsequent response to spawning and predation. The model is applied to the ecological scenario where one school of pre-spawning herring enters the spawning site. As time goes by, each fish develops its internal gonad state and switches to new gonad stages from given criteria followed by motivational changes. This creates a complex collective system, where interacting individuals with motivational differences enter the stage. We expect various effects to appear at the group level, and hence monitor all school activity and dynamics. We track number and shape of schools, how and how often they split and merge, for how long each school persists, and how well individuals with different motivations are sorted into different schools. We also expect the group behaviour to be dependent on the number of individuals in the group. As a main question we ask: what kind of collective dynamics should one expect to see in our modelled system as a function of population size and degree of motivational synchronisation?

2. Materials and methods

2.1. Biological background

Herring spawn once a year over a well-defined period, a reproduction mode sometimes termed synchronism (Le Clus, 1979). They are adapted to a life in the pelagic, but unlike most pelagic fish they have demersal spawning (Blaxter and Hunter, 1982). The preferences for both spawning substrate and spawning depth vary from population to population (Runnström, 1941; Blaxter and Hunter, 1982; Haegele and Schweigert, 1985). In this study we use the behaviour of NSSherring as a reference. They deposit the spawn directly on hard bottom and prefer spawning depths of 30–250 m (Runnström, 1941). The whole process of spawning in herring from the building-up of gonads to the deposition of eggs takes several months but the majority has reached maturation when they arrive at the spawning grounds (Iles, 1984). Before herring are said to be ripe and the deposition of eggs can start, a short pheromone induced period of spermiation and ovulation occurs (Gillis et al., 1990). For simplicity we merely refer to this period as ovulation in the model definition. After ovulation the release of milt from a male initiates the act of spawning in both sexes (Stacey and Hourston, 1982). NSS-herring spend from 1 to 7 days at the spawning site (Johannessen, 1986; Axelsen et al., 2000; Skaret et al., 2003), but at least for Pacific herring, the emptying of gonads for a single fish may be completed within 2-4 h (Holliday, 1958).

The great challenge for herring at the spawning site lies in maximising the chances of a successful reproduction without being eaten. The engagement in spawning necessarily results in a reduced alertness towards predators, and gadoids like cod and saithe feeding on the herring are abundant near the bottom at the spawning grounds (Høines et al., 1995; Høines and Bergstad, 1999). The bottom is not only a general high-risk predation zone, herring school organisation also becomes less appropriate for avoidance manoeuvres when they position themselves close to the bottom (Axelsen et al., 2000). Much of the elaborate schooling dynamics observed at the spawning ground has therefore been explained as the behavioural outcome of a trade-off between predation and reproduction (Nøttestad et al., 1996; Axelsen et al., 2000; Skaret et al., 2003). This may seem a straightforward trade-off but it does in a collective setting become more complicated. The motivation of herring to go down will change according to maturation state (Nøttestad et al., 1996), and the maturation state is not fully synchronised between individuals within a school or population. We aim at incorporating both a realistic trade-off between reproduction and survival and various degrees of conflicting individual motivations in our simulations in order to explore the resulting collective behaviour.

2.2. The model

2.2.1. General model structure

We adapt an individual based modelling approach, IBM (Grimm, 1999), defining a system consisting of N individual fish (i = 1, 2, ..., N), released in a continuous three-dimensional space defined by a cylindrical volume with fixed boundary. The top and bottom of this cylinder represent the water surface and sea bottom. A cubic grid of cells covers the cylindrical volume, each cell containing reference indexes to the individuals present in the cell. This enables monitoring of schools and a faster spatial interaction algorithm. Time, t, is modelled in discrete steps, dt. Predation pressure is represented by a vertical profile following the depth of the cylinder. During a simulation all individuals are initially placed randomly within a 4 m diameter sphere at the centre of the cylinder, initiating the system as one school.

2.2.2. The individual-based model

Our IBM is rule-based and similar to models used in earlier studies of schooling fish and can be thought of as belonging to the type of models first introduced by Huth and Wissel (1992, 1994). In our model, however, responses of the fish are acceleration of swimming velocity (not only direction change) and we introduce a model framework able to combine schooling behaviour with reaction to predation and motivation towards spawning. The motivation towards spawning and predation is controlled by an internal gonad state, s, varying continuously through four behavioural stages (mature, ovulation, spawn, spent) where individuals are initialised as mature (see section below). When using an IBM, the model is defined on the level of individual fish, determining the action of each fish, i, during each time step. The action calculated by our IBM is the change in swimming velocity, i.e. acceleration, **a**^t_i. This acceleration response gives the change in position (\mathbf{p}_i) and velocity (\mathbf{v}_i) of each fish, through the standard dynamic equations:

$$\mathbf{v}_i^t = \mathbf{v}_i^{t-dt} + \mathbf{a}_i^t \, dt \tag{1}$$

$$\mathbf{p}_i^t = \mathbf{p}_i^{t-1} + \mathbf{v}_i^{t-dt} \, \mathrm{d}t + \frac{1}{2} \mathbf{a}_i^t \, \mathrm{d}t^2 \tag{2}$$

where dt is the duration of a time step. Vectors are indicated by bold notation.

2.2.2.1. Rule combination. The IBM is defined as a combination of five behavioural rules, k, each generating an acceleration vector (\mathbf{a}_k) as a response.

- **a**₀: Avoid boundaries (bottom, surface, cylinder walls).
- **a**₁: Social repulsion.
- a_2 : Social attraction.
- a_3 : Move towards bottom to spawn.
- a₄: Avoid predation.

These rules are combined using a priority scheme, executed in their listed order until the accumulated acceleration $|\mathbf{a}_i^t|$ reaches a maximum acceleration (\mathbf{a}^{\max} , Table 1).

$$\mathbf{a}_{i}^{t} = \mathbf{a}_{0}\mathbf{a}^{\max} + \mathbf{a}_{1}\mathbf{a}_{1}^{\mathrm{avail}} + \mathbf{a}_{2}\mathbf{a}_{2}^{\mathrm{avail}} + \mathbf{a}_{3}\mathbf{a}_{3}^{\mathrm{avail}} + \mathbf{a}_{4}\mathbf{a}_{4}^{\mathrm{avail}} + \mathbf{N}\eta \qquad (3)$$

Each term in this equation represents a rule, and is added subsequently as long as the available acceleration $\mathbf{a}_k^{\mathrm{avail}} > 0$. The acceleration available after the k - 1 other rules have been applied, is therefore:

$$\mathbf{a}_{k}^{\text{avail}} = \mathbf{a}^{\max} - |\sum_{m=0}^{k-1} a_{m} \mathbf{a}_{m}^{\text{avail}}|$$
(4)

If there is a full response on social repulsion, i.e. $|\mathbf{a}_1| = 1.0$, the succeeding rules have no available acceleration. N represents stochastic noise ($|N| = |\mathbf{a}_i^t|$), which is always applied, giving perturbation on the final acceleration vector where η is the amount of noise (Table 1). When fish are solitary, responses to predation or spawning are not applied. Instead a "random turn" search rule is applied (Vabø et al., 2004). This rule enables the fish to gradually turn to the left or right until contact with other fish is attained.

2.2.2.2. Motivation and response. Each behavioural rule, k, defines the response as a unit vector (\mathbf{u}_k) pointing in the accelerated direction, multiplied by a response factor $(f_k \in [0, 1])$. The response factor is a function of situation (density, depth, distance to a neighbour, etc.) and defined differently for each rule. In addition a fish may have a specific motivation towards the influence the rule represents. The motivation factor $(m_k \in [0, 1])$ then determines the maximum applied response to the influence in question. The final rule acceleration \mathbf{a}_k is therefore less or equal to a unit vector and can be expressed:

$$\mathbf{a}_k = m_k f_k \mathbf{u}_k \tag{5}$$

The true acceleration response (in units of ms⁻²) from each rule is then $\mathbf{a}_k \mathbf{a}_k^{\text{avail}}$ as in (3). The motivation for avoiding boundaries and schooling is always 1.0. Motivation towards spawning, and predation are functions of internal gonad state (s), hence we replace m₃ and m₄ with the notations $M_s^{\text{Sp}}(M_s^{\text{Sp}} \in [0, 1])$ for spawning and $M_s^{\text{Pr}}(M_s^{\text{Pr}} \in [0, 1])$ for predation, respectively. They reflect a trade-off between avoiding predation and spawning thus we apply $M_s^{\text{Sp}} = 1.0 - M_s^{\text{Sp}}$ in all stages except for spent herring where spawning motivation is

Parameter	Symbol	Value	Comment
Simulation			
Time step	dt	0.1s	
Total simulated time	Т	1 h	Corresponds to 36000 time steps
System			
Cylinder radius		30 m	Cylinder volume = 84780 m ³
Total depth	D	30 m	The height of the cylinder
Light dampening factor	κ	-0.1	Used in Beer's law
Individual parameters			
Fish length	L	30 cm	
Max acceleration	a ^{max}	5 BL s ⁻²	Corresponds to 1.5 ms ⁻²
Maximum swimming speed	v^{\max}	$2 \mathrm{BL}\mathrm{s}^{-1}$	Corresponds to 0.6 ms ⁻¹
Minimum swimming speed	v^{\min}	$0.1 \text{BL} \text{s}^{-1}$	-
Field of view	φ	300°	
Visual range	λ	1.6 m	Equal to twice the grid cell size
State shift probability 1	$ ho^0$	$0.0006 \mathrm{s}^{-1}$	Changing from mature to ovulation
State shift probability 2	ρ^1	$0.003 \mathrm{s}^{-1}$	Changing from ovulation to spawning
Gonad state increment	ds	$0.000833 \mathrm{s}^{-1}$	Corresponds to 1.0 in 20 min.
Spawning motivation, spawn	M ₂ ^{Sp}	0.9	
Predation motivation, spent	$M_3^{\overline{p}r}$	0.1	
Spawning motivation, spent	$M_3^{ m pr} M_3^{ m Sp}$	0.0	
Repulsion range	R _{rep}	90 cm	
Repulsion rule parameter	α^0	100	
Attraction rule parameter	α^1	0.1	
Density threshold attraction	δ^{thr}	$2.1 {\rm m}^{-3}$	Based on local number of fish within 1 m
Noise parameter	η	0.05	

turned off $(M_3^{Sp} = 0)$, but M_3^{Pr} is in this stage kept at the value of M_2^{Pr} , which is fixed to 0.1 (Table 1). M_1^{Sp} (ovulation) is set to vary linearly between the M_0^{Sp} (mature) and M_2^{Sp} (spawn) and M_1^{Pr} changes accordingly (Fig. 1).

2.2.2.3. Gonad state development. Around spawning, herring go through four phases: mature, ovulation, spawn and spent. These are implemented as four different behavioural states reflecting discrete gonad maturation stages. The gonad state increases continuously within these stages ($s \in [0, 4]$), except in the first stage (mature) where it is fixed to s = 0 (Fig. 1). In the mature stage each fish has a given probability of switching to the ovulation phase. During ovulation ($1.0 \le s < 2.0$) each individual can switch into the spawning stage with a given probability if a generated Gaussian random number N(2.0, 0.3) is below the current gonad state, provided that the fish is within 1 meter from the bottom. When the closest neigh-

State shift	stoc	chastic	stochastic	conti	nuous ⇒
Gonad stage	Mature	Ovulating		Spawning	Spent
Gonad State (s) Spawn Motivation	0.9 M ₀ ^{Sp}	$1.0 \rightarrow 1.99$ $M_0^{Sp} \rightarrow 0.9$		$\begin{array}{c} 2.0 \rightarrow 3.0 \\ 0.9 \end{array}$	$3.0 \rightarrow 0.0$

Fig. 1 – Overview of gonad state development and motivation towards spawning in relation to gonad stages. How the shifts between one behavioural stage to the next are implemented, is indicated by the thick arrows at the top. The small arrows indicate that there is a linear increase of the value in the given behavioural stage. Simulations explore different values of M_0^{Sp} .

bour is spawning, this probability increases by a factor of 100. Note that this is the only case when fish are explicitly influenced by the state of other fish. If the gonad state during ovulation reaches s = 1.99 it stops increasing. During spawning ($2.0 \le s < 3.0$), s increases whenever the fish is within 1 m from the bottom and twice as fast as during ovulation. An individual automatically enters the spent stage when s > 3.0 and s continues to increase until the simulation stops. The rate of the physiological process of gonad state development has been speeded up considerably in our simulations in order to capture the physiological development within 1 simulated hour (36 000 time steps). However, this rate of change is still slow in comparison with the time scales determining changes, stabilisation and organisation of spatial distributions.

2.2.2.4. Avoiding boundaries rule. When the position of an individual 1s ahead in time, will be less than two body lengths from the boundary, it responds by accelerating away from the boundary.

2.2.2.5. Schooling rules. The schooling behaviour of the fish is modelled using a combination of two rules: social repulsion within a repulsion zone (R_{rep}), or social attraction outside this zone. These are *social rules* implementing how fish interact. Perception is limited by a specified perception range (λ) and field of view (φ). Laboratory studies suggest that close behavioural interaction between fish is a function of distance squared or distance cubed (Partridge, 1981). The repulsive response to nearby fish is therefore implemented as a function decreasing by distance cubed, resulting in high repulsion at

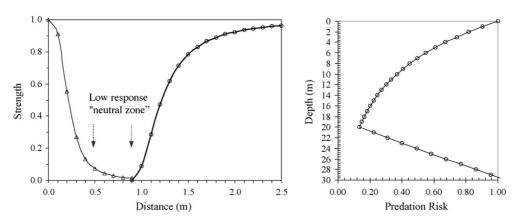


Fig. 2 – Model definitions for interaction strength and predation risk profile. Left: The shape of the repulsion and attraction functions applied with repulsion as triangular marks and attraction as circular marks. Right: The predation risk profile applied, incorporating Beer's law of light attenuation by depth and adding a linear increase from 2/3 of total depth towards the bottom.

close range and a rapid decreasing repulsion in a low responding (neutral) zone (Fig. 2). The presence of such a neutral zone has recently been identified in laboratory experiments (Tien et al., 2004). Attraction is defined to increase with distance following a square relationship expressing that distant fish apply stronger attraction response (Fig. 2). However, if the local density (δ_i) exceeds a density threshold (δ^{thr}), attraction is not applied at all. In this way mainly peripheral individuals apply attraction towards other fish, while fish inside a school simply respond with repulsion or ignorance towards other fish. This enables the fish to exhibit individualistic tendencies like responding to the environment (Gueron et al., 1996). For each of the observed neighbours, N^{obs}, each fish responds either with repulsion, attraction or no response according to:

$$\mathbf{a}_{1} = \sum_{j \neq i}^{N^{\text{obs}}} \frac{-\mathbf{e}_{ij}}{1 + \alpha^{0} r_{ij}^{3}} \quad \text{for } 0 < r_{ij} \le R_{\text{rep}}$$
(6)

$$\mathbf{a}_{2} = \sum_{j \neq i}^{N^{\text{obs}}} \frac{\mathbf{e}_{ij}}{1 + \alpha^{1} (\mathbf{r}_{ij} - \mathbf{R}_{\text{rep}})^{-2}} \quad \text{for } \mathbf{R}_{\text{rep}} < \mathbf{r}_{ij} \le \lambda \text{ and } \delta_{i} < \delta^{\text{thr}}$$
(7)

The responses are normalised if necessary, i.e. $\max|\mathbf{a}_1| = 1.0$ and $\max|\mathbf{a}_2| = 1.0$. \mathbf{e}_{ij} is the unit vector from fish i towards fish j, r_{ij} is the corresponding distance. α^0 and α^1 are fixed positive constants (Table 1). In terms of Eq. (5), the expression in (6) and (7) represents $f_{1j} \cdot \mathbf{u}_{1j}$ and $f_{2j} \cdot \mathbf{u}_{2j}$, respectively, as response and response direction are calculated for each neighbour (*j*). Our repulsion and attraction rules reflect smooth transitions in behavioural response to variations in distance and are illustrated in Fig. 2. The social interaction rules are independent of internal state.

Observing surrounding fish and responding accordingly are only done with a 50% probability at each time step, i.e. with a time step of 0.1 s each fish responds to other fish five times per second on average. This introduces a stochastic element representing periods of ignorance, similar to a "swim and glide" behaviour commonly observed in fish. If a fish has been ignorant for more than 0.5 s it is forced to respond. Response to predation risk and spawning motivation is applied every time step.

2.2.2.6. Move towards bottom to spawn rule. Spawning is the simplest rule with $f_3 = 1.0$ and a unit vector (**u**₃) always pointing straight down. The strength of the acceleration response towards spawning is therefore only determined by the motivation, M_s^{Sp} , which is a function of gonad state. The initial motivation, M_s^{Op} , is a parameter explored in the simulations.

$$\mathbf{a}_3 = \mathbf{M}_{\mathrm{s}}^{\mathrm{Sp}} \mathbf{u}_3 \tag{8}$$

2.2.2.7. Avoid predation rule. Predation risk is implemented as a vertical profile following Beer's law of light attenuation by depth, d (Aksnes and Giske, 1993; Aksnes and Utne, 1997). We have set the corresponding response scaling factor, f_4 , equal to this predation risk profile:

$$f_4 = \begin{pmatrix} e^{(\kappa \times d)} & \text{for } 0 < d < D_{2/3} \\ e^{(\kappa \times d)} + \frac{d - D_{2/3}}{D - D_{2/3}} & \text{for } d \ge D_{2/3} \end{pmatrix}$$
(9)

where D is the total depth and $D_{2/3}$ is the depth at two-third of the total depth. The predation risk increases linearly up to 1.0 close to the bottom (Fig. 2). The rule determining the response to predation checks the changes in predation risk between the current depth of the fish vs. the depth of the fish one second ahead (given the velocity of the fish). The responding unit vector (\mathbf{u}_4) points straight up or down, in the same vertical direction as the fish is swimming if predation risk decreases or in the opposite vertical direction if predation risk increases. The response to predation is a function of both depth and motivation (gonad state).

$$\mathbf{a}_4 = M_{\rm s}^{\rm Pr} f_4 \mathbf{u}_4 \tag{10}$$

2.2.3. Measurements

Using a "virtual ecologist" approach, we measure and monitor a range of different parameters, mostly at the school level. One individual level parameter, 'duration of ovulation' is also recorded using the average and standard deviations for the whole population. Duration of ovulation is recorded as the ratio of ovulation time to the total simulation time (60 min), and a low ratio reflects high speed or effectiveness of moving towards the bottom to start spawning. All measurements are automatically saved to disk for later analyses during each simulation.

2.2.3.1. Monitoring of schools. Every simulated second the system is scanned in order to detect schools. A cubic grid of 208124 cells, $80 \text{ cm} \times 80 \text{ cm} \times 80 \text{ cm}$ each, covers the cylindrical volume keeping track of which fish are occupying each cell. A school is registered if a region of space contains more than five individuals within an interconnected chain of nonempty cells. Each simulated second, this algorithm compares the identified schools with the previously identified schools allowing us to track the formation of new schools and monitor the development of persistent schools. At each simulated minute, various metrics are recorded for each existing school. The total number of schools produced during a simulation is also recorded. School dynamics is monitored through the detection of different events, which can occur to a school. These events are: (1) appear, (2) split, (3) join, (4) leave and (5) merge. A school appears if more than five loose individuals not part of a school aggregate. A school splits into two new schools if >20% of the fish in the original school leave. If <20% leave, a new school forms provided that more than five fish leave, but the original school is recorded as the same school subjected to a leave event. If a school increases with <20% it experiences a merge event, else, two schools join forming a completely new school. Schools are therefore born through events of either appear, join or split. The type and frequency of events help us characterise the behaviour of the system.

2.2.3.2. School metrics. Different metrics are recorded for each school including: (1) size (number of fish), (2) vertical extension, (3) horizontal extension, (4) age, (5) standard deviation of gonad stage (mixing), (6) events.

Mixing: The standard deviation of the discrete gonad stage of the fish within a school is denoted the mixing. If all fish within a school have the same gonad stage, e.g. spent, the standard deviation is zero and there is no mixing, i.e. there is perfect sorting. The mixing parameter measured at each time step is the average of all schools present weighted by the number of individuals in each school. School shape: The school algorithm classifies each school as belonging to one of three different school shapes, determined by the ratio (μ) between the vertical and horizontal extension of the school. We have slightly modified the classification given by Axelsen et al. (2000), into the shapes: flat ($\mu \le 0.75$), ball (0.75 < $\mu \le 1.25$) and cylinder ($\mu > 1.25$).

2.2.3.3. System metrics. Measures at the level of the system include the total number of schools produced during a simulation, the frequency of small schools (<10% of population size) occurring and the number of schools present. In order to have a measure of the characteristic school size during a simulation we calculated a relative school size (S_{rel}) defined by:

$$S_{rel} = \sum_{s=0}^{N^{Sc}} S^{Sc} \times \frac{S^{Sc}}{N^2}$$
(11)

where N^{sc} is the number of schools, N population size and S^{sc} school size. If there are two equal sized schools then $S_{rel} = 0.5$. If most fish are in a large school the relative school size will be close to 1.0. For instance with $N^{sc} = 6$ and N = 1000 where five schools have size 20 and one school have size 900, $S_{rel} = 0.812$.

2.2.4. Simulation settings

We have investigated three versions of the model, of which two are preliminary versions. This was done to see the range of various system behaviours and then formulate a more general as well as simplified model when exploring the collective behaviour more systematically. The first model runs used a discrete shift in gonad state from $M_0^{\rm Sp}$ to $M_1^{\rm Sp}$ while in the final model, $M_1^{\rm Sp}$ gradually changed linearly from $M_0^{\rm Sp}$ towards $M_2^{\rm Sp}$. A second version of the model used a density dependent response factor modulating each individual's acceleration towards the bottom substrate and response to predation as a function of the number of surrounding neighbours. Lessons from the preliminary model runs are briefly reported. The final model version investigates the behaviour of the system as a function of $M_0^{\rm Sp}$ and population size (Table 2). All fixed model parameters are summarised in Table 1.

3. Results

Our results are based on a quantitative analysis of individual and school metrics as well as a qualitative evaluation of

Table 2 – Overview of simulation trials							
Simulation trial group	Parameter values explored	Number of simulations					
	N	M ₀ ^{Sp}					
1	500	0.05–0.50	100				
2	50, 100, 200, 1000, 2000, 4000, 8000	0.3	65				
3	50, 100, 200, 1000, 2000, 4000, 8000, 16000	0.05	66				

The simulations are organised into three groups or trials. The first 100 simulations explore the behaviour of the system as a function of initial spawning motivation M_0^{Sp} with the standard population size. The other two groups of simulations explore the characteristics of two different system behaviours as a function of population size.

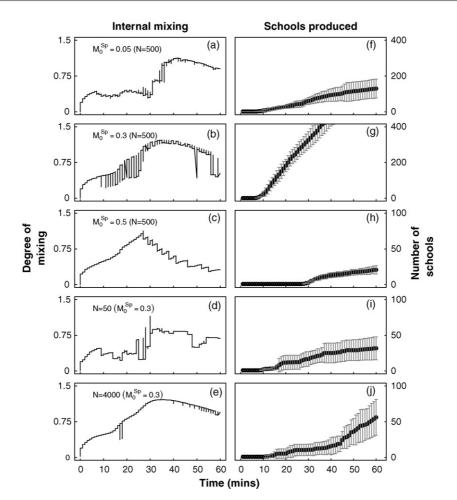


Fig. 3 – Mixing and school production (±S.D.) with five different simulation settings. The mixing refers to individual gonad maturation stage calculated as the standard deviation in each school and averaged over all the schools present weighted by school size. A value of 0 represents a school which is perfectly sorted by gonad stage. Each curve represents one typical simulation run with the given setting. The degree of mixing is measured each simulated second. School production is counted using a school detection algorithm (see text for details) scanning the system each simulated second. The mean school production over time is averaged over 10 runs. Note the differences in scaling for the number of schools produced.

overall system behaviour. The simulated system can be understood as containing three levels of behaviour; individual-(model definition), school- (emerging group) and emerging system-behaviour. Our main focuses are how variation in initial motivation for spawning ($M_0^{\rm Sp}$) and population size affect school dynamics and global system behaviour. We recognise a general trend in the global response of the system which we have chosen to classify into three different system types; split-off system System 1, dynamic connected system System 2 and integrated system System 3. Fig. 3a–c and f–h shows the mixing of schools according to gonad stage and the numbers of produced schools typical for the three systems. The characteristics of these three systems are described in the following:

o System 1: Split-off system

The system is characterised by unstable dynamics where small schools or groups of ovulating individuals split-off like droplets from a larger pre-spawning component to start spawning. The small schools are often well sorted according to gonad stage, but overall there are several smaller leaps in the mixing parameter following splits (increased sorting) and joins of schools (decreased sorting). There is generally good sorting in the first part of a run. There are frequent events of splits, joins, leaves and merges in the system. Typically there are several schools present at the same time. The pre-spawning and spawning components are separated.

o System 2: Dynamic connected system

This system is characterised by high vertical plasticity where two separate layers or components of the same school structure continuously connect and disconnect. The two components consist of spawning herring at the bottom and pre-spawners (mature) herring some meters above bottom where ovulating herring are represented in both layers and responsible for establishment of contact between the two. In the second half of the simulation, spent herring also participate in the establishment of connections, as they are motivated to move up. System 2 is identified from the sudden leaps in the sorting parameter as well as the high number of registered events and new schools due to the subsequent splitting and joining of the same group of fish (Fig. 3b and g). The pre-spawning and spawning components are dynamically connected.

o System 3: Integrated system

In this system mainly one large school is formed, persistent as one unit through the mature, ovulation and spawning phases. Then spent herring form small schools, which splitoff and leave the bottom area. Before spent herring appear, there are few or no events in this kind of system and hence no schools produced (Figs. 3h and 5). The degree of mixing is also high (Fig. 3c). The vertical extension of this system is low, indicated by the low value of the form parameter (Fig. 5). The pre-spawning and spawning components are integrated.

In the first preliminary model version where motivation for spawning changed in discrete steps we mainly found the kind of behaviour typical for System 1. In the second model version explicitly incorporating density dependency, high densitydependence drove the system towards hesitation resulting in a more integrated behaviour (System 3) and disabling very small schools to approach the bottom. System 2 appeared for lower or intermediate density dependency. Our final model version captures all three types of system behaviour, and we removed the density-dependence making our model simpler and easier to analyse. Our implementation of the school model results in certain school characteristics, which are not within the focus of our study but briefly reported in order to give readers a signature of the school behaviour for comparison with similar models and real observations. These metrics include speed $0.35 \pm 0.08 \, \text{ms}^{-1}$, average nearest neighbour distance 0.44 ± 0.14 m, average density 2.73 ± 0.97 m⁻³, average collisions per minute 0.014 ± 0.028 and degree of polarisation $89.52 \pm 40.18^{\circ}$. The values are means over all individuals averaged over 60 measurements during one simulation with N = 500 and $M_0^{\text{Sp}} = 0.05$. Density will tend to increase slightly for large population sizes.

Fig. 5 summarises the results of all simulation runs, including three groups of simulation trials. All measurements presented in Fig. 5 describe school characteristics except duration of ovulation, which is an individual level measure. Simply by varying the initial spawning motivation for the standard number of individuals, N = 500 in the first simulation trial, the three different systems reveal their characteristics through a combination of various measurements of school dynamics. Fig. 3 also shows the degree of mixing and school production characterising the three different systems.

System 3 reveals itself unmistakably for $M_0^{\text{Sp}} \ge 0.4$ by the very low number of schools emerging in the first half of the simulation (Fig. 3h), the very low number of small schools (<10%), and the high maximum age of schools (Fig. 5a). In addition schools are mainly flat shaped since the motivation and therefore depth preference are quite similar for mature, ovulating and spawning herring. Since all fish are integrated in one school until spent herring appear, the mixing in System 3 simply follows the gradual development of gonad state where the maximum is reached halfway through the simulation when all gonad stages are present (Fig. 3c). When spent herring appear, they split-off from the bottom layer forming separate schools without mixing with pre-spawners and

thereby causing distinct drops in the mixing. This increases the sorting in the second half of the simulation (Fig. 3c). For lower values of M_0^{Sp} , maturing herring await higher up in the water column mixing with spent herring through the simulation. For $M_0^{Sp} = 0.35$ the system is in a transition between System 3 and System 2, resembling System 3 in terms of number of schools in the first half and number of small schools as well as maximum school age. The total number of schools, however, is more than five times higher than for $M_0^{Sp} \ge 0.4$ and there is a significant number of cylindrical shaped schools and a high frequency of split and join (Fig. 5a). This leads us to System 2, which dominates in the small range $0.25 \le M_0^{Sp} \le 0.3$. The total number of schools emerging for these values of M_0^{Sp} is dramatically higher than for other values of M_0^{Sp} (Fig. 3g). Despite this, the number of small schools is very low, as the high school count comes from subsequent vertical splitting and rejoining of larger schools forming cylindrical structures. This is confirmed by the high number of cylindrical shaped schools (30%) for $M_0^{Sp} = 0.3$ and the fact that more than 90% of the events are splits or joins (sixth row of graphs in Fig. 5a). Most events therefore lead to new schools and Fig. 5a illustrates how the number of events is maximised around $M_0^{sp} =$ 0.3. Another consequence of this dynamics is that schools are short lived (since two schools joining create a completely new school), and we find that the mean and maximum school age values are very low. Summing up, System 2 is distinctively identified in Fig. 5a through the five graphs: total number of schools, mean/max school age, ratio of cylindrical shapes and frequency of split/join events. In addition, the dynamical contact leads to sudden leaps and subsequent drops in the mixing, characteristic only for System 2 (Fig. 3b). The main characteristic of System 1 is the unstable school dynamics where small schools or groups of fish leave the pre-spawning layer. The number of small schools within the range of System 1 $(M_0^{Sp} \le 0.2)$ is high (around 10) compared to System 2 and 3 (0-2). This relates to the number of schools present which also is high compared to System 2 and 3 (Fig. 5a, row 2). Further, due to the frequent leaving and merging of small groups of fish in System 1 where an event of merge per definition does not result in two new schools produced as is the case with split, there are more school events than the total number of schools produced (graph "Total events"). Since ovulating fish rapidly split-off from the pre-spawning layer the sorting in the first half of the simulation is very good in System 1 (Fig. 3a).

We are particularly interested in the characteristics of System 2 since the school structures emerging here display interesting similarities with observations in the field. Our second simulation trial therefore varies population size with initial spawning motivation fixed at $M_0^{\text{Sp}} = 0.3$ (Fig. 5b). For small population sizes (N < 200) there is a tendency that the two school components (lower spawning layer and upper layer) are not able to establish vertical contact like they are with N = 500. This results in several small schools present at the same time. The System 2 type of behaviour, where two school components continuously connect and disconnect in the vertical therefore vanishes for small population sizes. The low population size, however, results in less horizontal extension and thus frequent occurrences of short and long cylinders as ovulating herring stretch the pre-spawning school down-

ward. In Fig. 6 this is evident from the high height-to-area ratio. Due to the low population size, most school events are also split and join. In simulation trial two, the dynamic connected system behaviour characterising System 2 appears for intermediate population sizes ($200 \le N \le 2000$) and is at a peak for N = 500 and N = 1000 (Fig. 5b). For N = 500 the average number of schools present (1.62) tells us that there are more often two schools than one, while for N = 1000 there is more often one connected school (1.34). In both cases there is an extensive dynamic contact where about 90% of school events are split and join (Fig. 5b). Notably, for N = 1000, small schools (<10%) are completely absent, i.e. we mostly have two major school components connecting and disconnecting. For $N \ge 2000$ the system becomes more permanently connected for long periods of time, pushing the average number of schools present down towards 1.0 (Fig. 5b). The total number of schools emerging drops accordingly. For N = 4000 we therefore have mainly one school present (1.05) connecting the system completely for long periods of time, resembling System 3 behaviour. The relative school size is consequently close to 1.0. In Fig. 4a this is illustrated through barely any school production in the time

period between 10-40 min for N = 4000. The cylindrical school

shape typical for System 2 for N = 500 is also largely replaced by one flattened school. The flat shapes we see with high N's

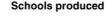
emerge as a response to the narrow vertical area of low preda-

tion defined by the predation profile (Fig. 2). With an increasing

population size the fish will squeeze out horizontally within

the preferred low-predation belt (Fig. 6). For the even larger population size of N = 8000 an even more connected system may be expected, but in fact the system is less connected producing more schools than for N = 4000 (Fig. 4a). This is directly related to the horizontal expansion of the pre-spawning layer. Larger population sizes lead to a new and unexpected kind of parallel system behaviour that shows up even more pronounced in the third simulation trial.

Our third simulation trial investigated how the most apparent System 1 configuration ($M_0^{\rm Sp}=0.05)$ would respond to changing population size (Fig. 5c). Our expectations were that by simply increasing the population size, we could move the system from System 1 towards a dynamic connected system (System 2) and further towards an integrated system (System 3). We were partly wrong in this assumption. For these simulations there is a systematic increase in number of schools emerging, schools present and school events as a function of population size (Figs. 4b and 5c). The frequency of cylindrical shaped schools is also relatively high. There is always a direct connection between the number of schools present and the number of small schools. These measures increase for larger population sizes as opposed to the second simulation trial ($M_0^{Sp} = 0.3$), where they almost vanished. What does this imply? Instead of moving towards a dynamic connected system, larger population sizes create parallel dynamics where small schools leave the upper layer from different locations simultaneously. For N = 4000 there are more than five schools



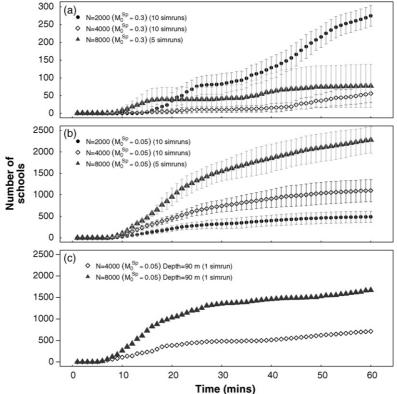


Fig. 4 – School production for simulation runs with high population numbers (N \ge 2000). Parts (a) and (b) show the school production from simulation settings with medium and low initial motivation towards spawning ($M_0^{\text{Sp}} = 0.3$ and $M_0^{\text{Sp}} = 0.05$), whereas (c) shows results from runs with low initial spawning motivation using a system depth of 90 m as compared to the standard depth of 30 m. Note the different scaling in (a).

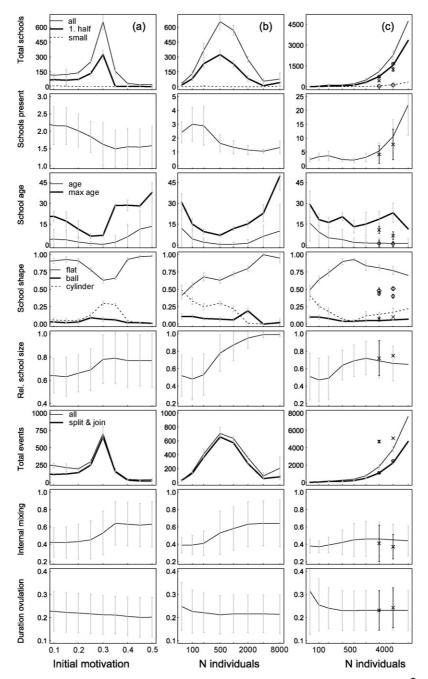


Fig. 5 – Results from all the simulation runs. (a) Simulation trial 1 (N = 500), (b) simulation trial 2 ($M_0^{Sp} = 0.3$) and (c) simulation trial 3 ($M_0^{Sp} = 0.05$). Each mean value represents an average of 10 simulation runs. 'Total schools' counts the schools emerging during the whole simulation run, '1.half' only the first 30 min, and '<10%' number of schools containing fewer than 10% of total fish population if $N \le 500$, and fewer than 50 individuals if N > 500. 'Schools present' denote the mean number of schools simultaneously present, counting each minute. 'School age' is the unweighted age average (in minutes) for a simulation run. 'School shape' is the number of the three different school shapes relative to the total number of schools. 'Rel. school size' has a value of 1 if one school compromises the whole population (further described in Section 2.2.3.3). 'Internal mixing' is the mixing of individual gonad maturation stages within a school with 0 being 100% identical maturation stages. 'Split & join' is the ratio between the sum of the events 'join' and 'split' and the total number of events. In the last row of graphs two simulation trials with a different system depth of 90 m is included for 4000 and 8000 individuals. These are indicated with cross marks, and circles ('split & join', 'ball' shape, 'max age' and '1.half') and diamonds ('cylinder' shape and total number of 'small' schools). In the one simulation trial with $N = 16\,000$ only two simulations were performed. Some measures including 'Schools present', 'School age' and 'Internal mixing' use the mean standard deviation from the 10 runs. In 'Duration ovulation' the standard deviation is across the population from the 10 runs.

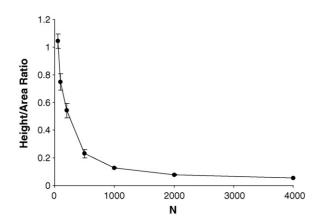


Fig. 6 – Mean ratio \pm S.D. between school height (m) and cross-section school area (m²) as a function of population size (N) with medium initial spawning motivation ($M_0^{Sp} = 0.3$). School area is given as $1/4 \times W \times L \times \pi$, where W and L are the horizontal width and length of the school measured from above. The mean represents an average for a whole simulation run with samples taken every minute.

simultaneously present on average. These schools must consist of one or two large schools and several small schools because the relative school size is still high (0.69, Fig. 5c). If all schools were of similar size, the relative school size would be around 0.2! But there are also indications that the upper and bottom layer may be connected from time to time because the average school age is not very high for $N \ge 2000$ indicating periodical contact (Fig. 5c). The high values of maximum school age are caused by the isolation of some small schools not merging with the major layers. In general, high school ages imply either isolation of schools or tight integration (System 3). Another effect of the parallel dynamics is the increasing portion of cylindrical shaped schools due to the schools forming vertical bridges between layers (Fig. 5c). By plotting the 3D spatial distribution we can clearly see how such a system is parallel dynamically connected (Fig. 7e). This is as if a System 2 kind of behaviour occurred simultaneously at different locations. We ran two simulation with 16 000 fish pushing our computational limits, to see if the system finally approached System 2 or 3 behaviour. The outcome was rather an even more parallel system, doubling the number of schools produced, small schools and schools present (Fig. 5c).

The increasing horizontal extension of the pre- and post spawning layers emerging for larger population sizes, both in the second, but especially in the third simulation trial, relates to the combination of system depth and the applied predation profile. Fig. 6 illustrates this flattening of schools as a function of population size. The narrow zone with low predation risk at 2/3 depth expands for larger system depths (Fig. 2). For comparison we therefore included further simulation trials with extended system depths and large population sizes. The extra measurements included in Fig. 5c represent these simulations for 90 m system depth. The number of schools produced was similar to the third simulation trial for large N (Fig. 4b and c), but these simulations with extended depths revealed even new surprising system behaviours in terms of vertical dynamics (Fig. 7d). Instead of making contact between pre-spawning and spawning layers even more rare with the distance between layers extended to 30 m instead of 10 m, the opposite was the case. Interestingly, the system initially behaves as System 1, but as ovulating herring become abundant, one large cylinder connecting the two layers establishes. This hourglass morphology is amplified by herring entering the spent stage and kept for several thousand time steps throughout the simulation (Fig. 7d).

As a measure of spawning performance, the duration of ovulation is included as a measure in the last row of graphs in Fig. 5. When post spawners are situated closer to the bottom (System 3) the duration of the ovulation is markedly reduced. In the second and third simulation trials we are able to see the effects of population size on the proportion of time spent during ovulation. In general, low population sizes (N \leq 200) perform badly as fish spend more time in the ovulating phase. Larger population sizes tend to increase performance until a certain level is reached for N \geq 1000. The effect of population size is thus important.

4. Discussion

In this study we have demonstrated interesting characteristics in overall system behaviour relevant for understanding the dynamics of spawning herring schools by using a relatively simple individual based school model incorporating response to predation and spawning. Simply by varying the population size and the difference in trade-off between spawning and predation in pre-spawning and spawning herring, we learn three main lessons: First, the behavioural synchronisation of herring with different gonad states is likely to determine whether or to what degree schools will split and sort into separate units or remain unified. Second, the population size or school size has a significant influence on the emerging school structures and dynamics. There are new levels of organisation emerging for large population sizes (N \ge 1000) not present with low population sizes (N \leq 200). Third, emergent properties including sorting of individuals with similar gonad states into separate schools or layers, or the establishment of dynamic large-scale structures do not require explicit coding in the model. Even in a simplified model system, complex group behaviour emerges.

Our concept of motivational synchronisation relates to the motivational difference between pre-spawners and spawners in the trade-off between spawning and predation. One may speculate why the physiological gonad states of herring entering the spawning ground are not perfectly synchronised in the first place to prevent the motivational conflict between pre-spawners and spawners. Having in mind that all natural systems contain variation and taking into account that the building up of gonads takes about 6 months (Iles, 1984), a variation of a few days in timing should be expected. Field observations indicate that spawning in herring takes between one (Johannessen, 1986) and several (Axelsen et al., 2000; Skaret et al., 2003) days, probably reflecting the variation in gonad stage. In addition there are different age groups entering the spawning site at different times (Slotte et al., 2000). Given that there are differences in gonad state in the system, behavioural synchronisation between pre-spawners, ovulating and spawning herring (high values of M_0^{Sp}) leading to

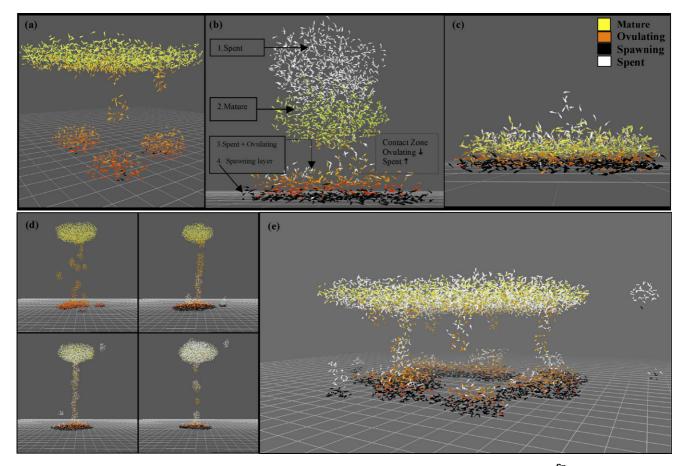


Fig. 7 – Illustration of different system behaviours. (a) Split-off system (system 1) with N = 2000 and $M_0^{Sp} = 0.05$ with five schools present. (b) Dynamic connected system (System 2) with N = 2000 and $M_0^{Sp} = 0.3$. (c) Integrated system (system 3) with N = 2000 and $M_0^{Sp} = 0.5$. In (b) four different layers are indicated emphasizing the rich vertical structures emerging in System 2. In the contact zone ovulating herring are moving down, connecting with spent herring moving up. (d) Emergent system behavior for extended system depth, D = 90 m, for N = 4000 and $M_0^{Sp} = 0.05$. The four frames (top left, top right, lower left and lower right) represent different times in the simulation at 16, 26, 36 and 48 min, respectively. (e) Parallel dynamics emerging for large population sizes and low behavioral synchronisation, $M_0^{Sp} = 0.05$ and N = 8000. This illustrates the horizontal extension of the pre-spawning layer occurring for larger population sizes. Ten different schools are present, but most are small while vertical bridges connect the pre-spawning layer with the spawning layer into one connected school. The vertical connections are established by ovulating and spent herring moving in opposite directions across the bridges. Color indications: Mature herring (yellow), ovulating herring (orange to read), spawning herring (black) and spent herring (white).

one integrated school may still seem an optimal solution. However, in this scenario mature herring, still not ready for ovulation have to spend much time in the high-risk predation zone close to the bottom. On the other hand, with low degree of synchronisation our simulations predict separation between pre-spawners and ovulating herring. This may not either be desirable, as mature herring about to switch into ovulation, would benefit from having contact with the spawning layer. An intermediate scenario where the herring compromise their motivation with the behaviour of the school might be the most favourable in an evolutionary context. In the most comprehensive field study concerning schooling behaviour of spawning herring, extensive vertical structures connecting a pelagic and a demersal component were observed during several days (Axelsen et al., 2000). A collective strategy of "await in the pelagic" was suggested, with pre- and post-spawners residing higher up in the water column with assumed less predation pressure, without losing contact with the spawning component. One large school containing 15-20 000 individuals was followed through a 5-day period and vertical structures with explicit contact were observed the first two days and the fourth day, while during the third day there was a partial vertical split into two components (Axelsen et al., 2000). We find it particularly interesting that our simulations demonstrate that with a moderate behavioural synchronisation between pre-spawners and spawners ($M_0^{\rm Sp}\sim 0.3$) the system behaviour displays clear similarities with the observations in the field: one school splits into two components or layers keeping a dynamic vertical contact. Acoustic recordings from such vertical structures in the field are given in Fig. 8. Our results suggest that such structures are able to emerge as a result of collective behaviour without the need for individual fish to be aware of the larger school structure, a possible second school component, the state of neighbouring

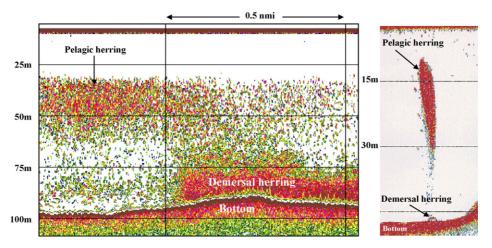


Fig. 8 – Left: Layers of herring and vertical split from main spawning area off Møre, Western Norway. Right: Cylinder shaped and vertically split single school from spawning area (Axelsen et al., 2000).

fish or to execute any "strategy" regarding preferable school behaviour.

Simulation studies on schooling fish have typically used a few fish (10-100) to simulate the principal mechanisms leading to schooling (Aoki, 1982; Huth and Wissel, 1992, 1994; Inada, 2001; Inada and Kawachi, 2002; Parrish et al., 2002). The results presented in such studies mainly focus on measures like nearest neighbour distance, cohesion and polarisation, which are possible to compare to laboratory studies where similar numbers of fish are used (Huth and Wissel, 1994). Some studies investigate variations in collective behaviour for different model settings (Couzin et al., 2002) and varying population size (2-128 fish) (Viscido et al., 2005). We are interested in the understanding of emergent school structures for large number of individuals in an ecological context. In our simulations, we find entirely new kinds of system behaviour emerging for very large population sizes. This strongly suggests that in large aggregations like spawning herring there are collective effects, which impossibly can emerge in a simulation of 100 individuals or in a small laboratory. This is a highly important recognition. The number of individuals is by itself an essential factor determining the behaviour of the system as a whole. The parallel dynamics emerging in our third simulation trial with large population sizes demonstrates this principle. A group of 100 fish with the same trade-off and behavioural rules obviously cannot generate such dynamic spatial structures. There are additional implications of these large-scale structures. An important recognition of pattern formations involving social aggregations is that the nonlinearity inherent in such interactive systems couples various scales together (Flierl et al., 1999). This means that not only does small-scale behaviour shape large-scale patterns but large-scale structures also influence individual behaviour (top-down). The establishment of vertical bridges between layers enables ovulating herring to climb down across the vertical structure and spent herring to climb up without waiting for a separate small school to form. Individual behaviour is in this way influenced by the large-scale structure, and importantly their influenced behaviour represents

a positive feedback maintaining the existing structure. Similar positive feedback mechanisms are well-known features of self-organised social systems, for instance the lane formations in ants maintained by attractive pheromones deposition in the track (Deneubourg et al., 1989). Such systems can be thought of as having a collective response adapted to the environmental conditions, executed by interacting individuals.

It is important to emphasize that the influence of the environment is an essential aspect contributing in forming the complex school structures we see for large population sizes. When fish in a school only interact with neighbouring fish, principal characteristics of schooling may very well be revealed through laboratory studies or simulation studies using a few fish. It is the environment (the predation profile) acting on individuals with different spawning-predation trade-offs, which set the conditions in which new system behaviours can emerge for larger population sizes. With no environmental influences our simulations would produce spherical shaped schools regardless of population size. This role of the environment for pattern formation in selforganised social systems is well recognised in other fields of biology (Camazine et al., 2001). Our last additional simulation trials with the extended system depth of 90m demonstrate dramatic effect on the collective response of the system. Even if the motivational synchronisation is the same as in the third simulation trial, the extended cylinder depth (90 m) gives a broader low-risk predation zone around 60 m allowing for more spherical shaped schools, which effectively reduces the parallel dynamics seen in simulation trial three. With the extended system depth the pre-spawning and spawning layers are 30 m apart instead of 10 m, apparently making contact even more difficult given the same population size. To our surprise, the system instead emerged into forming one major cylindrical bridge across the 30 m depth, first consisting of ovulating herring, then amplified by spent herring 'climbing' the bridge upwards. Interestingly this "super cylinder" emerges as a response to the combination of population size, motivational synchronisation and environmental constraints without changing individual level behavioural rules.

Population size also affects the spawning performance in our simulations. This is clearly seen in the second and third simulation trials. Small schools are more unstable leading to separation in the horizontal plane further disabling contact. Since the switching from ovulation to spawning explicitly is coded to have a higher probability if the nearest neighbour is already spawning, fish in larger schools will have a higher probability of switching from ovulation to spawning. This is because a larger school of ovulating herring after a given time will contain more spawners than a small school. There is a domino effect, and the result is higher throughput or shorter duration of ovulation (Fig. 5c).

Most simulation studies assume that all individuals are identical. When individuals are defined with different values of the rule parameters, simulation studies have shown that this produces sorting (Romey, 1996; Couzin et al., 2002). This complies with empirical studies showing that fish schools tend to be assorted by phenotypes including body length, species, parasite load and body color (Hoare and Krause, 2003). Fish within schools also tend to be close to others of similar size (Pitcher et al., 1986; Parrish, 1989), or in multi-species groups to conspecifics (Parrish, 1989). If variation in phenotypes is correlated with variation in behaviour, self sorting mechanisms have been suggested to explain the observed segregations (Couzin and Krause, 2003). These authors also demonstrated this self-organization principle using a simulation model. The important discovery is that variation in behaviour between individuals can produce sorting without explicitly encoding complex recognition and decision-making capabilities (Couzin and Krause, 2003). The results of our simulation trials support this conclusion. Our model fish are neither able to observe or respond to the gonad state of local neighbours (except the nearest neighbour for ovulating herring being within 1m from the bottom). The repulsion and attraction rules working between individuals are ignorant to the state of neighbouring fish. They only respond to the neighbour's position. Still, schools tend to be sorted by gonad state when they split. In addition, larger schools containing fish in various stages tend to be segregated into different vertical sections or layers. We have not explicitly quantified this vertical segregation within a school or layer, but it can be seen from the position plots (Fig. 7). Whenever sorting is emergent, it is essential that it is the difference in behaviour that produces sorting, whether this is imposed by variation in phenotypes or by motivation as in our case.

The spawning behaviour of herring is a vertical migration problem with strong collective behavioural aspects. Several different modeling approaches have been used to address vertical migration in fish including stochastic dynamic programming (Mangel and Clark, 1988; Rosland and Giske, 1994, 1997) and IBMs (Strand et al., 2002; Grimm and Railsback, 2005). The IBMs focusing on vertical migration typically look at vertical migration as a trade-off between foraging and light dependent predation risk. As in our model, vertical positioning strategy is both influenced by the internal states and the environment, but internal states are often related to stomach fullness and individuals act independently of each other (Rosland and Giske, 1994, 1997). Some models also use the swimbladder volume as an internal state and incorporate bioenergetic costs associated with negative buoyancy (Strand et al., 2005; Strand and Huse, 2007). Other approaches incorporate adaptation where generations of individuals are evolved to learn how to combine internal states with changing environmental factors using neural networks and genetic algorithms (Giske et al., 1998; Huse et al., 1999). To our knowledge, no IBM's where collective behaviour like schooling is included have been used to study trade-off situations in an ecological context and the process of spawning has hardly been studied using IBMs at all. A couple of IBM's where schooling individuals have different motivation or information have been used to study collective decision processes (Huse et al., 2002; Couzin et al., 2005) but then without environment or trade-offs incorporated.

Our school model is defined relatively simple without explicitly including velocity matching as several basic school models do (Huth and Wissel, 1992; Couzin et al., 2002). This could be criticised. On the other hand, some studies do insist on leaving out explicit velocity matching in the formulation of a school model (Parrish et al., 2002; Viscido et al., 2005). With a minimal school model we were able to incorporate spawning and predation and explore system behaviour in parameter space within reasonable computational effort. We have used a high temporal resolution of 0.1s in our model, which is essential in order to include individual interactions within a school properly. This sets computational limits to the total time period we can simulate for large population sizes. The physiological process of gonad state development has therefore been speeded up accordingly, enabling it to change from mature to spent within one simulated hour. The process is still slow compared to the temporal scale determining changes in the spatial distributions and vertical dynamics, e.g. a 30 cm fish moving at 1BLs⁻¹ would be able to move 30 m vertically in a water column a hundred times during 1h. Since our focus is how school patterns emerge through variations in motivation and population size we find the choice of simulation time justified. Our modelled herring and spawning area also represent other simplifications of the real world and we deliberately ignore some factors that can influence schooling dynamics during spawning. Diel patterns in schooling have been observed in a range of field studies from the spawning area (Brawn, 1960; Johannessen et al., 1995; Slotte, 1998; Skaret et al., 2003) probably as a result of the visibility influencing both schooling flexibility and predation pressure from visual predators. In our model we assume a permanent daytime situation. There is no distinction between sexes in our model even though there well may be differences in the spawning behaviour between males and females. In an ancient publication by Ewart (1884) sexual dimorphism in Atlantic herring is described with only the females touching the spawning substrate, but identical behaviour for both gender was observed in Pacific herring (Stacey and Hourston, 1982). We also acknowledge other factors that may influence the spawning behaviour and schooling dynamics such as fish length, swimming abilities and visual range as well as environmental influences of temperature (Flierl et al., 1999), oxygen (Domenici et al., 2000) and current. Sensitivity analyses for these and other factors would have been appropriate, but outside the scope and capacity of this work.

As a conclusive remark, our main results are indeed relevant for NSS-herring, but also provide new insight into possible mechanisms behind collective behaviour in fish schools in a more general sense. Cases of conflicting motivations within groups of social animals are not extraordinary and we show that they may not only initiate and maintain collective formations, but also that the formations may exhibit properties rendering them adaptive behaviours in nature. This is important for a deeper understanding of the morphology of schools (Gerlotto and Paramo, 2003). We further argue that the ability to simulate large population sizes when modelling fish schools is imperative when investigating the mechanisms behind large collective formations and school morphology as observed in nature. With large populations we show that even minor changes to our relatively simple model system are enough to reveal the plasticity in school morphology and how it is dependent on individual motivation and surrounding environment. School morphology changed from a pure hourglass formation to a system with parallel dynamics merely through indirectly decreasing the range of preferred distribution depth for single fish. In an ecological context similar mechanisms may be relevant for schools of fish in any motivational conflicting situation where the preferred vertical position is changing due to varying environmental factors.

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